Doctoral Thesis

Generic Risk Assessment for Fire Safety

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GENERIC RISK ASSESSMENT FOR FIRE SAFETY –
PERFORMANCE EVALUATION AND OPTIMISATION OF DESIGN PROVISIONS

A thesis submitted to attain the degree of
DOCTOR OF SCIENCES of ETH ZURICH
(Dr. sc. ETH Zurich)

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Abstract

Decisions concerning investments into fire safety should not only focus on the reduction of the consequences, but also on the costs of fire safety measures. Accordingly, a balanced ratio between costs and consequences should be aspired, not only at object but also at societal level. The latter concerns especially regulatory agencies, which set fire safety provisions for society, and influence building construction practice. Such optimal fire safety solutions may be considered as outcome of a rational decision-problem.

The goal of this thesis is to demonstrate the benefits of generic fire risk assessment as a practical tool to face decision-problems and to provide the basis to improve fire safety provisions for society. This applies for prescriptive as well as for performance-based fire safety code provisions. The performance of such safety provisions is evaluated under realistic conditions by a probabilistic approach, in order to consider the inherent randomness of fire events and the incomplete knowledge on the system. Probabilistic models are derived for basic variables that are used to represent realistic fire conditions, e.g. describing either the fire exposure, the interaction of fire safety measures with the fire, or the model uncertainties. A generic risk model can be used to evaluate the consequences at object level and aggregate them over the building portfolio, in order to estimate the expected consequences at societal level. Assessing the risk at portfolio level allows, on one hand, to validate and to calibrate the model to observed consequences, which are usually collected at portfolio level as well. On the other hand, the risk reduction of fire safety measures can be evaluated and provide the basis for rational decision-making. Different strategies for decision-making can be followed and are discussed within the application of the framework for generic risk assessment.

One strategy, followed mainly by fire authorities, is to demand the same level of safety of alternative fire safety solutions as standard fire safety solutions, which is not explicitly defined. A reliability-based approach is used to evaluate the level of safety of current prescriptive and performance-based design provisions for steel structures under realistic fire conditions. The level of safety between different design approaches can be compared and the equivalence of a sprinkler concept to a standard structural design concept can be demonstrated.

The LQI (Life Quality Index) acceptance criterion is used as another decision strategy and is a risk-based efficiency criterion to derive the optimal allocation of societal resources for life safety. The criterion is applied to optimise the minimal required door width for retail buildings as part of the means of egress. The risk is assessed by probabilistic engineering models that represent the fire as well as the evacuation situation.

Monetary optimisation of decision alternatives can be performed if the acceptability regarding life safety – as evaluated by the LQI acceptance criterion – is fulfilled. A generic risk model is developed based on an engineering-driven approach to model the financial consequences of a fire in single family houses. The model is calibrated at portfolio level to data, in order to reduce the bias associated with the engineering models. The generic risk model is used to judge the cost efficiency of home smoke alarms for single family houses.
Zusammenfassung


Das LQI (Life Quality Index) Akzeptanzkriterium ist eine andere Strategie und basiert auf einer Effizienzbetrachtung, die es ermöglicht Investitionen von gesellschaftlichen Ressourcen für den Personensicherheit zu optimieren. Das Kriterium wird zur Optimierung der minimalen erforderlichen Türbreite angewandt als Teil der Fluchtwegbestimmungen für Verkaufsgeschäfte. Das Risiko wird anhand eines probabilistischen Ingenieurmodells berechnet, das sowohl die Brandeinwirkung als auch die Evakuierung berücksichtigt.

# Contents

## 1 Introduction

1.1 State-of-the-art ...................................................... 2  
   1.1.1 Decision-making in safety engineering ......................... 2  
   1.1.2 Fire risk assessment ........................................... 3  
   1.1.3 Techniques for uncertainty treatment in probabilistic models ........................................... 5  
1.2 Objective of the thesis .............................................. 7  
1.3 Outline of the thesis ................................................ 7  

## 2 Principles of fire safety design ........................................ 9  

2.1 Prescriptive design .................................................. 9  
   2.1.1 Comparison of structural fire safety requirements in Europe ........................................... 10  
   2.1.2 Alternative prescriptive design solutions ............................ 10  
2.2 Performance-based design ............................................ 11  
   2.2.1 Design objectives ................................................ 11  
   2.2.2 Performance level ............................................... 12  
   2.2.3 Design methodology ............................................. 13  

## 3 Probabilistic risk assessment and decision-making ..................... 15  

3.1 Generic risk assessment ............................................. 15  
   3.1.1 Definition of risk ................................................ 15  
   3.1.2 System representation ............................................ 16  
   3.1.3 Risk indicators and model parameters ........................................... 18  
   3.1.4 Risk reduction measures ........................................ 20  
3.2 Risk equivalence .................................................... 21  
3.3 Risk-based decision-making ......................................... 21  
   3.3.1 Acceptability regarding life safety ........................................... 22  
   3.3.2 Monetary optimisation ............................................ 23  
3.4 Absolute risk assessment and model bias ..................................... 24  
   3.4.1 Bias resulting from empirical models ........................................... 24  
   3.4.2 Bias resulting from engineering models ............................ 25
CONTENTS

3.4.3 Assessing and reducing the model bias ......................................................... 25

4 Probabilistic representation of the fire exposure ................................................. 29
  4.1 Fire ignition ................................................................................................. 30
  4.2 Heat release rate ......................................................................................... 31
    4.2.1 Mass loss rate ..................................................................................... 32
    4.2.2 Heat of combustion ............................................................................. 33
    4.2.3 Combustion efficiency ......................................................................... 34
    4.2.4 Maximum heat release rate .................................................................. 34
    4.2.5 Fire load density .................................................................................. 34
  4.3 Pre-flashover compartment fire ..................................................................... 37
  4.4 Flashover ..................................................................................................... 40
  4.5 Post-flashover compartment fire ................................................................... 40
    4.5.1 Fuel-controlled regime ........................................................................ 40
    4.5.2 Ventilation-controlled regime ............................................................... 41
    4.5.3 Ventilation conditions .......................................................................... 41
    4.5.4 Decay stage ........................................................................................ 42
  4.6 Mathematical models for compartment fires ............................................... 43
    4.6.1 Standard fire curves ............................................................................ 43
    4.6.2 Parametric fire curves ......................................................................... 44
    4.6.3 Zone models ....................................................................................... 44
  4.7 Correlation between fire parameters ............................................................. 47

5 Performance of fire safety measures under realistic fire conditions .................... 49
  5.1 Passive fire protection .................................................................................. 50
    5.1.1 Thermal exposure of the element ......................................................... 51
    5.1.2 Thermal resistance of an element ....................................................... 52
    5.1.3 Mechanical properties ........................................................................ 53
    5.1.4 Mechanical loads in a fire .................................................................... 53
  5.2 First-aid measures ........................................................................................ 54
  5.3 Fire brigade intervention time ....................................................................... 55
    5.3.1 Notification time ................................................................................ 56
    5.3.2 Response time .................................................................................... 58
    5.3.3 Set-up time ........................................................................................ 61
  5.4 Rescue and fire suppression by the fire brigade .......................................... 62
    5.4.1 Rescue activities ................................................................................ 62
    5.4.2 Fire suppression by the fire brigade .................................................... 63
  5.5 Fire detection devices and systems ................................................................. 65
    5.5.1 Systems with alarm transmission ......................................................... 66
    5.5.2 Systems without alarm transmission .................................................. 66
  5.6 Sprinklers ..................................................................................................... 69
## 8 Generic fire risk model facilitating calibration

### 8.1 Modelling the fire damage in single family houses
- **8.1.1 Fire ignition**
- **8.1.2 Consequence model and damage states**
- **8.1.3 Fire loss in the room of fire origin - minor loss model**
- **8.1.4 Fire spread beyond room of fire origin - major loss model**
- **8.1.5 Fire brigade model - major loss model**

### 8.2 Calibration of the generic risk model

### 8.3 Application of the generic risk model
- **8.3.1 Application of the generic risk model at object level**
- **8.3.2 Judging the cost-efficiency of home smoke alarms**

### 8.4 Conclusions

## 9 Conclusions, discussions and outlook

### 9.1 Conclusions

### 9.2 Relevance for fire safety science

### 9.3 Relevance for fire safety engineering practice

### 9.4 Towards a risk-optimised fire safety code format

### 9.5 Data requirements

### 9.6 Limitations

### 9.7 Outlook and further research possibilities

## A Probabilities and random variables

### A.1 Notation

### A.2 Probability distributions

## B Polynomial chaos expansion and global sensitivity analysis

### B.1 Polynomial chaos expansion

### B.2 Global sensitivity analysis

## C Parameters to assess the risk to life

## Bibliography
Chapter 1

Introduction

The aim of fire safety is to reduce the consequences in case of a fire, i.e. human and financial losses, as much as reasonably possible. Fire safety measures reduce these consequences and can be regarded as decision alternatives for a decision-maker, e.g. an individual or also a regulatory agency which is located at societal level. These measures are not free of charge and allocate societal resources, e.g. costs, materials or public space, that arise either during the construction, the life-time or the use of a building. Therefore, from an economical point of view a complete reduction of the consequences by implementing all possible fire safety measures is not desirable for a decision-maker. Instead, a balanced ratio between consequences and costs should be aspired. This is especially true for regulatory agencies or authorities, which set fire safety provisions for society and have to justify the associated investments into fire safety and their social and economic consequences. In this context, providing fire safety provisions that optimise costs and consequences of safety measures can be regarded as outcome of a rational decision-problem. In addition, investments into life safety should not be considered in isolation to fire safety but more in a holistic way, including different hazards and threats to human life, aiming at the maximal possible risk reduction that a society is willing to pay for.

To achieve such a balanced ratio between consequences and costs by a rational decision-making framework, the costs and the corresponding risk reduction of measures have to be quantified. The risk may be understood as the quantification of the expected consequences due to a fire, e.g. in terms of human or financial losses. The consequences of a fire are always associated with uncertainties due to the inherent randomness of fire events and due to incomplete knowledge of the system, e.g. a building. Therefore, decisions have always to be made under uncertainty. To account this uncertainty and to support decision-making, probabilistic risk assessment is applied successfully in many engineering fields. The overall goal of risks models is the quantification of the impact of safety measures on the expected consequences, e.g. to quantify the associated risk reduction. Such a risk-based performance evaluation of safety measures is useful for both, individual and societal decision-makers. For regulatory authorities, as a societal decision-maker, it is essential to estimate the effect of code provisions on society, especially when these provisions are changed. To assess the risk for a portfolio of buildings, a generic risk model can be used, which is applicable – without any further model modification –
to any building within a portfolio. This makes generic risk modelling particularly useful for portfolio risk assessment and societal decision-making (JCSS, 2008) and provides the basis to optimise fire safety provisions for society and finally leads to risk-optimised fire safety provisions including prescriptive and performance-based design approaches. Since generic risk models are based on a probabilistic assessment of the consequences depending on various (uncertain) parameters, they are also useful to identify the most influencing parameters on the risk and the influence of the associated uncertainty. This is especially useful for fire safety engineering, where a design format may be chosen in order to especially consider the most influencing parameters and, in contrast, to neglect parameters whose influence is small. The latter may be useful to simplify code formats and simplify the application of fire safety engineering methods, e.g. within a performance-based design approach.

Risk models aim to represent the consequences in reality and are subjected themselves to uncertainty, since the representation of reality – by engineering or empirical models – is associated with incomplete knowledge. This gap between prediction and reality is a bias that leads to difficulties when costs and consequences are compared. A generic approach for risk assessment provides the basis for validation and calibration of probabilistic risk models to loss data and leads to a quantification or even a reduction of this bias.

1.1 State-of-the-art

1.1.1 Decision-making in safety engineering

As already mentioned, a balanced ratio between consequences and costs should be aspired when implementing fire safety measures. A decision-maker has the choice between different decision alternatives and may choose one according to its preferences. Von Neumann & Morgenstern (1944) introduced the basic rules for rational decision-making to represent the decision-maker’s preferences for a set of investments and to find the optimal decision, in order to maximise the utility for the decision-maker. Due to the inherent randomness of the fire event and the incomplete knowledge of the underlying phenomena the decisions are associated with uncertainties. Raiffa & Schlaifer (1961) extended these decision-rules to consider uncertainties related with the decision process, introducing the expected utility theory. In this context, risk models can be used to derive the expected utility of decision-alternatives.

The monetary optimisation of decision-alternatives in fire safety engineering has been performed from early on, e.g. performing cost-benefit analysis (see Shpilberg & Neufville, 1974), and is broadly accepted in engineering practice (see Ramachandran, 1998). In contrast, optimisation of decision-alternatives regarding life safety is more controversial, since it involves the comparison of monetary investments into life safety with the reduction of the risk to life. Since human life is of immeasurable value, there is a clear ethical dilemma to decide how much of our limited societal resources should be invested in life saving measures and different approaches exist to deal with this dilemma (see Fischer, 2014).
One of the most accepted approaches in economics literature, in accordance with the maximal utility theory, is the Willingness To Pay (WTP) approach. The concept refers to the amount of money that an individual is willing to invest for a marginal increase of safety or a marginal reduction of the risk. This approach avoids the assignment of a value to a human life and aims to find the decision-alternative, which reduces the risk in a most efficient way. Nathwani et al. (1997) introduced the Life Quality Index (LQI) as an indicator to reflect the expected length of life in good health and wealth, in order to quantify the Societal Willingness To Pay (SWTP). The SWTP can be used to judge the efficiency of safety measure on individual but also on societal level (e.g. for code provisions). The LQI principle is a central component of the guideline for risk assessment provided by the Joint Committee of Structural Safety (JCSS, 2008) and is applied in fire safety engineering so far by Hasofer & Thomas (2008) and by Fischer (2014). Fischer (2014) formulated guidelines to apply these decision-making principles to fire safety engineering, especially concerning the interaction between monetary optimisation and societal risk acceptance for life safety measures. These decision-making principles compare the investment costs with the risk reduction of safety measures in absolute terms. Therefore, the bias associated with both the costs and the risk estimation, should be reduced as much as possible and coincide with the real expectations.

1.1.2 Fire risk assessment

Risk in fire safety engineering is currently assessed by different methods. Risk assessment methods may be subdivided in four categories (see Watts & Hall, 2002):

- checklists
- narrative methods
- indexing methods
- probabilistic methods

A checklist is a practical tool, especially for persons without a strong background in fire safety engineering, to identify potential hazards and perform some actions, if necessary. Narrative methods provide recommendations to manage fire hazards and represent the experience gained from past fire events. Both, checklists and narrative methods, are non-quantitative approaches and are implemented usually in prescriptive codes, e.g. VKF 1-03 (2003) or NFPA 101 (2006). These safety measures do not evaluate the fire risk quantitatively and may not capture entirely the interaction of factors that affects the risk (Watts & Hall, 2002).

Indexing methods, e.g. the Gretener method that is implemented in VKF 115-03 (2003), provide a quantitative method to assess the risk relative to a standard solution (see Watts, 2002 for details). Weights are assigned to fire safety measures and to risk factors, e.g. building characteristics and the potential hazards, to derive a risk index. This risk index can be used to compare decision alternatives, e.g. different fire safety measure, and to demonstrate code equivalence. The method has a subjective component, due to the assignment of non-measurable weights to the indicators. Moreover, the risk is not quantified in terms of expected consequences, e.g. in terms of life of financial losses, which makes it hard to validate the method to data.
Nevertheless, some correlation with indexing methods with financial fire losses could be found [Fontana et al. 1999].

The most informative approaches are probabilistic methods, which aim to quantify the expected consequences of a potential hazard, in order to enhance rational decision-making. In the last decades, guidelines appeared for probabilistic fire risk assessment, e.g. [Watts & Hall 2002], [PD 7974-7] (2003) or [ISO/IEC 31010] (2009). The focus of these guidelines is to support decisions in the design process and to determine appropriate fire scenarios (with corresponding likelihoods and consequences). A general guideline for risk assessment is provided by the Joint Committee on Structural Safety (JCSS) and is applicable in many different fields of civil engineering (JCSS 2008). This guideline provides guidance for generic risk assessment to be applied for portfolio risk assessment and promotes risk-based decision-making at object (building) as well at social level. Guidance on the quantification of uncertainties associated with engineering structures and their exposure (including fire) is provided as well (JCSS 2001).

Within the probabilistic methods two different approaches can be distinguished: empirical approaches and engineering-driven approaches. The empirical approach is a kind of top-down method where observed loss data is used to quantify the risk reduction of a safety measure, see e.g. [Ramachandran 1998], [Thomas 2002], [Ahrens 2009] or [Hall 2010]. If enough data is available this frequentistic approach provides a good basis to compare the costs and the corresponding benefits. Such data does, however, not always exist (e.g. when relaxing or implementing new safety provisions) or it is not detailed enough (e.g. when data contains poor information about the system and the loss cannot be described appropriately by the risk indicators). In addition, some risks are usually dominated by rare events associated with large losses, e.g. structural collapse due to a fire event, and these events are difficult to be represented by an empirical model, due to the small number of observations.

Engineering models overcome this disadvantage by modelling and quantifying the physical effects of fire safety measures to assess the associated risk reduction. This leads to the engineering-driven approach, which is a kind of bottom-up approach that use basic risk indicators to model the loss by engineering models, e.g. pyrolysis models, combustion models, fire models, heat transfer models, mechanical models or evacuation models. Based on this approach several computer-based fire risk models have been developed, e.g. FiRECAM (Beck & Yung 1990), CRISP II (Fraser-Mitchell 1994), CESARE-RISK (Zhao & Beck 1997), CURisk (Hadjisophocleous & Fu 2005) and B-RISK (Wade et al. 2013). These models have been mainly developed to support performance-based design situation and evaluate the risk at object level, e.g. for a single building with known characteristics. This is problematic for the validation of a risk model, since building fire incidents are rare events and are likely to occur – if ever – only once in the life-time of a building. The validation of these risk models is usually limited to the validation of the engineering models that are used to model the risk and not on the entire risk model. Nevertheless, a relative risk comparison is possible and it often provides economic and safe decisions.
1.1.3 Techniques for uncertainty treatment in probabilistic models

Uncertainties arise from both the inherent natural variability of building fire events and from the incomplete knowledge of the representation of such events, e.g. by probabilistic or engineering models. Most risk models differ from each other by the technique by which these uncertainties are considered. The most common techniques used in fire safety engineering are listed below and might be combined with each other:

- logic trees
- graphical networks
- approximation methods
- simulation methods

Logic-trees represent causal relationships between events within a defined scenario. The most used logic-trees in fire safety engineering are event- and fault-trees representing a sequential progression of branching points at which several outcomes of the events can be assigned. Each branch is associated with a probability of occurrence, which can be based on statistical data or probabilistic engineering models. Where the structure of an event-tree is organised by events with a temporal sequence (e.g. fire ignition – fire spread within the room of ignition – fire spread beyond the room of ignition), the fault-trees are organised by logical dependencies that refer to the success or failure of a fire safety measure (e.g. if sprinkler failure then fire spread within the room of ignition). For a detailed discussion, see Rasbash et al. (2004), Hasofer et al. (2007) and ISO/IEC 31010. Logic trees are a convenient tool to systematically model basic dependencies between events and are widely applied in fire safety engineering. Time-dependencies between events (e.g. interaction between the time of fire brigade intervention and the fire spread) can be represented by logic-trees as well, but it is not an easy task (see Platt, 1989). This applies also for continuous events or system stages (e.g. the time of fire brigade intervention or the fire growth rate in a building) leading to an infinite number of branches at a branching point. A common simplification is the discretisation of the continuous events, which can be critical especially for events or system stages that have a large variability. Another difficulty of logic-trees (especially for event trees) is the representation of events that are dependent on common-cause effects. An example for a common-cause effect is an earthquake that may damage the engine of a pump and simultaneously damage the pipes of a sprinkler system, which may lead to a failure of the activation of the sprinklers.

Graphical networks may be seen as simple substitute of logic-trees to overcome the difficulty to represent common-cause effects. The conditional dependency between random variables is represented by directed acyclic graphs (Bayesian networks) or undirected graphs (Markov random fields). Especially Bayesian networks (see Jensen & Nielsen, 2007) have been applied recently in fire safety science by different authors to model complex systems regarding the evacuation of occupants (Maag, 2004; Hanea & Ale, 2009) and to model fire spread in building fires considering time-dependent effects (Ling & Williamson, 1985; Cheng & Hadjisophocleous, 2011; De Sanctis et al., 2011). The graphical representation of the system enhances the understanding of a complex system and the dependencies between the risk indicators. In addition, the formu-
lation of a Bayesian network provides the formal basis to consider prior knowledge about the system and to use Bayesian inference techniques to update this knowledge by observed data (see Gilks et al., 1996; Jensen & Nielsen, 2007).

A common difficulty of both techniques, logic-trees and graphical networks, is the quantification of the probability of the events. Whereas in some cases a frequentistic approach can be followed by relying on statistical data (e.g. sprinkler reliability = number of fires suppressed by a sprinkler / number of fires where a sprinkler was present), in other cases this data is missing. Then, an engineering driven approach can be used as discussed in the previous section. The probability of an event (e.g. a structural failure) can be assessed by a capacity-demand approach, e.g. by introducing a limit state function, and is derived by a reliability analysis. The uncertain stages of the system are represented as random variables and the reliability is assessed either by approximation methods or by simulation methods.

**Approximation methods** can be used to assess the reliability of systems using First or Second Order Reliability Methods (FORM/SORM), which approximate the limit state function close to the failure region by a first or second order function, see Melchers (2002) and Hasofer et al. (2007). This method is mainly used to calibrate partial safety factors for a semi-probabilistic design format, e.g. Magnusson et al. (1996), Schleich et al. (2002) and Hosser et al. (2009). Though, if the system is non-linear (regarding the propagation of uncertainties), the approximation by a first or second order function might not be appropriate.

**Simulation methods** consider the uncertainties associated with a system by evaluating an engineering model for a numerous number of realisations of the random variables, e.g. by Monte Carlo or Latin Hypercube sampling. If the number of evaluations is large enough, the system evaluations can be used to estimate the reliability on a frequentistic basis. The large number of simulations can be reduced by variance reduction techniques, e.g. importance sampling (Melchers, 2002; Kroese et al., 2011). Advanced simulations techniques, such as subset simulation (Au & Beck, 2001) are especially useful to estimate small failure probabilities. These methods have been applied in fire safety engineering by Au et al. (2007), Albrecht (2011) and Zhang et al. (2014).

Unlike to the approximation methods, these simulation methods are not affected by non-linearities of the system, but require many model evaluations, which leads to problems, especially for computationally expensive models. Surrogate models (or meta-models) overcome this problem by providing an easy-to-evaluate function as an approximation of the real system and are constructed based on an experimental design, which is computationally affordable. The Polynomial Chaos Expansion (PCE) is a spectral approach introduced by Ghanem & Spanos (1991) to surrogate the random output of the model by a linear combination of orthonormal multivariate polynomials and has recently been applied in fire safety engineering by Xie et al. (2013).
1.2 Objective of the thesis

The goal of this thesis is to evaluate and optimise the performance of fire safety provisions within the JCSS framework for generic risk assessment (JCSS 2008). The following objectives are pursued:

- Introducing an approach for generic risk assessment to be used for risk-based decision-making for individual as well as for societal decision-makers.
- Evaluating fire safety provisions by a thorough probabilistic modelling approach that considers the interaction of different fire safety measures.
- Comparing the level of safety of prescriptive and performance-based design provisions using a probabilistic risk-based approach.
- Optimisation of fire safety provisions considering acceptability criteria regarding life safety as well as monetary optimisation by a risk-based approach.
- Reviewing and modelling basic variables for the fire hazard to be used for a probabilistic representation of the building fire situation.
- Assessing and reducing the bias associated with probabilistic risk models enhancing an absolute estimation of the expected consequences.
- Applying the state-of-the-art of uncertainty quantification techniques.

1.3 Outline of the thesis

Chapter 2 reviews the current fire safety design principles, e.g. prescriptive and performance-based design approaches, and it is discussed how the level of safety is defined and achieved by the code provisions. An overview is provided in which context current risk assessment is used in fire safety engineering. For the risk based evaluation and the optimisation of these provisions, in Chapter 3 a framework for generic risk assessment and risk-based decision-making is presented. Three decision strategies are discussed: risk equivalence, acceptability regarding life safety and monetary optimisation.

To provide the basis for risk-based decision-making, in Chapter 4 probabilistic and engineering models are presented for a realistic fire exposure. Chapter 5 provides an overview of the most common fire safety measures and it is discussed how their performance under realistic fire exposure, e.g. exposures that are likely to occur in reality, can be evaluated by a probabilistic approach.

The introduced framework is applied to three studies focusing on the evaluation of the performance of design provisions and the application of different strategies for decision-making. In Chapter 6 the level of safety is assessed for prescriptive as well as for performance-based structural fire design of steel structures. The risk equivalence of those design concepts, which is demanded by the codes, is analysed for steel structures. In Chapter 7 a probabilistic risk model is developed based on an engineering-driven approach to assess the risk of evacuation. The egress provision for the minimal required door width is optimised based on an acceptability criterion regarding life safety. In Chapter 8 an engineering and a data-driven approach are combined
by developing a generic fire risk model that can be calibrated to data at portfolio level. The calibration of the risk model leads to a reduction of the bias associated with the used engineering models. The unbiased risk model is used to judge the efficiency of smoke alarms associated with a reduction of the financial damage due to fire.

Chapter 9 completes the thesis with the conclusions and the outlook for future research.

The notation and basic definitions of probabilities and random variables are found in Appendix A.
Chapter 2

Principles of fire safety design

The protection of life and property are the top-level code objectives in fire safety engineering (CIB W14, 1986) and are achieved by an appropriate fire safety design for a building. Two different design approaches provide guidance to achieve these objectives, e.g. by a prescriptive design or a performance-based design. The approaches are discussed in Sections 2.1 and 2.2 respectively.

2.1 Prescriptive design

Prescriptive codes provide standard requirements for the design to achieve the top-level code objectives without a specific quantification of the objectives. Those standard requirements are deemed-to-satisfy provisions and it is supposed that all relevant fire hazards are covered when the standard requirements are implemented. The requirements for construction products, e.g. structural elements or separating elements, are distinguished by their performance criterion and by their fire resistance. According to ISO 834-1, the performance criterion refers to the function of a construction product in a fire, e.g. the load bearing capacity (R), the integrity (E) or the insulation (I), where the fire resistance denotes the period, for which a construction product demonstrates compliance with these criteria under a predefined thermal exposure. Not only construction elements are subjected to prescriptive design requirements, but also the means of egress, e.g. requirement for the escaping length, the number of staircases or the width of escaping routes.

The level of safety in prescriptive designs is determined by the fire resistance of construction products and is usually set by the fire authorities. The fire resistance requirements depend on the risk classification of a building, e.g. by considering the probability of a fire event and its potential consequences. For load bearing structural members the fire resistance class is denoted by e.g. R30, R60 or R90 (EN 13501-2). The values denote the duration in minutes under which a structural element has to maintain its performance criteria (e.g. the load bearing capacity) exposed to standard fire conditions (ISO 834-1). To keep the complexity of prescriptive codes as low as possible, usually only a few building properties that are supposed to have a major influence on the risk are considered for the risk classification, e.g. by differentiation in the occupancy type,
Chapter 2. Principles of fire safety design

by the number of storeys or by the area of the building. This makes prescriptive codes easy
to use, but limits their application for common fire hazards and makes the application difficult
especially for special types of buildings, e.g. tall or large buildings or buildings associated with
a higher risk.

In most prescriptive codes the fire safety requirements are determined by experience rather
by a systematic evaluation of fire safety [Bennetts & Thomas, 2007]. Rare and severe fire
hazards (usually associated with high consequences) have led to code modifications in the past.
This ”design-by-disaster” strategy is very efficient in an early stage of code development, where
the level of safety may be increased by implementing simple and effective fires safety measures
to reduce the risk. In the long term, this strategy may turn to be inefficient especially when the
associated risk reduction does not justify the costs of a safety measure.

2.1.1 Comparison of structural fire safety requirements in Europe

Table 2.1 shows a simplified review of fire resistance requirements for structural members in
dwellings for different European countries [Sheridan et al., 2002; VKF 14-03, 2003; HBO, 2002].
The requirements vary with the number of storeys (or the height of the building), which is con-
sidered in many codes as an indicator for the risk classification. Any interpretation of Table 2.1
should be done with care, since the code format of the different countries differs, but it gives
an idea of how different fire resistance requirements can be set by the authorities for similar
buildings. One reason for the difference might be a non-optimal code making due to ”design-
by-disaster”, where codes have been modified based on experienced fire incidents. There might
be nothing wrong about having a higher or lower fire resistance compared to the other countries
and the requirement should instead be seen in the context of the overall safety concept of a
code. Authorities may adapt the fire requirements according to the actual fire occurrence rate
or according to the performance-level of the local fire brigades, which lead to less structural fires
due to faster intervention times and higher suppression capabilities. Therefore, to evaluate the
level of safety of a prescriptive approach, a holistic approach has to be followed and all safety
aspects of a code or a concept have to be considered.

2.1.2 Alternative prescriptive design solutions

The aim of an alternative prescriptive design solution is to provide the same level of safety
as the standard prescriptive solution, but enhancing the application of safety technologies. For
example, some codes allow the reduction of the fire resistance of a structural member if sprinklers
are installed (see VKF 14-03), because sprinklers will reduce the risk of structural failure due
to a fire. This is often denoted as a compensation solution and does not actually change the
level of safety of the code, but provides more design flexibility and provides the basis for cost
optimisations within the limitations of the prescriptive codes.

Implementing compensation solutions in prescriptive codes takes time and requires the al-
ternative solution to be approved by the authorities. This may prevent the application of many
new safety solutions, in the face of the rapid-changing modern construction practices.
2.2 Performance-based design

In the past decades, there has been an ever-growing global trend towards performance-based fire safety design approaches, since prescriptive design approaches are not supposed to be always cost-efficient or even safe for some type of buildings (despite the fact the safety level of prescriptive design approaches has never been quantified). Performance-based design approaches not only provide an object-specific safety approach, but also allow a greater design flexibility and promote innovation and a better use of resources. In this approach, quantifiable performance requirements are defined to achieve the top-level code objectives and the designer has to demonstrate that the design fulfils those requirements. There is no agreement in the fire safety community on the definition and quantification of the performance requirements (see Bennett & Thomas 2007). Following Hadjisophocleous et al. (1998), the concept of a performance-based approach may be understood by answering the following questions and are discussed in the next sections:

1. What are the design objectives and who is setting them?
2. What is the performance level under which the objective have to be reached and how is it quantified?
3. What is the design methodology to be applied to demonstrate compliance with the level of safety?

2.2.1 Design objectives

The top-level code objectives in fire safety engineering are the protection of life and property. In some cases it is necessary to extend the objectives, e.g. protection of the environment, protection of cultural heritage or to maintain the operation of a company after a fire. A review of possible
objectives in performance-based designs is provided by Hadjisophocleous et al. (1998). The top-level objectives are expressed as design-objectives or threshold values and specify under which conditions a top-level objective is reached or not. Usually, the design-objectives can be formulated according to a capacity-demand approach, e.g. by a limit state function. In some cases, multiple design objectives may have to be formulated to reach one top-level objective. To meet the life safety objective during an evacuation, for example, no structural failure and no exposure of occupants to toxic gases are allowed.

While some objectives are clearly in accordance with an individual decision-maker’s benefit, e.g. own life safety, own property loss or maintenance of operation, some objectives should be placed in a societal context, e.g. life safety of other people or protection of cultural heritage. Thus, a regulatory agency may formulate minimal societal objectives and a designer is allowed to formulate individual objectives in accordance to the needs of an individual decision-maker.

2.2.2 Performance level

The performance level may be understood as the level of safety of a design and defines under which performance the design-objectives are reached to provide an acceptable level of safety. There are different ways to define a performance level (Bennetts & Thomas, 2007).

One approach is to prove that a performance-based design reaches the same level of safety of a prescriptive approach. Codes do not always provide guidance to assess this equivalence. A risk-based approach can be used to demonstrate this equivalence as proposed by He & Grubits (2010). Though, the risk classification of prescriptive codes is usually coarse and leads to a large scatter of the level of safety for different building types, which makes the proof of the equivalence of performance-based approaches to prescriptive ones problematic. This effect is discussed in detail in Chapter 6, where the performance level of a prescriptive approach is derived for different building characteristics.

A conservative approach is to demand that the objective has to be reached under "probable worst-case" conditions (see Hadjisophocleous et al. 1998). This simplifies the assessment of the performance level by using a deterministic design method. However, the determination of the probable worst-case condition is usually not defined, comprises a subjective component and is problematic, especially when the variability of risk-governing factors is large. To assure a conservative design, often (arbitrary) global safety factors are applied to the design methodology. As a result of this approach, the level of safety is not explicitly quantified and the design is just considered to be sufficient (deemed to satisfy). The lack of this quantification makes it difficult to compare different design solutions for the same design-objective, e.g. when comparing compensation solutions to standard solutions (see Section 2.1.2).

A more sophisticated approach is to define the level of safety based on a probabilistic approach, e.g. by a target reliability $\beta_t$, which is associated with an accepted annual probability of failure (see Table 2.2). This target reliability $\beta_t$ may be differentiated by the consequences of a failure and the relative cost of safety measures (see JCSS 2001): If high consequences can be expected and/or if additional safety measures are cheap to be implemented then a higher target
2.2. Performance-based design

Tab. 2.2: Tentative target reliability indices $\beta_t$ (and associated target failure rates) related to one year reference period and ultimate limit states according to [JCSS (2001)].

<table>
<thead>
<tr>
<th>Relative cost of safety measure</th>
<th>Minor consequences of failure</th>
<th>Moderate consequences of failure</th>
<th>Large consequences of failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large</td>
<td>$3.1 \ (p_{f,t} \approx 10^{-3})$</td>
<td>$3.3 \ (p_{f,t} \approx 5 \cdot 10^{-4})$</td>
<td>$3.7 \ (p_{f,t} \approx 10^{-4})$</td>
</tr>
<tr>
<td>Normal</td>
<td>$3.7 \ (p_{f,t} \approx 10^{-4})$</td>
<td>$4.2 \ (p_{f,t} \approx 10^{-5})$</td>
<td>$4.4 \ (p_{f,t} \approx 5 \cdot 10^{-6})$</td>
</tr>
<tr>
<td>Small</td>
<td>$4.2 \ (p_{f,t} \approx 10^{-5})$</td>
<td>$4.4 \ (p_{f,t} \approx 5 \cdot 10^{-6})$</td>
<td>$4.7 \ (p_{f,t} \approx 10^{-6})$</td>
</tr>
</tbody>
</table>

reliability should be defined. The design concept for structural safety of [EN 1991-1-2] is based on such an approach and is evaluated and discussed in detail in Chapter 6. Nevertheless, the target reliabilities have been derived for the persistent design situation ([Rackwitz, 2000]) and are different for the fire safety design, due to different costs and consequences. [Fischer, 2014] derived optimal target reliabilities for structures exposed to fire in order to enhance an efficient fire safety design.

The differentiation of the target reliabilities by the consequences of a failure and the relative cost of safety measures is very coarse and may not provide the required level of detail (see Table 2.2). Therefore, the level of safety may be assessed by probabilistic risk-based methods and is evaluated directly by risk acceptance criteria, e.g. by the ALARP principle, by cost-benefit approaches or by the life quality acceptance criterion. The benefit of such an approach is that a design solution can be optimised by considering the risk reduction of safety measures and the corresponding costs. Such a design leads to an optimal investment of social resources and can be considered to be efficient in providing safety. Though, using probabilistic risk-based methods for optimisation requires an absolute and unbiased estimation of the risk. The principles of probabilistic risk-based methods are discussed in Chapter 3 and are applied in Chapters 7 and 8 to judge the efficiency of fire safety measures.

2.2.3 Design methodology

The design methodology aims to quantify the design-objectives, e.g. the limit-state function, and depends on the definition of the performance level. Hence, either a deterministic or a probabilistic (or risk) analysis has to be performed. A discussion of the evaluation methods used in fire safety engineering is found in [Hadjisophocleous et al., 1998]. In the following, the general principles to achieve the defined level of safety are discussed.

To prove equivalence with a prescriptive design, a risk-informed approach ([VKF 115-03]) based on the Gretener method is used in Switzerland. This method is used to check if an alternative design solution is code-compliant to the standard solution, e.g. a reference case that is considered to be acceptable and that corresponds to a prescriptive design solution. Relative to this case, object-specific fire characteristics and safety measures can be considered and compared with the reference case. Note that the fire characteristics are usually not evaluated by a thorough engineering approach and may not be considered appropriately by these indexes.
Another way to prove equivalence with a prescriptive design is to relate realistic fires (severity) to a standard fire, which is in general used for certification of building materials, e.g. the standard fire exposure (ISO 834-1). This equivalent-fire-severity concept (reviewed by Buchanan, 2001; Wade et al., 2014) has been developed to increase the design flexibility for structural fire safety design. Though, there is still research needed to find a proper formulation of the equivalence between a realistic fire and a standard fire (Wade et al., 2014).

Methods of risk assessment (see Section 1.1.2), e.g. event and fault trees, are usually used to support a deterministic analysis by assessing the probable worst-case conditions. These methods include the assessment of probabilities of certain scenarios that are most likely to occur or associated with large consequences. Then, those design fire scenarios are used to assess the performance of safety measures. This approach should not be mistaken by a full probabilistic analysis and should rather be interpreted as a risk-informed assessment of the design fire scenario.

If the performance level is defined by a target reliability then the design methodology requires a probabilistic analysis, which is cumbersome for practical engineering applications. The semi-probabilistic design is a simplification of the probabilistic approach and builds the basis for different codes like the Eurocode (EN 1990). The principle of this design is to define a design format that includes partial safety factors applied to the characteristic values of the basis variables. The safety factors are calibrated in order to assure that the target reliability $\beta_t$ is achieved with the design format (Faber & Sørensen, 2003). Thus, the design format is actually deterministic, but leads to the same level of safety (target reliability $\beta_t$), which is achieved by a probabilistic analysis. The approach is well known for the persistent design of structures and Schleich et al. (2002) extended this approach for structural fire safety and derived safety factors for the characteristic fire load, which are integrated in EN 1991-1-2.

Finally, probabilistic risk-based approaches require an holistic representation of the system and an appropriate quantification of the uncertainties. This usually exceeds the capacities of a designer and is not suited for common fire safety engineering. Though, similar to the semi-probabilistic design concept, simplified design rules may be derived and be implemented in performance-based as well as in prescriptive codes.
Chapter 3

Probabilistic risk assessment and decision-making

The aim of this chapter is to provide the fundamentals of probabilistic risk assessment and risk-based decision-making that are relevant for this thesis.

Section 3.1 introduces the principles of generic risk assessment\(^1\) and is based on the framework introduced by the Joint Committee of Structural Safety (JCSS, 2008). Probabilistic risk assessment quantifies the risk and provides the basis to compare the risks of different decision alternatives, and is discussed in Section 3.2. Risk-based decision-making aims to find a balanced ratio of costs and consequences, i.e. an optimal decision, and to consider both acceptability regarding life safety as well as monetary optimisation. A framework for optimal decision-making in the context of fire safety is proposed by Fischer (2014) and is presented in Section 3.3. This approach requires an absolute risk assessment and is discussed in Section 3.4.

3.1 Generic risk assessment

A generic risk model allows to assess the risk of an individual building using risk indicators. Moreover, the model can be applied – without any modification – to buildings with different characteristics, e.g. size or occupancy type (see also JCSS 2008). The components of such a model are illustrated in Figure 3.1 and are discussed in the following sections. The risk at portfolio level can be estimated by aggregating the consequences of individual buildings and provides the basis for societal decision-making (see Figure 3.2).

3.1.1 Definition of risk

Engineering systems are usually exposed to random effects due to the interaction with environmental conditions, humans and materials. During the life-time of a system some effects may lead to a damage state \(d\), e.g. system failure or exceedance of a certain threshold, and may

\(^1\)The principles are already discussed in De Sanctis et al. (2011) and in De Sanctis et al. (2014b)
result in consequences $c$, e.g. loss of lives, injuries, economical losses, business interruption or cultural losses.

With regard to decision-making, it is convenient to express the consequences in monetary terms or in the number of fatalities, though, not all consequences can be quantified in those terms. Risk can be defined as the expected consequences $R = E[C]$ considering all possible damage states of a system $D_D$ and is formulated by:

$$R = E[C] = \int_{D_C} c \cdot f_C(c) dc$$  \hspace{1cm} (3.1)

$$= \int_{D_D} c(d) \cdot f_D(d|EX) \cdot P(EX) dD$$

The probability density function $f_C(c)$ describes the distribution of the consequences $C$. 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 consequence that results from the damage state $d$. $P(EX)$ denotes the probability of occurrence of an exposure $EX$. The risk $R$ is assessed by an integration over all possible damage states $D_D$, which may occur due to the exposure $EX$. This formulation of risk is similar to the definition in the conceptual framework for fire risk analysis proposed by Hall & Sekizawa (1991).

A common approach in risk assessment is the selection of incident scenarios. For each scenario, a probability of occurrence and the associated consequences are derived. This leads to a discretisation of the problem and the integral of Equation [3.1] becomes a sum. The scenarios are usually represented by an event tree, where each branch is associated with a probability of occurrence and consequences.

### 3.1.2 System representation

A main issue in the representation of a system is to facilitate and enhance the identification of scenarios in terms of exposure, vulnerability and robustness (see Figure [3.1]). The vulnerability is related to the risk associated with direct consequences and is defined as the ratio between the
3.1. Generic risk assessment

risk due to direct consequences and the total value of the considered asset. The robustness is related to indirect consequences and expresses the ability of a system to sustain a given damage state and to limit the consequences to the direct consequences. For a fire hazard, for example, the fire ignition may be associated with the exposure, the fire spread in the compartment of fire origin with the vulnerability and the fire spread beyond the compartment of fire origin with the robustness. The definition of these 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. Additional details and the mathematical formulation of the risk associated with each level is found in JCSS (2008) and De Sanctis et al. (2011).

The risk or the individual risk levels may be assessed by either an engineering approach or an empirical approach. The empirical approach uses observed consequences, e.g. financial losses or human losses, to quantify the risk reduction of a safety measure, see e.g. Ramachandran (1998) and Rasbash et al. (2004). 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. 1999). Those rare events are difficult to be represented by an empirical model due to the small number of observations. The engineering-driven approach, on the other hand, represents the physical phenomena of the system by engineering models which consider basic risk indicators (see Section 3.1.3). Usually, a bottom-up representation of the system is followed in order to model sequentially the causes and effects of an exposure, e.g. fire ignition leads to fire spread, fire spread leads to flashover and so on. The uncertainties of the risk indicators are usually propagated through the engineering model by probabilistic methods (see Melchers 2002, Hasofer et al. 2007). This approach is useful when data on the consequences are lacking and have to be modelled instead. But due to simplification and assumptions, engineering models seldom represent the real behaviour of a system and the resulting risk estimation is biased. Additional discussion on the bias is found in Section 3.4. Of course, the empirical and the engineering approach may be combined and allows to include all possible information available on the system, e.g. the physical understanding of the system and the data.

Identification of the decision-maker

A decision-maker is either a person, an organisation or an institution, which assigns resources and bears the responsibility over the costs and benefits of the associated decision. The decisions can have an impact at different societal levels, either on society, on a part of society or on an individual level. The decision-maker and the possible impact to these levels has to be identified before the decision is made (JCSS 2008).

In the present thesis, a distinction is made between private decision-makers and societal decision-makers, who both follow a different strategies for optimal decision-making. A private decision-maker aims to optimise the personal utility, whereas a societal decision-maker aims to optimise the utility of a society. In the context of fire safety engineering, a regulatory agency or
a fire authority are typical societal decision-makers. Their decisions affect society by providing design provisions for buildings.

3.1.3 Risk indicators and model parameters

According to JCSS (2008), a generic risk model (e.g. Figure 3.1) enables to assess the risk of an individual building and can be applied to different buildings within a portfolio. The risk is assessed based on risk indicators that characterise the system (e.g. a building exposed to a hazard) and are input variables for the risk model. Risk indicators $x$ are defined as any observable or measurable characteristic of the system influencing the risk. Risk indicators describe the exposure, the vulnerability and the robustness of a system and constitute the basic parameters to assess risk. They are usually associated with uncertainties and can be represented by random variables $X$.

Uncertainties may be distinguished between aleatory uncertainties (which address the inherent natural variability of a system) and epistemic uncertainties (which address the model and the statistical uncertainties in a system). In contrast to aleatory uncertainties, the epistemic uncertainties can be reduced by data, e.g. observations on the outcome of a random process. The distinction between aleatory and epistemic uncertainties is determined by the modelling choice and the purpose of application (Kiureghian & Ditlevsen 2009). This distinction is useful for posterior (or pre-posterior) probability analysis (see Faber 2005), where additional information on the system can be used to update the epistemic uncertainties.

