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Response surface modelling in quantitative risk analysis for life safety in case of fire

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ABSTRACT

This paper proposes part of a framework for the development of a risk assessment methodology to quantify the life safety risk of building occupants in the context of fire safety design. An important aspect of quantitative risk analysis (QRA) concerns taking into account the variability of the design parameters. In QRA for life safety in case of fire, one of the key research challenges to take probability into account is the complexity of the different submodels. Another key aspect is the high computational time for performing a set of simulations. In order to tackle these problems, a response surface model (RSM) for sub-models, which support the global QRA method, is useful. In this paper, this is illustrated in particular for the modelling of smoke spread. More specifically, the focus is on the development of a method and a model for estimating the RSM using a Least Squares (LS) technique or the Polynomial Chaos Expansion (PCE) approach. Both methods were found to be suitable for the intended purpose, but PCE provides the best fitting response surface model based on the obtained data for the case at hand. The model is tested in a practical case study with Computational Fluid Dynamics (CFD) incorporating the Fire Dynamics Simulator (FDS) model.

1. Introduction

In prescriptive fire safety legislation it is often implicitly assumed that when all the rules of the regulation are applied, the fire safety level is acceptable [1–3]. However, architectural demands have become increasingly challenging during the last decades as advances in structural engineering as well as material sciences have made it possible to realize buildings with complex configurations, which cannot always be built in accordance with existing codes. Therefore, globally, more and more countries change their legislation regarding fire safety and proceed designing buildings in function of objectives. Possible formats are objective-based [2], performance-based [1,4] or risk-informed [5,6] design, where the implicit acceptable safety level assumption in prescriptive rules now becomes explicit by showing the verified safety level. Although the aforementioned approaches still show some shortcomings [6], there is a consensus that a holistic approach is necessary in which the building configuration, user, content, safety systems and procedures are analysed together.

Risk-based methods provide a way to evolve towards such a holistic approach. More specifically, quantitative risk assessment techniques provide an opportunity to determine the safety level in a representative measure. The advantage is that both the magnitude and likelihood of hazards versus safeguards can be determined [7]. One of the main objectives of risk-based probabilistic methods is to take into account uncertainties (in addition to the deterministic quantification of scenarios and consequences) in a quantitative risk analysis (QRA), whereas in deterministic performance based designs uncertainty is generally dealt with by using safety factors [8]. However, one of the key problems when taking probability into account is the complexity of the different submodels such as fire spread, smoke spread, evacuation, etc. [9]. Another problem is the high computational time for performing a series of simulations (e.g. using finite difference models) which makes it impossible to analyse a high number of scenarios (according to a random set of input parameters). In order to tackle these problems, the number of samples has to be reduced. Several sampling techniques exist, such as importance sampling, Latin Hypercube sampling, surrogate-modelling, etc. Here, a response surface model (RSM) [10] is suggested for different types of submodels in order to significantly reduce the computational time when evaluating a high number of samples.

The purpose of the RSM, or 'surrogate' model, is to create a response surface with only a few solver evaluations. The creation of

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the response surface makes it possible to generate a (linear) interpolation function by which for a new combination of input data, the output can be generated without evaluating a new sample [11]. As a result, a high number of input combinations can be analysed with hardly any additional computational effort, which is of large importance when performing limit state analysis in order to evaluate probabilities and – consecutively – risks. The focus is on the development of an appropriate methodology and a surrogate model is proposed. The main advantage of the method is an increase of computational speed, from 10-fold up to 100-fold compared to Monte Carlo sampling and Importance sampling, while retaining an error of similar magnitude [11].

In the next section, the basic concept of surrogate modelling is explained. Two methods are investigated: traditional Least Squares (LS) techniques and a Polynomial Chaos Expansion (PCE) technique. In the subsequent section, a case study is performed using both methods. In this paper, the focus is on the proof of concept of the methodology for the CFD model in the context of smoke spread, based on a comparison of the results (in terms of slice files) for CO concentrations.

2. Response surface concept

The basic concept of a response surface model is to approximate the response in the global domain for a certain model without relying upon the physics of the system. This can be the case when the modelling of the response becomes physically too complex. The results of a finite set of detailed model simulations are translated in a meta-model, which does not model the physics in any way. The formulation can be [12]:

$$y = f(X) \tag{1}$$

in which y is the response and **X** is the vector of input variables (Fig. 1).

A response surface model (RSM) can be used for limit state design [13] when the problem statement is not explicitly formulated [14]. It can be used when the limit state function is implicitly formulated which is the case for numerical models [11]. It is the goal of a RSM to replace the output information of the complex model $f(x)$ by an equivalent function $\overline{f}(x)$ by which the computational procedures can be simplified. An example can be a linear combination of second order polynomials:

$$\overline{f}(x) = a + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} c_i x_i^2 \tag{2}$$

in which x_i, (i = 1,...,n) are the variables and the parameters a, b_i, c_i, (i =1,…,n) are to be determined.

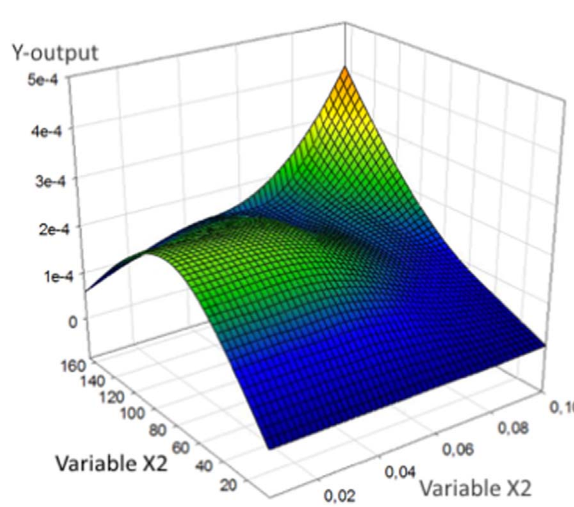

Fig. 1. Example of a response surface model.

It should be mentioned that in some cases the response surface may not be sufficiently accurate if it does not take interactions properly into account, e.g. when interactions are expected between fire parameters such as fire growth and fire area size. In the latter case, mixed terms