Based on this distinction between aleatory and epistemic uncertainties, it is useful to distinguish between two types of risk indicators for the generic representation of a system: object specific risk indicators $X_O$ and event (e.g. fire) specific risk indicators $X_E$. The object specific risk indicators $X_O$ are observable and constant at any time during the life-time of a system or are likely to be known if the risk is evaluated for a specific building, e.g. the use of a building, the floor area of the compartment or the number of floors of the buildings. Accordingly, the uncertainty of these indicators can be reduced by collecting information on the system at any time since these indicators are unlikely to change in time. The event specific risk indicators $X_E$ characterise the event and are only observable during or after an event, e.g. the fire load involved in a fire or the intervention time of the fire brigade. Hence, the event specific risk indicators $X_E$ may only be quantified when the specific indicators are measured during or after an event. However, some data may be collected before an event in order to estimate the event specific indicators, e.g. survey on the fire load surveys or on the occupant load density. Since, these event specific risk indicators are likely to change in time it is uncertain what value they have when a fire occurs. This uncertainty has to be considered in the risk assessment and surveys can be conducted to quantify this uncertainty, e.g. Fontana et al. (1999); Holborn et al. (2004); Thauvoye et al. (2008); De Sanctis et al. (2014c).

The distinction between object and event specific risk indicators is useful in the context of a-priori risk assessment, where the event specific risk indicators $X_E$ are random and provide no additional information for the risk assessment. Hence, the total probability theorem can be
applied over the domain $D_{X_E}$, which marginalises the event specific risk indicators $X_E$. The probability density function of the loss $f_C(.)$ depends only on the object specific risk indicator $x_O$ and on the model parameters $\theta$:

$$f_C(c|x_O, \theta) = \int_{D_{X_E}} f_C(c|x_O, x_E, \theta) \cdot f_{X_E}(x_E) \, dx_E$$  \hspace{1cm} (3.2)

This generic formulation of the consequences can be used to aggregate the consequences over a building portfolio (see Figure 3.2) if the object specific indicators for each object of a portfolio are known. This allows to estimate the expected consequences at portfolio level and can be used for societal decision-making (see Fischer, 2014), e.g. to optimise fire safety provisions set by a societal decision-maker.

Model parameters $\theta$ (see Figures 3.1 and 3.2) form another group of variables and are neither directly observable nor measurable. They are used to express mathematical relationships in the risk model and result either from assumptions made in the models, from model simplifications or from empirical relationships, e.g. the coefficients or the degree of a regression function in empirical models. These parameters can be deterministic or uncertain. The uncertainty of the model parameters $\Theta$ is associated either with statistical uncertainties, which arise either due to incomplete statistical informations when calibrating the model to the data, e.g. due to a small number of data, or with model uncertainties, which express the uncertainty of the chosen model to represent the data or the phenomena (see Faber, 2012). For risk assessment, the uncertainty of the model parameters $\Theta$ can be treated similar to the event specific uncertainties and marginalised in analogy to Equation 3.2 i.e. integrating over the domain $D_{\Theta}$. For calibration purposes, as discussed in Section 3.4.3, it is necessary to express the consequences conditional on the model parameters that are calibrated to data.

As illustrated in Figure 3.2, the model uncertainties can be defined at object level, e.g. each object has an own model parameter. This means that the mathematical relationship is
depending on the object. Alternatively – especially for empirical models – they can also be defined at societal level, e.g. parameters of an empirical model that are calibrated with portfolio data. Thus each object has the same model parameter.

### 3.1.4 Risk reduction measures

A common approach to manage risks is to implement risk reducing measures, i.e. safety measures. Usually, different safety measures are available and may be considered as decision alternatives in the context of decision-making. These measures are usually part of the design of a building and affect the building characteristics. They can be considered as (a-priori) known object specific risk indicators $x_O$ for the generic risk assessment.

The reduction of the risk by safety measures can be associated with a certain benefit for the decision-maker, e.g. in terms of reduction of monetary losses or life losses. This reduction can be assessed by performing a risk analysis for the different decision alternatives. The decision alternatives are associated with investments costs and should be considered in the decision-making process.

**Cost modelling**

Risk reduction measures are always associated with investments costs. In civil engineering, costs are usually related to construction, maintenance, service and disposal costs of a safety measure. Guidance to assess these cost can be found in Ramachandran (1998) and Fischer (2014).

The estimation of the costs should include all investments over the whole life cycle of a building. It is convenient to derive the cost based on equivalent annual investments (annuity method) accounting for initial and future investments, e.g. annualising the life cycle costs. Accordingly, the initial investment costs should be discounted with a rate of return $r$ over the life-time of the building $LT$. The factor $a_0$ for the annuity method is multiplied by the investment costs and is derived by (Ramachandran, 1998):

$$a_0 = \frac{r \cdot (1 + r)^{LT}}{(1 + r)^{LT} - 1} \quad (3.3)$$

In the process of risk-based decision-making (as discussed in Section 3.3), the costs should be assessed in collaboration with the decision-maker and other experts, e.g. designers, construction companies and producers of fire safety products. Consequently, producers have not only the possibility to show that products, e.g. smoke alarms, sprinkler or protective coatings, are effective in reducing the risks, but also the possibility to lower its production costs, in order to achieve the same risk reduction for the lower costs. This is especially interesting for societal decision-makers that aspire a balanced ratio of costs and consequences while setting code provisions. It is likely that the production costs of a measure that is demanded by the code can be reduced, since these provisions affects a large number of buildings.
3.2 Risk equivalence

Some safety measures may perform well in reality and may be deemed to be acceptable to provide safety by experience. Based on such measures, a risk level can be quantified (e.g. by a risk analysis) and used to prove equivalence to an alternative design solution (e.g. Section 2.1.2), if the risk associated with the alternative design solution $R_A$ is equal or lower than the risk associated with the standard solution $R_{acc}$, which is considered to be acceptable, i.e. $R_A \leq R_{acc}$. This risk comparison can be used to compare and rank different design solutions. The most prominent comparative risk assessment method in fire safety engineering is the Gretener method, which is implemented in the Swiss fire safety codes [VKF 115-03 (2003)]. Despite the fact that this method does not provide a realistic estimate of the expected loss, it can be used to check if alternative design solutions are code-compliant to the standard solution, i.e. a reference case that is considered to be acceptable. Though, the costs of the solutions can only be considered by a comparative approach in the decision-making process. Thus, it is hard to decide whether the (absolute) risk reduction of a measure justifies the investments. A risk-based decision-making approach overcomes this disadvantage but requires an absolute treatment of the risk.

3.3 Risk-based decision-making

Risk-based decision-making aims to optimise a certain utility (benefit) by an optimal allocation of resources. Decision-making in engineering is always associated with uncertainties, which arise either from the random variability of the system variables or from simplifications in the description of the physical phenomena and the mathematical models related to the system variables. The principles of rational decision-making under uncertainties are introduced by Von Neumann & Morgenstern (1944) and Raiffa & Schlaifer (1961) and build the methodological basis for the present thesis.

Life safety is one of the top-level code objectives in fire safety engineering (see Chapter 2) and should be considered in a societal context. A rational acceptance criterion for decisions influencing life safety can be derived based on the Life Quality Index (LQI). This societal index, first introduced by Nathwani et al. (1997), can be seen as an indicator expressing the societal preference for investing resources into life safety and derives acceptability regarding life safety from efficiency considerations (efficient measures have to be implemented).

Fischer (2014) introduces this criterion as a societal boundary condition to perform monetary optimisation. The boundaries should be set by a societal decision-maker in form of optimised minimal requirements for the fire safety design. The monetary optimisation can be done either by the private or the societal decision-maker within the acceptable region. This interaction between the LQI criterion and the monetary optimisation is illustrated in Figure 3.3 and is discussed in detail by Fischer (2014). The following two sections provide a summary of the framework.
3.3.1 Acceptability regarding life safety

Investments into life safety should not be considered only with regard to a certain hazard, e.g. the fire hazard, but by a more holistic approach considering all possible threats to life, e.g. diseases, falls, transport accidents, accidental poisoning, accidental drowning, malnutrition, assault or exposure to fire (listed by decreasing frequency of occurrence according to the WHO European Mortality Database for Switzerland). At first glance this problem seems impossible to solve. Nathwani et al. (1997) put the problem in the context of decision-making posing the question: How much of our limited resources can we devote to maximising safety and minimising harm? To answer this question, the Life Quality Index (LQI) was introduced as an indicator to reflect the expected length of life in good health and wealth. The LQI is composed of social indicators, including the Gross Domestic Product (GDP), the life expectancy $l$ and the fraction of total lifetime spent for work $w$ (e.g. to produce the GDP). These indicators are expected to provide the basis for a life in good health and wealth. Following Rackwitz (2008), the LQI can be formulated by:

$$LQI(g, l) = \frac{q^g}{q} \cdot l \cdot (1 - w)$$  \hspace{1cm} (3.4)

The parameter $q$ denotes the labour-leisure trade-off. When comparing the two major indicators of the LQI, e.g. the GDP and the life expectancy, there is some empirical verification for the formulation of the LQI as discussed by Kübler (2006) and by Rackwitz (2008) – especially for well-developed countries.

Based on this formulation the link to decision-making can be made by requiring that any decision should lead to an increased or at least constant $LQI$, e.g. by increasing the life expectancy (reduction of the fatalities) or by increasing the societal wealth (reduction of the invested resources). Thus, any decision-alternative $a$, which is associated with a marginal investment of resources $dc_I$ and which leads to a reduction of the risk to life (e.g. a marginal change in the mor-
3.3 Risk-based decision-making

tality rate \(dm\) should lead to a marginal increase or at least constant LQI, i.e. \(dLQI(g,l) \geq 0\). This formulation corresponds to the LQI net benefit criterion (or just LQI criterion) introduced by [Nathwani et al. (1997)] and can be used to judge the efficiency of regulatory requirements, e.g. code provisions. Accordingly, only efficient safety measures should be required (\(dLQI \geq 0\)) as illustrated as the grey area in Figure 3.3. The efficiency may be evaluated by:

\[
dc_I(a) \leq -J_\Delta \frac{g}{q} n_{\text{pop}} \cdot dm(a) = -SWTP \quad \Leftrightarrow \quad \frac{dc_I(a)}{da} \leq -J_\Delta \frac{g}{q} dn_f(a) \quad (3.5)
\]

\(dc_I\) are the marginal investment cost for life saving [CHF]
\(J_\Delta\) is a demographic constant [a]
\(g\) is the GDP per capita per year [CHF/a]
\(q\) is the labour-leisure trade-off [-]
\(n_{\text{pop}}\) is the population size [pers]
\(dm\) is the mortality change [number of deaths/n_{\text{pop}}/a]
\(SWTP\) is the societal willingness to pay [CHF]
\(J_\Delta \frac{g}{q} = SWTP_{\text{life}}\) is the \(SWTP\) per life saved [CHF/pers]
\(dn_f\) is the change of the number of fatalities

Guidance to quantify the societal willingness to pay \(SWTP\) is found in [Fischer (2014)] and widely available statistical data can be used. For Switzerland the \(SWTP_{\text{life}}\) per life saved, e.g. \(J_\Delta \frac{g}{q}\), can be estimated to 5 million CHF.

[Fischer (2014)] introduces the LQI acceptance criterion to judge the societal acceptance of a decision, requiring the implementation of all efficient safety measures as evaluated by the LQI net benefit criterion starting with the most efficient and correspond to the acceptable region in Figure 3.3. This simply changes the inequality sign of Equation 3.5 and can be used to derive a minimum investment threshold for private decision-makers, in order to prove that their decision is acceptable from a societal point of view. The threshold value can be derived from the net benefit criterion as well. From the perspective of the LQI net benefit criterion, the acceptable region might be judged as inefficient since it leads to a reduction of the LQI (\(dLQI \leq 0\)) due to an overmuch allocation of resources. In contrast to a societal decision-maker, a private decision-maker bears the costs of these decisions and can usually choose freely to enter this region or not. A good reason to enter this region is monetary optimisation.

3.3.2 Monetary optimisation

If the acceptability of safety measures in terms of risk to life is fulfilled (see Equation 3.5), it is reasonable to compare the costs of safety measures with the economic benefits, i.e. to perform a monetary optimisation of the overall (discounted) costs. For each decision alternative, e.g. a combination of risk reducing measures, the cost \(c_I\) and the expected consequences \(E[C]\) (see Section 3.1) can be estimated. The economic optimum is found by performing a cost-benefit analysis ([Rasbash et al. (2004)]). The optimal decision \(a_{\text{opt}}\) minimises the total expected costs \(c_T\) of a decision alternative \(a:\)

\[
c_{T,\text{opt}}(a_{\text{opt}}) = \min_a (c_I(a) + E[C(a)]) \quad (3.6)
\]
Actually, the LQI criterion can also be used for monetary optimisation, transforming the expected loss of lives (based on the SWTP per life saved) into monetary units and entering the optimisation as costs (or benefits). Fischer & Faber (2012) and Fischer (2014) recommend to separate the two parts of the decision-problem for both private and societal decision-makers and to use the LQI criterion only as boundary condition for monetary optimisation (as illustrated in Figure 3.3). The advantage is that all possible decision-makers use the same acceptance criterion. Thus, a societal decision-maker may define some minimal requirements for safety (as a boundary condition) and a private decision-maker may perform economic optimisation satisfying these requirements. In addition, when separating these two parts, no human compensation costs have to be defined (see Ramachandran (1998) Fischer & Faber (2012), which is often referred to as ”putting a price on human life” and is often judged as ethically questionable.

3.4 Absolute risk assessment and model bias

An absolute comparison of costs and benefits (in terms of risk reduction) of decision alternatives is needed for the application of risk-based decision-making framework (see Section 3.3). Absolute risk assessment means that the expected consequences estimated by the risk model are comparable with the average observed consequences in reality. Deviations between these values may be associated with a bias and are the result of simplifications and assumptions made in the models used to quantify the risk, e.g. engineering models or empirical models that describe the uncertainty of the input parameters. A bias can be quantified by model validation, e.g. comparing values estimated by the model with data. Nevertheless, it is difficult to validate a risk model that assesses the expected consequences only for a single building, since fire incidents are rare events and are likely to occur – if ever – only once in the life-time of a building. The number of observations can be increased when assessing the consequences at portfolio level. Consequences are likely to be influenced by object specific risk indicators, which vary from building to building and have to be considered appropriately. Generic risk models can be applied (without any modification of the model) to various different buildings within a portfolio to assess the consequences of each building in the portfolio. At portfolio level, it is possible to validate a risk model, in order to quantify and may reduce the associated bias. Usually, the quantification of the bias depends whether an empirical or an engineering approach is followed.

3.4.1 Bias resulting from empirical models

In the empirical approach, observed loss data (statistical data) is used to quantify the risk reduction of a safety measure, see e.g. Ramachandran (1998) and Rasbash et al. (2004). If enough data is available, this frequentistic approach provides a good basis to compare the costs and the corresponding risk reduction. The bias associated with the model is small, since it is usually calibrated based on the observed losses. But often this data does not exist (e.g. when implementing new safety regulations without any experience) or it is not detailed enough (e.g. when data contains poor information about the system). Some incidents (e.g. structural failure) are associated with rare events and are difficult to be represented by an empirical model due to
the small number of observations. Further, empirical models are prone to the overall changes of building characteristics within a portfolio and may not be able to consider new trends in building construction practice. In those cases, the bias of empirical models may change in time.

### 3.4.2 Bias resulting from engineering models

Probabilistic engineering models can be used to quantify the physical effects of fire safety measures and can be used to assess the associated risk reduction of a safety measure, e.g. Hasofer et al. (2007) and Yung (2008). Such bottom-up approaches seldom represent the real behaviour of a system, either due to simplifications and assumptions on the underlying engineering models or due to assumptions on the statistical models that describe the input parameters. The resulting risk estimation is biased and makes an absolute comparison of costs and benefits difficult.

The bias associated with an engineering model can be assessed within the validation process of the model and may be represented by a model uncertainty. Increasing the level of detail of an engineering model may reduce the model uncertainty and thus the associated bias. Though, additional input is often required, which increases the complexity of engineering models and may introduce new sources of uncertainty.

### 3.4.3 Assessing and reducing the model bias

The bias associated with models affects the decision-making process. In the following paragraphs, some methods are discussed to quantify this bias (e.g. by introducing model uncertainties) and to estimate their importance on the overall system response (e.g. by a sensitivity analysis). If data is available, it is even possible to reduce the bias by calibration.

#### Model uncertainty

The bias associated with models can be considered by introducing model uncertainties (as random variables) that represent the gap between model prediction and reality. This gap may associated with an average value but also with a variance. According to JCSS (2001), the model uncertainty accounts for random effects that are neglected in the models and simplifications in the mathematical relations. In the ideal case, the model uncertainty of engineering models is quantified by experiments and is usually part of the validation process of the model itself. In many cases, however, such data are missing and the model uncertainty has to be estimated instead.

In a complex system, which consists on a concatenation of different models, the model uncertainty may be introduced for each of these models. The benefit is that the importance of model uncertainties on the overall response of the system can be assessed under consideration of the complete probabilistic formulation of the system, e.g. related to the uncertainties associated with the risk indicators. The importance of the model uncertainty may be used as an indicator for the required accuracy of engineering models. Thus, there might be no need for improvements of an engineering model (e.g. by increasing the level of detail), if the importance of the model...
uncertainty is small enough in respect to other random variables. The importance of random variables can be assessed by variance-based sensitivity measures.

**Sensitivity analysis**

The representation of a system by probabilistic engineering models often includes subjective choices in the selection of probabilistic models. Often other probabilistic models, e.g. distribution types and parameters, can be chosen with equal heuristic justification. Therefore, it is necessary to investigate the robustness of such choices on the model response and on the ranking of decision alternatives. In this context, robustness means that different choices between plausible model assumptions should not lead to significant changes in the decision. If assumptions are not robust the model has to be revised, e.g. by reducing the model uncertainties, or the epistemic uncertainty of the probabilistic models has to be reduced, e.g. by collecting additional data. A sensitivity analysis can be performed to assess this robustness.

The aim of a sensitivity analysis is to assess the importance of deterministic and random variables (e.g. risk indicators) on the output of probabilistic engineering or risk models. The information can be used for example either as an indication to improve engineering models (e.g. increasing the level of detail), to judge if additional data is required to improve probabilistic models (e.g. to reduce the epistemic uncertainties) or to reduce the dimensionality to simplify the uncertainty propagation of engineering models (e.g. reducing the number of random variables).

There is a number of different assessment methods and the choice depends on the goal of the sensitivity analysis and on the problem. An overview and comparison of different sensitivity assessment methods is provided by Saltelli et al. (2000). In general, four different approaches can be distinguished: parametric analysis, derivative-based methods, variance-based methods and probability bounds analysis.

In a parametric analysis the model is evaluated for a sequence of a specific input parameter holding the other parameters constant. This method is very intuitive and may be used for object specific risk indicators $x_O$ and the decision variables, since they are likely to be fixed by the decisions-maker in order to find an optimal design solution. Though, this method does not assess the importance of random variables on the overall outcome of the model.

The derivative-based methods (e.g. a local sensitivity analysis) assess the local impact of variables $x$ on the output $y(x)$ and are in general assessed by computing partial derivatives of the output function with respect to the input variables, e.g. $S(x_p) \sim \frac{\partial y}{\partial x}|_{x_p}$. The sensitivity measure depends on the choice of the local base point $x_p$. For reliability problems, the First-Order Reliability Method (FORM) can be used to find such a base point, which is related to the probability of failure of a system (see Melchers (2002)). The sensitivity measures provide an estimate of how much a certain random variable drives the probability of failure of a system.

The variance-based methods (e.g. a global sensitivity analysis) aim to identify the individual contribution of the random variable $X_i$ to the variability of the response of a model $Y(X)$. This can be done by decomposing the variance of the outcome $\text{Var}[Y]$ into contributions of the variance of each random input parameter $X_i$. This method is known as ANOVA (ANalysis Of VAriance) decomposition. In contrast to other global sensitivity measures, e.g. Pearson’s or
Spearman’s correlation coefficient, the variance-based method provide better estimates of the importance of variables especially for non-linear and non-monotonic models (see Saltelli et al., 2000).

Homma & Saltelli (1996) introduced Sobol indices $S$ to quantify the variance decomposition. The indices can be distinguished between first-order $S_i$ and total effects $S_{T,i}$ of a random variable $X_i$. The first-order effects represent the main contribution of an input variable $X_i$ to the variance of the output $\text{Var}[Y]$ and are defined by the first-order Sobol indices $S_i \leq 1$.

$$S_i = \frac{\text{Var}[E(Y|X_i)]}{\text{Var}(Y)}$$ (3.7)

The total effect indices $S_{T,i}$ is a measure for the total contribution of an input variable $X_i$, including the interactions with all other variables $X_{\sim i}$ (all random variables $X$ except variable $X_i$). The total effect index $S_{T,i}$ provides an indication if the variance of an input variable $X_i$ can be neglected, i.e. $S_{T,i} \approx 0$, and be replaced by a deterministic value. The total effect is defined by:

$$S_{T,i} = \frac{E[\text{Var}(Y|X_{\sim i})]}{\text{Var}(Y)} = 1 - \frac{\text{Var}[E(Y|X_{\sim i})]}{\text{Var}(Y)}$$ (3.8)

The first-order sensitivity indices of a purely additive model sums up to $\sum_{i=1}^M S_i = 1$ and the total sensitivity index are $S_{T,i} = S_i$. The difference of the first-order indices and the total effect indices of a variable $S_{i,T} - S_i$ provides an indication of the interaction effects of the variable $X_i$ with other variables $X_{\sim i}$.

One way to assess those indices are statistical estimators based on sampling methods (Monte Carlo sampling, Latin Hypercube sampling or by Sobol sequences) and are discussed in Homma & Saltelli (1996) and Janon et al. (2013). Another way is proposed by Blatman & Sudret (2010), who linked the assessment of the global sensitivity indices with a spectral approach for surrogate modelling (see Appendix B).

A probability bounds analysis can be used when only an upper or lower estimate of a probability or probability density is known. The idea is to create a probability box (p-box) with an upper and lower bound for the cumulative distribution function of a variable (see Ferson & Hajagos, 2004). This can also be applied when different types of probability density distributions are plausible to represent the uncertainty associated with a variable. These probability bounds are used to generate decision-bounds and in this way the robustness of the assumptions associated with the probabilistic models is assessed.

Sensitivity analyses should always be a part of the model-building and should be performed at different model instances. This has been done for the risk models that have been developed for the case studies in Chapters 6 to 8, but are – for the reasons of clarity – not formally reported. An exception is Chapter 7 where the various sensitivity methods are applied at different instances of the model.

Calibration of a generic risk model

A generic probabilistic risk assesses probability density distribution $f_C(c|\mathbf{x}_{O,i}, \theta)$ of the consequences $c$ for each object $i = 1, \ldots, n$ in a building portfolio and depends on building specific
risk indicators $x_{O,i}$ and model parameters $\theta$ (see Equation \ref{eq:3.2}). If an engineering approach is used, then the prediction is usually associated with a bias, e.g. due to simplifications in the engineering models. Model parameters $\theta$ can be selected, which affect this bias to be calibrated to data. Data consists on loss data $\hat{c}_i$ as well as data on corresponding object specific risk indicators $\hat{x}_{O,i}$. The hat $\hat{\cdot}$ denotes an observation of a value $\cdot$. The calibration of the selected model parameters $\theta$ to data leads to a reduction of the bias. A framework for such an approach is proposed by De Sanctis et al. (2014b) and Fischer et al. (2014). The latter publication focuses on the calibration of risk models and proposes the Maximum Likelihood method for calibration. The Maximum Likelihood method estimates the model parameters in order to maximise the likelihood of the observation as evaluated by the model. The likelihood $L$ and the log-likelihood $l$ for $n$ independent observations is given by:

$$L(\theta | \hat{c}, \hat{x}_O) = \prod_{i=1}^{n} f_C(\hat{c}_i | \hat{x}_{O,i}, \theta) \quad (3.9a)$$

$$l(\theta | \hat{c}, \hat{x}_O) = \sum_{i=1}^{n} \log (f_C(\hat{c}_i | \hat{x}_{O,i}, \theta)) \quad (3.9b)$$

where $\hat{x}_O = [\hat{x}_{O,1}, ..., \hat{x}_{O,n}]$ and $\hat{c} = [\hat{c}_1, ..., \hat{c}_n]$. The model parameters $\theta^*$ that maximise the likelihood of the observation are derived by:

$$\theta^* = \arg \min_{\theta} (-l(\theta | \hat{c}, \hat{x}_O)) \quad (3.10)$$

The difficulty of this approach is that the data results from a non-homogeneous building portfolio, e.g. in respect to varying building characteristics. Though, loss data may not include all relevant building characteristics (e.g. object specific risk indicators $x_{O}$) to be used for a generic risk model and the calibration has to be performed with incomplete data. The basic idea is to express this lack of knowledge probabilistically and introduce object specific risk indicators as random variables $X_{O}$ (alike the event specific risk indicators $X_E$). Guidance to account such data and to perform calibration is found in Fischer et al. (2014).

The Maximum Likelihood method can be used to calibrate the parameters of a probabilistic engineering model $Y(x_O)$, when observations of the outcome $\hat{y}$ are available with the corresponding building specific properties $\hat{x}_O$. The variables in Equations \ref{eq:3.9} and \ref{eq:3.10} related to the consequences $C$ or $c$ are substituted with $Y$ or $y$, respectively. The benefit of the Maximum Likelihood method is that the statistical uncertainty (i.e. the covariance matrix) associated with the estimation of the parameters can be determined by the Fisher information or the Hessian matrix as well. The quantification of the statistical uncertainty provides an estimate to judge uncertainty associated with the estimation of the parameters.
Chapter 4

Probabilistic representation of the fire exposure

A fire is an exothermic chemical process of combustion releasing heat, gases and soot. The fire development in an enclosure depends on the combustible material (e.g. type, amount and storage density), the ventilation conditions (e.g. exchange of oxygen, gases and heat with the outside), the boundary elements (e.g. geometry and thermal inertia of the elements affecting the heat transfer) and the fire fighting measures (fire suppression by the fire brigade or sprinklers). The latter is discussed in Chapter 5 and this chapter focuses on the fire development without any fire suppression.

To provide a systematic approach to understand natural building fires (henceforth referred to as fire), it is helpful to idealise a fire in five different stages: ignition, growth, flashover, fully developed fire and decay (see Figure 4.1). The chemical and physical processes involved in a fire are broad, complex and a research field of its own. The aim of this chapter is to discuss the main physical processes of a fire, to introduce the mathematical models that describe those processes and to identify and quantify the uncertainties associated with those processes. For a detailed physical and chemical description of the processes, see e.g. [Drysdale, 2011] and [Quintiere, 2006].

![Figure 4.1: Fire stages of a compartment fire (see also Drysdale, 2011).](image-url)
4.1 Fire ignition

A solid material exposed to sufficient heat starts to decompose and release combustible gases. If there is enough heat and enough oxygen, combustion of these gases occurs and a flame is produced. This process describes the ignition of a fire. In this section, the fire ignition is not addressed on a physical or chemical basis (see Drysdale [2011]), but on a statistical basis.

The fire ignition rate can be described by the annual probability of fire occurrence in a building $P(EX)$ ($EX$: exposure). Ramachandran (1980) proposed to derive this probability $P(EX)$ by a power law as a function of the floor area of an enclosure $a_E$. The floor area is used as an indicator to address the number of potential ignition sources in an enclosure, e.g. electrical devices or the average number of occupants in a building. Since the occupancy type is expected to have a large influence on the ignition frequency, the model is calibrated to loss data for different occupancy types. According to Bennetts & Thomas (2002), this simple approach might not represent all characteristics that are likely to be significant, e.g. age of building, level of maintenance, housekeeping and occupant characteristics. Nevertheless, the approach of Ramachandran is widely used.

A similar approach is followed by Fischer et al. (2012) using either the volume $vol$ or the insured value $v$ of a building instead of the total floor area, e.g. Equations 4.1a and 4.1b. Depending on the available information of the building, the one or the other equation is more suited to represent the ignition rate. The model is calibrated to fire loss data provided by Swiss cantonal fire insurance agencies leading to the parameters $\beta_1$ and $\beta_2$ (see Table 4.1). In this context, the fire ignition is defined by the frequency of a claim by a building owner after a fire event. Swiss insurance data is suited to represent the fire ignition rate, because the cantonal insurance agencies have the obligation to insure all buildings in a canton. Therefore, the overall building characteristics are well represented. In addition, the data includes also small fires, where there is no intervention of the fire brigade.

\[
P(EX|x_0 = vol) = \exp(\beta_{1,vol}) \cdot vol^{\beta_{2,vol}}
\]
\[
P(EX|x_0 = v) = \exp(\beta_{1,v}) \cdot v^{\beta_{2,v}}
\]

Tab. 4.1: Parameter of fire ignition model according to Fischer et al. (2012)

<table>
<thead>
<tr>
<th></th>
<th>Equation 4.1a</th>
<th>Equation 4.1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{1,vol}$</td>
<td>-11.76</td>
<td>0.8700</td>
</tr>
<tr>
<td>$\beta_{2,vol}$</td>
<td>0.8700</td>
<td>-10.73</td>
</tr>
<tr>
<td>$\beta_{1,v}$</td>
<td>-10.73</td>
<td>0.368</td>
</tr>
<tr>
<td>$\beta_{2,v}$</td>
<td>-10.78</td>
<td>0.342</td>
</tr>
</tbody>
</table>
4.2 Heat release rate

A solid material exposed to heat starts to decompose and release combustible gases, e.g. volatiles. This corresponds to a mass loss of the item and is known as pyrolysis, which is schematically illustrated in Figure 4.2. If enough heat and oxygen are available, then the combustion of the pyrolysis gases occurs, which is an exothermic chemical reaction accompanied by the release of heat. Describing this heat release is the most significant predictor of the fire hazard (Babrauskas & Peacock, 1992). The heat release rate $\dot{q}$ of a combustible material (characteristic $x$ of single item denoted as $\tilde{x}$) may be expressed as:

$$\dot{q}(t) = \chi_c(t) \cdot \Delta h_c(t) \cdot \dot{m}(t)$$

(4.2)

The heat release rate $\dot{q}$ [W], when a quantity of a fuel is completely oxidised, depends on its heat of combustion $\Delta h_c$ [J/kg-fuel] and the mass loss rate of the fuel $\dot{m}$ [kg/sec]. Tewarson (1982) introduced a combustion efficiency factor $\chi_c \leq 1$ to account for incomplete combustion, e.g. when the actual heat release rate is smaller than the heat release rate under complete oxidation. In Equation 4.2 all components are in general time dependent.

Many data can be found on the heat release rate of different materials or single items, e.g. Grayson & Babrauskas (1992) and Särdfvist (1993). In real fires, different items are involved and contribute commonly to the heat release rate over a specific area $a_f$. An uniform heat release rate $\dot{q}$ over a fire area $a_f$ may be obtained by averaging the parameters in Equation 4.2 and leads to (Babrauskas, 2002):

$$\dot{q}(t) = \int_0^{a_f} \dot{q}''(t, x, y, z) da \approx \chi_c \cdot \Delta h_c \cdot \dot{m}'' \cdot a_f(t)$$

(4.3)

The benefit of this representation is that the time-dependency of the heat release rate $\dot{q}(t)$ can be expressed by the time-dependent fire spread area $a_f(t)$, whereas the other parameters are
Chapter 4. Probabilistic representation of the fire exposure

Tab. 4.2: Tentative probabilistic models for the assessment of the heat release rate.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>$X$</th>
<th>$x$</th>
<th>Dist.</th>
<th>$E[X]$</th>
<th>$\sqrt{Var[X]}$</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass loss rate [kg/sec/m$^2$]</td>
<td>$\dot{m}''$</td>
<td>$\ddot{m}''$</td>
<td>$\mathcal{LN}$</td>
<td>0.02</td>
<td>0.004</td>
<td>Section 4.2.1</td>
</tr>
<tr>
<td>Heat of combustion [MJ/kg]</td>
<td>$\Delta H_c$</td>
<td>$\Delta h_c$</td>
<td>$\mathcal{LN}$</td>
<td>18.0</td>
<td>3.6</td>
<td>Section 4.2.2</td>
</tr>
<tr>
<td>Combustion efficiency [-]</td>
<td>$X_c$</td>
<td>$\chi_c$</td>
<td>$\mathcal{N}$</td>
<td>0.7</td>
<td>0.07</td>
<td>Section 4.2.3</td>
</tr>
</tbody>
</table>

assumed to be constant during a fire. The next sections discuss the probabilistic characterisation of these values.

4.2.1 Mass loss rate

The mass loss rate per unit area $\dot{m}''$ [kg/sec/m$^2$] is characterised by the chemical decomposition of a solid material, e.g. the pyrolysis process. The pyrolysis of a material depends on the irradiance upon the element (Figure 4.2), i.e. the imposed radiant heat flux that results from hot materials or from particles in the smoke layer. Therefore, the mass loss rate $\dot{m}$, involving different combustible materials, is scenario dependent and a-priori unknown. Further, the mass loss rate depends on the composition of the material, e.g. the density and the surface-to-volume ratio of the burning material, and is in general time-dependent. Usually, a constant value is assumed to model the mass loss rate $\dot{m}$ for simplicity.

The mass loss rate per unit area $\tilde{\dot{m}}''$ depends on the location, the number and the chemical composition of the items in a building and is of random nature. Therefore, the mass loss rate per unit area is introduced as a random variable $\dot{M}''$ and represents the variability of the mass loss rate over the fire area $a_f$. To the author’s knowledge no systematic assessment of this variability has been conducted over the past years. One reason is that the research focused rather on ventilation-controlled fires (see Section 4.5.2), where the heat release rate is dominated by the available oxygen and the mass loss rate has a minor influence. The probabilistic model for the mass loss rate $\dot{M}''$ is referred to data and a review of:

- Small-scale cone calorimeter tests for wood (Tran 1992, Spearpoint 1999) with an irradiance of $\approx 25 - 75$ kW/m$^2$, which corresponds to a perfect black-body radiator with a temperature of 550 – 800°C.
- Small-scale cone calorimeter tests for plastics (Hirschler 1992) with a constant irradiance of $\approx 25 - 75$ kW/m$^2$.
- Free mass loss rates of cribs burning tests (Utiskul 2007).
- Mass loss rates based on (fuel-controlled) room fire tests (Zehfuss et al. 2003).

As a result, a mean mass loss rate per unit area $E[\dot{M}''] = 0.02$ kg/sec/m$^2$ and a coefficient of variation of $CoV[\dot{M}'] = 0.2$ is proposed. A Lognormal distribution is chosen to represent the data. This probabilistic model should be considered as a first estimate and can be updated (if necessary) to improve the probabilistic assessment of the fire hazard.
4.2. Heat release rate

4.2.2 Heat of combustion

The heat of combustion refers to the total amount of heat released when a quantity of a fuel is completely oxidised under standard temperature conditions and atmospheric pressure (Drysdale, 2011). The heat of combustion of a material depends on the aggregate state of the reactants and on the combustion products. If the reactants and products are in their standard states, the heat of combustion is defined as the gross heat of combustion. The net heat of combustion refers to the case where water is in vapour state after the combustion. This corresponds to real fire cases, where vapour may vanish through openings by the mass transfers involved in a fire. The influence of the moisture content can be considered by accounting for the latent heat of evaporation of water (CIB W14). In the following, the net heat of combustion is denoted as heat of combustion \( \Delta h_c \) [MJ/kg].

The heat of combustion is almost constant for uniform and non-char-forming materials for a given irradiance (see Drysdale, 2011). The dependency to the irradiance is not as strong as in the case of the mass loss rate. Therefore, in a good approximation the heat of combustion of materials is often considered as constant and independent on the irradiance (referring to data presented by Tran, 1992; Hirschler, 1992). For char-forming materials such as wood, the char oxidation dominates after the flaming and the heat of combustion rise to that of carbon (Tran, 1992). Thus, the heat of combustion of char-forming materials is actually scenario dependent. A constant averaged heat of combustion is assumed, alike in the design formats of EN 1991-1-2 and CIB W14.

The heat of combustion depends on the chemical configuration of the composites and can be assessed by weighting the net heat of combustion of the individual components \( \Delta \tilde{h}_i \) by their mass fraction \( \tilde{m}_i \) (CIB W14). Values for different materials and products can be found in CIB W14 and in SFPE (2002).

The heat of combustion \( \Delta h_c \) is stochastic because of changing materials in a enclosure and is introduced as a random variable \( \Delta H_c \). Despite the many surveys that have been done on the fire load density, which involves a systematic assessment of the heat of combustion (see Section 4.2.5), little attention has been paid to assess the variability of the heat of combustion in real buildings. Therefore, the probabilistic model for the overall heat of combustion is referred to data and a review of:

- Proposed values for the heat of combustion for different materials used in typical buildings (CIB W14, 1986; SFPE, 2002).
- Range of the values for the heat of combustion observed in real fire load surveys, e.g. between 18 – 25 MJ/kg (Bwalya et al., 2008).
- Main contribution to the fire load in office and retail buildings by wooden (≈ 18 MJ/kg) and cellulosic (13 – 21 MJ/kg) materials, e.g. 80 – 90% (Thauvoye et al., 2008).

A Lognormal distribution is proposed to represent the variability of the net heat of combustion with a mean value of \( E[\Delta H_c] = 18 \) MJ/kg and a coefficient of variation of \( CoV[\Delta H_c] = 0.2 \). Alike to the mass loss rate, these values should be considered as a first estimate and can be updated to improve the probabilistic assessment of the fire hazard.
4.2.3 Combustion efficiency

The combustion in reality is incomplete and does not lead to the stoichiometric theoretical heat release rate, e.g. \( \dot{q} = \dot{m} \cdot \Delta h_c \). Tewarson (1982) used a combustion efficiency factor \( \chi_c \) to account the incomplete combustion and derived values for different materials and liquids by assessing the actual heat release rate by measurements. For cellulose, Tewarson (1982) derived a combustion efficiency of \( \chi_c = 0.72 \). The value ranges for other materials between \( \chi_c = 0.33-0.71 \).

EN 1991-1-2 proposes a combustion factor of \( \chi_c = 0.8 \) for materials which are mainly composed of cellulosic materials.

As a result, a Normal distribution of the combustion efficiency is proposed with a mean value of \( E[X_c] = 0.7 \) and a coefficient of variation of \( \text{CoV}[X_c] = 0.1 \). Since the combustion efficiency is defined over \([0,1]\) the Normal distribution should be truncated at the borders. However, the exceedance probability for the proposed model at the boundaries is very small and a (non-truncated) Normal distribution can be used without the risk of exceeding the boundaries in a probabilistic analysis.

4.2.4 Maximum heat release rate

The maximal heat release rate per square meter \( \dot{q}_{\text{max}}'' [\text{W/m}^2] \) is achieved if enough oxygen is available for the complete combustion of all volatiles. Such fires are comparable to free burning fires (Babrauskas 1984) and can be represented as:

\[
\dot{q}_{\text{max}}''(t) = \chi_c(t) \cdot \Delta h_c \cdot \dot{m}''
\]  

(4.4)

Some free burning full scale tests have been performed to measure the maximal heat release rate, e.g. Babrauskas (1984) and Zehfuss et al. (2003). To the author’s knowledge, no publication exists on the quantification of the uncertainty associated with the maximal heat release rate in real building fires. EN 1991-1-2 proposes a design value for \( \dot{q}_{\text{max}}'' \) without explaining the probabilistic background, e.g. without specifying the associated quantile value and the probability distribution type. Hosser et al. (2009) interpreted this value as a mean value of a Normal distributed random variable with a \( \text{CoV}[Q_{\text{max}}''] = 0.2 \) (see Figure 4.3).

The tentative probabilistic models introduced in Section 4.2.1 to 4.2.3 are used to derive the maximal heat release rate \( \dot{q}_{\text{max}}'' \) according to Equation 4.4 and is illustrated as a probability density distribution in Figure 4.3. The distribution shows a good agreement with the estimated probabilistic model of Hosser et al. (2009).

4.2.5 Fire load density

The fire load \( q_x [\text{MJ}] \) in an enclosure is defined as the total quantity of heat, which is released by the complete combustion \((\tilde{\chi}_c = 1)\) of all combustible materials in a fire. The fire load is assessed by integrating Equation 4.2 over time and aggregated over all combustible items \( i \) in an enclosure.

\[
q_x = \sum_i \int_0^\infty \Delta \tilde{h}_{c,i} \frac{d\tilde{m}_i}{dt} dt = \sum_i \Delta \tilde{h}_{c,i} \cdot \tilde{m}_i
\]  

(4.5)
4.2. Heat release rate

Fig. 4.3: Comparison of the probability density function (PDF) of the maximal heat release rate.

In practice it is common to use the fire load density \( q'' \) [MJ/m\(^2\)], e.g. the fire load per unit area:

\[
q''_X = \sum_i \Delta \hat{h}_{c,i} \cdot \hat{m}_i / a_E
\] (4.6)

The fire load in an enclosure varies in time and space and can be represented by a stochastic field \( \text{(Fontana et al., 2015)} \). The spatial distribution of the fire load is important when a localised fire has to be considered, e.g. in a large compartment where a flashover may occur only in a part of the area. In small compartments and for a fully developed fire, the spatial distribution of the fire load can be neglected, since per definition all combustible materials are ignited and participate to the fire (see Section 4.4).

The fire load is distinguished between the variable fire load, e.g. furniture, equipment and stored goods, and the permanent fire load, e.g. combustible components of the structure and boundary elements.

**Permanent fire load**

Especially for timber structures, the amount of permanent fire load should be considered in the quantification of the total fire load, including the fire load of structural elements, but also of walls, floors and ceilings. Though, only a part of the combustible structure will contribute to the fire without losing its functionality (structural stability). Therefore, a first estimate of the permanent fire load can be the amount of structural material that is not necessary for the structural stability in case of fire.

Structural combustible components can be protected by encapsulation and may not participate to the fire. Whether a protected material participates in a fire or not is case dependent and may be assessed probabilistically by assessing the probability of a falling off of the protection. \( \text{CIB W14} \) proposes a semi-probabilistic approach to account protected fire loads by derating-
Variable fire load

In contrast to the permanent fire load, the variable fire load may change in time and is the major stochastic component of the total fire load. Surveys in different countries for different occupancy types are available to assess the fire load in buildings. An international overview until 1986 is given in CIB W14 (1986) where the fire loads of the most common occupancy types are listed. Since 1986, different surveys have been conducted for the occupancy types, e.g. dwellings (Bwalya et al., 2008; Kumar & Rao, 1995), offices (Milke & Caro, 1996; Kumar & Rao, 1997), retail buildings (Thauvoye et al., 2008; Zalok et al., 2009) and industrial buildings (Klein, 2008).

The average values in EN 1991-1-2 are comparable to the data found in CIB W14. The coefficients of variation CoV for all occupancy types in EN 1991-1-2 are 0.3 and contradict the data of CIB W14 and the literature. Remarkable is the discrepancy between the CoV of office and retail buildings. The CoV for office buildings in CIB W14 is ranging between 0.2 to 1.43 (European data) and, excluding rooms with special use (e.g. technical rooms and communication rooms), the CoV is around 0.5. The high CoV for office buildings is supported by the surveys of Milke & Caro (1996) and Kumar & Rao (1997).

Thauvoye et al. (2008) assessed the fire load density of 36 stores in France. The mean value is comparable to the value provided in EN 1991-1-2, but the CoV of 0.65 differs. The Canadian survey of Zalok et al. (2009) supports the high CoV of Thauvoye et al. (2008).

Tentative sample statistics for the fire load density related to dwellings, office buildings and retail buildings in Europe are provided in Table 4.3.

In the literature two different probabilistic distribution types are used to represent the fire load: the Lognormal distribution and the Gumbel distribution. It is proposed to use a Lognormal distribution, because the Gumbel distribution belongs to the family of extreme value distributions, while the fire load is considered as a point-in-time realisation of a fire event. In addition, in contrast to the Gumbel distribution, the Lognormal distribution represent only values greater than zero. The probability density functions for the fire load density for three different occupancy types are illustrated in Figure 4.4.
4.3. PRE-FLASHOVER COMPARTMENT FIRE

Alike to the permanent fire load, a part of the combustible materials may be protected against fire exposure and may not participate to the energy released in a fire. Whether a protected material participates in a fire depends on the fire and is associated with uncertainties. [CIB W14] proposes a semi-probabilistic approach to account protected fire loads. Derating factors can be used to represent the probability for a participation of the protected material in the fire.

4.3 Pre-flashover compartment fire

Pre-flashover fires are important especially to assess the risk to life in an enclosure and for the activation of technical fire safety measures like sprinklers and fire detection devices. Although the reliability of structures is more associated with post-flashover fires, in some cases, local fire exposures can be important as well. Especially in buildings where a high heat release rate can be expected (but a flashover is unlikely to occur) the assessment of localised fire exposure is necessary, e.g. in very large enclosures or in compartments with large openings (car parks). This local fire exposure is not addressed in this thesis, but more details can be found in [Stern-Gottfried 2011].

A common representation of a pre-flashover fire is illustrated in Figure 4.5. The upper layer is hot and consists mainly on combustion products, e.g. smoke particles and gases. The lower layer is nearly smoke free (except in the region of the plume) and contains mainly fresh air with little amount of combustion products. The fire plume provides a convective transport of combusted material and heat to the upper layer. The entrained air enlarges the volume of the plume and has a cooling effect. The smoke free layer height $z_s$ (see Figure 4.5) is variable and depends on the fire development. The most common way to describe the fire development in the pre-flashover stage is by the fire growth rate.
Fire growth rate

After fire ignition, the heat release of a flame leads to the local combustion of adjacent fuels and the fire starts to grow in size. In this early stage of a fire, enough oxygen is provided for the combustion and a free burning fire can be expected. A common simplification of the fire growth stage is to consider a constant radial fire spread on an uniform layer of fuel, e.g. by a constant radial flame spread \( s \). For such a case, the heat release rate \( \dot{q} \) is proportional to the square of time \( t \), to the heat of combustion \( \Delta h_c \) and to the mass loss rate \( \dot{m}'' \).

\[
\dot{q}(t) = \frac{\chi_c \cdot \Delta h_c \cdot \dot{m}'' \cdot \pi \cdot s^2 \cdot \dot{q}}{\alpha} = \alpha \cdot t^2 \tag{4.7}
\]

This relationship is known under the \( t \)-square fire and can be represented by the fire growth rate \( \alpha \). The pre-flashover fire spread area \( a_f \) is assessed by:

\[
a_f(t) = \frac{\dot{q}(t)}{\dot{q}_{\text{max}}} = \frac{\alpha \cdot t^2}{\chi_c \cdot \Delta h_c \cdot \dot{m}''} \tag{4.8}
\]

For design purposes, Lawson et al. (1983) conducted large-scale calorimeter experiments with different furnitures and defined four different fire growth rates: ultra-fast, fast, medium and slow fire growth rates (see Table 4.4). Fire tests on single items have been conducted to assess the fire growth rates (e.g. Särdqvist, 1993). This, however, does not reflect the frequency of fire growth rates in real fires. In real buildings the fire growth rate \( \alpha \) is associated with uncertainties in space and time (the arrangement, the amount and type of combustible materials in an enclosure) and due to the simplified representation of the fire spread mentioned above. For a probabilistic representation of the fire growth rate, it is important to include real fire events and assess the frequency of the fire growth rates. Since the fire growth rate for real fire events cannot be measured directly, two different approaches are used in the literature.

The first approach to derive the fire growth rate \( \alpha \) is based on reported fire areas \( a_f(t) \) at certain event times that are reported by the fire brigade or investigators. This approach is
Tab. 4.4: Comparison of sample statistics and quantile values $F_A(\alpha)$ of different authors.

<table>
<thead>
<tr>
<th>Occupancy type (# obs.)</th>
<th>$E[A]$</th>
<th>$\sqrt{Var[A]}$</th>
<th>$F_A(\alpha)$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>very slow$^1$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>slow$^2$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>medium$^3$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>fast$^4$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ultra-fast$^5$</td>
</tr>
<tr>
<td>Dwellings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holborn et al. (481)</td>
<td>0.00648</td>
<td>0.0455</td>
<td>56.3</td>
</tr>
<tr>
<td>Deguchi et al. (11598)</td>
<td>0.0524</td>
<td>0.06</td>
<td>72.0</td>
</tr>
<tr>
<td>Retail</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holborn et al. (37)</td>
<td>0.02746</td>
<td>0.1647</td>
<td>25.0</td>
</tr>
<tr>
<td>Nilsson et al. (2965)</td>
<td>0.01924</td>
<td>0.0371</td>
<td>40.8</td>
</tr>
<tr>
<td>Deguchi et al. (313)</td>
<td>0.0236</td>
<td>0.03</td>
<td>69.6</td>
</tr>
<tr>
<td>Offices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holborn et al. (19)</td>
<td>0.00417</td>
<td>0.0207</td>
<td>59.2</td>
</tr>
<tr>
<td>Deguchi et al. (601)</td>
<td>0.0236</td>
<td>0.034</td>
<td>75.8</td>
</tr>
</tbody>
</table>

$^1$ very slow: $\alpha = 0.00125$ kW/sec$^2$  $^2$ slow: $\alpha = 0.0029$ kW/sec$^2$

followed by [Holborn et al., (2004)] and [Deguchi et al., (2011)]. The fire growth rate $\alpha$ is assessed based on Equation 4.8. Holborn et al. (2004) analysed data collected by fire investigators (interviewing persons who discovered the fire) and derived probabilistic models for the fire growth rate. Though, not all of the fires merit such an investigation and only fires which meet some criteria have been reported, e.g. fires where four or more fire engines are sent to the scene and fires where persons have to be rescued. The data includes also smouldering fires, which lead to very slow fire growth rates and to a very long tail of the probabilistic model of the fire growth. Although these fire may lead to large financial consequences, they are less problematic for structural reliability and risk to life. Deguchi et al. (2011) used a similar approach to derive the fire growth rate, but excluded very slow growing fires from the survey. This leads to higher fire growth rates compared to the data of Holborn et al., but represents fires that may lead to structural failure or to fire deaths. Both surveys propose a Lognormal distribution to represent the fire growth rate. Sample statistics for different occupancy types are listed in Table 4.4.

The second approach to derive the fire growth rate $\alpha$ consists on the simulation of the fire growth rate based on the fire behaviour of items with a-priori known heat release rates (see e.g. [Särdqvist, 1993]) and is followed by [Baker et al., (2013)] and [Nilsson et al., (2014)]. Nilsson et al. (2014) assessed the fire growth rate $\alpha$ for retail buildings based on fire brigade reports including the first ignited item in real fires (see Table 4.4). The radiative fire spread to other adjacent items has not been considered by these authors so far. Thus, the derived probabilistic model for the fire growth rate represents mainly the fire spread of single items. Baker et al. (2013) considered the radiative fire spread to adjacent furniture items and developed a stochastic tool that is able to randomly select items from a database, position them in the enclosure and ignite a fire which spreads to other items by radiation. The fire growth rate $\alpha$ is estimated based on
the heat release rate $\dot{q}$ and the time of flashover, but a realistic fire ignition rate of the different items, as well as the incipient phase, are not yet considered in the model. Therefore, the derived fire growth rates are unlikely to represent realistic fire growth rates.

In this thesis, the models proposed by Deguchi et al. (2011) are used, since the fire growth rate is derived for dwellings, retail and office buildings and the sample size is larger compared to the sample size of Holborn et al. (2004).

4.4 Flashover

According to Walton & Thomas (2002) a flashover is defined as the transition of the fire growth stage to the fully developed fire that engulfs the whole floor area of the enclosure, i.e. $a_f = a_E$. This definition is not precise and different transient conditions for a flashover can be found in the literature. The most common is the simultaneous ignition of all combustible materials in an enclosure exposed to the upper layer’s radiation. This definition, however, is not practical, since it requires an exact knowledge of the thermal properties of all combustible materials in the enclosure. Different – more convenient – indicators are used to describe the occurrence of a flashover. Peacock et al. (1999) proposed a critical imposed heat flux of 20 kW/m$^2$, which corresponds to an upper layer temperature of 500°C, if it is considered as a perfect black-body radiator. According to Peacock et al. (1999) a considerable uncertainty is associated with this definition depending on the involved materials and room configuration.

4.5 Post-flashover compartment fire

All combustible materials in an enclosure release heat after a flashover. This stage is denoted as the post-flashover stage and consists on the fully developed fire stage and the decay stage. A schematic overview of the heat and mass transfers in this stage is illustrated in Figure 4.6. Depending on the incoming air flow rate $\dot{m}_{\text{air}}$, two different regimes can be distinguished: the fuel-controlled regime and the ventilation-controlled regime.

4.5.1 Fuel-controlled regime

In the fuel-controlled regime, enough oxygen is available for the combustion of the volatiles:

$$\dot{m} \leq \frac{\dot{m}_{\text{ox}}}{r} = \frac{0.23 \cdot \dot{m}_{\text{air}}}{r}$$

The stoichiometric ratio $r$ [kg air/kg fuel] describes the mass of oxygen required for the stoichiometric combustion of 1 kg of fuel. According to Cadarin & Franssen (2003), a value of $r = 1.27$ represents the combustion of wood. The oxygen flow $\dot{m}_{\text{ox}}$ through the opening is related to the air flow entering the enclosure $\dot{m}_{\text{air}}$, which is assumed to have an oxygen level of 23% (in mass). The complete combustion of the volatiles leads to the maximal heat release rate $\dot{q}_{\text{max}}$ (see Section 4.2.4), which is determined by the thermal combustion characteristics of the material:

$$\dot{q}_{\text{fuel}} = \chi_e \cdot \Delta h_e \cdot \dot{m}'' \cdot a_E = \dot{q}_{\text{max}}$$
4.5. Post-flashover compartment fire

Energy of the hot gases
θ_g

Heat release rate
q

Mass loss rate
m

Convective heat loss
q_c

Radiative heat loss
q_r

The air that enters the enclosure and is not consumed for combustion has a cooling effect and lowers the room temperatures. Therefore, fuel-controlled fires are less severe than ventilation-controlled fires.

4.5.2 Ventilation-controlled regime

In the ventilation-controlled regime, the available oxygen is insufficient for a complete combustion of the volatiles:

\[ \dot{m} > \dot{m}_{ox} = \frac{0.23 \cdot \dot{m}_{air}}{r} \]  

(4.11)

If the oxygen for the combustion of the volatiles is limited, then the fully developed fire becomes ventilation-controlled and the oxygen entering the enclosure is completely consumed. The remaining (unburnt) volatiles stream to the outside and produce a flame, since enough oxygen is again available for the combustion. Thus, flames coming out of the windows are an indication of ventilation-controlled fires. In ventilation-controlled fires only a part of the mass loss rate is transformed to heat and depends on the mass of oxygen flowing into the compartment \( \dot{m}_{ox} \).

The heat release rate of a ventilation-controlled fire is:

\[ \dot{q}_{\text{vent}} = \chi_c \cdot \Delta h_c \cdot \frac{\dot{m}_{ox}}{r} = \chi_c \cdot \Delta h_c \cdot \frac{0.23 \cdot \dot{m}_{air}}{r} \]  

(4.12)

4.5.3 Ventilation conditions

The severity of a fire in the fully developed stage significantly depends on the amount of oxygen available for the combustion. The oxygen comes from the air that enters the enclosure through openings, e.g. windows and doors. A common assumption is that all glass windows completely break and fall out after a flashover. This might not actually be the case for all fires. The probabilistic model code [JCSS 2001] proposes to introduce a random variable to account for a partial failure of the glass window. There is lack of statistical data to quantify this effect and it may be better treated by a parametric analysis of different opening conditions, since opening conditions are significant for the fire development in an enclosure.
According to Drysdale (2011), the mass flow of the air $\dot{m}_{\text{air}}$ can be derived by a mass balance: the outgoing mass flow $\dot{m}_{\text{gas}}$ (gases) is equal to the incoming mass flow $\dot{m}_{\text{air}}$ (air) used for the combustion (see Figure [4.6]). Bernoulli’s equation is used to describe the velocity distribution of the mass flow and results in:

$$\dot{m}_{\text{air}} \approx 0.52 \cdot a_v \cdot \sqrt{h_v} \quad (4.13)$$

where $a_v$ is the area and $h_v$ is the height of the ventilation opening. Harmathy (1972) proposed to relate Equation (4.13) to the burning area $a_f$, which corresponds to the floor area $a_E$ in a fully developed fire. This provides the basis for the introduction of the opening factor $o_E$, used in EN 1991-1-2 as an indicator for the size of the openings, and is related to the total area of the enclosure $a_t$ including wall, ceiling, floor and opening areas:

$$o_E = \frac{a_v \sqrt{h_v}}{a_t} \quad (4.14)$$

### 4.5.4 Decay stage

The decay stage of a fire indicates the decrease of the heat release rate and depends mainly on the quantity and the distribution of the fuel within the enclosure. The heat release rate is reduced successively, due to the non-uniform distribution of the fire load in an enclosure and due to the complete combustion of parts of the fuel. A ventilation-controlled fire may change to a fuel-controlled fire, which is the prevailing regime in this stage. To model the decay stage, EN 1991-1-2 proposes a linear decrease of the heat release rate when 70% of the combustible material is consumed. This value could be introduced as a random variable representing the uncertainty related to the distribution of the quantity of the fuel. In this thesis, this value is assumed to be deterministic for simplicity.

The duration of a fully developed fire (after a flashover) depends on the fire load $q$ and the mass loss rate $\dot{m}$. A high mass loss rate $\dot{m}$ leads to a short fire, but may increase the maximal heat release rate $\dot{q}_{\text{max}}''$. For design purposes, and to avoid critical assumptions on the mass loss rate $\dot{m}$, the duration of a ventilation-controlled fire is extended in EN 1991-1-2 supposing that all combustible materials release their heat in the enclosure (see Schleich et al., 2002). This does not correspond to reality, since there is a mass flow of combustible gases $\dot{m}_{\text{gas}}$ to the outside of the enclosure. To overcome this inconsistency, it is assumed that the duration of a ventilation-controlled fire depends on the mass loss rate $\dot{m}$ under free burning conditions, i.e. to the duration of a fuel-controlled fire. Burning tests of wood and plastic cribs (Quintiere & McCaffrey, 1980) indicated that the mass loss rate in an enclosure (in ventilation controlled conditions) tends to be higher compared to free burning conditions. Accordingly, this assumption may still overestimate the duration of a real fire.

Since the duration of a fire affects the structural reliability, the consistent representation of the physical phenomena of the decay stage is important and should be further investigated. This is especially important, when construction elements are combustible and participate to the fire development. In such a case, the complete combustion of the variable fire load does not correspond to the end of the fire exposure and the participation of the permanent fire load has
4.6 Mathematical models for compartment fires

In the beginning of the 20th century mathematical models have been developed based on fire tests in order to predict the time-temperature relationship of a fire and provided the basis for different standard fire curves. The first mathematical model, which relies on the modelling of the physical processes, has been developed by Kawagoe & Sekine (1963). Since then, many other models have been developed to predict the fire exposure, which are used for design purposes or for probabilistic analyses. This section focuses only on the models that are used for the risk models that are developed in this thesis. For other mathematical models, like field models, it is referred to the literature.

4.6.1 Standard fire curves

Standards for fire testing have been developed in the beginning of the 20th century to compare different building materials and systems. The aim of the standard fire exposures is to represent a worst-case post-flashover fire scenario, rather than a realistic fire exposure, and is a result of a limited understanding of fire dynamics at that time (Gales et al., 2012). Nevertheless, standard fire exposures, especially the [ISO 834-1] standard temperature curve, are nowadays widely used for certification of building materials. Standard fire exposures consist on a predefined mathematical time-temperature relationship, have no decay stage, and consider no building specific indicators (see Figure 4.7). For example the [ISO 834-1] standard temperature curve [°C] is defined by:

$$\theta_g = 20 + 345 \cdot \log_{10} (0.133 \cdot t + 1)$$ (4.15)
4.6.2 Parametric fire curves

Different parametric fire curves have been developed for design purposes, e.g. [Magnusson & Thelandersson (1970), EN 1991-1-2, Zehfuss & Hosser (2007) and Klein (2008), in order to assess the time-temperature relationship of a post-flashover compartment fire. The curves depend on some building specific indicators, e.g. opening factor, dimensions of the enclosure, thermal inertia of the boundary elements, and consider fire specific indicators, e.g. the fire load density and the fire growth rate.

Magnusson & Thelandersson (1970) derived, from heat balance calculations, time-temperature curves for ventilation controlled fires, which depend on the opening factor and the fire load density. The time-temperature curves are presented in the form of tabulated data and are known as the Swedish fire curves. The parametric fire curves of EN 1991-1-2 (2002) are derived in order to give a good approximation to the Swedish fire curves and provide an analytical assessment of the time-temperature curve (see Figure 4.7):

\[
\theta_g(t^*) = 1325 \left( 1 - 0.324 \cdot e^{-0.2t^*} - 0.204 \cdot e^{-1.7t^*} - 0.472 \cdot e^{-19.5t^*} \right)
\] (4.16)

The time \( t^* \) considers building specific properties like the opening factor \( a_E \) and the thermal inertia of the boundary elements \( b \). The fire load determines the duration of the fire, e.g. \( t_{\text{max}}^* \). The model is limited in the application for buildings with floor areas of the enclosure \( a_E < 500 \, \text{m}^2 \), with ceiling height \( h_E < 4 \, \text{m} \) and no horizontal ceiling openings. Zehfuss & Hosser (2007) and Klein (2008) extended the approach of EN 1991-1-2 (2002) and derived parametric fire curves that include the pre-flashover phase of a fire.

4.6.3 Zone models

Zone models divide the enclosure into zones, where the energy and mass balance equations are solved. The temperature in each zone is assumed to be uniformly distributed at any time. For the pre-flashover stage (see Figure 4.5), two zones can be used to separate the upper (hot) layer and the lower (cold) layer. The mass and the convective heat transport into the upper layer occurs through the plume. The entrained air into the plume is usually assessed by an empirical formulation, e.g. Heskestad (2002). The interface between the upper and the lower layer does not allow for mass exchange.

The post-flashover phase is usually modelled as one zone. The computational model used in this thesis is OZone, which has been developed at the University of Liège (Cadorin, 2003; Cadorin & Franssen, 2003; Cadorin et al., 2003). A typical time-temperature curve is illustrated in Figure 4.7. An overview of other zone models (and other mathematical models) is given in Olenick & Carpenter (2003).

The zone model OZone

OZone is a single compartment fire model that combines a two-zone model and a one-zone model. The switch from the initial two-zone model to the one-zone model occurs if one of four criteria is met:
4.6. Mathematical models for compartment fires

\[ q(t) = \alpha \cdot t^2 \]

\[ \dot{m}(t) = \frac{a \cdot t^2}{\chi \cdot \Delta h_c} \]

Fig. 4.8: Representation of a post-flashover fire

- if the upper layer temperature exceeds 500°C causing a radiant heat flux that ignites all combustible materials in the room
- if the gases in contact with the fuel have a higher temperature than its ignition temperature (e.g. 300°C)
- if the thickness of the upper layer is so high that an one-zone representation is more adequate
- if the fire area grows too much that a representation by a local fire is no longer adequate

OZone adapts automatically the heat release rate for ventilation-controlled fires according to the available oxygen (see Section 4.5). The basic input for OZone is the heat release rate, the mass loss rate and the fire area — all as a function of time.

Idealised input for OZone

The time-dependent fire area \( a_f(t) \) is assessed for the pre-flashover stage by Equation 4.8 and for the fully developed fire stage as \( a_f = a_E \). Accordingly, the area is a function of the time-dependent mass loss rate \( \dot{m}'(t) \) and of the time-dependent heat release rate \( \dot{q}''(t) \). Both are illustrated in Figure 4.8. The basic input for OZone is the fuel-controlled heat release rate without the consideration of the flashover. The routines in OZone adapts automatically the curves based on predefined criteria for the transition from the two-zone to the one-zone model (e.g. flashover). The program recognises the limited availability of oxygen as well and adapts the rate of heat release for ventilation-controlled fires (see Section 4.5).

The time-dependent fire area \( a_f(t) \) is assessed for the pre-flashover stage by Equation 4.8 and for the fully developed fire stage as \( a_f = a_E \). Accordingly, the area is a function of the time-dependent mass loss rate \( \dot{m}'(t) \) and of the time-dependent heat release rate \( \dot{q}''(t) \). Both are illustrated in Figure 4.8. The basic input for OZone is the fuel-controlled heat release rate without the consideration of the flashover. The routines in OZone adapts automatically the curves based on predefined criteria for the transition from the two-zone to the one-zone model (e.g. flashover). The program recognises the limited availability of oxygen as well and adapts the rate of heat release for ventilation-controlled fires (see Section 4.5).

There is a numerical instability in OZone, when the start of the decay phase of a fire is close to a flashover. A workaround for this problem is to increase the flashover criteria, e.g. up to 600°C and re-execute the program. The effect of this workaround on the temperature prediction is small because the room temperature decreases during the decay phase anyway.
Model uncertainty

Mathematical models are always associated with uncertainties due to simplifications and approximations of the physical formulation of the problem. Therefore, there might be a lack of fit between the prediction of the model and the observation (experimental data). This lack of fit is denoted as model uncertainty. In order to validate OZone, Cadorin & Franssen (2003) compared the maximal gas temperature $\theta_{g,\text{max}}$ measured in experiments ($\text{exp}$) with the temperatures predicted by the model ($\text{model}$) (see Figure 4.9b). The lack of fit is expressed by the ratio $\xi_{\theta_{g,\text{max}}} = \theta_{g,\text{max},\text{exp}} / \theta_{g,\text{max},\text{model}}$ and is illustrated in Figure 4.9b.

Figure 4.9b shows a negative correlation ($\rho_{\text{Pearson}} = -0.74$) of the predicted temperatures by the model and $\xi_{\theta}$. The model uncertainty is modelled by a Normal distribution. Its mean value depends on the predicted maximal room temperature and is represented by a linear regression and a constant coefficient of variation $\text{CoV}[\Xi_{\theta}]$. The parameters are estimated by the Maximum Likelihood Method. This uncertainty is illustrated in Figure 4.9b by its mean ($\mu_{\Xi}$) and its standard deviation ($\sigma_{\Xi}$). The constant coefficient of variation leads to a reduction of the variability for high temperatures, which is reasonable, since OZone has been developed to predict fires where high temperatures are reached.

\[
\Xi_{\theta} \sim \mathcal{N}(\mu_{\Xi}, \sigma_{\Xi}) \\
\mu_{\Xi} = E[\Xi_{\theta}] = 3.24 \cdot 10^{-4} \cdot \theta_{g,\text{max}} + 1.35 \\
\text{CoV}[\Xi_{\theta}] = \sigma_{\Xi} / \mu_{\Xi} = 0.076
\]
4.7 Correlation between fire parameters

The main parameters to describe the heat release of a fire, e.g. the fire growth rate \( \alpha \), the fire load density \( q'' \), and the maximal heat release rate \( \dot{q}_{\text{max}} \), are based on Equation 4.2. Thus, between the main parameters there is actually a dependency. This becomes obvious when considering densely packed combustible materials, which may lead to a higher fire load \( q \) since there is more mass per m\(^2\). Simultaneously, the fire growth rate \( \alpha \) might be higher as well, since densely packed materials enhance the radiative fire spread, (see also Equation 4.7). More material per m\(^2\) means also a higher burning rates \( \dot{m}'' \) and increases the maximal heat release rate \( \dot{q}_{\text{max}}'' \). The same reasoning can be made for the heat of combustion. Data surveys are usually only focused on the assessment of one main parameter, e.g. the fire load or the fire growth rate, and neglect this correlation. This might be acceptable if an engineering problem is dominated by only one of these parameters. For structural reliability problems, for example, usually a full burn-out scenario is assumed (including conservative assumptions on the mass loss rate, see Chapter 4.5.4) and the reliability depends mainly on the fire load rather than on other parameters (see Schleich et al., 2002; Hosser et al., 2009). There might be engineering problems, however, where such correlations may be more important and should be considered appropriately in the modelling of a fire.
Chapter 5

Performance of fire safety measures under realistic fire conditions

This chapter provides an overview of the most common fire safety measures and discusses how their performance under realistic fire exposures can be evaluated by a probabilistic approach. A detailed review of the behaviour and the operation of fire safety measures can be found in Rasbash et al. (2004) and will not be addressed in this chapter. In contrast to design fires that aim to represent a worst-case or severe fire, realistic fire conditions refer to fires that are likely to be observed in reality and are always subjected to uncertainty due to the random effects in reality, e.g. the amount of fire load in the building or the arrival time of the fire brigade. These random effects are considered by a probabilistic approach.

The time where the fire safety measures performs depends on the fire development. A qualitative overview is provided in Figure 5.1 indicating when the measures are performing and reducing the risk. The measures can be distinguished between organisational, passive and technical fire safety measures. Passive fire protection measures aim to contain the fire in the compartment of fire ignition and are part of the building structure. Their performance can be assessed by a reliability-based approach, as discussed in Section 5.1. In contrast to the passive fire protection measures, the active fire protection measures are reactive to a fire event. Those measures include, e.g. devices for the early detection of a fire, fire suppression by the occupants or by the fire brigade, sprinkler systems and other cooling or suppression systems. Their performance may only be evaluated in combination with passive fire protection measures. Therefore, in Sections 5.2 to 5.6 the probabilistic models that provide the basis for such an approach discussed. The main objective of the means of egress is to provide a safe evacuation of occupants to a place of safety, without exposing them to dangerous conditions. The performance of such measures is evaluated under realistic fire exposures, as well as the movement behaviour of the occupants. The related general principles are discussed in Section 5.7.
5.1 Passive fire protection

Passive fire protection measures are construction elements that are designed to keep a certain performance criterion under a certain thermal exposure, e.g. load bearing capacity (R), integrity (E), thermal insulation (I), or a combination of them exposed within a given time period to the standard fire curve (ISO 834-1). The aim of these elements is to contain the fire in the compartment of fire ignition and to protect life and property outside of the compartment. These elements can be considered as barriers for the fire propagation within the building. Fire resistant structural elements such as walls, doors or windows are representative passive fire protection construction elements. Their performance may be evaluated by assessing the reliability of a barrier under realistic fire exposure and may be formulated by a limit state function that considers the thermal exposure of a fire $S_T$ and the thermal resistance of the element $R_T$:

$$ G = R_T - S_T > 0 \quad (5.1) $$

The variables $R_T$ and $S_T$ are introduced as random variables since both are associated with uncertainties. This inequality reflects a capacity-demand approach and corresponds to the formulation of the basic reliability problem, e.g. Melchers (2002). Without the loss of generality, it is convenient to assess the probability of the complementary event, e.g. the failure probability. The probability of failure $p_f$ is assessed by integrating the joint probability density function $f_{RS}(r_T, s_T)$ over its failure domain $g(r_T, s_T) \leq 0$:

$$ p_f = P(G \leq 0) = \int_{g(r_T, s_T) \leq 0} f_{RS}(r_T, s_T) dr ds \quad (5.2) $$

Analytical solutions for this integral are only available for special cases, e.g. when $R_T$ and $S_T$ are Normal distributed random variables (which is seldom the case). Depending on the problem, this integral can be solved either by integration techniques, by simulation techniques, e.g. Monte Carlo Simulation techniques, or by approximation methods, e.g. First or Second Order Reliability

Fig. 5.1: Qualitative overview of fire safety measures operating during a compartment fire.
5.1. Passive fire protection

Method (FORM/SORM). An introduction in those methods is provided by Melchers (2002) and Hasofer et al. (2007).

Depending on the performance criteria, the limit state may be formulated either on the strength domain (e.g. R, I), on the temperature domain (e.g. R, E, I) or in the time domain (e.g. R, E, I) (Buchanan 2001). The time domain is not the failure time in real fires, but the failure time under standard fire conditions [ISO 834-1], which is assessed based on the equivalent fire-severity-concept (see Buchanan 2001). This concept aims to relate a realistic fire exposure to the standard fire exposure [ISO 834-1] in order to check if an element, which is tested under [ISO 834-1] conditions, resists a realistic fire exposure. The correlation between the severity of the exposures is often based on empirical relationships and there is a wide variation in the severity equivalence by various methods (see Kodur et al., 2010). In a risk-based approach, this can be considered by introducing additional (epistemic) uncertainties. However, a formulation in the strength or in the temperature domain should be preferred, if possible.

5.1.1 Thermal exposure of the element

The random variable $S_T$ represents all uncertainties which are associated with the exposure (see Chapter 4), with the active fire safety measures that may reduce the exposure (see Section 5.2 to 5.6) and with the net heat flux to the surface $h_{S,net}$ [W/m²] (irradiance). The net heat flux to the surface is, according to EN 1991-1-2, assessed by considering the net convective heat flux $h_{S,net,c}$ and the net radiant heat flux $h_{S,net,r}$ by:

$$h_{S,net} = h_{S,net,c} + h_{S,net,r}$$  \hspace{1cm} (5.3)

where $h_{S,net,c} = \alpha_c \cdot (\theta_g - \theta_S)$ \hspace{1cm} (5.4)

and $h_{S,net,r} = \psi \cdot \varepsilon_S \cdot \varepsilon_f \cdot \sigma \left[ (\theta_r + 273)^4 + (\theta_S + 273)^4 \right]$ \hspace{1cm} (5.5)

$\alpha_c$ is the convective heat transfer coefficient [W/m²K]

$\theta_g$ is the gas temperature in the vicinity of the fire exposed element [°C]

$\theta_r$ is the effective radiation temperature of the fire environment [°C]

which may be set $\theta_r = \theta_g$ for a fully fire engulfed element

$\theta_S$ is the surface temperature of the element [°C]

$\psi$ is the configuration factor, which takes into account the geometrical relationship between the radiation emitter and radiation receiver (see Drysdale (2011))

$\varepsilon_S$ is the surface emissivity of the element

$\varepsilon_f$ is the emissivity of the fire

$\sigma$ is the Stephan Boltzmann constant (= 5.67 \cdot 10^{-8} \text{ W/m}^2\text{K}^4)

The convective heat transfer coefficient $\alpha_c$ depends on the fire situation, e.g. the properties of the surrounding fluid, thermal characteristics of the material and the geometry of the surface. According to Drysdale (2011), typical values lie in the range 5-25 W/m²K for free convection and 10-500 W/m²K for forced convection in air. EN 1991-1-2 proposes a conservative value of
\( \alpha_c = 35 \text{ W/m}^2\text{K} \) for natural fire models. Though, the net radiant heat flux for high compartment temperatures may dominate the net heat flux and the uncertainties associated with the convective heat flux are reduced.

Both the emissivity of the fire as well as the emissivity of the surface are smaller than 1 and may be associated with uncertainties. EN 1991-1-2 proposes to consider the fire as a perfect black body radiator with emissivity of \( \varepsilon_f = 1 \) and the emissivity of the element as \( \varepsilon_S = 0.8 \). Both values are considered to be conservative for design purposes.

### 5.1.2 Thermal resistance of an element

An element designed to keep a certain performance criterion (e.g. \( R, E, I \)) resists a thermal exposure \( S \) until a critical threshold is reached. This threshold is denoted as the thermal resistance of the element and is introduced as a random variable \( R_T \) that represents all uncertainties associated with the thermal and mechanical properties of an element. The thermal resistance of an element depends on the heat flow in the material and is represented by Fourier’s law of heat flow. For non-steady state conditions, the rate of change of the energy content of a material leads to a change in the temperature of the specimen over time. For a general case, the heat conduction equation is (Drysdale, 2011):

\[
\rho \cdot c \frac{d\vartheta}{dt} = \nabla \cdot (\lambda \cdot \nabla \vartheta) + \dot{h}_S^m
\]  

(5.6)

- \( \rho \) is the mass density of the material [kg/m\(^3\)]
- \( c \) is the specific heat capacity of the material [J/kgK]
- \( \lambda \) is the thermal conductivity [W/mK]
- \( \vartheta \) is the temperature of the material [°C]
- \( \dot{h}_S^m \) is the volumetric internal heat generation rate [W/m\(^3\)]
- \( \nabla \) is the Nabla operator
- \( \bullet \) is the scalar product

The properties of a material (e.g. \( \rho, c \) and \( \lambda \)) are, in general, temperature-dependent and material models are found in the codes, e.g. EN 1993-1-2 (steel), EN 1994-1-2 (reinforced concrete) and EN 1995-1-2 (timber). There is very little treatment of the uncertainties associated with these thermal properties. For some materials like timber, the thermal properties are only known for a predefined exposure, e.g. the standard fire exposure (ISO 834-1), and cannot be applied to realistic fire exposures.

For combustible construction elements like timber, the oxidation of the char layer has to be considered as well. Char oxidation produces additional heat, which will influence the heat transfer in the element, and is strongly influenced by the oxygen supply close to the specimen, e.g. the air flow. This can be modelled as an additional heat source using the volumetric internal heat generation rate \( \dot{h}_S^m \). For non-combustible material the volumetric internal heat generation rate \( \dot{h}_S^m \) is usually set to zero.
5.1.3 Mechanical properties

The mechanical properties, e.g. strength, modulus of elasticity, of common construction materials at ambient temperature are well known and sophisticated probabilistic models exist, e.g. JCSS (2001). Those mechanical properties are temperature-dependent and the material properties may be considerably reduced and should be considered when the load bearing capacity of a member is assessed. Guidance to account for this reduction is provided in the codes, e.g. EN 1993-1-2 (steel), EN 1994-1-2 (reinforced concrete) and EN 1995-1-2 (timber). Uncertainties associated with the thermal properties at elevated temperatures have not been so well described so far. First approaches towards a probabilistic representation of steel properties at elevated temperatures are provided by Khorasani et al. (2012).

5.1.4 Mechanical loads in a fire

The load bearing capacity of a structural member depends, apart from the fire exposure, on the imposed load. Since a fire is an accidental event at a random point in time, it is unlikely that it coincide with another rare event, e.g. an earthquake, and a structure is more likely to be loaded only to a part of the designed critical load. This allows – especially if the design is dominated by a rare design scenarios unequal to a fire design scenarios – to use the partially loaded structure as mechanical reserves to bear the mechanical loads during a fire situation.

For a realistic representation of the mechanical loads during a fire situation, the occurrence probability, the duration and the point-in-time distribution of the loads should be considered. Ellingwood (2005) analysed different load combinations for the accidental fire design, on the basis of the occurrence rate of loads, and concluded that the major participation of the loads in a fire are due to the dead and the live load. Dead loads are permanent loads of the construction and are subjected only to small changes, if no remodelling of the construction (e.g. due to a change in the use) is considered. In contrast, live loads are caused by furniture, equipment, stored objects and persons and may change remarkably during the life-time of a building. The live load can be modelled by two components, e.g. the sustained and the intermittent load (see Figure 5.2). According to JCSS (2001), the two loads are defined as follow:

- The sustained load contains the weight of furniture and heavy equipment and represents the time average of the real fluctuating load. Changes in magnitude occur usually due to changes in the use or of the user of a building. Short term fluctuations are included in the uncertainties of this load.
- The intermittent load represents all kinds of live loads, which are not covered by the sustained load. The sources are gathering of people, crowded rooms during special events, or stacking of furniture during remodelling. The relative duration of an intermittent load is fairly small.

Due to the small occurrence rate (e.g. 1 ÷ 4 a year) and the short load duration (e.g. 1 ÷ 14 days) of the intermittent load, Ellingwood (2005) proposed to neglect this load and consider only the dead load and the sustained live load. Probabilistic models for these loads are provided...
Chapter 5. Performance of fire safety measures

5.2 First-aid measures

A fire in an early stage can be extinguished by occupants using first-aid equipment, e.g. portable fire extinguishers, fire blankets or a bucket of water. Thus, the rate of severe fires can be reduced by those measures. The model is used in this thesis to assess the rate of fire ignition (see Section 4.1) is associated with an insurance claim of building owners due to a financial loss by a fire event. Hence, fires are included where no fire brigade intervention occurred and the fire was extinguished by the occupants or by itself. Unfortunately, current fire statistics in Switzerland do not include information whether a fire brigade was present or not. Therefore, 525 Swiss fire brigade reports (for a period of 1.5 years) from the Canton Aargau (Switzerland) are evaluated to link the reports with the corresponding insurance claims, using the building’s address. A link to the insurance data is not always possible, either because the fire brigade reports contained a wrong address of the fire scene, because the incidents were not reported by the fire brigade, or because the fire did not cause any damage that is covered by the insurance. In addition, different fire brigades reported the same fire, which causes multiple counts for the same fire incident. The evaluation of the reports is supported by newspaper articles or by fire brigade articles that contain further information of the event. As a result, 239 of 739 claims could be associated directly with a fire brigade intervention. Regarding the other claims, there are claims where a fire brigade intervention is very likely, e.g. claims above 10’000 CHF, which applies for 72 claims. On the other hand, according to the description of the event, there are 143 unlinked fire brigade reports that may be associated with a fire damage in a building. Thus, the probability of a fire brigade intervention given a fire is between 42% and 61% per incident, resulting in a probability of successful suppression by occupants \( P(\text{Occ}) \) between 39% and 58%. The value presented in the German Annex of EN 1991-1-2 (\( P(\text{Occ}) = 50\% \)) and the value of Ramachandran & Charters (2011) (\( P(\text{Occ}) = 43\% \)) are within this range. The range of the value is below the value estimated by Fontana et al. (1999) (72% for dwellings and 59% for office buildings).

![Fig. 5.2: Load changes over the life-time of a building.](image-url)
5.3 Fire brigade intervention time

The fire brigade is an integral part of the fire safety concept of a building. Therefore, it should be considered appropriately in a risk-based approach. The fire brigade aims to reduce human and financial losses as well as to reduce the ecological impact of a fire. The fire brigade has many non-fire related tasks. In this thesis, only the building fire related services are addressed. These services can be subdivided in three tasks: rescue operation, fire fighting and fire prevention.

The prevention task is conducted in the context of fire safety management and aims at avoiding incipient fires. This task can be requested for single events by the authorities, e.g. fairs or festivals, and is beyond the scope of this thesis. Both rescue operation and fire fighting actions can start at the earliest, when the fire brigade is present at the scene of the fire, equipped and ready for suppression actions. This instant is referred to as the intervention time of the fire brigade and consists on sequential time intervals as illustrated in Figure 5.3.

\[ t_I = t_{Detect} + t_{Call} + t_{Disp} + t_{Prep} + t_{Travel} + t_{Setup} \] (5.7)

Fig. 5.3: Fire brigade intervention time (see also Tillander, 2004).
Tab. 5.1: Tentative probabilistic models for the fire brigade intervention.

<table>
<thead>
<tr>
<th>Time interval</th>
<th>Distribution</th>
<th>$E[X]$</th>
<th>$\sqrt{Var[X]}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection time [min]</td>
<td>$T_{Detect}$</td>
<td>$t_{Detect}$</td>
<td>$\mathcal{E}XP$</td>
</tr>
<tr>
<td>Call time [min]</td>
<td>$T_{Call}$</td>
<td>$t_{Call}$</td>
<td>$\mathcal{E}XP$</td>
</tr>
<tr>
<td>Dispatch time</td>
<td>$T_{Disp}$</td>
<td>$t_{Disp}$</td>
<td>$\mathcal{N}$</td>
</tr>
<tr>
<td>Preparation time</td>
<td>$T_{Prep}$</td>
<td>$t_{Prep}$</td>
<td></td>
</tr>
<tr>
<td>professional [min]</td>
<td>$\mathcal{LN}$</td>
<td>1.38</td>
<td>0.50</td>
</tr>
<tr>
<td>volunteering [min]</td>
<td>$\mathcal{LN}$</td>
<td>4.56</td>
<td>2.19</td>
</tr>
<tr>
<td>Travel time</td>
<td>$T_{Travel}$</td>
<td>$t_{Travel}$</td>
<td></td>
</tr>
<tr>
<td>professional$^1$</td>
<td>$\mathcal{GA}$</td>
<td>6.52</td>
<td>2.93</td>
</tr>
<tr>
<td>volunteer$^1$</td>
<td>$\mathcal{GA}$</td>
<td>4.10</td>
<td>3.26</td>
</tr>
<tr>
<td>volunteer$^2$</td>
<td>$\mathcal{GA}$</td>
<td>7.56</td>
<td>5.00</td>
</tr>
<tr>
<td>Set-up time [min]</td>
<td>$T_{Setup}$</td>
<td>$t_{Setup}$</td>
<td>$\mathcal{LN}$</td>
</tr>
</tbody>
</table>

1 performance criterion: 80% of all interventions within 10 min.
2 performance criterion: 80% of all interventions within 15 min.

All those times are associated with uncertainties and are modelled as random variables. In this section the probabilistic models are discussed to quantify those times. The influence of technical measures on the intervention time $t_I$ is discussed in Section 5.5.

5.3.1 Notification time

The notification time is, without technical fire detection devices, not manageable and is significantly subjected to human behaviour. A big effort has to be done to quantify this time, because, similar to the assessment of the fire growth time (see Section 4.3), fire investigators have to interview the occupants who discovered the fire or called the fire brigade.

Detection time

The detection time is the time from fire ignition to its discovery by the occupants and is considered to be the most difficult time interval to quantify. The difficulty is that the time of ignition is unknown and has to be estimated by fire investigators or the fire brigade and has, thus, a subjective component. Holborn et al. (2004) used fire brigade reports (London’s fire brigade) to derive sample statistics of the detection time (e.g. sample mean, standard deviation and quantile values) including flaming, flashover and non-flaming (smouldering) fires for different occupancy types. To reduce the influence of statistical outliers, especially on the mean and standard deviation, only the quantile values are used. It should be noted that not all of the fires merit such an investigation. Thus, only fires which meet some criteria have been reported, i.e. fires where four or more fire engines are sent to the scene and fires where persons have to be
rescued. Unfortunately, no information is provided regarding whether fires were detected by a fire detector or by the occupants.

The sample statistics of Holborn et al. (2004) indicate a large scatter of the discovery time. Typically, smouldering fires are associated with a long discovery time and cause a large tail of the distribution. In this thesis, the detection time is used especially in the context of severe fires, e.g. non-smouldering fires. The detection of severe fires is shorter than for smouldering fires. Therefore, it is assumed that detection times above 20 min are associated with smouldering fires and are excluded from the derivation of the probabilistic model. The adapted values are illustrated in Figure 5.4a.

In addition to the large scatter of the data, Charters et al. (2002) assumed the existence of a correlation between the fire growth rate $\alpha$ (see Section 4.3) and the detection time, because faster fire growths might lead to a faster fire detection by the occupants. Nevertheless, the data includes only eleven fire incidents and the majority of the fires have a slow fire growth time. In addition, the detection time may depend on whether people are awake or present in the building. This might weaken the correlation, which makes an accurate quantification of the correlation difficult.

The proposed probabilistic model for the detection time is based on the adapted quantile values of Holborn et al. (2004). The distribution of the detection time in Switzerland is assumed to be comparable to that in London. The detection of a fire can be treated as a Poisson process which describes the occurrence of statistically independent events in time. As a consequence, the waiting time until the first event occurs is Exponential distributed (Ang & Tang, 2007). The Exponential distribution is fitted to the quantile values with the least square method. As illustrated in Figure 5.4a, the distribution approximates the values quite well. No distinction of the occupancy type is made, since all values lie in the same range.
Call time

The call time is the time between the discovery of the fire and the call to the alarm centre. The call can be delayed because of different reasons: because people try to suppress the fire, because they are not sure if there is a fire, because they do not know how to make such a call, or because an alarm is not treated seriously, e.g. after repeated false alarms of smoke detectors (Holborn et al., 2004).

Similar to the detection time, quantile values are provided by Holborn et al. (2004) for the call times in dwelling and other buildings. The values are illustrated in Figure 5.4b. In addition, Holborn et al. (2004) analysed the influence of the fire suppression by occupants on the call time and observed a delay in the call time, especially in dwellings if occupants take some suppression actions. This effect is not considered in the present model.

The developed probabilistic model for the call time is based on the quantile values of Holborn et al. (2004). Alike to the detection of the fire, the call to the fire brigade can be represented as a Poisson process. Thus, an Exponential distribution is fitted to the quantile values using the least square method. No distinction of the occupancy type is made. The model and its parameters are illustrated in Figure 5.4b as well.

5.3.2 Response time

The response time includes the receipt and the processing of a fire alarm (dispatch time), as well as the notification and preparation of the fire brigade (preparation time), and the time from the fire station to the location of the event (travel time). Those times are in some extend manageable and verifiable.

Performance criteria are usually used to manage the response time and are derived in the German-speaking countries on the basis of the ORBIT-study (Beyerle et al., 1978). The response time is set based on the reanimation chances of a person that has been exposed to smoke.

Many information on the response time of the fire brigade and the set-up time can be found, e.g. Holborn et al. (2004), LFB (2011), Tómasson et al. (2008), Tillander (2004), Klinzmann (2013). The reason is that the response time is easy to measure and is often used to check if the performance criteria of the alarm centres and the fire brigades are fulfilled. No Swiss data is available to quantify the response time. Therefore, this time is modelled in order to account the performance criteria for the response time.

Dispatch time

The dispatch time is the time between the reception of the alarm and the notification of the fire brigade and includes the transfer of information from the persons who discovered the fire to the alarm centre. This time can be reduced by an automatic alarm transmission, e.g. a fire detection system or a push-button, that immediately notifies the fire brigade.

The probabilistic model for the dispatch time is chosen in order that the performance criterion of 3 min is fulfilled in 95% of all the incoming calls (FKS, 2009). A coefficient of variation of 15% and a Normal distribution is assumed, i.e. $N(\mu = 2.4 \text{ min}, \sigma = 0.36 \text{ min})$. 
5.3. Fire brigade intervention time

**Preparation time**

The preparation time (or turnout time) is the time between the notification of the fire brigade and the time where the fire brigade leaves the station. The majority of the fire brigades in Switzerland consist of volunteer firefighters. Professional fire brigades are established especially in locations associated with a higher risk, e.g. big cities or airports. Since professional firefighters are present at the fire station at all times and are ready on call, the voluntary firefighters have to get to the fire station first. The preparation time of the voluntary fire brigade takes usually longer and may vary between different fire stations. Therefore, the preparation time should be assessed for each fire station. Unfortunately, such data is not available for Switzerland and therefore foreign statistical surveys are used.

During the night, the preparation time of the voluntary and professional (if the nightshift is allowed to sleep) fire brigade is likely to be larger. On the other hand, the travel time might be shorter because of the reduced traffic during night and compensates to some extend this effect on the overall intervention time \(T\) \cite{toman2008}. Therefore, this dependency is neglected.

Simultaneous alarms to a fire station are rare but can significantly delay the preparation time of a fire brigade. \cite{toman2008} analysed professional fire brigade preparation times in Reykjavik (IS) and proposed a Lognormal distribution to represent the data (see Figure 5.5), arguing that the effect of simultaneous alarms is partly taken into account by the heavy tail of the distribution.

\cite{tillander2004} uses a Gamma distribution (respectively a Gamma-Gamma-Mixture distribution) to represent the preparation time of Finish fire brigades (see Figure 5.5). A differentiation between professional and volunteering fire brigade has not been made. Though, the major number of the Finish fire brigades is managed on a voluntary basis, which explains the long tail of the distribution. The skew to the left may be influenced by the professional fire brigades.

\cite{schwanitz2009} and the city of Leichlingen \cite{bsbp2011} analysed fire brigade data of several German fire brigade stations and provided sample statistics for the preparation time of volunteer and professional fire brigades. It is assumed that the preparation time in Germany is similar to the one in Switzerland and, therefore, based on this data, a Lognormal distribution is chosen to model the preparation time, as illustrated in Figure 5.5 (German data) and listed in Table 5.1.

**Travel time**

The travel time is the time between the fire brigade leaving the station and arriving at the fire scene. It depends, for example, on:

- the distance between fire brigade station and the fire scene
- the traffic conditions and the experience of the driver
- the accuracy of the description of the location from the fire call
- the weather conditions and topographical effects

One of the most influencing factors on the travel time is probably the distance between the fire brigade station and the fire scene, which is also used for fire brigade planning, e.g.
distribution of fire stations. This distance is a-priori known and could be represented by a building specific risk indicator. Including the travel distance in a risk assessment for a building (Tómasson et al., 2008), in order to adapt fire safety measures, should be done with care since it is not guaranteed that a fire station will remain at the same location during the life-time of the building. In this thesis, the distance of a building to the fire brigade station is not considered as a building specific property. The performance criterion for the fire brigade is used instead in order to derive the probabilistic model for the travel time.

In Switzerland, the performance criterion for the fire brigade intervention is differentiated between areas with high and low population densities. The criterion for high populated areas is an intervention within 10 min in 80% of all incidents, including the preparation and the travel time; and 15 min for low populated areas. Thus, a professional fire brigade with a shorter preparation time is able to cover a larger area, compared to a volunteer fire brigade with a longer preparation time. This affects especially the spatial allocation of the fire brigade stations, but not necessarily the distribution of the response time of the volunteer and professional fire brigades, since both have to fulfil the performance criterion. Thus, due to the shorter preparation time, the professional fire brigade can invest more time into travelling (Figure 5.5b) compared to the volunteering fire brigade (Figure 5.6a).

No Swiss data is available to quantify the travel time and in the most statistical surveys of other countries it is unclear which performance criterion is used. Therefore, the travel time is estimated indirectly by modelling the fire brigade movement time, e.g. the sum of preparation and travel time, as $T_{\text{Move}} = T_{\text{Prep}} + T_{\text{Travel}}$. A Lognormal distribution is chosen for representing $T_{\text{Move}}$. According to the data of Holborn et al. (2004) and Schwanitz (2009) the coefficient of variation of $T_{\text{Move}}$ is in the range between 0.32-0.43. The probability distribution of $T_{\text{Move}}$ is assumed to be Lognormal distributed, to have a $\text{Cov}[T_{\text{Move}}] = 0.37$ and to fulfil the performance criterion, i.e. 80% of all interventions within 10 min or 15 min. The travel time is assessed by $T_{\text{Travel}} = T_{\text{Move}} - T_{\text{Prep}}$ using Monte Carlo simulations (histograms in Figure 5.6). The

![Fig. 5.5: Probability density function (PDF) of the preparation time.](image-url)
5.3. Fire brigade intervention time

distribution of $T_{Move}$ is truncated for any realisation $t_{Prep}$ to assure that $t_{Move} > t_{Prep}$ for the simulation. The travel time can be represented by a Gamma distribution and is illustrated in Figure 5.6.

The preparation time $T_{Prep}$ and the derived travel time $T_{Travel}$ are statistically correlated due to the truncation. In reality, this correlation does not exist and is neglected for simplicity in the risk assessment. There is almost no effect on the movement time of the professional fire brigade, since the travel time dominates the movement time. For the volunteering fire brigade the movement time is overestimated, i.e. 80% of all interventions within 11.5 min or 16.2 min, since the preparation time has a larger effect on the movement time. Anyway, the model for the travel time should be considered as a first estimation because it is not based on real fire brigade data.

5.3.3 Set-up time

The set-up time is the time between the fire brigade arrived at the fire scene and the start of the rescue and fire suppression actions. This time interval includes the exploration of the fire scene and the preparation of the equipment and tactics for the rescue and suppression activities. The set-up time depends on:

- accessibility to the location of the fire, e.g. floor, location in the room and the availability of a fire fighter elevator
- accessibility to fire water supply
- type of the fire (smouldering, flaming or flashover fires)
- training, the physical constitution and the experience of the firefighters

Mailvaganam et al. (1992) conducted a questionnaire with Canadian fire brigades about the set-up time. The range of the set-up time has been estimated by the fire brigades to lie

Fig. 5.6: Distribution of the travel time with a performance criterion of 10 min (80% of all interventions) for a) volunteer fire brigades and for b) professional fire brigades.
Chapter 5. Performance of fire safety measures

between 3-7 min with an average of 4 min for dwellings and office buildings. The fire brigade’s estimated the average increase of the set-up time per floor to 1 min. To support the answers of the questionnaire they measured the set-up time under experimental conditions. A similar analysis has been conducted by [Schwanitz (2009)](published by [Klinzmann (2013)]), who found that the set-up time is in the range of 2-3.5 min for buildings up to three floors, depending on the location of the fire in the compartment.

For the risk assessment in this thesis, no distinction is made between the occupancy types and a Lognormal distribution is used to represent the set-up time. A coefficient of variation of 20% is assumed and the expected value is assessed according to [Mailvaganam et al. (1992)] by Equation 5.8 depending on the floor where the fire is located $n_{floor}$.

$$E[T_{Setup}] = 4 \text{ min} + \max(0, n_{Floor} - 2) \cdot 1 \text{ min} \quad (5.8)$$

5.4 Rescue and fire suppression by the fire brigade

The main objectives of the fire brigade are rescue and fire suppression activities. The rescue activities are clearly associated with life safety objectives and the fire suppression activities are aimed to reducing the financial and ecological consequences of a fire.

5.4.1 Rescue activities

Rescue activities of the fire brigade aim at rescuing occupants who are trapped in the building due to fire, or who cannot leave the building without the assistance of the fire brigade. Usually, rescue activities are prioritised over suppression activities. Therefore, the set-up time for fire suppression may be larger if there is a need to conduct rescue operations, which may lead to higher financial consequences. Reducing the number of rescue operation of the fire brigade, e.g. by providing efficient means of egress for self-evacuation, may lead to a simultaneous reduction of the financial loss due to fire. Note that rescue operations and suppression activities may be performed simultaneously, if the size of the fire brigade on site is large enough and the equipment for fire suppression is available. The fire brigade reports and insurance claims of Canton Aargau (Switzerland) are used (see Section 5.2) to support this hypothesis. The reports indicate whether a rescue or a commanded evacuation by the fire brigade took place or not. A rescue operation took place in 49 of the 239 reported fire events, where a fire brigade intervention occurred, and 10 reports can be associated with a rescue for the 143 fire brigade reports, which might be associated with a fire damage in a building. Thus, the probability of a rescue operation given a intervention of the fire brigade is between 15% and 21%. Note that the evaluation of the reports is associated with uncertainties as discussed in Section 5.2.

Linking the fire brigade reports with the insurance data allows to analyse the effect of a rescue operation and the associated delay of the suppression activities on the financial loss. In Figure 5.7 a box-plot of the financial losses is illustrated indicating that the losses associated with rescue operation tend to be larger and skewed towards large losses, compared to the loss
5.4. Rescue and fire suppression by the fire brigade

without a rescue. This supports the hypothesis stated above, but a thorough quantification of this effect is not possible using the available data.

One possible way to quantify this effect is to report the time between the arrival of the fire brigade and the start of fire suppression activities, and to report whether a rescue took place or not. Additional indicators, e.g. the number of rescued persons, building specific properties and size of the fire brigade may effect this time as well.

5.4.2 Fire suppression by the fire brigade

Suppression activities aim to reduce the financial damage and the ecological impact of a fire, as well as to protect adjacent buildings of further fire spread. The suppression of a fire can be achieved by:

- removing heat, e.g. cooling the fire by vaporisation of a cooling agent, such as water (mist) foam or wet chemicals
- removing oxygen to prevent oxidation (smothering), e.g. with water, CO₂ or foam
- interrupting the chemical reaction of a fire (inhibition), e.g. with dry chemical and halogenated agents
- removing the combustible material

Usually, the main suppression method is cooling with water, reducing the heat released by the fire. The amount of used water depends on the size of the fire and is provided by water pumps. According to Ramachandran & Charters (2011), the arrival time of the first pump determines mainly the final fire damage. Therefore, the intervention time of the first pump at the fire scene is a good indicator for the fire damage in a building. In the literature, two different approaches are used to quantify fire suppression, based on the control time and based on the maximal treatable fire size.
Control time

The control time describes the time needed to extinguish the fire or to prevent further fire damage and is closely related to the amount of water applied to a certain fire area. In general, the larger a fire is, the longer it takes to control it. Empirical and engineering methods for determining the required flow rate for fire-fighting operations have been developed in the past years. [Benfer & Scheffey, 2014] and [Davis, 2000] review and compare various models and show a wide range of analytical formulation of the models and a large difference of the required flow rate. Most of the models use a power law (range of the exponent varies from 0.5 to 2) to express the dependency between the required flow rate and the fire size. A method is proposed in Chapter 8 on how to choose the "right" suppression model based on observed loss data and an engineering model for fire suppression by the fire brigade.

Maximal controllable fire area

Not every intervention of the fire brigade is successful to prevent damage. If the fire has grown too large, the fire suppression might not be possible and a full burnout of the fire compartment has to be anticipated. In this case, the fire brigade must focus on preventing further fire spread to adjacent fire compartments or buildings. The success of fire suppression depends on the size of the fire brigade including their equipment and on the size of the fire at the time the suppression starts.

[Hosser et al., 2009] proposed a model to assess the success of suppression activities based on a maximal controllable fire area $A_{contr}$ of the fire brigade, which is used as an indicator for the fire suppression capability of a fire brigade (including the crew size and the fire-fighting equipment). [Hosser et al.] estimated the maximal controllable fire area based on fire-fighters experience and proposed a Normal distribution with a mean value of $E[A_{contr}] = 200 \text{ m}^2$ and a coefficient of variation of $\text{CoV}[A_{contr}] = 0.2$. According to [Davis, 2000], the water required to suppress a 200 m$^2$ fire is in the order of magnitude of 2500 l/min, which corresponds to the flow rate capacity of a typical fire-fighting vehicle in Switzerland.

A successful fire suppression may be formulated by a limit state function $G_{supp}$, comparing the maximal controllable fire area $A_{contr}$ with the area of fire spread at intervention time, e.g. $a_f(T_I|X_E)$. The fire growth phase is modelled as a t-square fire (see Section 4.3). The fire area $a_f$ depends on event specific fire characteristics $X_E$ (see Equation 4.8) and is limited by the floor area of the enclosure $a_E$. The two-zone model approach discussed in Section 4.6.3 is applied to assess the fire area $a_f$.

$$G_{supp} = A_{contr} - a_f(T_I|X_E = \left\{ A, X_c, \Delta H_C, M'' \right\}) > 0 \quad (5.9)$$

The probability that a fire brigade fails to suppress a fire $p_{f,supp}$ is expressed by:

$$p_{f,supp} = P(G_{supp} \leq 0) \quad (5.10)$$

The probability of suppression failure $p_{f,supp}$ is illustrated in Figure 5.8 for three different mean values of the maximal controllable fire area $E[A_{contr}]$. The failure probability is assessed for
5.5. Fire detection devices and systems

An early notification of the occupants and an early intervention of the fire brigade enhance the safe egress of occupants and a successful suppression of a fire. The notification time, i.e. the time between the ignition of a fire and the notification of the alarm centre (Figure 5.3) can be reduced by alarm systems. Such devices detect smoke, gases or heat and raise an alarm. Two different alarm systems can be distinguished: systems with alarm transmission, e.g. fire detection systems, and systems without alarm transmission, e.g. smoke alarms, which are predominately used in households.

Fig. 5.8: Probability of failure \( p_{f,\text{supp}} \) for fire brigade suppression.

different floor areas of a retail building by a crude Monte Carlo simulation with 5000 simulations. The fire load is assumed to be large enough to avoid total combustion of the material before an intervention of the fire brigade. A quadratic room layout and an opening factor of \( a_E = 0.04 \, \text{m}^{1/2} \) is assumed for the calculations. The suppression probability \( p_{\text{supp}} = 1 - p_{f,\text{supp}} \) depends on the mean value of the maximal controllable fire area \( E[A_{\text{contr}}] \) and is large for small fire areas \( a_E \). As the floor area \( a_E \) increases, the failure probability initially increases and, after a peak, decreases (see Figure 5.8). The reason is that the flashover conditions for small enclosures are reached soon, i.e. before the intervention of the fire brigade. In these cases, the fire area corresponds to the floor area \( a_E \) and the failure probability \( p_{f,\text{supp}} \) is only dominated by the maximal controllable fire area \( a_{\text{contr}} \). For larger floor areas \( a_E \), on the other hand, the fire brigade intervention may occur before the flashover and the maximal fire area \( a_E \) is reached less often, which benefits the suppression of a fire. Thus, the failure probability is influenced mainly by the intervention time \( t_I \) and the fire growth rate \( \alpha \).

5.5 Fire detection devices and systems

An early notification of the occupants and an early intervention of the fire brigade enhance the safe egress of occupants and a successful suppression of a fire. The notification time, i.e. the time between the ignition of a fire and the notification of the alarm centre (Figure 5.3) can be reduced by alarm systems. Such devices detect smoke, gases or heat and raise an alarm. Two different alarm systems can be distinguished: systems with alarm transmission, e.g. fire detection systems, and systems without alarm transmission, e.g. smoke alarms, which are predominately used in households.
5.5.1 Systems with alarm transmission

Fire detection systems detect smoke, gases or heat, raise an alarm and call automatically the fire brigade. Some systems initially raise an internal alarm to notify security staff in the building, who can investigate the situation and act as appropriate. After a delay of a few minutes, e.g. 3 to 5 min, the fire brigade will be called automatically by an external alarm, unless the security staff interrupts the alarm process within the delay time. In this way, the number of false alarms is reduced.

The operability of fire detection systems in Switzerland is high, because malfunctions are usually detected by the system and the alarm centre is notified accordingly. The link between alarm system and alarm centre is secured and is the main cost component of this system (ca. 800 CHF/year). Therefore, the probability of operable fire detection systems can be assumed to be close to 100%. Whether a device is activated in a fire depends on the smoke, gas and heat production as well as on the location of the fire relative to the device. The costs for the devices are ca. \(15 - 25\) CHF/m\(^2\) floor area.

An alarm system (without a delay) will reduce the detection and the call time. There is a significant reduction of the detection time especially in cases where no occupants are present in the area of fire development (e.g. no visual fire detection). Hence, the detection time is equal to the alarm activation time and depends on how fast a sufficient quantity of smoke, gas or heat reaches the device and activates it. The call time is reduced to a minimum because the alarm is transferred directly to the alarm centre.

The activation time of a detection system can be assessed by the temperature correlation method assuming that the smoke and heat production are correlated. The activation temperature of the device can be derived experimentally. Based on this method, Evans & Stroup (1985) developed DETACT-t2, a deterministic model to predict activation times of heat and smoke detectors. User-defined fire scenarios, e.g. fire development and location relative to the device, and detector properties have to be set as input parameters. In reality those input parameters are associated with uncertainties. Joglar et al. (2005) assessed the activation time with DETACT-t2 probabilistically by introducing random variables for the input variables. One of the most sensitive parameter is the fire growth rate \(\alpha\), which is used in DETACT-t2. Fischer et al. (2012) followed the same approach and derived a surrogate function depending on the fire growth rate \(\alpha\):

\[
\log (t_{Detect,FDS}) = \beta_0 + \beta_1 \log (\alpha) + \varepsilon
\]

(5.11)

where \(\beta_0 = 2.5109\), \(\beta_1 = -0.3641\) and \(\varepsilon\) is a zero-mean Normal distribution with standard deviation \(\sigma_\varepsilon = 0.3194\). The effect of the uncertainty associated with the location of the fire on the activation time of the device, is included in the model.

5.5.2 Systems without alarm transmission

A system without alarm transmission, e.g. smoke alarms, raise an alarm when the device detects smoke, heat or gas, but, in contrast to the detection systems, they do not transmit an alarm to an alarm centre and are therefore cheaper compared to the fire detection system (ca. 7.35 CHF/year
5.5. Fire detection devices and systems

Tab. 5.2: Summary of US (Ahrens 2009) and UK (DCLG 2006, 2011) smoke alarms statistics (related to fires where a smoke alarm was present).

<table>
<thead>
<tr>
<th></th>
<th>Ahrens (US)</th>
<th>UK statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smoke alarm raised an alarm</td>
<td>67.8%</td>
<td>63.3%</td>
</tr>
<tr>
<td>Smoke alarm failed to raise an alarm</td>
<td>32.2%</td>
<td>36.7%</td>
</tr>
<tr>
<td>Operating smoke alarm failed to raise an alarm</td>
<td>18.7%</td>
<td>11.1%</td>
</tr>
<tr>
<td>No operating smoke alarm</td>
<td>13.5%</td>
<td>25.5%</td>
</tr>
</tbody>
</table>

Smoke alarm raised an alarm

<table>
<thead>
<tr>
<th></th>
<th>Ahrens (US)</th>
<th>UK statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery-powered-alarm</td>
<td>75.0%</td>
<td>62.0%</td>
</tr>
<tr>
<td>Hard-wired-powered alarm</td>
<td>91.0%</td>
<td>86.0%</td>
</tr>
</tbody>
</table>

Fires discovered <5min

<table>
<thead>
<tr>
<th></th>
<th>Ahrens (US)</th>
<th>UK statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smoke alarm raised an alarm</td>
<td>-</td>
<td>63.0%</td>
</tr>
<tr>
<td>Device was absent or alarm failed to raise an alarm</td>
<td>-</td>
<td>51.2%</td>
</tr>
</tbody>
</table>

Fires confined to the item of fire ignition

<table>
<thead>
<tr>
<th></th>
<th>Ahrens (US)</th>
<th>UK statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smoke alarm raised an alarm</td>
<td>-</td>
<td>66.2%</td>
</tr>
<tr>
<td>Device was absent or alarm failed to raise an alarm</td>
<td>-</td>
<td>45.6%</td>
</tr>
</tbody>
</table>

1 Fires to be considered large enough to activate the alarm.
2 Data only available for 2002-2006.

for 1 battery powered device). Thus, a smoke alarm increases the probability of an early detection of the fire and reduces the discovery time. In contrast to fire detection systems, the smoke alarm is prone to human influence, reducing the reliability of the devices.

Probability of raising an alarm

According to UK and US fire brigade statistics (DCLG 2006, 2011; Ahrens 2009) an alarm was raised in between 63.3% and 67.8% of the fires in residential buildings (where smoke alarms were present). In between 11.1% and 18.7% of these fires, the operating smoke alarm did not raise an alarm because there was not sufficient smoke to activate the device. Besides fires with little smoke production, some of the fires may have been out of the range of the smoke alarm and an activation of the device was not possible. This rate can be reduced by a proper coverage of the apartment by smoke alarms. Other reasons for not raising an alarm are that the occupants raised the alarm before the system operated or that no persons were in earshot.

In between 13.5% and 25.5% of the fires where a smoke alarm was present, the device did not operate. This number is higher for the UK statistics, since fires where the fire products did not reach the detector are accounted for (“No operating smoke alarm”). In the US statistics, those fires were presumably accounted for the fires where no sufficient smoke has been present to activate the device (“Operating smoke alarm failed to raise an alarm”). This explains the different numbers in the statistics.
According to DCLG (2006) and DCLG (2011), the main reasons of non-operating battery-powered smoke alarms are missing batteries and fire products not reaching the detectors. For hard-wire-powered alarms (including batteries as backup power supply) the main failure reasons were the fire products not reaching the detector and because they were turned off.

**Effect on the detection time**

Activated smoke alarms increase the probability of an early detection of the fire and reduce the discovery time. This leads to an earlier notification and intervention of the fire brigade, which reduces the damage. In the literature, information to quantify the detection time depending on the presence of a smoke alarm is scarce. The data of Holborn et al. (2004), that is used in Section 5.3.1 to derive the probabilistic model for the detection time, provide no information whether a smoke alarm was present or not. The data from Holborn et al. consists of fire incidents with and without smoke alarms. According to UK statistics (DCLG, 2006), 77.6% of the buildings have been equipped on average with a smoke alarm during the survey period from 1996-2000. As listed in Table 5.2, the UK fire brigade statistics report the fire incidents that have been discovered within 5 min depending whether a smoke alarm was present and raised an alarm or not. Note that these times are estimations, because the point in time of ignition is unknown.

In Section 5.3.1, the values of Holborn et al. (2004) are adapted to exclude smouldering fires. The original data of Holborn et al. for the detection of a fire within 5 min (52%) correspond quite well with the UK data of the detection of a fire within 5 min without a smoke alarm. Unlike the data of Holborn et al., the circumstances of the data from DCLG (2006) is not clearly reported and it should be used carefully. Therefore, the model proposed in Section 5.3.1 is adapted to the data of UK statistics using the ratio fire detection within 5 min without and with a smoke alarm, i.e. $r = 0.630/0.512$ (see Figure 5.9):

$$F_{T_{Detect, Holborn} \text{ (5 min)}} = (1 - 0.776) \cdot F_{T_{Detect, noSA} \text{ (5 min, } \lambda_{noSA})} + 0.776 \cdot \frac{F_{T_{Detect, noSA} \text{ (5 min, } \lambda_{noSA}) \cdot r}}{F_{T_{Detect, SA}}} \quad (5.12)$$

**Effect on the early suppression of a fire**

An activated smoke alarm affects the fire spread in the room of fire origin by increasing the probability of an early suppression of the fire by the occupants or by the fire brigade. To consider this effect, data on minor losses is needed, including whether a smoke alarm is present or not. Only scarce information exists to quantify this effect. UK fire brigade statistics (DCLG 2006) provide statistics to assess the probability that the fire is confined to the item of ignition and the effect of the smoke alarm on this probability (45.6% without a smoke alarm and 66.2% with smoke alarm). This tends to underestimate the effect of a smoke alarm, because fire brigade statistics consider only cases where a fire brigade intervention was necessary. The reason is that a smoke alarm increases the probability of an early detection of a fire by the occupants and
allows them to suppress the fire in an early state. Thus the presence of the fire brigade is not required any more and no record will appear in the statistics.

5.6 Sprinklers

An activated sprinkler discharges water and cools the fire, i.e. reduces the heat release of a fire. The activation, arrangement and the amount of water discharged of a sprinkler system depends on the design and the maintenance strategy of the system and affects the success of fire suppression. For example, the activation of a sprinkler system is determined by the Response Time Index (RTI) and indicates the temperature and the corresponding time under which the bulb of the sprinkler breaks resulting in a release of water. A low RTI (with a low activation temperature, e.g. 68°C) leads to an early activation of the sprinkler and is suited for fast developing fires. The investment costs for sprinkler systems are ca. 20 − 35 CHF/m² floor area. Since the sprinkler systems in Switzerland is connected with the alarm centre by a secure link, the costs for this link has to be considered as well (ca. 800 CHF/year).

Sprinkler statistics are always related to the corresponding design requirements (or performance requirements) of sprinkler systems and may provide different system reliabilities. Moinuddin & Thomas (2014) proposed a component based fault-tree analysis to assess the reliability of sprinkler systems. The fault-tree can be applied to different sprinkler systems, which are designed according to different performance requirements. Accordingly, the reliability of each component of the sprinkler system is estimated. In such an approach, a target-reliability can be defined and used in a reliability-based design of sprinkler systems. Nevertheless, sprinkler systems are subjected to human errors, e.g. shutting off the system or lack of maintenance, and this should be considered in such an approach. Nevertheless, sprinkler statistics provide a good indication to judge the reliability of sprinkler systems.

A very detailed US sprinkler statistic is provided by Hall (2010), who analysed fires from 2003-2007 where a sprinkler has been present (wet-pipe, dry-pipe, chemical, carbon dioxide, foam and halogen systems). The majority of the fires (65%) were considered to be too small to activate...
the sprinkler. Sprinklers in the area of fire failed to operate in 7% of the reported structure fires that were large enough to activate the sprinklers. The main reason of non-operating sprinklers systems is because the system has been shut off (53%). The type of the sprinkler systems and the occupancy type influence the operability of the sprinkler as well. For further information, see the report by [Hall 2010].

Sprinklers are ineffective when water does not reach the fire or when not enough water is released. This occurs in 3% of all cases where a sprinkler is activated. Consequently, sprinkler effectively operated in \((1 - 0.07) \cdot (1 - 0.03) = 90\%\) of all fires large enough to activate the sprinklers. Wet-pipe sprinkler systems operated effectively in 92% of the fires, whereas dry-pipe sprinklers operated effectively in 79% of the fires. The reliability of the systems can be massively increased by an adequate design of the system and by assuring that the system is active.

The European research project "Natural Fire Safety Concept" ([Schleich et al. 2002]) calibrated the code format of the Eurocode EN 1991-1-2 for structural design. In order to estimate the reliability of sprinkler systems, different national sprinkler statistics (USA, AUS, UK, CH, D, FIN) have been studied. The reliability of well-maintained sprinkler systems is estimated between 96% and 99%. A default value of 98% has been seen as appropriate to calibrate the code format of the Eurocode.

### 5.7 Means of egress

The means of egress comprise all fire safety measures that allow occupants to reach a place of safety during a fire. Representatives of these measures are maximal travel distances, compartmentation, fire alarms, ventilation systems and widths of egress routes. To assure a safe evacuation it is necessary to avoid the exposure of occupants to untenable conditions, such as toxic gases and smoke. In performance-based design (see [ISO/TR 16738 2009]), a capacity-demand approach can be formulated, which compares the Available Safe Egress Time (ASET) with the Required Safe Egress Time (RSET). Both, RSET and ASET are illustrated in Figure 5.10. The \(T_{ASET}\) describes the time until untenable conditions are reached and the \(T_{RSET,i}\) describes the time needed for an occupant \(i\) to reach a place of safety, e.g. the outside of a building or the staircase. An evacuation of an occupant \(i\) is successful if:

\[
G_{Egress,i} = T_{ASET} - T_{RSET,i} > 0 \quad (5.13)
\]

Both, the \(T_{ASET}\) and the \(T_{RSET}\) are associated with uncertainties and are introduced as random variables. In analogy to Section 5.1, the probability of death, i.e. \(p_{f,i} = P(G_{Egress,i} \leq 0)\), of occupant \(i\) can be assessed by a reliability analysis. An evacuation may be considered to be unsuccessful if a fatality occurs. Accordingly, the probability of an unsuccessful evacuation, i.e. one or more fatalities in a fire, can be formulated by:

\[
p_f = P\left(T_{ASET} - \max_{i=1}^N (T_{RSET,i}) \leq 0\right) \quad (5.14)
\]

Approaches that are based on the probability of death have been investigated by different authors, e.g. [Magnusson et al. 1996], [Albrecht 2011], [Fischer 2014]. This approach does not
account for the number of occupants that might decease in a fire, but only for an occurrence of a fatality. Consequently, low-probability scenarios associated with high-consequences may not be considered appropriately and have the same participation on the probability of death \( p_f \) as high-probability low-consequences scenarios.

Risk-based approaches overcome this disadvantage and the expected number of fatalities is estimated instead. The time until untenable conditions are reached \( t_{ASET} \) determines the number of fatalities in an enclosure. Following the definition of risk of Chapter 3.1, this time can be considered as the damage state \( d = t_{ASET} \) and the number of fatalities \( p \) as the induced consequences of a damage state, i.e. \( c = p(t_{ASET}) \). The risk is formulated as:

\[
R = E[C] = \int_{D_D} c(d) \cdot f_D(d|EX) \cdot P(EX) \, dD = \int_{D_{t_{ASET}}} p(t_{ASET}) \cdot f_{t_{ASET}}(t_{ASET}|EX) \cdot P(EX) \, dt_{ASET}
\]  

The associated consequences \( p(t_{ASET}) \) is equal to the number of persons \( p \) in a room when untenable conditions are reached. This number is influenced by the evacuation processes and is associated with uncertainties. Therefore, Equation 5.15 can be reformulated to account for all uncertain parameters \( X \) affecting the number of fatalities \( p(t_{ASET}|x) \) and the time until untenable conditions \( t_{ASET}(x) \):

\[
R = \int_{\mathcal{D}_X} p(t_{ASET}(x)|x) \cdot f_X(x|EX) \cdot P(EX) \, dx
\]

Risk-based approaches that derives the expected number of fatalities have been used by different authors, e.g. [He et al. (2003), Maag (2004), Chu et al. (2007), Hanea & Ale (2009), Fischer (2014) and Zhang et al. (2014)]. Most authors solved Equation 5.15 either by discretisation of the problem or by simplifying the probabilistic models, e.g. neglecting uncertainties and introducing deterministic values.

In the next two sections, the ASET and the RSET are discussed more in detail.

### 5.7.1 Available safe egress time

According to [NFPA 92B](#), smoke can be defined as the airborne solid and liquid particles and gases, evolved when a material undergoes pyrolysis or combustion, together with the quantity of air that is entrained or otherwise mixed into the mass. Untenable conditions for occupants are reached, when the toxicity of the gases (e.g. carbon monoxide and hydrogen cyanide) or the inhaled particles exceed a certain threshold. Untenable conditions are also reached when the radiation of the hot smoke layer causes serious skin burns. In addition, obscuration may reduce the orientation in the room and hampers the movement of people during evacuation. Therefore, it is crucial to avoid an excessive exposure of the occupants to smoke and heat to provide safe means of egress. The smoke filling process in a compartment can be modelled by two- (or multi-) zone models or by computational fluid dynamic models.
5.7.2 Required safe egress time

The RSET is the time needed for occupants to reach a place of safety and is composed of three time intervals (see Figure 5.10 and ISO/TR 16738):

\[ t_{RSET,i} = t_{D+W,i} + t_{R+R,i} + t_{T+Q,i} \]  \hspace{1cm} (5.17)

- **Detection and warning** \( t_{D+W,i} \): Detection and warning: interval between fire ignition and the notification of the occupant, e.g. by an alarm or by visible smoke or flames.
- **Recognition and response** \( t_{R+R,i} \): Recognition and response: interval between the notification of the occupant and the time at which the first move towards an exit is made by the occupant.
- **Travel and queuing** \( t_{T+Q,i} \): Travel and queuing: interval from the evacuation start until the occupant reaches a place of safety.

**Detection and warning**

The detection and warning time \( t_{D+W} \) is the interval between fire ignition and the notification of the occupant, e.g. by an alarm or by visible smoke or flames. This time interval depends whether people are awake or are sleeping. Awake occupants in the room of fire ignition are likely to be notified visually by detecting smoke or flames. Other people not located in the room of fire ignition may be warned acoustically by an alarm signal. The detection and warning time can be reduced by fire safety measures like smoke alarms and fire detection systems (see Section 5.5).

**Recognition and response**

According to ISO/TR 16738, the recognition and response time (also known as the pre-movement time or pre-travel activity time) is the interval between the time at which a warning of a fire
is given and the time at which the first move towards an exit is made by an occupant. The recognition and response time is individual for each occupant in a room and depends on various factors mainly associated with the available information about the severity of the situation and the occupant’s perception. These factors include the way how occupant are warned (by an alarm or by visual detection), the building layout and the familiarity with the building. A detailed discussion and summary of the factors affecting the recognition and response time is provided by Proulx (2002).

Travel and occupant flow

After occupants decide to move towards a place of safety, they need to walk the distance from their individual location to this place. The distance that occupants have to walk is usually regulated by prescriptive codes that require a certain travel distance, e.g. the shortest path to the exit. The time needed to cross this distance depends on the chosen path to reach an exit and on the occupant’s moving velocity along this path. The moving velocity is an individual characteristic of an occupant and may be affected by different factors, e.g. exposure to smoke and interaction with other occupants leaving the building. The time $t_{W,i}$ of an occupant $i$ to cross a distance $d_i$ to reach a place of safety, with an individual velocity $v_i$, is derived by:

$$t_{W,i} = \frac{d_i}{v_i}$$ (5.18)

The flow $j$ [pers/sec] of persons can be characterised by the number of persons crossing a fixed location of a facility per unit of time. The flow through a facility with an effective width $w$ can be described in analogy to fluid dynamics by the product of the density $\rho$ and the average movement speed $v$:

$$j = \frac{dp}{dt} = \rho \cdot v \cdot w = j_S \cdot w$$ (5.19)

The specific flow $j_S$ [pers/m/sec] is the flow of persons per unit of time per unit of effective width of the route and may affect the movement velocity $v_i$ (see Nelson & Mowrer, 2002).

Queue formation

If the number of occupants arriving at a bottleneck exceeds its flow capacity $j_S \geq j_{S,\text{max}}$, people build a queue (or jam) in front of the bottleneck, e.g. an emergency door or corridor, and have to wait until they can pass to reach a place of safety. The maximal flow capacity of a bottleneck $j_{\text{max}} = j_{S,\text{max}} \cdot w$ respectively the maximal specific flow capacity, can be assessed by Equation 5.19. Queueing can be expected especially for buildings with a high occupant load density or bottlenecks with low flow capacities. In this case, the travel distances to the exit and the corresponding travel times have a subordinate role, because occupants have to wait in front of the bottleneck anyway until they can pass. In contrast, for sparsely occupied enclosures and for bottlenecks with a high flow capacity, queuing is unlikely to occur because the flow capacity of the bottleneck is not reached, i.e. $j_S < j_{S,\text{max}}$. The evacuation process is then dominated by the last few occupants reaching a place of safety. In this case, the individual characteristics, like
the recognition and response time as well as the walking speed, are significant for a successful evacuation \([\text{ISO/TR 16738}]\).

Queuing for densely occupied enclosures can occur along the evacuation path, e.g. at corridors, staircases and doors. Along the evacuation path, the bottleneck with the lowest capacity dominates the RSET. The evacuation process can be represented as a serial system, in which the bottleneck with the lowest flow capacity dominates the performance of the evacuation process. Thus, increasing, for example, the flow capacity of a door in the room of fire ignition only makes sense if the capacities of the sequential bottlenecks, e.g. corridors or the staircase, provide a larger flow capacity than the door.

**Occupant load density**

The occupant load density determines the number of occupants that participates on the evacuation process and influences the RSET. The occupant load density \(p'_0 \, [\text{pers/m}^2]\) is defined by the ratio of the number of persons \(p_0\) that are present in an enclosure at fire ignition and its floor area \(a_E\):

\[
p'_0 = \frac{p_0}{a_E} \quad \text{(5.20)}
\]

From a statistical point of view, a fire can occur at any time. Thus, alike the mechanical loads in a fire (see Section 5.1.4), a point-in-time distribution should be used. The probabilistic assessment of the occupant load density has been paid small attention in the fire safety community. The reason is that risk assessment is mainly used to support design situations (see Chapter 2). Fire safety codes provide, for these situations, a design value for the occupant load density, which is associated with the maximum probable number of occupants \([\text{NFPA 101 2006}]\). This value is already associated with a certain likelihood and is not well defined from a statistical point of view.

There might be a correlation between the number of occupants in a store and the probability of fire ignition, since the presence of more people in buildings will lead to a greater demand for electrical and mechanical services and thus an increase of actions that favour fire ignition, e.g. smoking or the use of electronic devices (see Bennett & Thomas (2002); De Sanctis et al. (2014c)). Thus, if the number of occupants changes, the probability of a fire is affected as well. Important is that the reverse of this dependency is not valid because the number of occupants will not depend on the ignition frequency of a fire. Bennett & Thomas (2002) discussed the effect of occupants on the frequency of fire ignition in office buildings. They concluded that the ignition frequency increases during the hours of operation without relating it to the occupant load density. Though, the probability that the fire is confined to the object of ignition increases simultaneously due to a higher chance that a fire is detected and suppressed by the occupants. Thus, a higher occupant load density might have a positive and a negative effect in the context of risk assessment.
Chapter 6

Risk equivalence of structural fire safety provisions

Some fire authorities query the application of performance-based design solutions, due to the lack of proof on the equivalence of these solutions to prescriptive design solutions. This applies also for alternative prescriptive design solutions, where e.g. passive fire protection measures are reduced by implementing active fire protection measures, such as sprinklers (see Section 2.1.2). In this chapter, a risk-based approach is discussed to quantify the level of safety, which is achieved either by a prescriptive or by a performance-based design approach. The risk is assessed by a bottom-up engineering driven approach modelling the fire exposure, the fire brigade intervention and the structural response under realistic conditions. Realistic conditions refers to conditions that are likely to occur in reality. This approach provides a common quantification of the level of safety and allows the comparison of different design solutions. This comparison allows to discuss the advantages and drawbacks of the risk equivalence approach. Further, some useful simplifications for a performance-based design approach are suggested concerning the fire brigade intervention.

The outline of the analysis is illustrated in Figure 6.1. The idea is to design a structure according to the prescriptive or performance-based code provisions. In a second step, the structure is exposed to realistic fire conditions in order to evaluate the risk respectively the reliability. A generic formulation of the design allows to compare and to discuss the results for different building characteristics by a parametric analysis.

The focus of this chapter is the performance evaluation of a structure of a two-story retail building. However, the same approach can be applied to buildings with different use. The approach is based on De Sanctis et al. (2014a).

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1The models and the results in this chapter may deviate slightly to the results presented in De Sanctis et al. (2014a). Apart from the probabilistic models, in this thesis, the fire models have been improved as well, especially the model for the onset of the decay phase, as discussed in Section 4.5.4. In contrast to De Sanctis et al. (2014a) and Schleich et al. (2002), in this chapter the extended fire model is not used in order to enhance a realistic fire representation.
6.1 Quantification of the level of safety of structures

The level of safety can be quantified by a probabilistic risk analysis for the structure, e.g. assessing the expected consequences that are related to life losses or to financial losses due to a structural failure. The consequences of a structural failure depends on the structural reliability and the ability of a structure to redistribute the loads if a member or parts of the structure fails (e.g. redundancy or robustness). A common simplification in structural reliability engineering is to assume no redundancies. Accordingly, it is expected that a failure of a structural member at floor $i$ leads to consequences at least over all overlying floors, e.g. floor 1 to floor $i-1$, of a $n$-storey building (top floor $i=1$). This simplification reduces the complexity of the risk assessment and leads to an overestimation of the risk, since an appropriate design comprises some redundancies. The risk $R$ associated with a structural failure of a $n$-storey building is formulated by:

$$R = E[C] = \sum_{i=1}^{n} p_{f,i} \cdot (i-1) \cdot c \quad (6.1)$$

where $p_{f,i}$ denotes the annual probability of structural failure due to a fire on floor $i$ and $c$ denotes the consequences per floor, which are assumed to be equal over all floors for simplification, i.e. $c = c_1 = \ldots = c_n$. The consequences associated with a fire spread, including fire spread in the enclosure of fire ignition, are not considered in this risk formulation. Considering these consequences in the risk assessment would mislead the evaluation of the performance of structures, since a change of the structural requirements does not affect fire spread within the enclosure of fire origin.

For a 2-storey building, as outlined in Figure 6.4, this equation simplifies to $R = p_{f,2} \cdot c = p_f \cdot c$. Note that the structural risk of the top floor equals 0, because it is expected that the induced structural consequences are negligible compared to the consequences due to a fire spread within the enclosure, e.g. the consequences due to a flashover in the top floor which can be seen as a pre-condition for structural failure.
The aim of this chapter is to compare different structural fire safety design approaches for a given building. The associated consequences of a structural failure are the same, since only buildings with the same cost-affecting characteristics (e.g. size and number of floors) are compared, and can be set arbitrarily to $c = 1$, which leads to the formalism of structural reliability, e.g. $R = p_f$ (see Section 5.1). The reliability of a structure can be expressed by the reliability index $\beta$ and is defined as $\beta = -\Phi^{-1}(p_f)$, where $\Phi^{-1}(\cdot)$ is the inverse of the cumulative standard normal distribution. Methods to assess structural reliability are discussed e.g. in Hasofer et al. (2007) and in Melchers (2002). This common quantification of the level of safety allows to compare the different design approaches, e.g. prescriptive and performance-based design approaches or standard design and alternative sprinkler concepts.

Note that the risk defined in Equation 6.1 can be seen as a lower estimate of the structural risk. A progressive collapse of the underlying floors due to a structural failure of the upper floors is a possible scenario and may lead to a complete loss of the building, e.g. $(n - 1) \cdot c$ (excluding again the loss due to the fire spread in the room of origin). This scenario can be associated with an upper estimate of the risk. For risk comparison, however, the same reasoning can be made as stated above and leads to the same formalism of structural reliability, which is used as an indicator for the risk.

Similar structural reliability analyses have been conducted by Schleich et al. (2002) and Hosser et al. (2009). Though, their focus is not a comparison of different design approaches, but the calibration of partial safety factors towards a target reliability $\beta_t$ (see Section 2.2.2) to be used in a semi-probabilistic design approach (see Section 2.2). There are some simplification for the fire exposure, e.g. simplifying the interaction between fire suppression by the fire brigade and the fire development.

### 6.2 Generic structural design

Structural safety is achieved by considering different design situations, e.g. persistent design situation (normal use), accidental design situation (exceptional conditions, e.g. fire), seismic and transient design situation. In the present case, only the persistent and accidental (fire) design situations are considered.

A generic representation of the structure is aspired to enhance the comparison between the different design approaches. The generic design implements the structural code provisions, e.g. for persistent and for accidental (fire) design situation. Based on this generic design the level of safety of a structure is achieved by providing a certain (minimal) required mechanical resistance and a certain (minimal) required thermal resistance.

### 6.2.1 Generic representation of the persistent design situation

The persistent design situation determines the mechanical resistance $R_d$ that has to be provided to resist a certain design load $E_d$. The most general way to formulate this requirement for mechanical resistance is by the ultimate limit state $g_d$ (see Equation 6.2). The required mechanical resistance is considered by a design variable $z$. In this variable all structural and
mechanical parameters are implicitly considered, e.g. the beam length, the shape of the profile or the moment of inertia. An optimal design of the structure ($z_{opt}$) is achieved by setting $g_d = 0$ and depends on: the design load $E_d$, the characteristic value of the limiting steel strength $r_{a,k}$ (e.g. yield stress) and the partial safety factor for the resistance $\gamma_M$.

$$g_d = R_d - E_d = z \cdot \frac{r_{a,k}}{\gamma_M} - E_d \geq 0 \quad \Rightarrow \quad z_{opt} = \frac{\gamma_M E_d}{r_{a,k}} \quad (6.2)$$

### 6.2.2 Generic representation of the accidental design situation for the fire exposure

For the structural design of steel members exposed to fire conditions the degree of utilisation $\mu_0$ is used and represents the minimal required mechanical resistance to sustain a fire. The degree of utilisation can only be used for a design, where the load bearing capacity is directly proportional to the effective yield strength (Franssen & Vila Real 2010). This applies e.g. for tension members, where different types of non-linearities (like buckling) can be excluded. This limitation has to be considered for any generalisations of the results of the reliability analysis.

According to Ellingwood (2005) the probability of a coincidence of a fire with a maximum live load, miscellaneous roof live load, significant wind loads or earthquakes is negligible for fire design (see Section 5.1.4 for discussion). Therefore, only the permanent load (dead load $d_k$) and the frequent value of the life load according to EN 1990 ($\psi \cdot l_k$) are considered. By introducing a load ratio $\alpha_L = l_k / (l_k + d_k)$ the degree of utilisation $\mu_0$ is expressed just by the partial safety factors ($\gamma_i$ and $\psi_i$) and the load ratio $\alpha_L$ and is independent on the number of storeys:

$$\mu_0 = \frac{E_{f_i,d}}{R_{f_i,d,0}} = \frac{E_{f_i,d}}{z_{opt} \cdot r_{a,k} \gamma_{M,f_i}} = \frac{1}{\alpha_L} \cdot (1 - \alpha_L) + \psi_1$$

(6.3)

The reduction of the steel strength at elevated temperatures is described as a function of the steel temperature $\vartheta$. EN 1993-1-2 provides a multi-linear function to assess this reduction, which can be approximated by a continuous function (see Equation 6.4). The critical steel temperature $\vartheta_{crit}$ corresponds to the temperature where a structural failure has to be anticipated and is derived based on the continuous formulation of the yield strength reduction. Hence, the design limit state $g_{d,f_i}$ can be formulated in the temperature domain:

$$g_{d,f_i} = \vartheta_{crit}(\mu_0) - \vartheta_d = 39.19 \ln \left[ \frac{1}{0.9674 \mu_0^{0.833} - 1} \right] + 482 - \vartheta_d \geq 0 \quad (6.4)$$

The steel temperature $\vartheta_d$ depends on the the thermal resistance (or thermal inertia) of a component and indicates how fast a specimen heat up under a thermal exposure. This thermal resistance can be considered as a design parameter for a structural member. An indicator for the thermal resistance of a protected steel member is the massivity factor $z_{f_i}$:

$$z_{f_i} = \frac{A_p}{V} \cdot \frac{\lambda_p}{d_p} \quad (6.5)$$
This factor \( z_{fi} \) depends on the section factor \( A_p/V \) of a steel profile, the thermal conductivity of the protection material \( \lambda_p \) and the thickness of the protection material \( d_p \). The steel temperature \( \vartheta(t) \) is assessed based on the massivity factor \( z_{fi} \) and the gas temperature \( \theta_g(t) \) by the simplified design method for the heat transfer described in EN 1993-1-2. The fire exposure depends whether a performance-based or a prescriptive design is used.

**Prescriptive design**

In the prescriptive design approach the design value of the steel temperature \( \vartheta_{d,R} \) is derived by the standard fire curve \( \theta_{g,ISO}(t) \) (ISO 834-1) and by the fire resistance criterion for the load bearing capacity, e.g. \( R = 30 \) min, \( R = 60 \) min (see Figure 6.2). The fire resistance criterion defines the period under standard fire exposure (ISO 834-1, 1999), where the load bearing capacity of a steel member is maintained. The design value for the steel temperature \( \vartheta_{d,R} \) is derived by:

\[
\vartheta_{d,R}(z_{fi}) = \vartheta(R|\theta_{g,ISO}(t), z_{fi})
\]  

(6.6)

**Performance-based design**

In contrast to a prescriptive design, the thermal exposure for the performance-based design approach of EN 1991-1-2 is given by a parametric fire exposure (see Section 4.6.2). The parametric fire exposure \( \theta_{g,EN}(t|x_O, x_{E,d}) \) describes the gas temperature per time and depends on:

- the fire (or event) specific design values \( x_{E,d} = \{q_d, \alpha_d\} \), e.g. design value of the fire load \( q_d \) and design value of the fire growth rate \( \alpha_d \)
- the building (object) specific properties \( x_O = \{a_E, o_E, b\} \), e.g. the floor area \( a_E \), the ventilation conditions \( o_E \) (see Section 4.5.3 for definition) and the thermal properties of the boundary of enclosure \( b \)

![Fig. 6.2: Gas temperature \( \theta_g \) and steel temperature \( \vartheta_d \) for \( a_E = 0.1 \text{ m}^{1/2} \) and \( a_E = 200 \text{ m}^2 \).](image)
Chapter 6. Risk equivalence of structural fire safety provisions

The design value of the steel temperature $\vartheta_{d,EN}$ is derived by the maximal steel temperature that is reached under the parametric fire exposure:

$$\vartheta_{d,EN}(z_{f_1}, x_O, x_{E_d}) = \max \left( \vartheta(t | \theta_{g,EN}(t), z_{f_1}) \right)$$ (6.7)

Active fire protection measures, e.g. sprinklers, can be considered in the semi-probabilistic design approach of [EN 1991-1-2] by reduction factors for the characteristic fire load. At first glance, a reduction of the fire load seems not to be reasonable, because the presence of a sprinkler does actually not reduce the fire load. Schleich et al. (2002) found a strong dependency between the failure state of a structure and the fire load. Thus, a change of the fire load affects the structural failure probability and this is used to calibrate the reduction factors for the fire load, within the semi-probabilistic design approach, in order to reach a target reliability $\beta_t$. Thus, the failure probability of the active fire protection measures is included in the reduction factor.

**Optimal accidental design**

In practice, a design always involves some thermal reserves due to the choice of commercially available cross sections or fire-resistant claddings. Alike to the persistent design situation, no reserves are considered for the generic design of the structural members. Thus, if the design value of the steel temperature $\vartheta_d(z_{f_1, opt})$ is equal to the critical steel temperature $\vartheta_{crit}$ then an optimal accidental design is found, e.g. $g_{d, f_1} = 0$ (see markers in Figure 6.2). This optimisation problem is solved numerically by minimising the error term $|\vartheta_d(z_{f_1}) - \vartheta_{crit}|$ by changing $z_{f_1}$. The resulting optimal massivity factors $z_{f_1, opt}$ are illustrated in Figure 6.3 for different floor areas $a_E$ and different opening factors $a_E$. Low massivity factors $z_{f_1, opt}$ denote a higher thermal resistance and leads to a slower heating of the steel section. The gap in the line (EN $a_E = 0.2$ m$^{1/2}$) indicates the transition from a fuel-controlled fire to ventilation-controlled fire, which is considered by the design format of [EN 1991-1-2].
6.3. Realistic fire exposure

Without performing a reliability analysis to quantify the level of safety in terms of a probability of failure, it can already be stated that for a building with opening factor $o_E = 0.04 \text{ m}^{1/2}$ (without a sprinkler) the design approach of EN 1991-1-2 leads to a higher reliability as for a design according to R30 or R60. The reason is that for the same building – and therefore for the same exposure – the EN 1991-1-2 approach provides a higher thermal resistance and thus a higher reliability.

Summarising, the structural design is characterised by two design variables: one for the mechanical resistance $z_{opt}$ and one for the thermal resistance $z_{fi,opt}$. In contrast to the prescriptive design approach, the optimal design of the performance-based design approach depends on fire specific design values $x_{E,d}$ and on building specific indicators $x_O$.

6.2.3 Representation of the building

The building is represented by building specific risk indicators $x_O$. In this analysis, five building specific indicators and three induced building specific indicators are used to characterise the building and are listed in Table 6.1. The induced building specific indicators are derived from the five building specific indicators assuming a quadratic floor area of the compartment (see Figure 6.4). The floor area of the enclosure $a_E$ and the opening factor $o_E$ are used for a parametric analysis to assess their effect on the level of safety. The other building specific properties are set to be constant (see Table 6.1).

6.3 Realistic fire exposure

The structure is analysed under realistic fire conditions to quantify the level of safety. It is important to consider all relevant processes that affect the structure including the fire exposure, the fire brigade intervention, the thermal response of the structure, the load conditions and the mechanical resistance. In this section, the engineering models are discussed that are used to represent the physical processes in reality. Since those processes are associated with uncertainties, a probabilistic approach is followed and probabilistic models are introduced for the basic risk

\[
\frac{a_E}{\# \text{walls with openings} \cdot h_{eq}}
\]

Fig. 6.4: Layout of the enclosure.
Chapter 6. Risk equivalence of structural fire safety provisions

Table 6.1: Summary of building specific indicators.

<table>
<thead>
<tr>
<th>Building specific properties</th>
<th>Induced building specific properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_E$</td>
<td>Floor area of the enclosure [m$^2$]</td>
</tr>
<tr>
<td>$o_E$</td>
<td>Opening factor [m$^{1/2}$]</td>
</tr>
<tr>
<td>$b = 1000$</td>
<td>Thermal inertia of the boundary elements [J/m$^2$/K/sec$^{1/2}$] (corresponds to common brick)</td>
</tr>
<tr>
<td>$\alpha_L = l_k/(l_k + d_k) = 0.5$</td>
<td>Load ratio [-]</td>
</tr>
<tr>
<td>$h_E = 3.5$</td>
<td>Height of the enclosure [m]</td>
</tr>
<tr>
<td>$h_{eq} = 0.8 \cdot h_E$</td>
<td>Ventilation height [m]</td>
</tr>
<tr>
<td>$a_t = 4 \cdot h_E \sqrt{a_E} + 2 \cdot a_E$</td>
<td>Total surface area of the enclosure [m$^2$]</td>
</tr>
<tr>
<td>$a_V = o_E \cdot a_t/(h_{eq})^{1/2}$</td>
<td>Total area of vertical openings [m$^2$]</td>
</tr>
</tbody>
</table>

Indicators that describes the system. The probabilistic models used for the reliability analysis are listed in Table 6.2.

The limit state function for structural failure of a steel member under realistic fire conditions can be formulated by a capacity-demand approach (see Section 5.1) in the temperature domain:

$$G_{fi}(X_E, x_O) = \vartheta_{cr}t(X_E, x_O) - \max(\vartheta(t|X_E, x_O))$$

(6.8)

This equation is similar to Equation 6.4. The difference to Equation 6.4 is that the fire specific indicators $X_E$ are introduced as random variables. The building specific indicators $x_O$ are deterministic and can be used for a parameter study, e.g. for the floor area $a_E$ and for the opening factor $o_E$. It is referred to De Sanctis et al. (2013) for a global sensitivity study in order to assess the importance of the individual random variables on the maximal steel temperature, e.g. $\max(\vartheta(t|X_E, x_O))$. The analysis shows that the uncertainty associated with the fire growth rate $\alpha$ has a major influence on the uncertainty associated with the maximal steel temperature.

6.3.1 Steel temperature under realistic fire conditions

Compartment fire model

The gas temperature $\theta_g(t|X_E, x_O)$ in the compartment is assessed based on a zone model (see Section 4.6.3). The heat release rate and the mass loss rate for the fire exposure are modelled according to Figure 1.8 and depend on building specific risk indicators $x_O$ and on fire specific risk indicators $X_E$. The probabilistic models for the fire specific indicators are discussed in Chapter 4 and are listed in Table 6.2. The use of an advanced fire model, which is based on energy and mass balance equations, allows to judge whether the parametric fire curves (which are used for the performance-based design) are able to represent a realistic fire exposure (supposing that the physical model represents reality more appropriately).
6.3. Realistic fire exposure

Fire brigade suppression model

The fire brigade is considered by the intervention time \( t_I \) (Section 5.3) and by the suppression activities (Section 5.4). The approach of the maximal controllable fire area \( a_{\text{contr}} \) proposed by Hosser et al. (2009) is used to account for the suppression activities. If the fire area at intervention time \( a_f(t_I) \) exceeds the maximal controllable fire size, i.e. \( a_f(t_I) > a_{\text{contr}} \), then the suppression of the fire might not be successful and a full burnout of the enclosure has to be anticipated. A full burnout means that the complete fire load participates to the fire and no reduction of the heat release rate take place before reaching the decay phase, see Figure 6.5. In contrast, if the fire area at intervention time is less than the maximal controllable fire size \( a_f(t_I) > a_{\text{contr}} \), then suppression takes place and it is expected that only a part of the fire load contributes to the fire. This is modelled by initialising the decay phase of a fire at the intervention time \( t_D = t_I \), see Figure 6.5. The fire area \( a_f \) is assessed based on Equation 4.8 and is limited by the floor area of the enclosure \( a_E \). The gas temperature \( \theta_g(t_t|X_E,x_O) \) can be derived by OZone (see Section 4.6.3) based on the modified heat release rate.

Thermal action on a steel member

The temperature of a steel member \( \vartheta(t|X_E,x_O) \) can be modelled based on the gas temperature \( \theta_g(t) \) and based on the heat flow equations discussed in Sections 5.1.1 and 5.1.2. The simplified calculation method of EN 1993-1-2, which approximates the heat conduction equation (Equation 5.6), is used to derive the steel temperature \( \vartheta(t|X_E,x_O) \). The massivity factor \( \varepsilon_{f,\text{opt}} \) (which is determined by the generic design) enters this equation and affects the heating of the steel member. The maximal steel temperature \( \vartheta_{\text{max}} = \max(\vartheta(t)) \) is derived based on the time-temperature development of the steel member.

Fig. 6.5: Qualitative heat release rate influenced by the suppression activities of the fire brigade.
6.3.2 Critical steel temperature

Mechanical load model

As discussed in Section 5.1.4, the structure during fire is likely to be loaded only to a part of the design load. For the reliability analysis the point-in-time distribution of the load during a fire event is used. According to Ellingwood [2005], the mechanical load in a fire is mainly composed by the dead load $D$ and by the sustained component of the live load $L_S$. Both can be quantified by probabilistic models as proposed by JCSS [2001]. The degree of utilisation $\mu_0$ in a realistic fire is assessed by the loads $d$ and $l_S$, by the limiting steel strength at ambient temperature $r_a$ and by the optimal design variable $z_{opt}$ of the persistent design situation (Equation 6.2):

$$\mu_0(x, z_{opt}) = \frac{E_d}{R_{b,0}} = \frac{d + l_S}{z_{opt} \cdot r_a}$$

The loads and the steel strength are introduced as random variables (see Table 6.2). The steel strength at ambient temperature $r_a$ is associated with uncertainties, which resulting mainly from the production process of steel members, and is therefore introduced as a random variable $R_a$.

Mechanical properties at elevated temperatures

Steel exposed to high temperatures loses its strength. This reduction of the steel strength can be described by a reduction factor $k_y(\vartheta) \leq 1$ and depends on the steel temperature $\vartheta$, where $k_y = 1$ indicates no reduction. Based on this formulation the critical steel temperature $\vartheta_{crit}$ can be assessed by setting $k_y(\vartheta_{crit}) = \mu_0$. The approximative function provided by EN 1993-1-2 is used to assess the critical steel temperature $\vartheta_{crit}$:

$$\vartheta_{crit}(X_E, X_O) = 39.19 \ln \left[ \frac{1}{0.9674 \mu_0^{3.833}} - 1 \right] + 482$$

The relationship between the reduction factor $k_y$ and the temperature $\vartheta_{crit}$ is associated with uncertainties. A first approach towards a probabilistic representation of this relationship is provided by Khorasani et al. [2012]. For simplicity this uncertainty is neglected. Though, a part of the uncertainty associated with this relationship can be explained by the uncertainty associated with the yield strength at ambient temperature $R_a$, which is considered in the present model.

6.4 Reliability analysis

Structural reliability is expressed as the annual failure probability of a steel member $p_f$ and is assessed based on conditional events by:

$$p_f = P(EX) \cdot P(SF|EX) \cdot P(F|SF, EX)$$
### Tab. 6.2: Tentative probabilistic models for the events specific risk indicators for Swiss retail buildings.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>$X$</th>
<th>$x$</th>
<th>Dist.</th>
<th>$E[X]$</th>
<th>$\sqrt{Var[X]}$</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fire growth rate</td>
<td>$A$</td>
<td>$\alpha$</td>
<td>$\mathcal{LN}$</td>
<td>0.0236</td>
<td>0.03</td>
<td>Deguchi et al. (2011)</td>
</tr>
<tr>
<td>Mass loss rate</td>
<td>$\dot{m}''$</td>
<td>$\dot{m}''$</td>
<td>$\mathcal{LN}$</td>
<td>0.02</td>
<td>0.004</td>
<td>Section 4.2.1</td>
</tr>
<tr>
<td>Heat of combustion</td>
<td>$\Delta H_c$</td>
<td>$\Delta h_c$</td>
<td>$\mathcal{LN}$</td>
<td>18</td>
<td>3.6</td>
<td>Section 4.2.2</td>
</tr>
<tr>
<td>Combustion efficiency</td>
<td>$X_c$</td>
<td>$\chi_c$</td>
<td>$\mathcal{N}$</td>
<td>0.7</td>
<td>0.07</td>
<td>Section 4.2.3</td>
</tr>
<tr>
<td>Fire load density</td>
<td>$q_X$</td>
<td>$q_X$</td>
<td>$\mathcal{LN}$</td>
<td>600</td>
<td>390</td>
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<td>Model uncertainty [-]</td>
<td>$\Xi_\theta$</td>
<td>$\xi_\theta$</td>
<td>$\mathcal{N}$</td>
<td>Eq. 4.17</td>
<td>0.076 $\cdot E[\Xi_\theta]$</td>
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<td>$\mathcal{LN}$</td>
<td>264</td>
<td>18.5</td>
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</tr>
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<td>Dead load [kN/m²]</td>
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<td>$d$</td>
<td>$\mathcal{N}$</td>
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<td>0.429</td>
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<td>Sustained live load</td>
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<td>$l_S$</td>
<td>$\mathcal{GA}$</td>
<td>0.901</td>
<td>1.21</td>
<td>JCSS (2001)</td>
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<td>Max. controllable fire area [m²]</td>
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<td>$a_{contr}$</td>
<td>$\mathcal{N}$</td>
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<td>40</td>
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<td>$t_{Detect}$</td>
<td>$\mathcal{EXP}$</td>
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<td>-</td>
<td>Section 5.3.1</td>
</tr>
<tr>
<td>Call time [min]</td>
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<td>$t_{Call}$</td>
<td>$\mathcal{EXP}$</td>
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<td>-</td>
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<td>Dispatch time</td>
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<td>$t_{Disp}$</td>
<td>$\mathcal{N}$</td>
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<td>0.8</td>
<td>Section 5.3.3</td>
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</table>

$P(\text{EX})$ is the probability of fire ignition (exposure $EX$),
$P(\text{SF}|\text{EX})$ is the conditional probability of a structural fire $SF$,
$P(\text{F}|\text{SF,EX})$ is the conditional probability of a structural failure $F$.

The probability of fire ignition $P(\text{EX})$ describes the annual probability of fire occurrence in a retail building and is discussed in Section 4.1 (using the volume of the enclosure $vol = a_E \cdot h_E$). Fire ignition in this context is the occurrence of a financial loss covered by the building fire insurance company and comprises also small fires, which can be suppressed in an early stage by the occupants. This scenario is considered by the probability of suppression by occupants, i.e. $P(\text{Occ}) = 0.5$ (see Section 5.2). A structural fire can also be avoided by a sprinkler $SP$. The reliability of sprinkler systems is discussed in Section 5.6 and the failure probability is assumed to lie in between of $p_{f,SP} = 0.02 \div 0.1$ (with tendency to the smaller probability). If the sprinkler
activates then it is expected that the fire does not affect the structural reliability any more. Thus, the probability of a structural fire can be assessed by \( P(SF|EX) = P(Occ) \cdot p_{f,SP} \).

### 6.4.1 Conditional probability of structural failure

Structural failure \( F \) occurs when the limit state function \( G_{fi} \) defined by Equation 6.8 turns negative, e.g. when the maximal steel temperature exceeds the critical temperature. The conditional probability of a structural failure \( P(F|SF,EX) \) is assessed by the probability of a negative outcome of the limit state:

\[
P(F|SF,EX) = P(G_{fi}(X_E,x_O) \leq 0|SF,EX) = \int_{g_{fi}(x_E,x_O) \leq 0} f_{X_E}(x_E)dX_E
\]  

(6.12)

The probability \( P(G_{fi}(X_E,x_O) \leq 0|SF,EX) \) is assessed by a numerical multidimensional integration over the probability densities \( f_{X_E}(.) \) of the random variables \( X_E \), where the limit state function is negative, e.g. \( g_{fi}(x_E,x_O) \leq 0 \). This numerical integration is computational very expensive and two different methods can be used to estimate the probability of failure: simulation methods and approximation methods.

Approximation methods, e.g. First Order Reliability Method (FORM), tend to be sensitive to non-linear behaviour of the limit state function. This is the case if the fire brigade intervention is considered as proposed in this chapter (see De Sanctis et al., 2013). In addition, the limit state function \( G_{fi} \) depends on the outcome of three events, which are in general dependent from each other:

- the fire brigade suppression possibility, which is assessed by \( G_{suppr} = a_f(T_I) - A_{contr} \) (see Section 5.4.2 and Section 6.3.1).
- the flashover conditions in an enclosure (see Section 4.4).
- the fire regime, e.g. ventilation- or fuel-controlled fires (see Equations 4.11 and 4.9).

This leads to a non-continuous behaviour of the limit state function \( G_{fi} \) and, thus, the application of approximation methods cannot be justified.

The reliability analysis based on simulation methods, such as Monte Carlo simulation, are not prone to non-linear models. An advanced simulation method named subset simulation (Au & Beck, 2001) is used to estimate the failure probability \( P(G_{fi} \leq 0|SF,EX) \) and has been already applied in fire safety engineering by Au et al. (2007). The basic idea of the subset simulation is to express the small failure probability \( P(F|SF,EX) \) as a product of larger conditional failure probabilities \( P(F_{i+1}|F_i) \) by introducing intermediate failure events (subsets) \( F_i = \{G_{fi}(X_E,x_O) \leq \Delta_i \} \):

\[
P(S|SF,EX) = P \left( \bigcap_{i=1}^{m} F_i \right) = P(F_1) \prod_{i=1}^{m-1} P(F_{i+1}|F_i)
\]  

(6.13)

The intermediate conditional failure events (subsets) are related to a threshold value \( \Delta_1 > \Delta_2 > ... > \Delta_m = 0 \). The first threshold \( \Delta_1 \) is derived from a crude Monte Carlo Simulation in which
the probability of the first subset is equal to \( P(F_1) \approx 0.1 \div 0.2 \). For the sequential conditional subsets \( i \) the threshold values \( \Delta_i \) are assessed similar, but through a Markov Chain Monte Carlo simulation based on a modified Metropolis-Hasting algorithm introduced by [Au & Beck (2001)]. This algorithm generates new realisations of the intermittent failure event \( F_{i+1} \) conditional on the realisations of the failure event \( F_i \). Assessing the individual probability of the conditional intermediate failure event \( P(F_{i+1}|F_i) \) is computational much more efficient compared to the case, where a small failure probability, e.g. \( P(F|SF,EX) \), has to be estimated directly by a Monte Carlo simulation. The subset simulation method is described in [Au & Beck (2001)] in detail and is implemented in the Matlab toolbox FERUM (Bourinet, 2010), which is used for the reliability analysis. The number of simulations depends on the probability of the conditional intermediate failure events \( P(F_{i+1}|F_i) \approx 0.1 \div 0.2 \) and the intended coefficient of variation (CoV <10%). This CoV is a measure for the error that occurs by estimating the probability \( P(S|SF,EX) \). For probabilities in the order of \( > 10^{-6} \) a few 1000 simulations are necessary; for probabilities in the order of \( < 10^{-6} \) a few 10000 of simulation are required. For probabilities \( < 10^{-6} \) a higher coefficient of variation (CoV>10%) is accepted to keep the computational effort in a reasonable range. The advantage of the subset simulation becomes evident when comparing the required number of simulations \( n \) to estimate a small failure probability \( P \sim 10^{-k} \). Whereas for the Monte Carlo simulation \( n \sim 10^{k+2} \) simulation are necessary, for the subset simulation only \( n \sim k \cdot 10^4 \) simulations have to be performed and shows clearly the benefit of using subset simulation especially to assess small failure probabilities.

6.4.2 Bias in the prediction of the failure probability

Due to assumption and simplification used in the probabilistic engineering models the prediction of the failure probability is associated with a certain bias. A statistical bias arise also by the estimation of the probability of fire ignition \( P(EX) \) and the probability of a structural fire \( P(SF|EX) \). Thus, absolute risk comparison, e.g. by comparing the reliability towards an target reliability \( \beta_t \) (see Section 2.2.2), is actually not appropriate. Hence, to be exact, only a relative comparison between the different designs approaches is possible. Nevertheless, it is expected that the prediction of the failure probability is in the order of magnitude of the unbiased probability of failure since the probabilistic models of the input parameters \( X_E \) have been chosen according to statistical data. The target reliability index \( \beta_t = 4.2 \) \( (p_{f,t} \approx 10^{-5}) \) (see Table 2.2) is illustrated in Figure 6.7 and represents an absolute reliability value that divides the acceptable and the non-acceptable region. Any interpretation whether the design is acceptable or not, should be done with care.

6.5 The level of safety of structural design concepts

6.5.1 The level of safety of prescriptive design

The annual failure probability \( p_f \) of a steel structure, which is designed by a prescriptive design, is assessed for three different opening factors \( o_E \) and for different floor areas \( a_E \) and is illustrated
in Figure 6.6. As expected, for the same building layout, the failure probabilities for R30 fire resistance requirements are higher compared to the ones with R60 requirements. The safety level depends on the building properties $o_E$ and $a_E$. This is comprehensible because the prescriptive design does not take the building properties into account (see Figure 6.3). Especially for small areas $a_E$ and small opening factors $o_E = 0.20 \text{ m}^{1/2}$ the failure probability is very low. The level of safety increases with larger openings and decreases with higher areas. Remarkable is the large bandwidth of the safety levels that comprises multiple orders of magnitude.

### 6.5.2 The level of safety of performance-based design

Figure 6.7a) shows the safety level of a performance-based design. In contrast to the prescriptive design, the failure probability for the large opening factors ($o_E = 0.20 \text{ m}^{1/2}$) is higher compared to the failure probability for small opening factors ($o_E = 0.04 \text{ m}^{1/2}$). This can be explained since the design-format of EN 1991-1-2 may include some conservative assumptions especially for severe fires that are likely to occur for small opening factors. The calibration of the safety factors for EN 1991-1-2 are based on small opening factors (Schleich et al., 2002). However, the treatment of the opening factors by the design format can be improved.

The bandwidth of the failure probabilities of the different design approaches are compared with each other in Figure 6.7b. The bandwidth of the failure probabilities is smaller compared to the prescriptive design. This is in agreement with the goal of a well calibrated semi-probabilistic design approach, i.e. to provide an equal level of safety for different buildings characteristics.

For large floor areas $a_E$ the bandwidth of the performance-based approach is comparable with a R60 fire resistance requirement. All in all, the performance-based design indicates a better treatment of the building specific properties compared with the prescriptive design, especially regarding the opening factors for small floor areas.
6.5. The level of safety of structural design concepts

When comparing the different design approaches, it can be seen that the level of safety of the EN 1991-1-2 design approach and the R60 fire resistance is above the required target reliability index $\beta_t = 4.2$. The R30 fire resistance is only suited for small compartment areas or for buildings with a lower required level of safety (see Table 2.2). Note that the model is associated with a bias (see Section 6.4.2) and makes an absolute comparison difficult, e.g. with a required level of safety.

6.5.3 Risk equivalence of sprinkler concepts

Sprinklers can be considered in the semi-probabilistic design approach of EN 1991-1-2 by reducing the design fire load (see Section 6.2.2). Some prescriptive design codes allow to reduce the required fire resistance, e.g. for R60 without sprinkler to R30 with sprinkler (see Section 2.1.2). The aim in both approaches is to reach the same level of safety as in the design without a sprinkler. The equivalence of the design can be verified by comparing the annual failure probability of the standard design (without a sprinkler) with the failure probability of the alternative design solution (with a sprinkler), see Figure 6.8. According to Section 5.6 the failure probability of a sprinkler is in the range of $p_{f,SP} = 0.02 \div 0.1$. This range is considered by an upper and a lower bound of the reliability of a sprinkler (see probability bound analysis of Section 3.4.3) and is considered in the assessment of $p_f$. The range is illustrated in Figure 6.8 by a grey bandwidth.

The failure probability of the sprinkler concept for both design approaches is lower than the standard solution, even for a sprinkler failure probability of $p_{f,SP} = 0.1$. Only for small floor areas the safety level of the standard concept cannot be reached. Though, for those cases the failure probability of both concepts is very low anyway. Figure 6.8b indicates a higher possible reduction of the design fire load in a performance-based sprinkler concept, which would enhance a better allocation of resources.

![Figure 6.7: a) Failure probabilities $p_f$ for a performance-based design and b) comparison of the different design approaches, (EN: performance-based design according to EN 1991-1-2, R30/R60: prescriptive design).](image)
6.5.4 Influence of the fire brigade model

A full burn-out fire is usually assumed in a fire safety design, i.e. the total combustion of the fire load. The fire brigade intervention and suppression activities are not considered or are considered only in a simplified way. For example, the partial safety factors for the design fire load in [EN 1991-1-2] have been calibrated by supposing a constant failure probability of the suppression activities independent on the building properties and on the fire conditions (see Schleich et al., 2002). The generic risk model is used to analyse the effect of this assumption by comparing the risk derived with the suppression model (introduced in Section 6.3.1), with the risk derived by a full burn-out fire model (as introduced in Section 4.6.3). Alike Schleich et al. (2002) a constant failure probability for the suppression activities of the fire brigade is chosen. Based on Figure 5.8 this probability can be set to $p_{f,\text{supp}} = 0.2$. The failure probabilities are illustrated in Figure 6.9.

The structural failure probability derived by the full burn-out model approximates the failure probability derived by the suppression model for $a_E > 200 \text{ m}^2$. The reason for this behaviour can be found in Figure 5.8 where the failure probability of the suppression activities approaches a stable value for larger areas, e.g. $p_{f,\text{supp}} \approx 0.2$. This is not the case for small enclosures $a_E < 200 \text{ m}^2$ and the failure probability derived by the suppression model can be much smaller compared to the failure probability derived by the full burn-out model. The transition between those two regions is influenced by the mean of the maximal controllable fire size $E[A_{\text{contr}}]$. Additional discussions is found in Hosser et al. (2009), De Sanctis et al. (2013) and De Sanctis et al. (2014a).

Assuming a full burn-out fire with a simplified consideration of the fire brigade suppression activities, e.g. by a constant failure probability $p_{f,\text{supp}}$, might be appropriate for a structural design of large enclosures. For small enclosures, however, the interaction between the fire development and the fire brigade intervention is more important and influence the safety level of the
6.6 Conclusions and implications for structural fire safety design

Fig. 6.9: Influence of the fire brigade intervention and suppression model on the level of safety.

structure. In those cases a full burn-out fire may be used as a (very) conservative design fire, accepting a non-optimal allocation of resources for small enclosures.

6.6 Conclusions and implications for structural fire safety design

A reliability based method is used to quantify the level of safety of either a prescriptive or a performance based design. The level of safety is quantified by the annual probability of failure of a structural element. To assess this probability the building and the structural design is represented generically and facilitates a parametric study of the building specific properties. An optimal generic design for the persistent and accidental (fire) design situation assesses the minimal mechanical and thermal requirements for the structure that are prescribed by the codes. The performance of the structural design requirements are analysed under realistic conditions by a probabilistic approach. Within this approach, engineering models are used to represent the physical processes in a fire event including the fire brigade intervention and the compartment fire development. To assess the failure probability of the structure, an advanced Monte Carlo Simulation named subset simulation is used. The subset simulation reduces the computational effort for the reliability analysis by many times and makes a parametric study possible. The reliability analysis is applied to a steel structure that is designed either according to prescriptive or performance-based design provisions. In addition, the reliability analysis can be used to prove the equivalence between a standard design concepts and alternative sprinkler concept. However, due to the large dependency of the failure probability on building specific indicators it is not clear which safety level of a prescriptive design approach has to be chosen in order to prove the equivalence of an alternative design approaches.

The level of safety of the prescriptive design is very sensitive to building specific indicators especially concerning the ventilation conditions. Thus, depending on the fire resistance requirement and the building properties, the failure probabilities can vary in a large bandwidth, since
the building indicators are not taken into account by the code format. In the performance-based design the building indicators are considered and influence the bandwidth of the safety level. Hence, applying a prescriptive design might be only suitable for a building portfolio in which building properties varies only in a small range. Otherwise, it might results in non-economical or even in non-safe buildings.

The performance-based design methodology of EN 1991-1-2 is applied for the structural design under fire conditions. The level of safety of the performance-based design varies – within the parameter study – in a smaller range compared to the prescriptive design. The performance-based design provides equal or even lower failure probabilities compared to the prescriptive design, except for cases where the floor area is small. For those cases the failure probabilities of the prescriptive design are very low anyway because of the favourable conditions for the fire brigade suppression.

Including more adequately the interaction between fire brigade suppression activities and fire development in the structural design (e.g. within a performance-based design approach), benefits especially small enclosures where the suppression of the fire by the fire brigade is very likely. For large enclosures this interaction can be neglected by assuming an overall probability of fire suppression and assuming a full burn-out fire. The same simplification can be applied to small enclosures accepting a (very) conservative design. Further, a parametric analysis of the opening factors indicate that the fire exposure given in EN 1991-1-2 e.g. the parametric fire curves, can be improved by representing the ventilation conditions more adequately.

The introduced methodology and the low computational costs for the reliability analysis provide the basis to calibrate partial safety factors for a semi-probabilistic design approach and to account advanced fire models and the fire brigade intervention.
Chapter 7

Optimisation of egress provisions

Life safety is the primary objective of fire safety design and is mainly ensured by the design of the means of egress, e.g. providing a certain number of exits, limiting travel distances or requiring a minimal door width. Adequate fire safety measures assure that people can reach a place of safety without being exposed to dangerous conditions and reduce the risk to life. An unlimited reduction of this risk by adapting safety measures is not desirable since it would lead to an immense investment of resources, e.g. building costs. As discussed in Section 3.3, the LQI acceptance criterion can be used to judge the efficiency of a safety measure to reduce the risk to life and can be used to optimise the investments into life saving measures.

The focus of this chapter is the optimisation of the required door width $w$, which influences the evacuation process and determines the flow capacity of exits when people are evacuating from the room of fire ignition. Usually, especially for larger floor areas, two or more exits are mandatory to provide redundancy for the evacuation process, e.g. for the case where a fire prevents the evacuation through one of the exits. An exit serves a certain floor area for a safe evacuation, which can be related to the maximal travel distance. Thus, for a given floor area the number of required exits depends on the travel distance and can be considered as a decision problem at its own. Further, it should be noted that the number of exits does not affect the flow capacity. Therefore, this optimisation problem is not part of this case study. The optimal door width can be associated with the total required door width (e.g. the sum of all door widths, when a linear dependency between door width and flow capacity is assumed), which reflects the optimal required flow capacity to provide a safe evacuation from the room of fire ignition.

The door width affects the flow of persons to the outside of the compartment especially in cases where many people evacuate to the outside through the same exit. In this case, reducing the number of persons exposed to dangerous conditions will also reduce the risk. Dangerous conditions are associated with the smoke development of the fire. According to Section 3.3.1 for the optimisation of fire safety measures according to the LQI criterion the derivation of the marginal life saving cost $dc_l(w)$ and the derivation of the marginal change of the number of fatalities by a safety measure $dm(w)$ is required. As discussed in Section 5.7 a risk-based approach can be followed to assess the expected number of fatalities $R(w)$. Thus, the acceptance
criterion can be formulated by:

\[
\frac{dc_I(w)}{dw} \leq -J^* \frac{dR(w)}{dw} = -SWTP_{life} \cdot \frac{dR(w)}{dw}
\] (7.1)

The societal willingness to pay $SWTP$ per life saved is used as a threshold value to derive the minimal required investments into life safety leading to an equivalence of Equation (7.1). Based on this equation the minimal required door width $w_{\text{opt}}$ can be derived. An overview of the optimisation strategy is given in Figure 7.1.

The risk is assessed by an engineering-driven approach by modelling the exposure (fire ignition, smoke development and tenability criteria for occupants) and the evacuation process. The risk is assessed based on Equation (5.16):

\[
R = \int_{\mathbb{R}^d} p(t_{\text{ASET}}(x) | x) \cdot f_X(x | EX) \cdot P(EX) \, dx
\] (7.2)

Engineering-driven approaches to assess the risk are applied by different authors, e.g. He et al. (2003), Chu et al. (2007), Albrecht (2011) and Fischer (2014). These risk models can be used for comparative risk evaluation and may provide valuable support for design situations. Nevertheless, these models have a significant bias and make the application of the (absolute) LQI criterion problematic. In addition, some authors simplified either the stochastic characteristics of some basic input parameters (like the occupant load density; e.g. He et al., 2003; Fischer, 2014; Chu et al., 2007), or the engineering models representing the fire model (e.g. He et al., 2003). A more thorough approach is followed by Albrecht (2011), who defined all relevant input parameters probabilistically and proposed an adaptive response surface method to represent the uncertainty propagation of an advanced fire model (computational fluid dynamics model) and an advanced behavioural evacuation model for the assessment of the probability of a fatality $p_f$. As discussed in Section 5.7 the probability of a fatality $p_f$ is not suited to consider low-probability high-consequence scenarios and should not be used for a risk-based acceptance criterion.

In this chapter, a generic risk model is developed to assess the risk to life, focusing on a realistic quantification of the uncertainties and the representation of the most relevant effects in an evacuation process. Accordingly, the Available Safe Egress Time (ASET) as well as the Required Safe Egress Time (RSET) are modelled probabilistically and are used to represent the evacuation process. The generic formulation of the model allows the comparison of the optimal door width between different building layouts and allows to estimate the bias associated
7.1 Representation of the system

The safe evacuation of occupants in a fire situation can be assured by implementing a variety of fire safety measures in a building, e.g. provisions for the means of escape, technical measures (forced ventilation and smoke extraction) or organisational measures (evacuation training of occupants). Representing such systems with an engineering approach is not a trivial task and leads to complex models. The aim of this chapter is to explain and discuss the application of the LQI criterion for evacuation problems and to identify risk indicators that have a major contribution to the outcome of a decision-making problem. Therefore, the problem is reduced in its complexity focusing on the most relevant risk indicators, but without compromises in the application of the general method and the treatment of the uncertainties.

Following the approach of a generic system representation, discussed in Section 3.1.2, the exposure is defined as the fire ignition. The fire may occur at any place, but does not prevent people to escape. The vulnerability is referred to all the fatalities that occur in the room of fire origin; the robustness may be referred to all deaths that occur beyond the room of fire ignition and is not part of this study.

The subject of this study are retail buildings and the evacuation of occupants to a place of safety, e.g. the staircase or the outside. As illustrated in Figure 7.2a, this can be achieved directly by a staircase (Egress route 1) or/and indirectly by a fire corridor heading toward a

Fig. 7.2: a) Example of a layout of the enclosure and b) generalised representation of the layout.

with the risk model. A sensitivity analysis identifies the most influencing parameters on the risk. The uncertainty associated with these parameters should be considered accordingly when a performance-based design approach is applied, e.g. within a probabilistic approach or within a semi-probabilistic approach (see Section 2.2). In addition, the sensitivity measures can be used as indication to simplify the physical models used for a performance-based design approach, e.g. reducing the complexity of a design format.
staircase (Egress route 2). In this case study it is assessed how fast persons can evacuate from the room of fire origin through an exit to the outside. All following bottlenecks should have at least the flow capacity of this exit to avoid a tailback in the room of fire origin. Therefore, there is no differentiation between different egress routes and it is assumed that the evacuation is mainly carried out through the staircase.

The door width \( w \) is considered as a risk reducing measure, which acts as a bottleneck for the room of fire ignition and limits the flow rate of an exit. The total flow rate out of the room can be related to the total door width \( w = w_1 + w_2 \) and is subject of this optimisation study. The optimisation is done based on the LQI criterion (see Section 3.3.1) leading to a minimal required (total) door width \( w_{\text{opt}} \). The marginal cost and the marginal risk reduction have to be assessed at societal level to apply the LQI criterion, e.g. at portfolio level. However, the costs and the risk are highly depending on building specific indicators, e.g. the floor area \( a_E \) and the height of the building \( h_E \), which are subjected to the design freedom of the individual designer. Therefore, the optimisation is performed given a specific design that is expressed by the object specific risk indicators, e.g. \( x_O = \{a_E, h_E\} \).

As generalised representation of a retail layout, a rectangular enclosure is considered without any subs-cells, e.g. sub-rooms, and with one single exit at the longer wall (see Figure 7.2b). The enclosure may represent a whole compartment or a single room in a larger compartment. The floor area of the enclosure \( a_E \) and the height of the enclosure \( h_E \) are considered as object specific risk indicators \( x_O = \{a_E, h_E\} \). The maximal distance \( l_E \) to the exit can be associated with the maximal travel distance that is usually provided by the codes (see VKF 16-03 [2003]). Given a maximal travel distance, the floor area of the enclosure can be maximised, e.g. \( l_E = \sqrt{a_E} \). The number of occupants is usually assessed by the the occupant load factor and the floor area. The maximal travel distance, thus, determines indirectly the maximal number of people that are using an exit for the evacuation. All occupants in this area are supposed to evacuate through this exit. In practice, two or more exits are required to provide redundancy for the evacuation process, e.g. for the case where a fire prevents an evacuation through one of the exits. As mentioned in the introduction of this chapter, the number of required exits can be considered as a decision problem at its own and is not part of this case study. Nevertheless, this study can be considered as a sub-problem of such a decision problem, since a single exit serves as a safe evacuation route for a part of a compartment that consists of several exits.

### 7.2 Modelling the available safe egress time

The probability of fire ignition \( P(EX) \) for retail buildings with a given floor area \( a_E \) and a given height \( h_E \) can be derived according to Section 4.1 (using the volume of the enclosure \( vol = a_E \cdot h_E \)). This ignition rate includes fire incidents, which occurred at night. In those cases, a shop is usually closed and no occupants are present. Therefore, using this probability of fire ignition leads to an overestimation of the risk.

The combustion products of a fire continually fill the room with smoke. As discussed in Chapter 4 this pre-flashover stage of a fire can be represented by \( l \)-square fire and modelled
by a two-zone approach, separating a smoke free (lower) layer and an upper layer that contains combustion products (see Figure 7.3). For the numerical analysis, the fire is supposed to occur in the centre of the room. Though, the exact location of the fire is not important in a two-zone modelling approach. This approach is not appropriate for situations where pressure differences in the room have to be expected, e.g. caused by forced ventilation, or for situations where the room layout is not cuboid. The smoke is contained in the upper layer of the room and no smoke flows through the openings. No suppression activities by the occupants are considered, since the suppression discussed in Section 5.2 rather refers to residential buildings. This may lead to an overestimation of the risk, since in retail buildings a suppression by occupants is also possible. The suppression by the fire brigade is excluded as well, because the evacuation process is likely to be finished before the arrival of the fire brigade.

As discussed in Section 5.7 the time until untenable conditions are reached $t_{ASET}$ can be considered as the damage state for the consequences. Performance-based design guidelines provide tenability criteria to account for the maximal acceptable exposure to heat, smoke obscuration (optical density) and the lethal dose of toxic gases. These criteria can be used to derive limit states for the tenability of occupants. The smoke obscuration is often used in the design to assure the visibility of exit signs for the occupants. Nevertheless, obscuration does not lead directly to a fatality. Therefore, only the heat exposure and the dose of toxic gases are considered.

The dose of toxic gases requires a detailed knowledge on the concentration of gases in the smoke layer. According to Cooper (1982), there is a physical relationship between the smoke free layer height $z_S$, the upper layer temperature $\theta_{upper}$ and the concentration of toxic gases in the smoke layer. To determine the available safe egress time $t_{ASET}$, Cooper (1982) proposed to estimate the earliest time when:

- the smoke layer interface $z_S$ is above a characteristic elevation $z_{S,crit}$, and $\theta_{upper}$ exceed a specified hazardous overhead value associated with an untenable flux of thermal radiation.
- the smoke layer interface $z_S$ is below $z_{S,crit}$ and either the concentration of toxic gases or the upper layer temperature $\theta_{upper}$ are hazardous for human health.
The characteristic elevation $z_{S,crit}$ can be associated with the body height of the occupants and the criterion on the concentration of toxic gases is conditional on $z_S < z_{S,crit}$. Consequently, the probability of death $p_f$ (exceeding a threshold value for toxic gases) is $p_f \leq P(z_S < z_{S,crit})$. Hence, the formulation of the limit state $g_{ASET,z}$ without considering the gas concentration (see Equation 7.3a) leads to an overestimation of the risk to life. This simplification avoids critical assumptions on the generation rate of the toxic gases.

The smoke free layer height $z_S$ of the two-zone model approach (see Section 4.3) and the upper layer gas temperature $\theta_{upper}$ are used as indicators to assess the untenable conditions and to quantify the Available Safe Egress Time (ASET). Thus, the limit state functions for a fatality are formulated by:

$$g_{ASET,z}(t_{ASET,z}) = z_S(t_{ASET,z}, x) - z_{S,crit} \leq 0 \quad (7.3a)$$

$$g_{ASET,\theta}(t_{ASET,\theta}) = \theta_{upper,crit} - \theta_{upper}(t_{ASET,\theta}, x) \leq 0 \quad (7.3b)$$

The time until untenable conditions are reached $t_{ASET} = \min\{t_{ASET,z}; t_{ASET,\theta}\}$ is assessed by solving Equations 7.3a and 7.3b for $t_{ASET}$. The numerical analysis shows that the limit state function $g_{ASET,\theta}$ is not critical for the tenability criteria for the occupants. Therefore, for convenience and without compromises in the general methodology it is only focused on the limit state $g_{ASET,z}$ and on $t_{ASET,z}$.

### 7.2.1 Probabilistic models for the ASET

The probabilistic models for the fire specific risk indicators for describing the pre-flashover state of a fire are chosen according to Chapter 4 and consists on the fire growth rate $A$, the mass loss rate $\dot{M}'', the heat of combustion $\Delta H_c$ and the combustion efficiency $X_c$. The indicators are listed in Table 7.1. The fire load is considered to be large enough in order to start the decay phase after the evacuation is finished.

The assessment of the smoke free layer height $z_S$ is associated with uncertainties due to the idealisation of the two zones and other approximations (see Section 4.3). Similarly to the model uncertainty for the gas temperature (see Section 4.6.3), a model uncertainty for the smoke layer height $\Xi_{Smoke}$ is introduced. The smoke layer height is assessed by $z_{Smoke} = \xi_{Smoke} \cdot (h_E - z_S)$. The prediction of the smoke layer height for unforced ventilation conditions by OZone match the observations of the validation tests (Cadorin 2003). Thus, an unbiased model uncertainty $\Xi_{Smoke}$ is introduced, which is defined in Table 7.1. NUREG-1934 (2012) assessed the model uncertainty for other zone models, e.g. CFAST (Jones et al. 2004) and MAGIC (Gay 2005), and is comparable with the proposed model.

The critical threshold for a lethal dose of toxic gases and smoke particles might differ for occupants, e.g. for children and adults, small and tall persons, males and females. Therefore, the critical smoke free layer height $z_{S,crit}$ is associated with uncertainties and is modelled as a random variable $Z_{S,crit}$. The design values for the critical smoke free layer range between 2-3.5 m (CIBSE 2010) and are associated with a high degree of conservatism. As a tentative probabilistic model, a Normal distribution with mean value 1.8 m and a standard deviation of 0.16 is chosen in order to represent the variability of the body height (80% within 1.6 and 2 m).
7.2. Modelling the available safe egress time

Tab. 7.1: Tentative probabilistic models for fire specific risk indicators determining the ASET.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>$X$</th>
<th>$x$</th>
<th>Dist.</th>
<th>$E[X]$</th>
<th>$\sqrt{Var[X]}$</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fire growth rate [kW/sec$^2$]</td>
<td>$A$</td>
<td>$\alpha$</td>
<td>LN</td>
<td>0.0236</td>
<td>0.03</td>
<td>Deguchi et al. (2011)</td>
</tr>
<tr>
<td>Mass loss rate [kg/sec/m$^2$]</td>
<td>$\dot{m}''$</td>
<td>$\dot{m}''$</td>
<td>LN</td>
<td>0.02</td>
<td>0.004</td>
<td>Section 4.2.1</td>
</tr>
<tr>
<td>Heat of combustion [MJ/kg]</td>
<td>$\Delta H_c$</td>
<td>$\Delta h_c$</td>
<td>LN</td>
<td>18</td>
<td>3.6</td>
<td>Section 4.2.2</td>
</tr>
<tr>
<td>Combustion efficiency [-]</td>
<td>$X_c$</td>
<td>$\chi_c$</td>
<td>N</td>
<td>0.7</td>
<td>0.07</td>
<td>Section 4.2.3</td>
</tr>
<tr>
<td>Model uncertainty [-]</td>
<td>$\Xi_{Smoke}$</td>
<td>$\xi_{Smoke}$</td>
<td>N</td>
<td>1.0</td>
<td>0.1</td>
<td>estimated</td>
</tr>
<tr>
<td>Critical smoke free layer height [m]</td>
<td>$Z_{S,crit}$</td>
<td>$z_{S,crit}$</td>
<td>LN</td>
<td>1.8</td>
<td>0.16</td>
<td>estimated</td>
</tr>
</tbody>
</table>

7.2.2 Surrogate model for the ASET

The assessment of the ASET involves the application of a two-zone model, which is associated with a certain computational effort. Although a single run of a two-zone model is performed fast, e.g. a few seconds, for simulation-based risk assessment multiple runs of the model are required and increase the computational costs remarkably and make the assessment of risk problematic.

A widely used approach in probabilistic modelling is to represent the outcome of a computational demanding model by a surrogate-model (or meta-model) providing an easy-to-evaluate function as an approximation of the original model. The surrogate model can be used to propagate the uncertainties of the input variables through the model, e.g. by Crude Monte Carlo simulations, since the evaluation of the function is fast. This approach has been followed by different authors in fire safety engineering, e.g. Magnusson et al. (1996), Hasofer & Qu (2002), Albrecht (2011) and Xie et al. (2013) and is used in this section to surrogate the ASET.

The Polynomial Chaos Expansion (PCE) is a spectral approach to surrogate a model response and is introduced by Ghanem & Spanos (1991). One of the benefits of this approach is that the polynomials are directly linked to the global sensitivity of the random variables and allow a better construction of the surrogate model with a small experimental design (small number of simulation points). This makes the application of a PCE especially beneficial for models with a very high computational effort. The PCE is discussed in Appendix B and is used to surrogate the ASET. The discussed approach reduces the model uncertainty of the surrogate model, e.g. the leave-one-out-error, for a given experimental design to a minimum, which is not necessarily the case when applying different surrogate techniques, e.g. regression analysis with non-orthonormal multivariate polynomials.

For each combination of the object specific risk indicators, e.g. $a_E$ and $h_E$, a PCE is constructed based on the model response of an experimental design that consists of $N = 10^4$ model evaluations generated by the Sobol sequence. The Sobol sequence is a quasi-random sample strategy to assure a low discrepancy between the sample points. The Matlab toolbox UQLab (Marelli & Sudret, 2014) is used for the construction of the PCE. The toolbox optimises the polynomial degree $p$ in order to reduce the leave-one-out-error of the PCE (Blatman 2009).
Due to the large number of the experimental design $N$, a polynomial degree up to $p = 15$ is evaluated. Figure 7.4a shows that the PCE approximates the model response very well.

The probability density of the ASET is illustrated in Figure 7.4a for different floor areas $a_E$. With increasing area $a_E$ the $t_{ASET}$ increases on average as well. This is due to the larger volume available for the smoke filling, leading to a slower decline of the smoke layer. The coefficient of variation $\text{CoV}[T_{ASET}]$ remains almost constant, leading to an increase of the variance with increasing floor area.

**Global sensitivity analysis for the ASET**

The global sensitivity indices can be estimated based on the coefficients of the PCE and are illustrated in 7.4b (see Appendix B). These indices identify the individual contributions of the random input parameters (or their interaction) to the variability of the response of a model (see Section 3.4.3). The model indicates a high sensitivity to the fire growth rate $\alpha$. Thus, a reduction of the variability of the fire growth time, e.g. reducing the epistemic uncertainties associated with the proposed probabilistic model, may reduce the variability of the ASET. This can be achieved by increasing the sample size and/or the level of detail of the data used to develop the probabilistic model of the fire growth time $\alpha$ (see Section 4.3) or by introducing an advanced probabilistic engineering model that models the fire growth rate under real conditions, e.g. an item-based probabilistic fire spread model (e.g. \textit{Baker et al.}, 2013).

In contrast, the contributions of the random variables associated with the heat release rate, e.g. $\dot{m}'$, $\chi_c$ and $\Delta h_c$, are minor and they could be introduced as deterministic variables. This applies also for the model uncertainty $\xi_{Smoke}$, which indicates that the two-zone modelling approach provides a sufficient level of detail and there is no benefit to use an advanced engineering model (e.g. a computational fluid dynamics model). In addition, the model indicates almost no
Tab. 7.2: Tentative probabilistic models for the individual RSETs and the evacuation process.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>X</th>
<th>x</th>
<th>E[X]</th>
<th>(\sqrt{Var[X]})</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Global</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupant load density [pers/m(^2)]</td>
<td>(P''_0)</td>
<td>(p'_0)</td>
<td>(GA)</td>
<td>0.076</td>
<td>0.068</td>
</tr>
<tr>
<td>Model uncertainty for detection and warning [sec]</td>
<td>(E)</td>
<td>(\varepsilon)</td>
<td>(N)</td>
<td>0</td>
<td>0.32</td>
</tr>
<tr>
<td>Door flow capacity [pers/sec/m]</td>
<td>(J_{S,Door})</td>
<td>(j_{S,Door})</td>
<td>(N)</td>
<td>1.75</td>
<td>0.11</td>
</tr>
<tr>
<td>Model uncertainty RSET [-]</td>
<td>(\Xi_{RSET})</td>
<td>(\xi_{RSET})</td>
<td>(LN)</td>
<td>1</td>
<td>0.2</td>
</tr>
<tr>
<td><strong>Individual</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detection and warning (visual) [sec]</td>
<td>(T_{D+W,i})</td>
<td>(t_{D+W,i})</td>
<td>(\mathcal{E}\mathcal{X}\mathcal{P})</td>
<td>Eq. 7.5 (^2)</td>
<td>-</td>
</tr>
<tr>
<td>Recognition and response [sec]</td>
<td>(T_{R+R,i})</td>
<td>(t_{R+R,i})</td>
<td>(\mathcal{L}\mathcal{N})</td>
<td>32</td>
<td>16</td>
</tr>
<tr>
<td>Movement velocity [m/sec]</td>
<td>(V_i)</td>
<td>(v_i)</td>
<td>(W)</td>
<td>1.34</td>
<td>0.16</td>
</tr>
<tr>
<td>Location [m]</td>
<td>(X_i)</td>
<td>(x_i)</td>
<td>(U^3)</td>
<td>(-\sqrt{2}/2 \cdot l_E)</td>
<td>(\sqrt{2}/2 \cdot l_E)</td>
</tr>
<tr>
<td>Location [m]</td>
<td>(Y_i)</td>
<td>(y_i)</td>
<td>(U^3)</td>
<td>0</td>
<td>(\sqrt{2}/2 \cdot l_E)</td>
</tr>
</tbody>
</table>

\(^1\) \(\log(t_{D+W}) = \beta_0 + \beta_1 \log(\alpha) + \varepsilon \) with \(\beta_0 = 2.5109\) and \(\beta_1 = -0.3641\)
\(^2\) Note that \(E[T_{D+W,i}] = 1/\lambda\). \(^3\) Lower and upper bounds are listed instead of the moments.

interaction effects among the input parameters. Note that the sensitivities are strongly related to the tentative probabilistic models listed in Table 7.1 and may change for different probabilistic models and for different engineering models to derive the ASET.

### 7.3 Required safe egress time

The required safe egress time (RSET) is the time needed for an occupant \(i\) to reach a place of safety and is composed of three individual time intervals, which are defined in Section 5.7.2 and illustrated in Figure 5.10

\[ t_{RSET,i} = t_{D+W,i} + t_{R+R,i} + t_{T+Q,i} \]  

\(7.4\)

The basic parameters to assess these time intervals are discussed in the following sections and are summarised in Table 7.2.
Chapter 7. Optimisation of egress provisions

7.3.1 Detection and warning

As discussed in Section 5.3.1, the detection time is modelled based on data published by Holborn et al. (2004). Though, the data includes fire incidents whose ignition occurred after the opening hours of the shops or in a different (unoccupied) room, which leads to much higher detection times. In the present study, the fire is assumed to occur in an occupied room during opening hours. Therefore, the detection time derived in Section 5.3.1 does not represent the evacuation scenario. Nevertheless, it is expected that the distribution type, e.g. the Exponential distribution, is also valid for these situations, because most of the fires are detected shortly after ignition.

The detection time may be formulated by the time where the visual detection of smoke or flames occurs and depends on the velocity of the fire development: the faster a fire develops, the sooner it will be detected. In this case, the detection time corresponds to the warning time, e.g. $t_{D,i} = t_{D+W,i}$. Fischer (2014) used the fire growth rate $\alpha$ to model the detection time by assuming that 99% of the occupants notice a fire at latest, when the heat release rate equals 50 kW. This heat release rate is comparable to a waste bin fire. The distribution parameter $\lambda$ for the Exponential distribution of the detection time $T_{D,i} \sim \mathcal{E}(\lambda = 1/E[T_D])$ can be assessed by Equation (7.5). The distribution is illustrated in Figure 7.5.

$$\lambda = -\log (0.01) \sqrt{\frac{\alpha}{50 \text{ kW}}}$$ (7.5)

This relationship may not be applicable for very large enclosures, because the reduced likelihood of a visual detection of the fire. Thus, the visual detection might be interpreted as an early boundary for fire detection (see Figure 7.5). Since retail stores are required to have smoke alarms, the occupants are notified at the latest by the raise of an alarm of the fire detection system. Alike to the visual detection, detection by a fire detection system depends on the fire growth rate $\alpha$ as well: the faster a fire develops, the sooner the detection system raises an alarm. The probabilistic model derived by Fischer et al. (2012), which is summarised in Section 5.5.1.

Fig. 7.5: Probability bounds for the detection time $t_D$; visual detection as lower bound and detection by a fire detection system as an upper bound.
7.3. Required safe egress time

<table>
<thead>
<tr>
<th>Tab. 7.3: Summary of the response times observed in the unannounced evacuation drills by Sandberg (1997) and Shields &amp; Boyce (2000).</th>
</tr>
</thead>
<tbody>
<tr>
<td>---------------------------------------------------------------</td>
</tr>
<tr>
<td>Drill 1</td>
</tr>
<tr>
<td>Drill 2</td>
</tr>
<tr>
<td>Drill 3</td>
</tr>
<tr>
<td>Drill 4</td>
</tr>
<tr>
<td><strong>Sandberg (1997)</strong></td>
</tr>
<tr>
<td>Drill 1</td>
</tr>
<tr>
<td>Drill 2</td>
</tr>
<tr>
<td>Averaged</td>
</tr>
</tbody>
</table>

is used to model the detection time depending on the fire growth rate $\alpha$. In Figure 7.5 the CDF of the detection time is illustrated for the case of visual detection and for the case of detection by a fire detection system. These CDFs represent a lower and an upper bound for the detection time and are subject of a probability bound analysis in terms of a sensitivity analysis for the decision outcome (see Section 3.4), e.g. the optimal door width $w_{opt}$. The "real" distribution of the detection time is between these curves.

The detection system in a retail shop can have an internal warning, in order to allow an investigation of the cause of an alarm by the staff before notifying the occupants. This delays the warning time, e.g. 3-5 min, but reduces the number of false alarms and unwanted evacuations. Therefore, the warning time does not necessarily follow the detection time. For the present case, no delay is assumed and the warning time equals the detection time $t_{D,i} = t_{D} + W_{i}$.

7.3.2 Recognition and response

Sandberg (1997) and Shields & Boyce (2000) conducted unannounced evacuation drills in retail stores to quantify the recognition and response time and to analyse the behaviour of occupants and staff members in evacuation situations (see Table 7.3). Both studies are comparable in their results. Of course, such evacuation drills only approximate the real behaviour in a fire due to the lack of a hazard and induced effects like stress. Nevertheless, the results provide valuable data for risk analysis. In both studies, the occupants (including the uninformed staff members) were notified by an alarm bell. Sandberg (1997) proposed a Lognormal distribution to represent the variability of the recognition and response time, which is consistent with Rinne et al. (2010), who proposed a Lognormal distribution for different occupancy types, e.g. cinemas, schools and churches. Note that Sandberg (1997) and Shields & Boyce (2000) observed a major influence of well trained (even though uninformed) staff members, who motivated occupants to leave the building and guided them to a place of safety.
7.3.3 Travel and queuing

The required time for travel and queuing describes the time from the first movement towards an exit until the time when an occupant reach a place of safety, e.g. a staircase or the outside. In the first part of this section the assessment of the travel time is discussed. As discussed in Section 5.7.2, queuing occurs if the number of occupants arriving at a bottleneck exceeds the flow capacity of the bottleneck and they have to wait until they can go through. Accordingly, the flow capacity of a door determines the queue formation and is discussed in the second part of this section.

Travel time

The travel time $t_{T,i}$ of an occupant $i$ is the time needed to cross the path from his/her location to the exit $d_i$ and is assessed based on the individual movement velocity $v_i$:

$$t_{T,i} = \frac{d_i}{v_i} = \frac{\sqrt{x_i^2 + y_i^2}}{v_i}$$ (7.6)

The occupant’s walking velocity $v_i$ depends on the ability to move freely, e.g. without the physical interaction with other occupants (unaffected movement velocity) and can be related to the crowd density along the path: low densities allow a higher walking speed, because of the larger space between occupants (see Nelson & Mowrer [2002]). This is illustrated in Figure 7.6, where for low densities $< 1 \text{ pers/m}^2$, the specific flow $j_S$ [pers/m/sec] is increasing almost linearly (see Section 5.7.2 for definitions). According to Proulx (2002), the walking velocities are more variable at low densities, because the main factors that determine the speed, are more likely to be the characteristics of the occupants, e.g. age, physical limitations and group effects.

Rinne et al. (2010) analysed the movement velocities of adults in evacuation drills and proposed a left skewed Weibull distribution to represent the uncertainty associated with the unaffected movement velocity. This distribution is suited to represent rare cases that are associated with a reduced movement velocity, e.g. for pregnant women, children, disabled or old persons.

Another factor, which influences the walking speed $v_i$ is the exposure of occupants to irritant smoke and the reduction of the visibility due to obscuration. This scenario can be avoided by an appropriate design of the means of egress. Providing means of egress, which expose the occupants in the room of fire origin to smoke will lead to additional problems along the evacuation route. For example, it is likely that the stairwell will be contaminated with smoke, because occupants open the door while leaving the room, even if the stairwell is over-pressured (Proulx, 2002). This causes especially problems in tall buildings, when the fire is located in a lower floor and smoke enters the staircase, while people from the upper floors are still evacuating in the staircase.

Albrecht (2011) compared evacuation situations with and without the interaction of smoke and occupants and concluded that the walking speed is not affected by the smoke, if the occupants have to wait in front of an exit door. In this case, the walking speed is controlled by the flow capacity of the door and not by the visibility conditions.

In the present study no reduction of the movement velocity is considered, neither by obscuration nor by the flow density. The effect of this assumption is discussed in Section 7.4.
7.3. Required safe egress time

**Flow capacity of a door**

Seyfried et al. (2009) summarised flow measurement of different evacuation drills (see Figure 7.6) and concluded that the flow $j$ [pers/sec] through a bottleneck is compatible with a continuous and almost linear increase of the bottleneck width (for $w > 0.7$ m). Further, a high initial density (1.8 to 5 pers/m$^2$) in front of the bottleneck increases the resulting flow values. This is in agreement with the findings of Daamen & Hoogendoorn (2010), who assess the specific flow capacity $j_S$ [pers/m/sec] by evacuation drills for emergency doors of different widths (50 cm to 275 cm). They exposed the participants to different stress levels, e.g. exposing them to visual and acoustic noise, and concluded that the highest flow capacities are reached for the highest stress level and lowest for the lowest stress level. Despite the participants were not exposed to life-threatening conditions, more pushing behaviour did not lead to the "faster-is-slower" effect as discussed by Helbing et al. (2000). Moreover, there are some self-organising effects, e.g. the zipper effect, which lead to an optimisation of the available spaces and velocities inside the bottleneck (Seyfried et al., 2009). In addition, Daamen & Hoogendoorn (2010) observed a high variability of the average flow capacities depending on different door widths, ranging between 2.2 and 3.1 pers/m/sec. No trend of the specific flow capacity $j_S$ could be observed when the door width changed. This supports the linear dependency between door width $w$ and flow capacity $j$. These results are in contradiction with the fundamental diagrams in the SFPE handbook (Nelson & Mowrer, 2002), where a reduction of the flow is suggested at a density of 2 pers/m$^2$ in front of a door (see Figure 7.6).

If a queue is formed then the density in front of the bottleneck is likely to be larger than 1 pers/m$^2$ and it can be expected – based on the review of Seyfried et al. (2009) – that the maximal specific flow capacity of a door $j_{S,Door}$ ranges between 1.5 and 2 pers/m/sec. A Normal distributed random variable $J_{S,Door}$ is introduced with mean value $E[J_{S,Door}] = 1.75$ pers/m/sec.
and $CoV[J_{S,Door}] = 0.11$, as illustrated in Figure 7.6. The 10% and 90% quantile values of the proposed distribution correspond to the range of 1.5 and 2 pers/m/sec. A reduction of the flow capacity for very high densities in front of a door ($> 6$ pers/m²) is not considered, since it is expected that occupants will rather choose a different exit or wait at an appropriate distance until they can pass, as long as they are not exposed to life-threatening conditions.

### 7.3.4 Occupant load density

In retail buildings, the occupant load density $p'_0$ is highly influenced by the individual choice and the necessity of a person to visit the store. This causes a high variability of the occupant load density in time and can be represented probabilistically. Albrecht (2011) showed that the occupant load density can be one of the most influential parameters for assessing the RSET. Therefore, an accurate representation of the variability of the occupant load density is required for an unbiased assessment of the risk.

The probabilistic assessment of the occupant load density for retail buildings has not been adequately addressed in the literature. The reason is that risk assessment is currently mainly used to support design situations and for those situations, usually a (deterministic) design occupant load density is provided by the codes. This value can be associated with the maximum probable number of occupants (NFPA 101), which is already associated with a certain likelihood. De Sanctis et al. (2014c) assessed the occupant load density probabilistically based on data from a long-term survey for different types of retail chains. The data consists of frequency measurement of customers, e.g. number of sales or the number of people crossing a light barrier, and has been provided by different major retail chains in Switzerland. Based on this data and the queuing theory, probabilistic models are derived to represent the point-in-time distribution of the occupant load density $P'_0$. The queuing theory is applied, because the frequency measurements represent only people entering or leaving the building and cannot be directly used to develop the probabilistic models for the occupant load density $P'_0$. Four different retail types are analysed, e.g. supermarkets, department stores, furniture stores and hardware stores. The occupant load density is very much depending on the retail type and the coefficient of variation is large, e.g. CoV = 0.8. The recommended design value in Switzerland of 0.5 pers/m² (VKF 16-03) is larger than the 99%-quantile value of the distribution for $P'_0$ and indicates a very conservative design value. In the present study, the probabilistic model for the retail type ”supermarket” is used and is listed in Table 7.2.

### 7.4 Modelling the evacuation process

The consequences $c$ for the risk assessment can be derived by assessing the number of the remaining occupants in the room $p$ when untenable conditions are reached, e.g. $p(t_{ASET})$. Both the occupant load density $p'_0$ in retail buildings and the specific flow capacity of the door $J_{S,Door}$ are associated with uncertainties (see Table 7.2). As a result, by a certain likelihood, either queued, unqueued or a mix of both situations occur. Therefore, a mathematical model for the evacuation process should consider both queued and unqueued situations. There are a large
number of evacuation models based on different modelling techniques. For a review of evacuation models see Kuligowski & Peacock (2005) and Schadschneider et al. (2009).

In this study, a simplified movement model is developed to consider the individual travel times and the queueing formation. This simplified model can be replaced by an advanced model, e.g. a behavioural model, an advanced movement model or an partial behavioural model (see Kuligowski & Peacock, 2005, for definitions). The basic idea of the model is that if the occupant flow rate $j$ is below the flow capacity of the door $j \leq j_{Door}$, the flow is controlled by the individual RSETs; otherwise the flow is dominated by the flow capacity of the door $j_{Door}$. Figure 7.7 illustrates qualitatively the number of occupants in the room over time $p(t)$, which is the outcome of the simplified movement model. In Figure 7.7a, the queueing occurs only during the period $j > j_{Door}$ and the queue dissolves in time, where in Figure 7.7b, the queue formation lasts to the end of the evacuation process.

Four steps are performed to assess the number of occupants in the room over time $p(t)$:

1.) The individual random characteristics are generated individually for each occupant $i$, e.g. detection and warning time $t_{D+W,i}$, location $(x_i$ and $y_i)$, recognition and response time $t_{R+R,i}$ and movement speed $v_i$. The detection and warning time is dependent on a realisation of the fire growth rate $\alpha$ (see Section 7.3.1). The time needed to reach a place of safety $t_{RSET,i}$ is assessed by:

$$t_{RSET,i} = t_{D+W,i} + \frac{\sqrt{x_i^2 + y_i^2}}{v_i} + t_{R+R,i}$$  \hspace{1cm} (7.7)

2.) The number of occupants $p(t)$ in the room at a given time $t$ is assessed by subtracting the number of persons that already reached a place of safety from the initial occupant load $p_0 = p'_0 \cdot a_E$. This leads to the grey lines in Figure 7.7 and is valid for the case where the
Chapter 7. Optimisation of egress provisions

Interaction effects

First order effects

\[ \alpha tD+W,i tR+R,i vi \epsilon x_i y_i \]

Visual detection Notified by an alarm

Global sensitivity index

Fig. 7.8: Global sensitivity indices for the random variables affecting the individual RSETs \( t_{RSET,i} \); a) for visual detection and b) for notification of the occupants by an alarm (evaluated for \( a_E = 1500 \text{ m}^2 \)).

The occupant flow rate \( j \) is below the flow capacity of the door \( j \leq j_{Door} \).

\[ p_{j \leq j_{Door}} (t) = p_0 - \sum_{i=1}^{p_0} 1_{RSET,i} (t) \quad \text{and} \quad 1_{RSET,i} (t) = \begin{cases} 1 & t_{RSET,i} \leq t \\ 0 & t_{RSET,i} > t \end{cases} \quad (7.8) \]

3.) If the number of occupants arriving at the exit at time \( t \) exceeds the flow capacity of the door, e.g. \( j = \frac{dp}{dt} > j_{Door} \), then the occupants build a queue and the flow is dominated by the flow capacity of the door \( j_{Door} = j_{S,Door} \cdot w \) and correspond to the queue formation period in Figure 7.7:

\[ p_{j > j_{Door}} (t) = p_{j \leq j_{Door}} (t_j > j_{Door}) - j_{S,Door} \cdot w \cdot (t - t_j > j_{Door}) \quad (7.9) \]

4.) If the queue dissolves, e.g. \( j = \frac{dp}{dt} \leq j_{Door} \), then the number of persons in the room is assessed again by Equation 7.8; otherwise by Equation 7.9.

This procedure leads to the black lines in Figure 7.7. The influence of the global random variables \( p_0 = p_{0'} \cdot a_E \) and \( j_{Door} = j_{S,Door} \cdot w \) on the evacuation process is illustrated in Figure 7.7 as two-sided arrows. The realisation of the random variable \( J_{S,Door} \) will directly influence the queue formation process and is related to the decision-variable \( w \).

The modelling of the evacuation process comprises some simplifications which may not represent the real evacuation behaviour (see Section 7.3). Therefore, a model uncertainty \( \xi_{RSET} \) for the evacuation process is introduced to account for these simplifications and is listed in Table 7.2. This model uncertainty increases the RSET for \( \xi_{RSET} > 1 \) and leads to a scaling of \( p(t) \) along the time-axis:

\[ p(t) = p(\xi_{RSET} \cdot t^*) \quad (7.10) \]

Sensitivity analysis for the RSET

The parameters to assess the individual RSETs \( t_{RSET,i} \) are associated with uncertainties and lead to an uncertain outcome of Equation 7.7. The individual contribution of the individual
and global random variables to the variability of the output \( t_{\text{RSET},i} \) are expressed by the global sensitivity indices in terms of applying a variance-based method (see Appendix B) and are illustrated in Figure 7.8. The uncertain parameters associated with the travel time \( t_{T,i} \), e.g. the movement velocity \( v_i \) and the location of the occupants given by \( x_i \) and \( y_i \), have – in relation to the other random variables – only a minor contribution to the variability of \( t_{\text{RSET},i} \). Thus, neglecting the reduction of the occupant movement velocity because of the interaction with smoke and neglecting the physical interactions with other occupants (see Section 7.3.3) may not influence the individual RSETs as much as simplifications and model uncertainties associated with the other parameters, e.g. the fire growth rate \( \alpha \), the detection and warning time \( t_{D+W,i} \), and the recognition and the response time \( t_{R+R,i} \). Note that the global sensitivity indices have been derived for a floor area of \( a_E = 1500 \text{ m}^2 \) and the sensitivity indices of the parameters related to the travel time may increase for larger compartment areas, e.g. \( a_E \gg 3000 \text{ m}^2 \), where the contribution of the travel time on the the individual RSETs \( t_{\text{RSET},i} \) increases.

According to Figure 7.5 the variability of the detection time \( t_D \) is larger when the occupants are notified by a fire detection system compared to the visual detection. Therefore, for those cases, the sensitivity is larger for parameters that are used to assess the detection time, e.g. the fire growth time \( \alpha \) and the model uncertainty \( \varepsilon \) for Equation 5.11. Interaction effects are observable for the parameters \( \alpha \) and \( t_{D+W,i} \) (respectively \( \varepsilon \) for notification by an alarm). This is reasonable because in both cases the detection of the fire is modelled as a function of the fire growth rate \( \alpha \). The uncertainty propagation of the individual random variables for the location \( X_i \) respectively \( Y_i \) and the moving velocity \( V_i \) is non-linear (see Equation 7.7) and should lead to interaction effects. However, due to the low sensitivity of these variables the interaction effects are negligible.

Fig. 7.9: a) Distribution of the RSET for two different door width and b) probability of queuing for two different door width (notified by an alarm).
The total evacuation time $RSET$ is assessed based on the probabilistic models defined in Table 7.2 for different floor areas $a_E$ and two different opening widths $w = 1.0$ m and $w = 2.0$ m. The model uncertainty is set to $\xi_{RSET} = 1$ for simplicity. Figure 7.9 illustrates the effect of the floor area $a_E$ and the door width $w$ on the distribution of the RSET. The 10%-quantile values are practically equal for both door widths. The reason are small realisations of the occupant load density $p'_0$ that lead to a total evacuation time $RSET$ that is dominated by the individual RSETs (no queuing, see also Figure 7.7a). Therefore, the door width has almost no influence. For high realisations of the occupant load density $p''_0$, it is more likely that the occupants arriving at the door exceed the flow capacity of the door and produce a jam. Accordingly, the total evacuation time is dominated by the flow capacity of the door $j_{S,Door}$ (see Figure 7.7b). This leads to a longer RSET compared to a larger opening and is illustrated by the 90%-quantile values. Figure 7.9b illustrates the probability that the RSET is dominated by the flow capacity of the door, e.g. $RSET > \max(t_{RSET,i})$, which is higher for smaller door widths.

### 7.5 The expected number of fatalities

Fatalities occur at the time when untenable conditions are reached ($t_{ASET}$) and all occupants remaining in an enclosure may perish. The number of these remaining occupants is expressed by $p(t_{ASET}|x_G, x_I)$ and is illustrated in Figure 7.7. The number of fatalities depends on ten global event specific risk indicators (Table 7.1 and Table 7.2):

$$X_G = \{ A, M'', \Delta H_c, X_c, \Xi_{Smoke}, Z_{S, cirt}, P''_0, E, J_{S,Door}, \Xi_{RSET} \}$$

and five individual event specific risk indicators (Table 7.2):

$$X_{I,i} = \{ T_{D+A,i}, T_{D+A,i}, V_i, X_i, Y_i \}.$$

To simplify the notation, a random vector $X_I = \{ X_{I,1}, X_{I,2}, \ldots, X_{I,P_0} \}$ that contains all individual risk indicators $X_{I,i}$, which represent the random individual characteristics of the occupants, is introduced. The number of the individual random variables accounts to $P_0 \cdot 5$ and can be very large for large realisations of $p_0 = a_E \cdot p''_0$. In addition, some individual random variables are conditional on global risk indicators, e.g. the detection and warning time $t_{D+A,i}(\alpha)$ is dependent on the fire growth rate $\alpha$ (see Section 7.3.1). The dependencies are illustrated schematically in Figure 7.10. Thus, based on Equation 7.2 the expected number of fatalities $R = E[C]$ can be assessed by:

$$R = E[C] = P(EX) \cdot \int \int p(t_{ASET}|x_G, x_I) \cdot f_{X_I|x_G} (x_I|x_G) \cdot f_{X_G} (x_G) \, dx_I \, dx_G \quad (7.11)$$

Individual-based evacuation models (with individual realisation of occupant’s characteristics) are in principal deterministic models, providing the same output for exactly the same input. In the present study, all (individual) random variables are accepted as inherent randomness of the evacuation model that leads to a stochastic response for the same global input parameters.
7.5. The expected number of fatalities

This view corresponds to the evaluation of the inner integral of Equation \ref{eq:7.11} and can be interpreted as the expected fatalities, given a realisation of the global risk indicators $x_G$. Note that $t_{ASET}(x_G)$ is a function of $x_G$ and for the ease of notation it is denoted as $t_{ASET}$. The inner integral is denoted as:

$$p(t_{ASET}|x_G) = \int_{D_{X_I}} p(t_{ASET}|x_G, x_I) \cdot f_{X_I|x_G}(x_I|x_G) \, dx_I$$

This integral can be estimated by simulation techniques, e.g., by Crude Monte Carlo (CMC) simulations with $n_I$ realisations of the random variables $x_I^{(k)}$ for a given realisation of the global random variables $x_G$. A statistical estimator is provided by:

$$\hat{p}(t_{ASET}|x_G) = \frac{1}{n_I} \sum_{k=1}^{n_I} p(t_{ASET}|x_G, x_I^{(k)})$$

Crude Monte Carlo simulation can also be used to solve the remaining outer integral of Equation \ref{eq:7.11}. Though, the simulation generates samples, which are usually not located in the region of interest, e.g., in the region where a failure (or fatality) contributes to the risk. Accordingly, a very high number of simulations is required to assess small risks and to reduce the statistical error inherent in the CMC method and often leads to computational problems. One of the most commonly used method in structural reliability analysis to reduce this statistical error is importance sampling \cite{Melchers2002, Kroese2011}, where the simulation is performed in a region where failures are likely to occur and have a major contribution on the estimation of the failure probability.

### 7.5.1 Importance sampling for risk assessment

In the context of risk estimation, the failure points, i.e., cases where a fatality is likely, may have only a small contribution to the risk (high-probability low-consequences scenarios). In contrast, scenarios with a small probability might have a major contribution to the risk (low-probability high-consequences scenarios). Thus, the importance sampling method used to derive failure probabilities cannot be directly applied for risk assessment. Nevertheless, the mathematical problem of risk assessment, i.e., Equation \ref{eq:7.11} is equal to reliability analysis and can be reformulated following the general formulation of importance sampling used for sampling based
integration ([Kroese et al., 2011]):

\[
R = P(EX) \cdot \int_{R_{XG}} \hat{p}(t_{ASET} | x_G) \cdot \frac{f_{XG}(x_G)}{f_{S}(x_G)} \cdot f_{S}(x_G) \, dx_G
\]  
\[\tag{7.14a}
= P(EX) \cdot E_S \left[ \hat{p}(t_{ASET} | x_G) \cdot \frac{f_{XG}(x_G)}{f_S(x_G)} \right]
\]  
\[\tag{7.14b}
\]

in which \(f_S(.)\) denotes the importance sampling density function. The integral in Equation 7.14a corresponds to the expected value of \(\hat{p}(t_{ASET})\). A statistical estimator for the expected value of Equation 7.14b is given by:

\[
\hat{E}_S \left[ \hat{p}(.) \cdot \frac{f_{XG}(.)}{f_S(.)} \right] = \frac{1}{n_G} \sum_{j=1}^{n_G} \hat{p}(t_{ASET} | x_{G}^{(j)}) \cdot \frac{f_{XG}(x_{G}^{(j)})}{f_S(x_{G}^{(j)})}
\]  
\[\tag{7.15}\]

Combining Equation 7.13 and 7.15 leads to the assessment of the expected number of fatalities:

\[
\hat{R} = P(EX) \cdot \frac{1}{n_G} \frac{1}{n_l} \sum_{j=1}^{n_G} \sum_{k=1}^{n_I} p(t_{ASET} | x_{G}^{(j)}, x_{I}^{(k)}) \cdot \frac{f_{XG}(x_{G}^{(j)})}{f_S(x_{G}^{(j)})}
\]  
\[\tag{7.16}\]

A good choice of \(f_S(.)\) leads to a reduction of the statistical error of the estimation of \(\hat{R}\). In the present thesis the importance sampling density function is chosen as a Multivariate Normal distribution \(N(u_H, \sigma = 1)\) in the standard normal space, located at the point \(u_H\) with the highest participation on the estimator \(\hat{E}_S\). For an adaptive sampling approach to find a suited importance sampling density function \(f_S(.)\) see [Albrecht, 2011]. Consequently, the random variables \(X\) in the physical space are transformed to the standard normal space \(U\). Since the random variables \(X\) consists of uncorrelated random variables the transformation is simply expressed by the inverse of the cumulative standard normal distribution \(\Phi^{-1}(.)\):

\[
u = \Phi^{-1}(F_X(x))
\]  
\[\tag{7.17}\]

The point with the highest participation on the estimator \(\hat{E}_S\) corresponds in reliability analysis to the design point, e.g. the point with the highest failure probability, and can be derived by the First or Second Order Reliability Method (FORM or SORM, see [Melchers, 2002]). For risk assessment this technique is not applicable. The point \(u_H\) with the highest participation on the risk is used instead and, similar to [Bucher, 1988], a statistical estimator for the importance point \(\hat{u}_H\) is chosen by:

\[
\hat{u}_H = \frac{\sum_{j,p \geq 0} h_j \cdot u_{G}^{(j)}}{\sum_{j,p \geq 0} h_j} \quad \text{with} \quad h_j = \hat{p}(t_{ASET} | x_{G}^{(j)}) \cdot \frac{f_{XG}(x_{G}^{(j)})}{f_S(x_{G}^{(j)})}
\]  
\[\tag{7.18}\]

This equation may be interpreted as the mass centre of individual realisations of \(x_G\) respectively \(u_H\) weighted according to the participation to the risk \(h_j\). The point \(\hat{u}_H\) is assessed sequentially.
### 7.5. The expected number of fatalities

#### 7.5.2 Risk evaluation

The estimated risks $\hat{R}$ are illustrated in Figure 7.11 for different floor areas $a_E$ and different door widths $w$. If visual detection of the fire occurs (Figure 7.11a) then the risk is lower compared to the case where the notification of the occupant occurs by a detection system (Figure 7.11b). Since both scenarios are used as a lower and an upper estimation of the risk, respectively, the "real" risk lies in between.

The risk decreases exponentially for small door widths (linearly in the logarithmic scale) because for those cases a queuing situation is likely to occur and thus increasing the door width will accelerate the evacuation process, which leads to a reduction of the risk. For cases where the evacuation process is dominated by the individual RSETs, e.g. for dissolving or non-queued conditions (see Figure 7.7a), an increase of the door width does not lead to an additional reduction of the risk. This effect is illustrated as a convergence to a constant risk value for larger door widths. This value depends on the floor area $a_E$ and is influenced by:

- the probability of fire ignition, which depends on the floor area (risk increases for larger floor areas).
- the ASET which is higher for larger floor areas (risk decreases for larger floor areas).
the likelihood of a person with a long individual RSET $t_{RSET}$, which is more likely for high number of occupants $p_0 = p_0' \cdot a_E$ (risk increases for larger floor areas).

The estimated risk $\hat{R}$ is associated with a statistical uncertainty since it is derived by a simulation method. This is especially problematic for the application of the LQI where a larger door width leads to a higher risk compared to a smaller door width (for the same building specific risk indicators). To overcome this inconsistency, the estimates for $R$ are represented by a mathematical function, which fulfils the requirement that the risk is exponentially decreasing and the requirement that the risk is converging to a constant value. Such a function is given by (solid lines in Figure 7.11):

$$R(w) = r_1 \cdot \exp (-r_2 \cdot w) + r_3$$

(7.19)

The parameters $r_1$, $r_2$ and $r_3$ are estimated by a non-linear fit (in the least-square sense) to the simulation results for the risk values $\hat{R}$ and are given in Appendix C. Equation 7.19 can be used to evaluate the change of the number of fatalities by a change of the decision variable, which is used for the LQI criterion (see Equation 7.1):

$$\frac{dR}{dw} = -r_1 \cdot r_2 \cdot \exp (-r_2 \cdot w)$$

(7.20)

7.5.3 Model bias

In Switzerland the majority of the fire deaths occur in residential buildings. This was shown by an analysis of incident reports over a period of 8 years by Fischer et al. (2012). For retail buildings almost no fatalities have been observed. As a reference value the Swiss annual fatality rate related to fire deaths is used, e.g. 5 pers/1million inhabitants and is illustrated in Figure 7.11, which includes all fire deaths that occurred over all different building occupancy types.

Despite the realistic modelling approach and the use of probabilistic models, which are predominantly based on real data, the developed risk model over-predicts the risk at least by a factor of 10. This bias is the result of the bottom-up engineering approach, which includes both simplifications in the development of the models and epistemic uncertainties that are associated with the risk indicators used as input parameters for the models. One way to consider this bias is to multiply Equation 7.19 with a corresponding factor. This approach does not address the inherent bias in the engineering models or in the probabilistic models of the input variables and might be critical especially for models where the uncertainty propagation is non-linear. One option to address the inherent bias is to reduce the bias associated with the engineering models by either improving the engineering models or improving the data basis used to model the input parameters for these models. The other option is to introduce calibration factors, specifically to parts of the model, where the lack of knowledge is considered as high. These parameters can be calibrated in order to reduce the gap between the consequences predicted by the model and the observed consequences. This approach is discussed in Chapter 8.

Alternatively, the overestimation of the risk model can be accepted, leading to an overestimation in the change of the mortality rate $dR/dw$. Accordingly, the application of the LQI criterion leads to optimal decisions that are associated with higher investments into life safety
as society is willing to pay for. From a life safety point of view, this decision can be judged as
conservative, but is not optimal regarding the allocation of societal resources.

7.6 Cost modelling

In order to derive the marginal life saving costs $dc$ that are required to apply the LQI criterion
(see Section 3.3.1), the annualised life cycle costs are estimated according to Section 3.1.4, which
are dependent on the door width $w$ (decision variable). Accordingly, all costs that arise due to
a change of the door width have to be considered.

To avoid a tailback into the room of fire origin the flow rate of the staircase $j_{S,Stair}$ should
be equal or greater than the flow rate of the door $j_{S,Door}$, see Section 5.7.2. Thus, changing the
door width influences also the required flow rate of the staircase $j_{S,Stair}$ and thus the dimensions
of the staircase. The width of the stairs $w_{Stair}$ is increased to provide a constant flow over the
whole evacuation path, since the flow on stairs is smaller than the flow through doors. The
dimensions of the staircase are illustrated in Figure 7.12 and are assessed based on the design
values for the specific flow rates $j_{S,Door,d}$ respectively $j_{S,Stair,d}$ by (Nelson & Mowrer, 2002):

$$w_{Stair} \geq w_{j_{S,Door,d}} \approx w_{j_{S,Stair,d}} \frac{1.3\text{pers/sec/m}}{1.0\text{pers/sec/m}} = 1.3w$$

(7.21)

The additional flow of persons from the upper and lower floors should be considered in the
design of a staircase and leads to an increase of the required flow rate of the staircase. For
simplicity, only the flow resulting from the enclosure of fire origin is considered in the present
study.

Estimation of the costs

An increase of the the door width $dw$ leads to additional investments, e.g. due to larger doorway-
leafs. The estimated costs per meter door width are listed in Table 7.4 and are based on construc-
tion cost tables (CRB, 2011) and represent the total construction costs including installation
costs.

The costs for the staircase are also assessed based on construction costs tables (CRB, 2011)
and are summarised in Table 7.4. The costs include the construction costs for walls $c_{Walls}$,
Tab. 7.4: Costs for the staircase and the enlargement of the door.

<table>
<thead>
<tr>
<th>Type</th>
<th>Values</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost for the door</td>
<td>$c_{\text{Door}}'$</td>
<td>CRB (2011)</td>
</tr>
<tr>
<td>Construction costs for the staircase</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walls of the staircase</td>
<td>$c_{\text{Wall}}''$</td>
<td>CRB (2011)</td>
</tr>
<tr>
<td>Stairs</td>
<td>$c_{\text{Stairs}}''$</td>
<td>CRB (2011)</td>
</tr>
<tr>
<td>Foundation</td>
<td>$c_{\text{Found}}''$</td>
<td>CRB (2011)</td>
</tr>
<tr>
<td>Cost for the parcel of land</td>
<td>$c_{\text{Parcel}}''$</td>
<td>CRB (2011)</td>
</tr>
<tr>
<td>Maintenance cost</td>
<td>$c_{M}$</td>
<td>estimated</td>
</tr>
<tr>
<td>Rate of return</td>
<td>$r$</td>
<td>Fischer (2014)</td>
</tr>
<tr>
<td>Life-time</td>
<td>$LT$</td>
<td>SIA 260 (2003)</td>
</tr>
</tbody>
</table>

stairs $c_{\text{Stairs}}$ and foundation $c_{\text{Found}}$, as well as costs for maintenance $c_{M}$ and for the parcel of land $c_{\text{Parcel}}$. The cost for the parcel of land and foundation can be divided over the number of floors $n$. The costs in Table 7.4 should be interpreted as a first estimation and should be derived in correspondence with the decision maker and other experts as discussed in Section 3.1.4. The initial investment costs are discounted with a rate of return $r$ over the life-time of the building $LT$ (see Table 7.4) to derive the equivalent annual investments costs $c$ (annuity method). The factor for the annuity method $a_0$ is assess by Equation 3.3.

The composition of the costs per floor for a two-storey staircase is illustrated in Figure 7.13a. The costs for the parcel of land $c_{\text{Parcel}}''$ dominate the overall costs especially for larger door widths. The marginal costs $dc_l/dw$ (see Figure 7.13b) are derived for three different cost models addressing the influence of the costs for the parcel of land: a two-floor building ($n = 2$, which can be considered an upper estimate of the costs); a building with many floors ($n = \infty$, where the costs for the parcel of land and the for the foundation is negligible), and a single-floor building ($c_{SC} = 0$, which can be considered as the minimal investments into the safety measure). All three marginal cost models can be represented analytically by a linear function $dc_l/dw = c_1 \cdot w + c_2$ (see Figure 7.13).

7.7 Application of the LQI criterion

For the present study, both the marginal risk reduction $dR$ and the marginal costs $dc_l$ can be expressed by an analytical function. Based on Equation 7.1, the optimal door width $w_{\text{opt}}$ can be derived by:

$$\frac{dc_l}{dR} = \frac{c_{1} \cdot w_{\text{opt}} + c_{2}}{-r_1 \cdot r_2 \cdot \exp \left(-r_2 \cdot w_{\text{opt}} \right)} + SWTP_{\text{lifetime}} = 0 \quad (7.24)$$
7.7. Application of the LQI criterion

For $c_1 = 0$ this equation has an analytical solution, for $c_1 \neq 0$ the equation can be solved numerically. The optimal door widths $w_{opt}$ are illustrated in Figure 7.14 for the three different cost models and for the two different detection scenarios (Figure 7.14a and Figure 7.14b). The SWTP is set to $SWTP_{1\text{life}} = 5$ million CHF/(per saved life).

The figures illustrate the LQI concept – used as an efficiency criterion – quite well: As cheaper the measure, the larger the optimal door width. The risk reduction of large door widths are not large enough to justify more investments into larger door widths. Further, by applying the LQI acceptance criterion, it is not the risk that is deemed to be acceptable, but the efficiency of a safety measure to reduce the risk. Accordingly, the optimal door widths may provide different risk levels for a given set of building specific indicators, e.g. the floor area $a_E$ and the room height $h_E$.

Figure 7.14 indicates also the limitations of acceptance criteria that are based on an absolute value, e.g. a predefined risk level (for example, the Swiss fatality rate as indicated in Figure 7.11). This applies of course also for a predefined target reliability. There might be no possibility within the decision-alternatives (e.g. by increasing the door width) to reach such a value, since the risk converges to a constant value. Further, the acceptance of a measure is totally depended on the inherent bias of the risk model. This bias affects the application of the LQI criterion as well, but to a smaller extend, since only the marginal risk reduction is considered. Further, the bias can be treated better with regard to the classification of the optimal decision either by accepting the "waste" of money for safety (for a bias as in the present case) or by increasing the investments compared to the optimal solution.

Figure 7.15 shows the optimal door width plotted against the floor area $a_E$ including the different detection scenarios. Interestingly, the uncertainty associated with the detection scenario
Chapter 7. Optimisation of egress provisions

![Diagram showing optimal door width and corresponding risk levels for visual detection and notification by alarm.](image)

**Fig. 7.14:** Optimal door width and corresponding risk levels for a) visual detection and b) notification by alarm ($h_E = 3$ m).

For the warning time (represented as upper and as lower bounds of the CDF as illustrated in Figure 7.5), does influence the optimal decision only in a small range. More meaningful are the marginal costs of the measure. For single floor buildings ($c_{SC} = 0$) only the cost for enlarging the door width arises (without any investments for the staircase) and are comparatively small. Therefore, the optimal door width is higher compared to the other (more expensive) cost models. Thus, the ground floor of a multi-storey building could be configured with larger door widths in comparison with the upper floors since the investments are smaller in providing larger egress widths. Note that the model derives the same risk for different floor levels given the same door width and the same building specific indicators ($a_E$ and $h_E$). This may be not the case in reality, where for example the occupant load density may change over the floors of a building and influences the risk to life.

The optimal door width $w_{opt}$ can be compared to current code provisions as well, e.g. VKF 16-03 (CH), ADB (UK) and C/AS4 (NZ). They correspond quite well with the code provisions for floor areas $a_E \approx 500$ m$^2$. However, there is a clear deviation for larger floor areas and code provisions tend to require more investment into life saving measures compared to the optimal case.

Note that the derived optimal door widths are only optimised for the fire situation. There are good reasons to enlarge the door width e.g. to provide an appropriate serviceability for the customers of a store. This is in accordance with the optimisation strategy discussed in Section 3.3.1 where the LQI acceptance criterion is used as a boundary condition for any further optimisation of fire safety measures by the decision-maker. Thus, an individual decision-maker may choose a larger door width as the optimal one because of own benefits, e.g. monetary benefits or benefits in serviceability, accepting the additional investment in a life saving measure.
Sensitivity of the global random variable on the risk

A measure for the individual contribution of the global random variables \( x_G \) on the risk may be formulated (in analogy to the reliability analysis) by the individual contribution of the variables to the point with the Highest Participation on the Risk (\( h_{PR} \)). This point can be associated with the occurrence probability of the scenario with highest participation on the risk, e.g. \( p(t_{ASET}(x)) \cdot f_X(x) \). Such a point corresponds to the defined importance point \( u_H \) by Equation 7.18 and the individual contribution may be normalised by:

\[
    h_{PR} = \frac{u_H^2}{\|u_H\|^2} \tag{7.25}
\]

This is not a sensitivity measure in the classical sense, but allows to judge the importance of single random variables on the occurrence probability of the scenario that is associated with the highest participation on the risk. The higher the sensitivity measure of a variable – ranging between 0 and 1 – the more the occurrence probability of this scenario is affected when a variable changes its value. This sensitivity measure corresponds to an empirical estimate of a (normalised first-order) derivative-based sensitivity measure for the probability of the scenario with the highest participation on the risk (see Section 3.4.3). The values \( h_{PR} \) for the highest participation on the risk are illustrated in Figure 7.16 for three different floor areas \( a_E \) and for the corresponding optimal door width \( w_{opt} \). Major participations have the occupant load density \( p'_0 \), the fire growth rate \( \alpha \) and the model uncertainty associated with the evacuation process \( \xi_{RSET} \). The uncertainty associated with the detection and warning time may be especially relevant for small compartments (random variable \( \alpha \) and \( \varepsilon \)). As discussed in Section 7.5.3 one of the reasons for the bias in the risk prediction results from the epistemic uncertainties involved in the modelling process. Accordingly, an improvement of the risk model in order to reduce the model bias can be evaluated based on the sensitivity measures and may include:

---

**Fig. 7.15:** Comparison of the optimal door width with design provisions (\( h_E = 3 \) m).
Fig. 7.16: Participation of global random variables to the averaged importance point ($h_E = 3$ m).

- a reduction of the epistemic uncertainties which are associated with the probabilistic model for the occupant load density $p_0''$ (see De Sanctis et al. [2014c])
- a reduction of the epistemic uncertainties which are associated with the probabilistic model for the fire growth rate $\alpha$ (see Section 4.3)
- a validation of the proposed evacuation model to reduce the model uncertainty $\xi_{RSET}$ and if necessary a replacement with a behavioural evacuation model (see Kuligowski & Peacock, 2005)

There is no need to improve the model for the ASET so far, e.g. by a detailed assessment of the mass fraction of toxic gases, since the uncertainties associated with other parameters dominate the optimisation problem. This may change for other types of buildings where the variability of the occupant load density is reduced, e.g. for cinemas, theatres or canteens. Thus, the complexity of an engineering model should be chosen in accordance to the participation of random input parameters – especially the model uncertainties – on the optimal decision. Sensitivity measures help to assess this participation and may justify the use of simplified engineering models.

Since the sensitivity measures reflects the importance of a variable for the scenario that is associated with the highest participation on the risk, they indicate also which basic variables should be considered appropriately in a design format. Variables with a high sensitivity should be considered e.g. by high quantile values and/or by safety factors which may be applied to these variables. The safety factors can be calibrated within a semi-probabilistic design approach towards a target acceptance criteria, e.g. a target reliability value (or a target risk value), and are usually related to these sensitivity measures (see Melchers, 2002). Alternatively, also a number of design scenarios can be selected based on the most sensitive variables focusing on the scenarios with a major effect on the risk. However, a discussion on a suitable design format for evacuation problems is beyond the scope of this thesis and it is referred to Magnusson et al. (1996).
7.8 Conclusions

The LQI criterion is applied to an evacuation problem optimising the door width of an exit for retail buildings. The optimisation leads to clearly lower door widths compared to current code provisions, indicating that these provisions are not optimal regarding the allocation of societal resources. The LQI criterion is an efficiency criterion that optimise the investments into life saving measures in regard to the associated risk reduction. As a result only efficient measures have to be implemented.

The risk reduction is assessed based on an engineering-driven approach modelling the available safe egress time (ASET) and the evacuation process including the required safe egress time. The focus is the realistic representation of the physical relationships and the realistic representation of the input parameters, which are usually of random nature. The ASET is derived by a two-zone modelling approach and the polynomial chaos expansion is used to surrogate the computational demanding model for the ASET. The individual reaction of the occupants to the fire hazard is considered probabilistically and the required safe egress time $RSET$ is derived. This time is influenced by the overall evacuation process, specifically by the flow capacity of the door, which determines whether queued, un-queued or a mix of both conditions are present. The risk is assessed based on an importance sampling approach, simulating in the region with the highest participation on the risk. The probabilistic risk-based approach considers low-probability high-consequence as well as high-probability low-consequence events. The risk evaluation for different door widths shows that the risk reduction by increasing the door width is limited and converge to a constant risk value. The marginal costs for the application of the LQI criterion are modelled by assessing the life cycle costs due to the increase of the door width and any further costs that arise, e.g. the costs for the staircase.

Sensitivity measures are applied to understand the role and effects of risk indicators on the outcome of engineering models, e.g. the ASET and the evacuation process. A major influence has the fire growth rate $\alpha$ and the occupant load density $p_0$ and a thorough probabilistic representation may significantly reduce the associated bias. The sensitivity of the introduced model uncertainties can be used to judge whether an engineering model has to be improved (or validated) or not. This may be the case for the evacuation model, but not for the ASET model so far.

The estimated risk overestimates the observed Swiss fatality rate and is therefore associated with a bias. This bias is accepted in the present study and leads to decisions that invests to much of societal resources into safety. This bias can be reduced either by improving the data basis used to model the probabilistic risk indicators (used as model input) or by reducing the uncertainties associated with the engineering models (by increasing the complexity of the models or by validation). Another option is to introduce calibration factors, specifically to parts of the model, where the lack of knowledge is considered as high and to calibrate them to observed consequences. This approach is discussed in Chapter 8.
Chapter 8

Generic fire risk model facilitating calibration

The bottom-up approach presented in Chapter 7 shows that the risk estimation by engineering models can be associated with a bias, e.g. a deviation of risk prediction by the model and observed expected consequences. An unbiased risk estimation is necessary for absolute decision-making, e.g. the application of the LQI criterion and cost-benefit analyses.

In this chapter and in Fischer et al. (2014) it is demonstrated how to reduce the bias in the portfolio risk assessment by calibrating a generic risk model to loss data. The generic risk model is based on an engineering-driven approach and assesses the financial loss due to a fire spread in single family houses. After analysing the effect of building characteristics and uncertainties on the fire spread by an engineering approach, a simplified fire spread model is developed in order to consider the most important indicators. The time-dependent interaction between fire brigade intervention and fire development is modelled on a physical basis in order to consider smoke alarms as a risk reducing measure. The engineering models are influenced by assumptions and simplifications and lead to a bias in the risk estimation. Calibration parameters are introduced in the model to account for these influences and are calibrated at portfolio level based on loss data in order to reduce the bias. The calibrated generic risk model makes an absolute risk assessment at portfolio level as well as at building level possible and can be used for risk-based decision-making, e.g. a cost-benefit analysis.

The focus of this chapter is on the development of a generic fire risk model for single family houses using an engineering approach to be calibrated by data. The generic risk model is discussed in Section 8.1 and outlined in Figure 8.1. Fischer et al. (2014) focuses on the calibration of the generic risk model using observed loss data and is briefly summarised in Section 8.2. In Section 8.3 the generic risk model is applied at object level and used for the analysis of the intervention time of the fire brigade and for a cost-efficiency study of home smoke alarms.

1The content of this chapter is based on De Sanctis et al. (2014b).
8.1 Modelling the fire damage in single family houses

This section describes the development of a generic fire risk model which facilitates calibration on the basis of observations for single family houses. The risk is defined according to Equation 3.1 (see Section 3.1.1) by:

\[
R = E[C] = \int_{D_C} c \cdot f_C(c) dc = \int_{D_D} c(d) \cdot f_D(d|EX) \cdot P(EX) dD \quad (8.1)
\]

The generic risk model is composed of different sub-models illustrated in Figure 8.1. Table 8.1 lists all risk indicators that are used in the model. The goal of the model is the quantification of the expected financial loss due to a fire event for single family houses in Switzerland. The engineering models are formulated such as to facilitate calibration based on available loss data.

Since single family houses in Switzerland are allowed to be built as one single fire compartment, no fire resistance of walls and structural elements are required. The focus is therefore on the fire spread within the fire compartment and without the consideration of fire resistant boundary elements. The structure is supposed to resist the fire exposure and the fire spread beyond the building to adjacent buildings is not considered in the model.

8.1.1 Fire ignition

The fire ignition is modelled by the annual probability of fire occurrence in a building and is derived according to Section 4.1 (using the insured value \( v \) of a building). For residential buildings with an insured value below 1 million CHF (Swiss francs) the parameters are estimated to \( \beta_1 = -10.73 \cdot 10^{-5} \) and \( \beta_2 = 0.368 \). Fire ignition in this context is the annual probability of
8.1. Modelling the fire damage in single family houses

Table 8.1: Building and fire specific indicators of the generic risk model.

<table>
<thead>
<tr>
<th>Random variable</th>
<th>Realisation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Building specific risk indicators</strong></td>
<td></td>
</tr>
<tr>
<td>Total building floor area [m$^2$]</td>
<td>$X_O$</td>
</tr>
<tr>
<td>Floor area of largest room [m$^2$]</td>
<td>$A_{tot}$</td>
</tr>
<tr>
<td>Average floor area of a room [m$^2$]</td>
<td>$A_{mean}$</td>
</tr>
<tr>
<td>Number of rooms [-]</td>
<td>$N_R$</td>
</tr>
<tr>
<td>Number of connections between rooms [-]</td>
<td>$N_C$</td>
</tr>
<tr>
<td>Insured value [CHF]</td>
<td>$V$</td>
</tr>
<tr>
<td><strong>Fire specific risk indicators</strong></td>
<td></td>
</tr>
<tr>
<td>Time of first flashover [min]</td>
<td>$T_{FO}$</td>
</tr>
<tr>
<td>Intervention time [min]</td>
<td>$T_I$</td>
</tr>
<tr>
<td>Time to prevent further damage [min]</td>
<td>$T_P$</td>
</tr>
<tr>
<td>Floor area of room of fire ignition [m$^2$]</td>
<td>$A_0$</td>
</tr>
<tr>
<td>Total loss acceptance ratio [-]</td>
<td>$A_{Limit}$</td>
</tr>
<tr>
<td>Area of fire spread [m$^2$]</td>
<td>$A_d$</td>
</tr>
<tr>
<td>Final fire spread area [m$^2$]</td>
<td>$A_{End}$</td>
</tr>
<tr>
<td><strong>Calibration parameters</strong></td>
<td></td>
</tr>
<tr>
<td>Distribution parameters for minor loss model</td>
<td>$\Lambda, Z$</td>
</tr>
<tr>
<td>”Fire spread coefficient”</td>
<td>$\Psi$</td>
</tr>
<tr>
<td>”Control time exponent”</td>
<td>$K$</td>
</tr>
</tbody>
</table>

occurrence of a financial loss covered by the building fire insurance company.

$$P(\text{EX}|\mathbf{x}) = \exp(\beta_1) \cdot v^{\beta_2}$$  (8.2)

8.1.2 Consequence model and damage states

In Switzerland the fire losses are insured separately with respect to losses caused by fire damages to the building structure and losses to the content. In this chapter only the loss associated with the building structure is considered. The analysis of Swiss loss data by [Fischer et al. (2012)] shows a high correlation between building damage and content damage. This implies that a risk reduction by a measure affects both types of losses.

The economic consequences, from an insurance point of view, describe the financial effort to compensate the loss caused by excessive heat exposure, smoke and water damage. In the engineering model, no distinction between these damages is made. The reason is that the data used to calibrate the model does not provide any differentiation of the loss related to the kind of the damage.

As data basis for the calibration, the building insurance company of the canton Aargau (AGV) provided portfolio data including information on the insured value $v$ of the building.
This value is used as building specific risk indicator for the model and defines the maximum possible loss associated with a fire. The total loss corresponds to the case when the fire spreads over the total building floor area $a_{tot}$. It is supposed that the loss $c$ is proportional to the fire area $a_d$. The fire area $a_d$ is considered as an indicator to describe the damage state of a fire (e.g. $d = a_d$) and the loss is expressed by:

$$c(a_d) = \frac{a_d}{a_{tot}} \cdot v \quad (8.3)$$

Fires that are limited to the room of fire ignition, mostly cause small damages (minor losses). Therefore, the vulnerability is referred to all costs associated with damages that occur in the room of fire ignition. The robustness is referred to as all costs associated with damages that occur beyond the room of fire ignition (major losses). In Figure 8.2 the probability density function of the damage is illustrated qualitatively. The damage state $d_0 = a_0$ refers to the transition of the minor loss to the major loss. Since the location of the fire ignition is uncertain, the floor area of the room of fire ignition $a_0$ is uncertain as well. Assuming that the probability of fire ignition $P(EX)$ is uniformly distributed over the entire building floor area $a_{tot}$, the probability of fire ignition for a room with floor area $a_0$ is given by:

$$P(A_0 = a_0) = \frac{a_0}{a_{tot}} P(EX|x) \quad (8.4)$$

The rooms in real buildings differ in their sizes. For simplicity, the distinction is made only between the fire ignition in the largest room of a building, e.g. $a_0 = a_{max}$, and the fire ignition in other smaller rooms with an average room area $a_0 = a_{mean} = (a_{tot} - a_{max})/(n_R - 1)$. The probability density function for the fire spread area $f_{A_d}(.)$ is illustrated in Figure 8.2 and is described by:

$$f_{A_d}(a_d|x, \theta) = \begin{cases} f_{A_d}^S(a_d|x, \theta) & a_d \leq a_0 \\ (1 - F_{A_d}^S(a_0|x, \theta)) \cdot f_{A_d}^L(a_d|x, \theta, a_d > a_0) & a_d > a_0 \end{cases} \quad (8.5)$$

The probability density function of the minor loss $f_{A_d}^S(\cdot)$ represents the small losses. The probability for $P(A_d > a_0) = 1 - F_{A_d}^S(a_0|x, \theta)$ corresponds to the probability of a fire resulting in a major loss, i.e. spreading beyond the room of fire origin, and is indicated as the grey area in Figure 8.2. The probability density function for the major loss $f_{A_d}^L(\cdot)$ is related to the large losses and is conditional on the case where the fire spreads beyond the room of fire origin $a_d > a_0$. The probability density functions of the minor and the major loss are modelled independently from each other - with no restriction on the transition point $a_0$ - resulting in a step in $a_0$ (see Figure 8.2).

### 8.1.3 Fire loss in the room of fire origin - minor loss model

Fontana et al. [1999] analysed fire insurance statistics and concluded that the sum of fire losses is highly dominated by rare events which cause large losses. Therefore, the losses with minor participation to the expected loss are modelled by a simplified empirical model based on fire loss data provided by AGV. The loss data includes also small damages, where fire suppression
8.1. Modelling the fire damage in single family houses

The fire spread without an intervention of the fire brigade is discussed first. In Section 8.1.5 it is explained how to consider the fire brigade intervention to assess the final fire area $a_{End}$, i.e. the area that is related to the fire damage after the intervention of the fire brigade.
Chapter 8. Generic fire risk model facilitating calibration

Fire spread process in a building

The modelling of fire spread in buildings is one of the major topics in fire safety engineering and is addressed by different deterministic and probabilistic methods, e.g. numerical fire simulation [Yeoh & Yuen 2009], event trees [Platt 1989], network models [Cheng & Hadjisophocleous 2011; De Sanctis et al. 2011]. In this thesis, a probabilistic approach is used to describe the fire spread in a single family house.

Fire spread in a single family house may occur in various ways, e.g. flame spread, radiation or ignition of unburned pyrolysis gases. The fire spread is expected to occur after a flashover and to occur from room to room. Each room is separated through boundary elements that may include doors or windows. The consecutive (serial) events for a fire spread from room \( X \) to an adjacent room \( Y \), given a flashover in the room \( X \), can be defined by:

1) the fire spread beyond the confining of a room \( FSC_{XY} \)
2) the fire ignition in the adjacent room \( Y \) \( FI_Y \)
3) the flashover in room \( Y \) \( FO_Y \)

It is supposed that those conditions will occur in any case when the fire spreads beyond the room of fire origin. Therefore, the fire will spread - without any intervention of the fire brigade - to all rooms in the building.

A flashover in the room of fire ignition is required to initialise the consecutive events \( FSC_{XY} - FI_Y - FO_Y \). The probability of this event is given by the probability of a major loss, i.e. \( P(A_d > a_0) \). Hence, the initial fire spread area of the major loss model, corresponds to the size of the room of fire ignition \( a_0 \) and is the transition of the minor to the major loss model.

The propagation of a fire over time depends on the durations \( t_{FSC,XY} \), \( t_{FI,Y} \) and \( t_{FO,Y} \) associated with the three consecutive events. The durations depend on various factors like: the type of the boundary elements (wall/wall with door/wall with windows/wall with openings, etc.), the state of the boundary elements (open/closed, etc.), the room size, the ventilation conditions (e.g. size of windows, broken windows during a fire) and the combustibility behaviour of the materials in the room. These factors underlie random variation and change from room to room. The resulting uncertainties associated with the durations of the intervals are represented by random variables \( T_{FSC,XY} \), \( T_{FI,Y} \) and \( T_{FO,Y} \). Only little information is available to quantify these variables. Tentative probabilistic models based on engineering judgement are shown in Table 8.2. Engineering judgement, in this context, is driven by experience or plausible estimates, which are based on experiments, observed fire events or numerical fire models; though, a certain subjective component is comprised. The estimates in Table 8.2 lead, therefore, to a biased risk prediction and are referred hereafter as the reference case. In the following sections, it is proposed to use calibration parameters to address this bias associated with engineering judgement. The resulting bias can be reduced by the calibration process.

The number of rooms \( n_R \) and their arrangement within the building should be considered, if the fire spread in a building is assessed. The fire spread through walls without any openings is assumed to have a minor influence on the fire spread in relation to the potential fire spread
8.1. Modelling the fire damage in single family houses

Tab. 8.2: Tentative probabilistic models for the reference case.

<table>
<thead>
<tr>
<th>Random variables $T$ [min]</th>
<th>Distribution</th>
<th>$E[T]$</th>
<th>CoV$[T]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time for fire spread through:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>open door $T_{FSC,XY}$</td>
<td>Deterministic</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>closed door $T_{FSC,XY}$</td>
<td>LN</td>
<td>10</td>
<td>0.3</td>
</tr>
<tr>
<td>Time of fire ignition $T_{FI,Y}$</td>
<td>LN</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Time of flashover $T_{FO,Y}$</td>
<td>LN</td>
<td>4</td>
<td>0.3</td>
</tr>
<tr>
<td>Probability of an open door</td>
<td>$P_{open} = 0.8$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

through doors and windows. The number of potentially open connections between the rooms $n_C$ (e.g. number of doors and windows) is used to assess the arrangement of the rooms, e.g. Figure 8.3a, and is considered by a binary arrangement matrix describing which room is connected with which, e.g. Figure 8.3b.

For a given room configuration (Figure 8.3a) and the probabilistic models according to Table 8.2 (the reference case), the fire spread in a building is simulated. For each room affected by a fire, the state of the door (open/closed) is determined randomly based on the probability in Table 8.2, e.g. by the Monte Carlo (MC) method. A single realisation of the random variables $T_{FSC,XY}$, $T_{FI,Y}$ and $T_{FO,Y}$ is generated for each room $Y$ and for each fire spread $XY$ (black and grey-dashed arrows in Figure 8.3a). The fire can spread from one room to several adjacent rooms, which so far have been unaffected by the fire (black arrows in Figure 8.3a). With this approach, the fire spread over time is assessed starting from the time of first flashover in the room of fire ignition $t_{FO}$. The fire spread over time is illustrated in Figure 8.4 as a dashed step curve (single fire spread). A jump in the line indicates a fire spread, e.g. the spread to an adjacent room, which is not affected by a fire (indicated as a solid arrow in Figure 8.3a). The MC simulations are repeated a few 1000 times to consider the different fire spread possibilities in the building. The number of simulations depends on the number of rooms and their arrangement, because the number of fire spread possibilities is increasing with the number of rooms.

For each room of fire ignition, the fire spread curves from the MC simulations are averaged resulting in one fire spread curve per room of fire ignition (dashed-dotted lines in Figure 8.4). Because a fire can spread from one room to several adjacent rooms, the number of adjacent rooms affects the fire spread velocity in a building. Figure 8.3 illustrates that the fire spread to the total building area $a_{tot}$ takes longer when the fire starts in the edges (ignition in room 1, 3, 7 or 9), compared to the case where the fire starts in the centre (ignition in room 5). To keep the model as simple as possible, the average fire spread in the building is obtained by averaging the fire spread curves for all different rooms of fire ignition. Consequently, one curve is derived to represent the average fire spread over time, given a specified room configuration and is illustrated as continuous line in Figure 8.4. The error made by averaging the curves for different rooms and neglecting the variability of the single fire spread curves, could be represented by a random
variable. However, to facilitate the calibration process, especially concerning computational costs, this uncertainty is neglected. The resulting bias in the risk estimation is reduced by the approach introduced in the following sections and the calibration process, briefly discussed in Section 8.2.

### Analytical representation

The assumptions made in Table 8.2, e.g. in estimating the probabilistic models for the three time intervals $T_{FSC,XY}$, $T_{FI,Y}$ and $T_{FO,Y}$, lead to a bias in the prediction of the fire loss. Changing these assumptions, lead to a shift of the fire spread curve to the right (decelerating fire spread conditions) or to the left (accelerating fire spread conditions). The shape of the curve remains nearly unchanged. This also applies when changing the room set-up (arrangement and number of rooms). The assumptions can be improved by collecting more data for the consecutive events $(F_{SC,XY} - F_{I,Y} - F_{O,Y})$ or by improving the physical model for those events. This is considered to be a rather extensive task. Here, another approach is presented based on a parametric function, which is able to represent the shape of the fire spread curves that are derived from the MC simulations of the previous section:

$$a_d(t) = a_0 + \frac{\Gamma(p_1 \cdot \psi \cdot (t - t_{FO}), p_2)}{\Gamma(p_2)} \cdot (a_{tot} - a_0)$$

The parametric function is illustrated in Figure 8.5 and can be seen as a surrogate function for the computational intensive MC simulations discussed before. Equation 8.8 comprises a Regularised Incomplete Gamma Function (RIGF) with parameters $p_1$ and $p_2$ and the Gamma operator $\Gamma(.)$. The domain of the RIGF is between 0 and 1. The RIGF is shifted to the right $(t - t_{FO})$ to account for the time of flashover in the room of fire ignition $t_{FO}$. This time is considered as a random variable $T_{FO}$ and is discussed later in this section. Because the major loss model addresses only the losses beyond the room of fire origin, the RIGF is shifted upwards by $a_0$. A scaling factor $(a_{tot} - a_0)$ is introduced to get areas smaller than or equal to $a_{tot}$. The parameters $p_1$ and $p_2$ are estimated by fitting the function to the average fire spread curve.

**Fig. 8.3:** Fire spread for a 9-room configuration: a) room configuration; b) binary arrangement matrix.
8.1. Modelling the fire damage in single family houses

Fig. 8.4: Fire spread for a 9-room configuration: fire spread in time.

in Figure 8.4 obtained by the MC simulation using the least squares method. The resulting parameters are considered to represent the reference case according to Table 8.2.

To address the bias of the model, e.g. due to the tentative probabilistic models used to generate the fire spread curves (Table 8.2) and simplifications in the development of the model, a calibration parameter \( \psi \) is introduced in the RIGF, to shift the curves to the right respectively to the left (see Figure 8.5). This parameter \( \psi \) describes how well the reference case represents reality. In particular, the parameter \( \psi \) characterizes the fire spread velocity in the building and is associated with the uncertainties in the modelling of the consecutive events \( FSC_{XY} - FI_Y - FO_Y \). The dashed lines in Figure 8.5 indicate the decelerated (\( \psi \downarrow \)) respectively the accelerated (\( \psi \uparrow \)) behaviour of the curve relative to the reference case (\( \psi = 1 \)).

Influence of risk indicators on fire spread

The fire spread curve is derived for a given room set-up (expressed by \( n_R, n_C, a_{tot} \) and \( a_0 \)). Real buildings, however, show a large variation in the number of rooms and their arrangement among each other. Figure 8.6b illustrates examples of seven different room arrangements in two dimensions for a one-storey building with 6 rooms. Of course, there are many more arrangement possibilities, even more if the third dimension is included. Therefore, an analysis of all possible room arrangements for a given number of rooms \( n_R \) is conducted. With a permutation of the binary arrangement matrix (e.g. Figure 8.3b) and the elimination of identical and impossible room arrangements, all possible room arrangements can be assessed (for 9 rooms, 2135 different possible binary arrangement matrices exist). For all those cases the MC simulation of the fire spread is conducted. As the number of connections \( n_C \) can be identical for different room arrangements (see Figure 8.6b), the fire spread curves are averaged for different binary
arrangement matrices with identical number of connections $n_C$. As an example, for a building with 6 rooms, e.g. $n_R = 6$, the average fire spread curves for 4 different numbers of connections $n_C = 5, 7, 8, 10$ are simulated, according to the description in the previous sections, and are illustrated in Figure 8.6a (black lines). For small numbers of connections $n_C$ a slower fire spread can be expected; and for high numbers a faster fire spread can be expected. The parametric function (Equation 8.8) is fitted to the simulations by estimating the parameter $p_1$ and $p_2$ based on a least square fit (grey lines). As a result, the parametric function is conditional on four building specific risk indicators ($n_R$, $n_C$, $a_{tot}$ and $a_0$).

Especially for a higher number of rooms ($> 10$) the arrangements possibilities are numerous, resulting in out-of memory problems or excessive run-times. Therefore, the parameters $p_1$ and $p_2$ for large $n_R$ and large $n_C$ are extrapolated from those, that are calculated for buildings with smaller number of rooms, as seen in Figure 8.7a. For a given number of rooms $n_R$, a linear correlation is assumed between the parameter $p_1$ and the number of connections $n_C$. A linear regression analysis leads to regression parameters $\beta_{1,p_1}(n_R)$ and $\beta_{2,p_1}(n_R)$. The regression parameters are extrapolated for higher number of rooms and higher number of connections and are indicated by a dashed line in Figure 8.7a. For higher number of rooms the influence of the room arrangement $n_C$ on the parameter $p_1$ of the fire spread curve decreases. Since there is almost a linear correlation between the parameters $p_2$ and $p_1$, the value of $p_1$ is used to assess the parameter $p_2$, see Figure 8.7b. A linear regression analysis leads to the parameter $\beta_{1,p_2}$ and $\beta_{2,p_2}$. The regression error is neglected because its influence on the risk estimation is considered to be small. Further, this error can be considered as a model uncertainty leading to an additional bias in the risk estimation, which can be reduced by the calibration of the model to statistical data.

The room size will affect the time to reach flashover conditions ($FO_Y$) given a fire spread $FS_{XY}$ and an ignition $FI_Y$. Therefore, a factor for the parameter $p_2$ is introduced which considers the relative influence of the mean room size $a_{tot}/n_R$ on the time of flashover related to a reference area $a_{ref} = 20 \text{ m}^2$. This factor qualitatively describes influence of the average room

Fig. 8.5: Fire spread model for the major loss model.
8.1 Modelling the fire damage in single family houses

![Diagram showing fire damage simulation results and floor plans]

Simulation results
Approximation
Eq. 8.8 (ψ = 1.0)

---

nC = 5
nC = 7
nC = 8
nC = 10

---

0 5 10 15 20 25 30 35
time − t_{\text{FO}} [\text{min}]
Simulation results
Approximation
Eq. 8.8 (ψ = 1.0)
nC = 5
nC = 7
nC = 8
nC = 10
nC = 5
nC = 7
nC = 8
nC = 10

---

Fig. 8.6: For number of rooms \( n_R = 6 \): a) influence of the number of connection between the rooms \( n_C \) on the fire spread and b) example of different room arrangements with identical \( n_C \).

size on the fire spread curves (e.g. a room size less than the reference area will shift the curve to the left, because flashover conditions tend to occur earlier). Now, the parameters \( p_2 \) and \( p_1 \) for Equation 8.8 can be described by:

\[
p_1 = \beta_1 \cdot p_1 (n_R) + \beta_2 \cdot p_1 (n_R) \cdot n_C
\]

\[
p_2 = (\beta_1 + \beta_2 \cdot p_1) \cdot \frac{a_{\text{tot}}/n_R}{a_{\text{ref}}}
\]

---

Time of first flashover

The time until flashover in the room of fire ignition \( t_{\text{FO}} \) depends, among other influences, on the floor area of the room of fire ignition \( a_0 \) and is simultaneously the time to start the fire spread beyond the room of ignition. A random variable \( T_{\text{FO}} \) is introduced to represent the uncertainties associated with the time of first flashover, e.g. due to varying ventilation condition or the fire growth rate. The two-zone fire model OZone ([Cadorin & Franssen, 2003]) is used to estimate the expected time of first flashover \( E[T_{\text{FO}}] \). The time of flashover depends on the room size. For a reference room of \( a_{\text{Ref}} = 20 \text{ m}^2 \) the expected flashover time is \( t_{\text{FO,Ref}} = 10 \text{ min} \). By changing the floor area \( a_0 \) a linear dependency between the floor area \( a_0 \) and the expected time to flashover \( E[T_{\text{FO}}] \) is found (see Table \[8.3\]), which may serve at least as a good approximation over the range of the most typical room floor areas \( a_0 \) found in the data, i.e. between 15 m² and 100 m². The coefficient of variation \( \text{CoV}[T_{\text{FO}}] \) is assumed to be 20%.

The probabilistic model for the time of flashover in the room of fire origin \( T_{\text{FO}} \) is associated with assumptions on the fire properties used in the two-zone model, e.g. the fire growth rate and the maximal rate of heat release, and with the model itself. The model for \( T_{\text{FO}} \) should be interpreted as a first estimation that can be revised, e.g. by a full probabilistic analysis based on the models discussed in Chapter 4. Since the flashover time \( t_{\text{FO}} \) affects the fire spread in
Chapter 8. Generic fire risk model facilitating calibration

Fig. 8.7: Linear regression model for $n_R = 4, 5, \ldots, 10$ and extrapolation for $n_R > 10$, model parameters a) $p_1$ and b) $p_2$.

Tab. 8.3: Tentative probabilistic models for the fire specific risk indicators $x_E$.

<table>
<thead>
<tr>
<th>Random variables $X$</th>
<th>Dist.</th>
<th>$E[X]$</th>
<th>$CoV[X]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time of first flashover</td>
<td>$T_{FO}$</td>
<td>$\mathcal{LN}$</td>
<td>$t_{FO,Ref} + m \cdot (a_0 - a_{Ref})^1$</td>
</tr>
<tr>
<td>Intervention time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without smoke alarm</td>
<td>$T_{I,SA}$</td>
<td>$\mathcal{LN}^2$</td>
<td>16.3 min</td>
</tr>
<tr>
<td>with smoke alarm</td>
<td>$T_{I,SA}$</td>
<td>$\mathcal{LN}^3$</td>
<td>15.1 min</td>
</tr>
<tr>
<td>Time to prevent further damage</td>
<td>$T_P$</td>
<td>$\mathcal{LN}$</td>
<td>Equation 8.10</td>
</tr>
<tr>
<td>Total loss acceptance $[-]$</td>
<td>$A_{Limit}$</td>
<td>$\mathcal{N}$</td>
<td>0.85</td>
</tr>
</tbody>
</table>

1 $m = 0.0924$ derived from OZone calculations
2 Shifted-Lognormal distribution with shift parameter $\varepsilon = 3.5$ min
3 Shifted-Lognormal distribution with shift parameter $\varepsilon = 3.4$ min

time $a_d(t)$ (Equation 8.8 and Figure 8.5), this estimation influences indirectly the calibration of the fire spread coefficient $\psi$. Consequently, an underestimation of the time of flashover leads to a higher fire spread coefficient and vice versa. Therefore, the influence of the flashover time on the risk estimation is reduced by the calibration. Though, the intention of the calibration parameter $\psi$ is not to address the uncertainties associated with the probabilistic models for the fire specific indicators, e.g. the time of first flashover. Therefore, it is important to reduce these uncertainties as much as possible before calibration, even if the calibrated risk model provides a good agreement with the data used for calibration (see Section 8.2).

8.1.5 Fire brigade model - major loss model

The fire brigade intervention is an active fire safety measure and will reduce the consequences of a fire. As discussed in Chapter 5.3 and 5.4, the success of the fire brigade is related to the
8.1. Modelling the fire damage in single family houses

Intervention time

The intervention time can be derived based on the probabilistic models derived in Section 5.3. For simplification, the intervention time is modelled based on (De Sanctis et al., 2013) as a single random variable and is represented by a Shifted-Log-Normal distribution. Note that the probabilistic models used to assess the intervention time $T_I$ are associated with uncertainties, e.g. due to uncertainties in the data collection process and in the modelling. Similar to the time of first flashover $T_{FO}$, the influence of these uncertainties on the risk estimation will be reduced by the calibration process, because the fire spread is influenced by the intervention time. It is important to reduce these uncertainties as much as possible before calibration, especially with regard to decision-making, when risk-reducing measures are considered in the engineering models (see Sections 8.3).

Damage prevention and final fire area

As discussed in Section 5.4.2, an indicator for the suppression performance of the fire brigade is the time until the fire spread is stopped, e.g. by the control time. It is assumed that no further financial damage occurs, once the fire spread has stopped. Actually, additional damage may occur because of salvage and overhaul actions, e.g. searching for fire sources. Since the data does not differ between different damage sources, this damage is accounted to the fire damage. Fire suppression depends on various factors like the building characteristics (e.g. number of storeys, number of rooms, etc.), the fire characteristics (e.g. fire size, heat release rate, accessibility of the fire) and the fire brigade characteristics (e.g. size of the crew, facilities for the extinguishment, water supply). A simplified approach is chosen to estimate the time needed to stop fire spread $T_P$.

On the basis of fire brigade reports, Särdqvist (2000) analysed the correlation between the fire area and the water application time. He concluded that the larger a fire is, the longer it takes to fight it. Therefore, it is assumed that the expected value of the time needed to prevent further damage $E[T_{P|I}]$ is related to the fire area $a_d(t_I)$ and therefore conditional on the fire brigade intervention time $t_I$. A power law describes this relationship:

$$E[T_{P|I}] = t_{P,ref} \cdot \left( a_d(t_I) \right)^\kappa$$

(8.10)

The parameters $a_{P,ref}$ and $t_{P,ref}$ define a reference point for the model. The parameter $\kappa$ is a shape parameter describing the functional dependency between $E[T_{P|I}]$ and $a_d(t_I)$. Särdqvist (2000) estimates the parameter to $\kappa = 0.52$. A comparison of various fire suppression models by Davis (2000) and Benfer & Scheffey (2014) suggests a wide range of possible functional forms. Most of the models use a power law (range of the exponent varies from 0.5 to 2) to address the dependency between the room area and the required flow rate per minute (which is assumed to...
be directly related to the time to prevent further damage). Therefore, the parameter $\kappa$ is used as a calibration parameter to deal with the lack of knowledge about the "right" power model. The reference point for this model is chosen according to the regression model by Särđqvist (2000) ($a_{P, \text{ref}} = 100 \text{ m}^2$ and $t_{P, \text{ref}} = 20 \text{ min}$). The coefficient of variation of the random variable $T_{PI}$ is assumed to be 10%, as listed in Table 8.3. It should be noted that the two variables $T_I$ and $T_{PI}$ are conditional (see also Figure 8.8). This has to be considered in the calculation.

The final fire area $a_{End}$ is assessed by Equation 8.8:

$$a_{End} = a_d(t_{End}) = a_d(t_I + t_{PI})$$ (8.11)

Not every intervention of the fire brigade leads to the limitation of the fire damage. A fire might be too large for a successful and safe intervention. Then, the fire brigade will accept a total loss of the building and focus on preventing further damage to adjacent buildings. An indicator for considering total damage is chosen to be the fire spread area at the intervention time related to the total building area $a_d(t_I)/a_{tot}$. Beyond a certain limit $A_{Limit}$, the fire brigade will accept a total loss. This limit is also associated with uncertainties due to the real fire situation and the perception of the fire brigade. The tentative probabilistic model is listed in Table 8.3 and can be improved by fire brigade data. The probability of a total damage $P_{tot}$ is used in the distribution of the major loss $f_{A_d}^L(\cdot)$ (see Equation 8.7) and is assessed by:

$$P_{tot}(x, \theta) = P \left( A_{Limit} > \frac{a_d(t_I)}{a_{tot}} \mid x, \theta \right)$$ (8.12)

The assessment of the final fire area $a_{End}$ is illustrated in Figure 8.8 and is used for the assessment of the probability distribution function of the major loss $f_{A_d}^L(\cdot)$ (see Equation 8.7). The grey nodes indicate a realisation of the random variables for the fire specific risk indicators $X_E = [T_{FO}, T_I, T_{PI}, A_{Limit}]$, which are defined in Table 8.3. The building specific risk indicators $x_O = [a_{tot}, a_{max}, n_R, n_C, v]$ influences all boxes in Figure 8.8, but are for reasons of clarity not illustrated.

8.2 Calibration of the generic risk model

The fire specific risk indicators $X_E$ are a-priori not observable and are not part of the available loss data used for the calibration. Therefore, they are marginalised according to Equation 3.2 (see Section 3.1.3) by using the numerical integration method. This method is applicable due to the low computational costs of the model and the small number of random variables $X_E$. Alternatively, Monte Carlo simulations can be performed to propagate the uncertainties of the fire specific risk indicators through the model. After the marginalisation of the fire specific risk indicators $X_E$, the risk $R = E[C]$ depends only on the building specific risk indicators $x_O$ and the calibration parameters $\theta$. The generic risk model can be applied to different single family houses within the building portfolio, where the object specific risk indicators are known, and allows a calibration of the generic risk model to observed loss data, which is typically collected at portfolio level.
8.2. Calibration of the generic risk model

The calibration and validation of the model is discussed in Fischer et al. (2014). This section provides a brief description of the calibration and of the most important results.

The principal idea of the calibration process is to calibrate the generic risk model to observed loss data in order to reduce the bias in the risk assessment. Four calibration parameters $\theta = [\lambda, \zeta, \psi, \kappa]$ (two for the minor loss model and two for the major loss model) are introduced in the engineering models to address the uncertainties in the modelling process. The calibration parameters $\theta$ and their purposes are summarised in Table 8.4. The parameters $\lambda$ and $\zeta$ for the minor loss model are used to describe the distribution of the fire area, if a fire is confined to the room of fire ignition (see Section 8.1.3). The parameter $\psi$ is introduced to deal with the lack of knowledge about all effects that affect the fire spread velocity in the building (related to the events $FS_{XY} - FI_{Y} - FO_{Y}$) and that are not considered by the risk indicators. This fire spread coefficient $\psi$ describes how well the reference case (see Table 8.2) fits to reality. The parameter $\kappa$ considers the lack of knowledge about the shape of the fire suppression model characterised by Equation 8.10.

The parameters are calibrated at portfolio level using insurance loss data provided by the AGV and are listed in Table 8.4. The data contains information on 1996 claims of building owners after a fire event. The Maximum Likelihood method is used to calibrate the model (see Section 3.4.3). More information on the calibration process and the data used for the calibration, is found in Fischer et al. (2014). Therein, the risk model is validated as well. The outcome of the calibration process is illustrated in Figure 8.9, where the loss data is compared to the outcome of the generic risk model. To enable the comparison at portfolio level, the generic risk model is evaluated for each building, where a fire event occurred, and the loss distribution $f_{C}(c)$ is aggregated at portfolio level. This leads to the loss distribution at portfolio level.
\[ \lambda^* = -0.13, \ zeta^* = 0.91 \]

Financial loss \( c \) [CHF]

... 

Before calibration (\( \psi = 1.0, \kappa = 0.52 \))

After calibration (\( \psi^* = 1.73, \kappa^* = 1.44 \))

Fig. 8.9: Comparison of the portfolio losses predicted by the risk model, before (\( E[C] = 13'448 \text{ CHF} \)) and after calibration (\( E[C^*] = 18'421 \text{ CHF} \)), with insurance data (\( E[\hat{C}] = 17'216 \text{ CHF} \)).

level, e.g. \( F_{C, \text{Portfolio}}(c) \). The vertical axis in Figure 8.9 denotes the exceedance probability \( 1 - F_{C, \text{Portfolio}}(c) \) of a loss \( c \). The assumptions that are made on the model parameters \( \theta \) before the calibration are not able to represent the data on the upper tale (dashed line). In contrast, the calibrated risk model represents the observed loss data at portfolio level quite well.

A comparison between the fire spread coefficient before and after calibration in Table 8.4 indicates that the reference case defined in Table 8.2 leads to an underestimation of the fire spread velocity. Though, it is not possible to identify the cause of this underestimation, e.g. whether the probability of a door being open is too low or the duration of the consecutive events \( t_{FSC,XY}, t_{FY}, t_{FO,Y} \) are too short. The reason is that the analytical model for the fire spread (Equation 8.8) does not explicitly contain this information. From a decision making point of view, this is not critical when judging the efficiency of a fire safety measure, as long as the measure does not affect the velocity of a fire spread in a building, e.g. by self-closing doors or fire rated windows.

It is important to use the calibrated values \( \theta^* \) only together with the probabilistic models for the fire specific indicators \( X_E \) that are used for the calibration. Changing the values in Table 8.3 requires a re-calibration of the risk model to the data. A re-calibration is also necessary if the risk model is applied to another building portfolio with different fire spread or fire control properties. For example, if a building portfolio consist predominantly of timber buildings - which is not a very common construction type in Switzerland - a re-calibration would be necessary.
8.3 Application of the generic risk model

The application of the generic risk model 

The components of the generic risk model are illustrated in Figure 8.1 and discussed in Chapter 8.1. Based on these components the expected consequences \( R = E[C] \) are assessed by Equation 8.1. The input for the risk model is given by four calibration parameters \( \theta = [\lambda, \zeta, \psi, \kappa] \) (see Table 8.4), five building specific risk indicators \( x_0 = [a_{tot}, a_{max}, n_R, n_C, v] \) (see Table 8.5) and four fire specific risk indicators \( x_E = [T_{FO}, T_I, TP[I, A_{Limit}]] \) (see Table 8.3). The fire specific risk indicators are introduced as random variables.

In Section 8.3.1 the risk model is applied at object level as a case study. For an application of the generic risk model on portfolio level, see Fischer et al. (2014). The risk model is used in Section 8.3.2 to judge the cost-efficiency of a home smoke alarm.

Tab. 8.4: Calibration parameters before calibration \( \theta \) and after calibration \( \theta^* \) (see Fischer et al. 2014).

<table>
<thead>
<tr>
<th>Calibration parameters</th>
<th>( \theta )</th>
<th>( \theta^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distribution parameters</td>
<td>( \lambda = -0.13 )</td>
<td>( \lambda^* = -0.13 )</td>
</tr>
<tr>
<td>for minor loss model</td>
<td>( \zeta = 0.91 )</td>
<td>( \zeta^* = 0.91 )</td>
</tr>
</tbody>
</table>

Model the fire spread within the room of fire origin.

"Fire spread coefficient" \( \psi = 1.00 \) \( \psi^* = 1.73 \)

Characterises the fire spread velocity in the building. Reduces the bias associated with the consecutive events for fire spread \( (FSC_{XY} - FI_Y - FO_Y) \) including:

- the state of doors (e.g. open/closed)
- the ventilation conditions
- the combustion behaviour of the materials in the room
- the neglected uncertainties in the modelling of the fire spread
- other effects that influence the fire spread velocity

"Control time exponent" \( \kappa = 0.52 \) \( \kappa^* = 1.44 \)

Models the fire brigade suppression. Reduces the bias associated with the time needed to prevent further damage, including:

- the lack of knowledge about the "right" power model
- other effects that influence the average time needed to prevent further damage, e.g.
  firefighting performance of the fire brigade

because the construction material may affect the fire spread velocity. Though, from a Bayesian perspective the calibrated values in Table 8.3 can be used as prior information.

The development of the generic fire risk model was not a straightforward task. Several iterations between modelling and calibration were necessary, because the calibration of a model that is not able to capture the behaviour of real fire events - at least qualitatively - cannot be successful. Therefore, the engineering models have been successively improved by considering physical relationships more adequately (at least qualitatively).
### Tab. 8.5: Building specific risk indicators $x_O$ for three representative buildings.

<table>
<thead>
<tr>
<th>Risk indicators</th>
<th>$x_O$</th>
<th>Type of building</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total building floor area [m$^2$]</td>
<td>$a_{tot}$</td>
<td>small medium</td>
</tr>
<tr>
<td></td>
<td></td>
<td>227 311</td>
</tr>
<tr>
<td>Floor area of largest room [m$^2$]</td>
<td>$a_{max}$</td>
<td>medium large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>75 95 139</td>
</tr>
<tr>
<td>Average floor area of the remaining rooms [m$^2$]</td>
<td>$a_{mean}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>19 24 35</td>
</tr>
<tr>
<td>Number of rooms [-]</td>
<td>$n_R$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>9 10 11</td>
</tr>
<tr>
<td>Number of connections between rooms [-]</td>
<td>$n_C$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>12 13 14</td>
</tr>
<tr>
<td>Insured value [CHF]</td>
<td>$v$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>400'000 550'000 870'000</td>
</tr>
</tbody>
</table>

#### 8.3.1 Application of the generic risk model at object level

The model is used to analyse the effect of the fire brigade intervention time on the risk prediction at object level. Figure 8.10 illustrates the expected consequences $E[C|x_O, T_I = t_I, EX]$, conditional on a fire ignition $EX$ and on a realisation of the fire brigade intervention time $T_I = t_I$. The expected consequences are assessed according to Equation 8.1 and by marginalising over all fire specific indicators $X_E$ except for $T_I = t_I$. The model is evaluated for three different buildings, which represent a typical small, medium and large Swiss building (see Table 8.5). The conditional risk $E[C|x_O, T_I = t_I, EX]$ tends to increase for larger buildings. This is not surprising since the value at risk, i.e. the insured value $v$, increases as well. Therefore, it is reasonable to normalise the conditional risk by the insured value $v$, (see Figure 8.10b). In both illustrations, a low and a high limiting value of a curve can be observed. The lower limiting value indicates the risk estimate provided by the minor loss model, e.g. when the fire is contained in the room of fire ignition. The higher limiting value is associated with the risk of a total loss determined by the insured value $v$ of the building and is reached earlier for small buildings. The reason is mainly the smaller floor area of the room of fire ignition ($a_{max}$ or $a_{mean}$), which benefits an earlier flashover. Therefore, as Figure 8.10 shows, small buildings are more vulnerable given a fire and a total loss is more likely. This implies that a reduction of the intervention time, e.g. by an earlier fire detection or a reduction of the fire brigade response time, will prevent total losses especially for small buildings. In Figure 8.5, a clear influence of the fire brigade intervention time $t_I$ on $E[C]$ can be recognised. Similar effects can be observed for the other fire specific indicators $x_E$ defined in Table 8.3.

The good fit of the calibrated model to the data (Figure 8.9) does not imply that the probabilistic models for those indicators (Table 8.3) are well chosen. Nevertheless, it is shown that the calibration can be successful, even if the probabilistic models are based on engineering judgement and are associated with large uncertainties. Uncertainties in the probabilistic models for the fire specific indicators will affect decision-making, if the decision alternatives, i.e. fire safety measures, affect these indicators. Therefore, a major concern should be, to use sophisticated probabilistic models especially for indicators that are affected by the decision alternatives.
8.3. Application of the generic risk model

8.3.2 Judging the cost-efficiency of home smoke alarms

Smoke alarms are obligatory for residential buildings in several countries and have been found to reduce the number of fatalities (Ahrens, 2009). Fischer et al. (2012) (see Fischer (2014) for English version) applied the LQI criterion to judge whether home smoke alarms should be prescribed by the codes in Switzerland or not. The life saving effects of home smoke alarms is assessed based on Swiss fatality data and the survival probability when an alarm is present. The survival probability is estimated based on data from the literature (e.g. Ahrens, 2009) and based on reported fire incidents where fatalities occurred containing detailed information on the fire events. This information is used to decide if a person could have hypothetically been saved by a smoke alarm. Fischer et al. (2012) concluded - based on the LQI criterion - that smoke alarms cannot be regarded to be an efficient life saving measure. This means that fire safety solutions with and without smoke alarms are deemed to be acceptable and a monetary optimisation can be performed (see Section 3.3.2).

In this section the cost-efficiency of a battery-powered home smoke alarm - without alarm transmission to the alarm central - is evaluated as an example. As discussed in Section 5.5.2 smoke alarms shorten the detection time and leads to earlier fire-fighting actions by the occupants or by the fire brigade, which reduce the potential financial loss. To judge the efficiency of a smoke alarm, the performance and the costs have to be assessed first.

Reliability of a home smoke alarm

The UK smoke alarm statistics are summarised in Table 5.2 (see Section 5.5.2) and are used to derive the reliability of a smoke alarm. Fire incidents where the fire products do not reach the
devices are usually not affected by the type of the smoke alarm, but by the poor placement in
the apartment. The failure probability of a smoke alarm accounts to \( P_{f,SA} = 0.111 + (1 - 0.62) = 49.1\% \) (see Table 5.2). The expected consequences given the installation of a smoke alarm can be derived by:

\[
R(SA) = E[C|SA] \cdot p_{f,SA} + E[C|SA] \cdot (1 - p_{f,SA})
\]  

(8.13)

Effect on the minor loss model

A smoke alarm, when raised, affects the fire spread in the room of fire ignition by increasing
the probability of an early suppression of the fire by the occupants or by the fire brigade. This
effect on the minor loss model is not modelled by an engineering approach and is estimated by
statistical data. According to Table 5.2 the probability that the fire is confined to the item of
ignition is 45.6\% without a smoke alarm; 66.2\% with smoke alarm.

The probability of a major loss \( P(A_d > a_0) \) decreased with the presence of a smoke alarm. Therefore, a scaling factor \( \chi \) is introduced, which scales the probability of a fire spread beyond the room of fire origin, e.g. \( P(A_d > a_0|SA) \cdot \chi \). The probability of a minor loss is derived by:

\[
P(A_d \leq a_0|SA) = 1 - P(A_d > a_0|SA) \cdot \chi
\]  

(8.14)

The value \( \chi \) can range between 1 (no effect of the smoke alarm on the minor losses) and 0 (smoke
alarm will reduce the probability of major losses to 0). \( P(A_d \leq a_0|SA) = 0.662 \) can directly
estimated by Table 5.2. It can be assumed that the probability of a major loss given a smoke
alarm \( P(A_d > a_0|SA) \) is smaller than the corresponding probability without a smoke alarm, e.g.
\( P(A_d > a_0|SA) < P(A_d > a_0|\overline{SA}) = 1 - P(A_d \leq a_0|\overline{SA}) \). Thus, the value in Table 5.2 can be
used to assess a lower estimate of \( \chi \):

\[
\chi > \frac{1 - P(A_d \leq a_0|SA)}{1 - P(A_d \leq a_0|\overline{SA})} = \frac{1 - 0.662}{1 - 0.456} = 0.62
\]  

(8.15)

Effect on the major loss model

An operating smoke alarm increases the probability of an early detection of the fire and reduces
the discovery time. This leads to an earlier intervention of the fire brigade as discussed in Section
5.5.2 and leads to a smaller damage, i.e. to a risk reduction. For simplification the intervention
time is modelled based on (De Sanctis et al., 2013) as a single random variable and is represented
by a Shifted-Lognormal distribution (see Table 8.3).

Costs of a smoke alarm

The yearly investment costs to install and maintain a smoke detector is assessed by the acquisition
costs and cost for the batteries considering their lifetimes. According to Fischer (2014) the
average yearly costs for a battery powered smoke alarm in Switzerland is 7.35 CHF/year. The
main part of the cost is due to the cost for the batteries (55%). The cost for the device (45%) might be higher in Switzerland compared to other countries.
8.3. Application of the generic risk model

The number of smoke alarms that have to be installed for a reliable monitoring depends on the number of rooms, floors and storeys. It can be assumed that on average three smoke alarms should be installed in a single family house to achieve a reliable monitoring.

**Application to decision making for single family houses**

The risk reduction $\Delta R$ of a smoke alarm (the effectiveness) is illustrated in Figure 8.11 as a function of the insured value $v$ of a building. Simple linear regression models based on portfolio data is used to determine the other building specific risk indicators for a corresponding insured value. The building specific risk indicators are indicated in Figure 8.11 as well. The scaling factor $\chi$ for the smoke alarm is varied to discuss the effect of this value.

The installation of a smoke alarm will always reduce the risk $\Delta R > 0$. The steps in each curve are due to the increasing number of rooms $n_R$ and the number of connections $n_C$. The risk reduction $\Delta R$ depends largely on the scaling factor $\chi$ that affects the probability of a major loss. For the case where the smoke alarm is assumed to have no influence on the minor losses ($\chi = 1$) it is seen that the risk reduction $\Delta R$ decreases with increasing insured value $v$ of the building. The reason is that the probability of a major loss $P(A_d > a_0)$ depends on the room size $a_0$ ($a_{\text{max}}$ respectively $a_{\text{mean}}$) and decreases with increasing room size. The room size $a_0$ depends itself on the insured value $v$. Thus, for buildings with a large insured value (e.g. large buildings), the risk $R$ is dominated by the minor losses. In contrast, buildings with a small insured value (e.g. small buildings), have a higher probability of a major loss because of the smaller room size $a_0$ and thus the risk is dominated by major losses. The scaling factor $\chi$ affects the probability of a major loss and influences therefore especially the risk reduction $\Delta R$ of buildings with a small insured value.

**Fig. 8.11:** Effectiveness of a battery-powered smoke alarm.
The costs for three smoke alarm are estimated to $3 \cdot 7.35 \text{ CHF} = 22.05 \text{ CHF}$ and exceeds the risk reduction $\Delta R$ by a factor of $2 \div 3$. Hence, it is not a cost-efficient fire safety measure for the corresponding building.

This cost-efficiency study is only valid for Switzerland as Swiss data has been used for determining the risk indicators and for the calibration. Especially the cost for smoke alarm devices in Switzerland are higher compared to other countries. This will affect the cost-efficiency and under different conditions (e.g. costs, building characteristics, fire brigade performance or probability of fire occurrence) the cost-efficiency of a smoke alarm might be fulfilled.

8.4 Conclusions

The approach presented in this chapter and in Fischer et al. (2014) demonstrate the benefits of using statistical data as a basis for improving engineering risk models by reducing the associated bias. Such risk models can be used for absolute risk comparison, e.g. cost-benefit analyses, where usually no statistical data on the effect of risk reducing measures is available.

The risk is assessed by risk indicators, which includes building and fire specific parameters. The associated uncertainties are identified and considered by a probabilistic approach. The generic fire risk model includes engineering models that quantify the fire spread and consider the fire brigade intervention. These models are influenced by simplifications and assumptions that lead to a bias in the prediction of the risk. Calibration parameters are introduced in the engineering models to address this bias. These parameters are calibrated using Swiss fire loss data, to reduce the bias of the risk model when predicting the expected loss. It is important, that the engineering models are in agreement, at least qualitatively, with the corresponding physical processes or the calibration will not be successful. Even if the calibrated risk model provides a good agreement with the data used for calibration, it is important to reduce the uncertainties associated with the fire specific risk indicators and with indicators that are affected by risk reducing measures as much as possible before calibration. The framework to calibrate such a risk model to statistical data is presented by Fischer et al. (2014). The calibrated and validated generic risk model is able to assess the absolute risk based on a few building specific risk indicators that are easy to quantify and allows the application of the model for portfolio risk assessment.

The risk model is applied to three typical Swiss buildings as a case study and the effect of the intervention time of the fire brigade on the expected consequences is discussed. The absolute assessment of the risk makes a cost-benefit analysis possible and the cost-efficiency of home smoke alarms in single family houses shows that smoke alarms are not cost-efficient in Switzerland.
Chapter 9

Conclusions, discussions and outlook

9.1 Conclusions

The present thesis demonstrates the benefits of generic fire risk assessment as a practical tool to face decision-problems at object and at societal level, and to provide the basis to improve fire safety provisions for both prescriptive and performance-based design approaches. Major conclusions related to the approach for generic risk assessment and decision-making are:

− The performance of design provisions is evaluated and optimised by a risk-based approach.

The performance of a fire safety measure are evaluated under realistic conditions, e.g. conditions that are likely to occur in reality, and considering the inherent natural variability of the system. A risk-based approach provides the basis to evaluate this performance and accounts for all relevant processes, in order to estimate the expected consequences and to quantify the safety level of design provisions. This quantification is the basis to optimise fire safety code provisions in order to achieve a balanced ratio of costs and safety.

The LQI acceptance criterion is an efficiency criterion for the optimal allocation of societal resources for life safety. This criterion is used as a threshold criterion to perform monetary optimisation, e.g. a cost-benefit analysis. These optimisation methods require an absolute quantification of the risk, either in terms of the expected number of fatalities or the expected monetary losses, which can be assessed by a probabilistic risk model.

− Generic risk models are used to assess the risk at both object and at societal level and support validation at societal level.

The generic assessment of the risk of objects allows to aggregate the individual consequences and to estimate the expected consequences at societal level. This provides the basis for decision-making by a societal decision-maker, e.g. a regulatory agency. Since loss data is usually collected at societal level as well, it provides the basis for validation of generic risk models. Within the validation, the bias of a risk model can be assessed. By calibration of the risk model to data, the bias of the engineering models is even reduced.
Advanced uncertainty propagation techniques improve a full probabilistic representation of the system.

The application of advanced simulation techniques (such as subset simulation and importance sampling) and advanced surrogate techniques (such as polynomial chaos expansion) allows the consideration of a large number of uncertainties associated with complex systems with a reasonable computational effort. Such techniques pave the way to a full probabilistic representation of the system and overcome the computational burden of advanced probabilistic engineering models. Sensitivity methods are used to identify the most important risk indicators and to determine actions in order to reduce the uncertainties of a system, e.g. by data collection, by validation of engineering models or by increasing or reducing the complexity of engineering models. It is important to assess the influence of assumptions associated with the probabilistic models on the decision alternatives (robustness) and this is done by applying these methods as well.

The framework for generic risk assessment is applied to three different engineering- and decision-problems in Chapters 6 to 8. For detailed conclusions it is referred to the corresponding part of each chapter. Below, major conclusions related to these applications are listed:

- **The level of safety of a prescriptive and a performance-based structural design is compared by a risk based approach** (Chapter 6). A reliability-based method is used to quantify and to compare the level of safety of a design approach under realistic conditions. Where the level of safety of the prescriptive design is very sensitive to building specific indicators, the level of safety of the performance-based design varies less. For a prescriptive and performance-based structural design approaches the level of safety of a sprinkler concept is higher than the corresponding standard solution. Only for small floor areas the safety level of the standard concept cannot be reached due to the extremely high level of safety of the standard concept. Requiring that an alternative design solution should have the same level of safety of a standard solution is not always reasonable.

- **Current code provisions for the required flow capacity of doors for retail buildings are judged to be very conservative resulting in a non-optimal allocation of societal resources** (Chapter 7). A risk-based approach is applied to assess the optimal required flow capacity of doors (determined by the door width) based on the LQI acceptance criterion. The study shows that the current egress provisions for the door width may be considerably reduced in order to achieve a balanced ratio of costs and consequences. There is a major participation of the uncertainty associated with the fire growth rate and with the occupant load density on the risk and it should be appropriately considered in further risk assessment studies.

- **Home smoke alarms for single family houses in Switzerland are judged as not cost-efficient** (Chapter 8). The cost efficiency of home smoke alarms is evaluated by a generic risk model that is
calibrated at portfolio level. The risk model considers the reliability of smoke alarms as well as the effect on the reduced fire spread area due to an earlier fire suppression either by the occupants or by the fire brigade. The comparison of the costs of smoke alarm with the associated monetary risk reduction shows that the investments cannot be justified for the majority of the buildings in Switzerland. Lowering their costs and/or increasing their reliability may increase the efficiency of home smoke alarms.

9.2 Relevance for fire safety science

Current risk assessment in fire safety is mainly used to support design situation, e.g. to find the worst-case or most probable fire scenarios. This thesis shows the benefits of probabilistic risk assessment that is used in an overall framework for the optimisation of fire safety provisions to achieve a balanced ratio of costs and consequences.

The novel idea of the introduced approach for probabilistic fire risk assessment is the risk-based evaluation of the performance of fire safety measures under realistic conditions, considering the interaction of different safety measures which are demanded by the codes. This assessment can be used to compare the level of safety of different safety measures that are designed according to different design approaches, e.g. prescriptive or performance-based design approaches. It is shown that the equivalence approach, which is demanded by some codes, is flawed since usually the same level of safety of a prescriptive design is required, which is very depending on building characteristics and does not necessarily provide an uniform safety level within a building class. The introduced risk-based approach allows to examine the design approach that is most suited for a building class. In addition, fire safety provisions can be optimised considering the costs of safety provisions. This optimisation requires an absolute quantification of the risk, e.g. an unbiased assessment of the expected consequences. Apart from the derivation of probabilistic models of basic input parameters to enhance the realistic representation of the system, this thesis demonstrates how to deal or even to reduce the bias associated with risk models, e.g. the gap between the model prediction and the real data. A generic representation of the building and the assessment of the risk at societal level supports the quantification of this bias.

9.3 Relevance for fire safety engineering practice

The developed risk models may also be used to support fire safety design for real buildings. Nevertheless, these models are not intended to be used as black-box models for engineers. The required probabilistic background and basic data to adapt the models for the specific design situation is usually lacking. The risk models are primarily used to discuss basic problems of fire safety engineering, e.g. the equivalence of fire safety measures or the influence of basic variables and their associated uncertainties. Therefore, some simplifications in the problem statement, e.g. the choice of the building layout, are made to facilitate the discussion and the application of the physical models. Buildings where fire safety engineering is usually applied, are more complex and more advanced physical models may be required to accurately represent the fire
phenomena. Nevertheless, especially the findings of Chapters 6, 7 and 8 may be also valid for these buildings and help fire safety engineers and fire authorities to focus on the most relevant factors to aspire a reasonable level of fire safety.

The risk-based evaluation of design provisions shows that not all provisions are optimal, e.g. the required width of doors for evacuation (Chapter 7), and in some cases even the concept is flawed, e.g. the proof of the equivalence of fire safety concepts (Chapter 6). The findings of this thesis may find the way into future fire safety provisions and safety concepts in order to provide a fire safety code that is based on probabilistic concepts – alike the safety concept for the structural design (see EN 1990).

9.4 Towards a risk-optimised fire safety code format

As shown in Chapter 7 and Chapter 8 risk models and the corresponding risk-based acceptance criteria are used to derive optimised fire safety solutions. This is applied for some prescriptive design solutions, e.g. the minimal required door width or whether smoke alarms should be required or not (from a financial point of view). The same risk models and decision criteria can be applied to optimise performance-based codes; though it is not trivial.

One option is to optimise a performance level, e.g. a target reliability index, as discussed in Fischer (2014). As a result, safety factors within a semi-probabilistic design format can be calibrated towards theses optimised reliability indexes (see Schleich et al., 2002; Hosser et al., 2009, for structural design). Chapter 6 demonstrates that a well-founded and well-calibrated code format can achieve a homogeneous safety level for buildings with different characteristics. However, as discussed in Chapter 5 and Chapter 7 a reliability index is not always suited for fire safety problems, e.g. in cases where events associated with low-probability high-consequences (or vice versa) dominate a system (see Chapter 7).

Another option is to optimise a system according to the risk acceptance criteria and the risk models as done in Chapter 7. Then, the optimised system can be used as a reference system. For this reference system a suited performance level or safety criterion and a code format is specified. The difficulty is – especially if low-probability high-consequences events should be considered – to set an appropriate performance level that is valid for a wide range of buildings and is simple enough to be used in a design format. The design format should consider the most influencing risk indicators and the state-of-the-art engineering design method. Following the same idea of a semi-probabilistic design concept, safety factors may be applied to the most important risk indicators and calibrated in order that the safety factors fulfil the performance level. Then, the calibrated safety factors may also be applied to systems which do not correspond exactly to the reference system, but are deemed to have the same influencing risk indicators.

9.5 Data requirements

The evaluation of fire safety measures under realistic conditions requires data in order to develop probabilistic models for basic input parameters that can be used in a probabilistic engineering
9.6. Limitations

For structural engineering, for example, the required data for a full-burnout scenario is on the fire load and on the reliability of the fire brigade suppression. Especially for the latter, more data on the performance of suppression activities of the fire brigade is needed. Even if there are many fire load surveys available, the probabilistic models proposed by EN 1991-1-2 should be revised and checked if the models are still suitable to represent actual fire loads in buildings.

Necessary data for probabilistic evacuation models may include surveys on the early fire development (e.g. fire growth rate) and on the occupant load density in buildings. Also data on the detection and warning time (in relation to the fire development), recognition and response of occupant to the fire and data on the flow capacities of bottlenecks is valuable for evacuation models. Where there is a clear effort to describe the fire growth rate (e.g. Holborn et al., 2004; Deguchi et al., 2011; Baker et al., 2013), there is only few research on the probabilistic representation of the occupant load density. Especially for buildings where the occupant load is varying (e.g. retail buildings, department stores, airports or stations) a probabilistic representation is useful to allow the optimisation of egress provisions.

Data on consequences of a fire is especially useful to allow the validation of risk models. The data can be in terms of financial losses, fire spread areas or human losses. Important for a survey is to include both building characteristics that may affect the fire (e.g. use of the building, building size, number of floors or building material) and information on the performance of safety measures during a fire. For example, informations on the fire spread area within a building may be useful to assess the performance of fire rated boundary elements (e.g. EI criterion). For this it is required to know if the boundary element sustained a fire and prevented fire spread or not. Then, risk models that consider building characteristics and fire safety measures can be validated and used for optimisation of fire safety provisions.

9.6 Limitations

The conclusions, resulting from the application of the framework for generic risk assessment and decision-making to the three different engineering- and decision-problems (Chapters 6 – 8), should always be analysed alongside with the underlying assumptions and simplifications as discussed in the related chapters. Note that the models have been developed for Swiss conditions and may not represent a realistic fire situation in other countries. Despite the developed risk models being intended to represent the fire situation as realistically as possible, the main focus of this thesis is to demonstrate the application of the introduced framework for risk-based decision-making.

9.7 Outlook and further research possibilities

The realistic representation of the fire situation by engineering models and especially the realistic representation of the associated uncertainties, should be the focus of future research on risk assessment for fire safety. While there are large advances in the physical representation of
the fire situation by engineering models (e.g. combustion models, computational fluid dynamic models or evacuation models), there is a considerable amount of missing basic data to accurately represent the uncertainties associated with the fire situation when aiming at a full probabilistic representation. A full probabilistic approach and the assessment of the importance of uncertainties associated to both risk indicators and model uncertainties, e.g. by the application of different sensitivity methods, can lead to the determination of the necessary level of detail of these engineering models. Judging this importance may improve performance-based design approaches, in order to accept simplified engineering models to derive optimal fire safety solutions. This is beneficial especially for engineering practice where "it is better to be roughly right than precisely wrong." Advanced engineering models, on the other hand, can be applied specifically, where they provide a considerable benefit, e.g. a reduction of the uncertainties.

While it is common to validate engineering models, risk models that are based on an engineering approach are currently not validated. The risk estimation is biased and the application of the models is limited to comparative studies. Quantifying and reducing this bias by data allows the application of absolute acceptance criteria and should be further investigated. The framework for generic risk assessment provides the basis to validate such models at portfolio level and to reduce the bias by calibration. Another way to reduce the bias is Bayesian updating (or Bayesian inference), which allows to consider prior information on random variables of a system, e.g. expert judgement or information on the performance of similar systems, and to update this information using loss data, e.g. financial or human losses.

Most performance-based design approaches rely on the determination of "probable worst-case scenarios", which are used for design purposes. A corresponding design is deemed to satisfy these scenarios and is likely to be associated with a non-optimal allocation of societal resources, e.g. costs. It has been demonstrated that generic risk assessment can be used to quantify the level of safety of design approaches and this paves the way to move from deemed-to-satisfy approaches to performance-based design approaches that are optimised towards a common acceptance criterion for fire safety, which aims to achieve a balanced ratio of costs and consequences. With the same risk models, also prescriptive design approaches can be optimised, at least within the risk classification of the buildings they are set for.

The LQI acceptance criterion is a promising concept for fire safety to face decisions regarding the optimal allocation of societal resources for life safety. The same criterion can be used as boundary conditions for monetary optimisation. This should be further applied in the field of fire safety engineering. Especially fire authorities that set fire safety provisions for society may use this approach to make and justify their decisions.

---

1 John Maynard Keynes, British economist (1883-1946)
Appendix A

Probabilities and random variables

A.1 Notation

- $P(A)$: Probability of an event $A$
- $P(A|B)$: Conditional probability of $A$ given $B$
- $X$: Random variable
- $x$: Realisation of a random variable $X$
- $X$: Vector of random variables
- $x$: Vector of realisation of the random variables $X$
- $f_X(x)$: Probability density function (PDF) of a random variable $X$
- $F_X(x)$: Cumulative distribution function (CDF) of a random variable $X$
- $F_X^{-1}(x)$: Inverse function of the cumulative distribution function, i.e. $F_X^{-1}(F_X(x)) = x$
- $E[X]$: Expected value of $X$
- $Var[X]$: Variance of $X$
- $CoV[X]$: Coefficient of variation of $X$, i.e. $CoV[X] = \sqrt{Var[X]/E[X]}$

A.2 Probability distributions

Normal distribution

If a random variable $X$ is Normal distributed $X \sim \mathcal{N}(\mu, \sigma)$ then its probability density function $f_X(x)$ is defined by:

$$f_X(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2\right) \quad (A.1)$$

The parameters $\mu$ and $\sigma$ are the distribution parameters of the Normal distribution. The probability density function is defined over $-\infty < x < \infty$. The expected value $E[X]$ of $X$ and the variance $Var[X]$ of $X$ is defined by:

$$E[X] = \mu \quad (A.2a)$$

$$Var[X] = \sigma^2 \quad (A.2b)$$
Gaussian distribution

The Gaussian or Standard Normal distribution is a Normal distribution with \( X \sim \mathcal{N}(0,1) \). The cumulative distribution function of this distribution is denoted as:

\[
\Phi(x) = F_X(x)
\]  

(Lognormal distribution)

If a random variable \( X \) is Lognormal distributed \( X \sim \mathcal{LN}(\mu, \sigma, \varepsilon) \) then its probability density function \( f_X(x) \) is defined by:

\[
f_X(x | \mu, \sigma, \varepsilon) = \frac{1}{(x - \varepsilon)\sigma \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{\ln(x - \varepsilon) - \mu}{\sigma} \right)^2 \right)
\]  

The parameters \( \mu, \sigma \) and \( \varepsilon \) are the distribution parameters of the Lognormal distribution. The probability density function is defined over \( x > \varepsilon \), where \( \varepsilon \) denotes a shift of the distribution. Unless otherwise stated the shift parameters is set to \( \varepsilon = 0 \). The expected value \( E[X] \) of \( X \) and the variance \( Var[X] \) is defined by:

\[
E[X] = \varepsilon + \exp \left( \mu + \frac{\sigma^2}{2} \right) \\
Var[X] = (\exp(\sigma^2) - 1) \cdot (E[X] - \varepsilon)^2
\]  

Exponential distribution

If a random variable \( X \) is Exponential distributed \( X \sim \mathcal{E\chi}(\lambda) \) then its probability density function \( f_X(x) \) is defined by:

\[
f_X(x | \lambda) = \lambda \exp(-\lambda x)
\]  

The parameter \( \lambda \) is the distribution parameter of the Exponential distribution. The probability density function is defined over \( x \geq 0 \). The expected value \( E[X] \) of \( X \) and the variance \( Var[X] \) of \( X \) is defined by:

\[
E[X] = Var[X] = \frac{1}{\lambda}
\]

Gamma distribution

If a random variable \( X \) is Gamma distributed \( X \sim \mathcal{G\chi}(a, b) \) then its probability density function \( f_X(x) \) is defined by:

\[
f_X(x | a, b) = \frac{1}{b^a \Gamma(a)} x^{a-1} \exp \left( -\frac{x}{b} \right)
\]  

The parameters \( a \) and \( b \) are the distribution parameters of the Gamma distribution and \( \Gamma(.) \) is the gamma operator. The probability density function is defined over \( x > 0 \). The expected value \( E[X] \) of \( X \) and the variance \( Var[X] \) of \( X \) is defined by:

\[
E[X] = a \cdot b \\
Var[X] = a \cdot b^2
\]
A.2. Probability distributions

The Exponential distribution is a special case of the Gamma distribution, i.e. $\mathcal{E}(\lambda = 1/b) = \mathcal{G}(a = 1, b)$.

**Uniform distribution**

If a random variable $X$ is Uniform distributed $X \sim U(a, b)$ then its probability density function $f_X(x)$ of $X$ is defined by:

$$f_X(x|a, b) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases} \quad (A.10)$$

**Weibull distribution**

If a random variable $X$ is Weibull distributed $X \sim W(a, b)$ then its probability density function $f_X(x)$ of $X$ is defined by:

$$f_X(x|a, b) = \frac{b}{a} \left(\frac{x}{a}\right)^{b-1} \exp \left(-\left(\frac{x}{a}\right)^b\right) \quad (A.11)$$

The parameters $a$ and $b$ are the distribution parameters of the Weibull distribution. The probability density function is defined over $x > 0$. The expected value $E[X]$ of $X$ and the variance $Var[X]$ is defined by:

$$E[X] = a \Gamma \left(1 + \frac{1}{b}\right) \quad (A.12a)$$

$$Var[X] = a \sqrt{\Gamma \left(1 + \frac{2}{b}\right) - \Gamma^2 \left(1 + \frac{1}{b}\right)} \quad (A.12b)$$
Appendix B

Polynomial chaos expansion and global sensitivity analysis

This chapter provides the mathematical background of the polynomial chaos expansion, which is implemented in the Matlab toolbox UQLab\(^1\) (Marelli & Sudret, 2014) and which are used in the present thesis. The global sensitivity analysis is implemented in the toolbox as well and some further details are provided to compute the indices.

B.1 Polynomial chaos expansion

Consider \( y \) as the output of a deterministic computational model, e.g. \( y = \mathcal{M}(x) \), with an input vector \( x \) of size \( M \) (number of input variables). The inputs are usually associated with uncertainties and can be represented by a random variable \( X \). For simplicity the random variables \( X \) are assumed to be independent and follow a standard Normal distribution \( X_k \sim \mathcal{N}(0,1) \). This is without loss of generality and can be achieved by a transformation of the physical space \( X \) to the standard Normal space \( U \) using an isoprobabilistic transformation (see Melchers, 2002). The propagation of the uncertainties associated with \( X \) leads to a random response of the model \( Y = \mathcal{M}(X) \).

The computational costs to evaluate the model \( y = \mathcal{M}(x) \) can be large and prevent the application of simulation based methods for a probabilistic approach in order to propagate the uncertainty through the model, e.g. by Monte Carlo simulations. Surrogate models (or metamodels) overcome this problem providing an easy-to-evaluate function as an approximation of the real model. The Polynomial Chaos Expansion (PCE) is a spectral approach introduced by Ghanem & Spanos (1991) to surrogate the random output \( Y \) of the model by a linear combination of coefficients \( c_\alpha \) and orthonormal multivariate polynomials \( \Psi_\alpha(X) \):

\[
Y = \sum_{\alpha \in \mathbb{N}^M} c_\alpha \Psi_\alpha(X) \quad \text{where} \quad \Psi_\alpha(X) = \prod_{k=1}^{M} \psi_{\alpha_k}(X_k) \tag{B.1}
\]

\(^1\)UQLab is currently under development at ETH Zurich and a pre-alpha version (0.500.201406251501) was kindly provided by the Chair of Risk, Safety and Uncertainty Quantification of the Institute of Structural Engineering.
This equation is known as the \textit{Wiener-Hermite polynomial chaos expansion} where \( \alpha = (\alpha_1, \ldots, \alpha_k, \ldots, \alpha_M) \) are the multi-indices in which \( \alpha_k \) is the degree of the orthonormal polynomial \( \psi_{\alpha_k}(X_k) \) for the random variable \( X_k \). Since \( \alpha \in \mathbb{N}^M \) determines the number of linear combination and the polynomial degrees and is further an infinite vector, the surrogate model converges to the exact solution. A detailed discussion of this approach is provided by Sudret (2007) and Blatman (2009) and is summarised in the following.

\textbf{Construction of the orthonormal basis}

Orthogonal polynomials for a random variable \( X_k \) can be defined as:

\[
\langle \psi_i(x_k), \psi_j(x_k) \rangle = \int_{D_k} \psi_i(x_k) \psi_j(x_k) f_{X_k}(x_k) dx_k = \delta_{ij} \tag{B.2}
\]

where \( \delta_{ij} = 1 \) if \( i = j \) and \( \delta_{ij} = 0 \) if \( i \neq j \). The formulation of the orthogonality involves the marginal probability density function \( f_{X_k}(\cdot) \) of the random variable \( X_k \) and is one of the major differences compared to other surrogate modelling techniques, e.g. regression with non-orthonormal polynomials. In this way, the surrogate model defined by Equation [B.1] depends on the probabilistic models of the input variable \( X_k \) which provides an additional information for the meta model. Orthogonal polynomials for a standard Normal random variable \( X_k \) can be generated by the Hermite polynomials with the following recurrence scheme:

\[
egin{align*}
    h_{-1}(x_k) &= h_0(x_k) = 1 \\
    h_{n+1}(x_k) &= x_k \cdot h_n(x_k) - n \cdot h_{n-1}(x_k)
\end{align*} \tag{B.3, B.4}
\]

The first five Hermite polynomials are:

\[
\begin{align*}
    h_0(x_k) &= 1 \\
    h_1(x_k) &= x_k \\
    h_2(x_k) &= x_k^2 - 1 \\
    h_3(x_k) &= x_k^3 - 3x_k \\
    h_4(x_k) &= x_k^4 - 6x_k^2 + 3 \\
    h_5(x_k) &= x_k^5 - 10x_k^3 + 15x_k
\end{align*}
\]

It can be seen that \( h_n \) denotes a polynomial of degree \( n \). The Hermite polynomials \( h_n \) are not orthonormal and have to be normalised with the use of Equation [B.2] by:

\[
\psi_n(x_k) = \frac{h_n(x_k)}{\|h_n(x_k)\|} \quad \text{where} \quad \|h_n(x_k)\| = \sqrt{\langle h_n(x_k), h_n(x_k) \rangle} \tag{B.5}
\]

For standard Normal random variables it holds that \( \|h_n(x_k)\| = \sqrt{n!} \).

\textbf{Truncation scheme}

For computational reasons the formulation of the PCE according to Equation [B.1] has to be truncated, e.g. by reducing the number of linear combinations \( c_{\alpha} \Phi_{\alpha}(X) \).
proposes a hyperbolic scheme for the truncation up to a polynomial degree $P = \sum_{k=1}^{M} \alpha_k$ and by a $q$-norm value:

$$Y = \mathcal{M}^{PCE}(X|c_\alpha) = \sum_{0 \leq \|\alpha\|_q \leq P} c_\alpha \Psi_\alpha(X) + \varepsilon \quad \text{where} \quad \|\alpha\|_q = \left( \sum_{k=1}^{M} \alpha_k^q \right)^{\frac{1}{q}} \leq P \quad (B.6)$$

The parameter $P$ and $q$ can be considered as model parameters for the surrogate model, which define the functional structure of the PCE. The error made by the truncation can be represented by a random variable $\varepsilon$. A low $0 < q \leq 1$ penalise especially the high-rank indices (interaction terms), e.g. the multivariate polynomials $\Psi_\alpha$ which are composed by multiple orthonormal bases, and converge for $q \to 0$ to a purely additive model. In contrast, multivariate polynomials composed of only one orthonormal basis, e.g. $\alpha = (0, \ldots, \alpha_k \geq 0, \ldots, 0)$, are not affected by the truncation scheme, e.g. $\|\alpha\|_q = \alpha_k \leq P$. Thus, the polynomial degree $P$ and the $q$-norm value determine the number of coefficients $c_\alpha$ that have to be estimated. For further details it is referred to Blatman & Sudret (2011).

### Computation of the coefficients

The representation of $Y$ by the PCE depends on the polynomial degree $P$ and the $q$-norm value and can be considered as model components. Given those components, the coefficients $c_\alpha$ can be estimated by a regression approach, e.g. by a least-square regression. Accordingly, the model $\mathcal{M}(x)$ is first evaluated for a experimental design, which consists of $i = 1, \ldots, N$ samples of the random variables $X$, e.g. $y^{(i)} = \mathcal{M}(x^{(i)})$. Quasi-random methods can be used, such as Latin-Hypercube sampling or Sobol-sequences (Saltelli et al., 2008) to assure a low discrepancy of the experimental design. The regression scheme is formulated by:

$$\hat{c}_\alpha = \arg \min_{c_\alpha} \frac{1}{N} \sum_{i=1}^{N} \left( \mathcal{M}(x^{(i)}) - \mathcal{M}^{PCE}(x^{(i)}|c_\alpha) \right)^2 \quad (B.7)$$

The regression minimise the error term $\varepsilon$ of Equation (B.6) for a given polynomial degree $P$ and a given value for the $q$-norm. Since the number of coefficient depends on those two model parameters, this number can grow very large for a high polynomial degree $P$ and a large number of random variables $M$. Especially, if the sample size of the experimental design $N$ is close to the number of coefficients then the problem leads to over-fitting. In this case, the experimental design has to be enlarged.

A quantitative criterion, which is used to check if a surrogate model is able to predict accurately the response of inputs, which are not part of the experimental design, are cross validation techniques. The idea is to split the experimental design into two subsamples: a training set and a validation set. The training set is used to build the model, e.g. estimating the coefficients $c_\alpha$. The validation set is used to estimate the model error. Blatman (2009) proposes to use the leave-one-out error and derived a relative error measure for the PCE, which is based on the experimental design and needs no additional model evaluations. The leave-one-out error decreases with increasing number of coefficients $c_\alpha$ and increases if the the number of
coefficients is close to the sample size of the experimental design. Thus, given a threshold value for the leave-one-out error, the polynomial degree \( P \) (and the value for the \( q \)-norm) of PCE can be optimised for a given experimental design of size \( N \).

### B.2 Global sensitivity analysis

Global sensitivity analysis can be assessed by a variance-based analysis (see Section 3.4.3) aiming to identify the individual contribution of the random input parameters \( X \) (or interaction of them) to the variability of the response of a model \( Y = M(X) \). Homma & Saltelli (1996) introduces Sobol indices \( S \) to decompose the variance to assess the individual contribution of the random input parameters \( X \). The indices can be distinguished between first-order \( S_k \) and total effects \( S_{T,k} \) of a random variable \( X_k \) and are defined in Section 3.4.3.

One way to assess those indices are statistical estimators based on sampling methods (Monte Carlo sampling, Latin Hypercube sampling or by Sobol sequences) and are discussed in Homma & Saltelli (1996) and Janon et al. (2013). The estimator proposed by Janon et al. seems to performed better and is used in the present thesis to estimate the indices. Another way is proposed by Blatman & Sudret (2010), who linked the spectral approach by the PCE with the assessment of the global sensitivity indices and the estimation of the PC-based Sobol indices based on the PC-coefficients \( c_\alpha \). No additional model evaluations are required except for the experimental design. All mentioned methods to estimate the Sobol indices are implemented in UQLab (Marelli & Sudret, 2014).
Appendix C

Parameters to assess the risk to life

The parameters $r_1$, $r_2$ and $r_3$ in Section 5.10 are estimated by a non-linear fit to the simulation results and are listed in Table C.1. The parameters depends on the floor area of the enclosure $a_E$ [m$^2$], on the height $h_E$ [m] and if there is visual detection (VD = yes) or notification of the occupants by an alarm (VD = no). The equation is given by:

$$R(w) = r_1 \cdot \exp(-r_2 \cdot w) + r_3$$

(C.1)

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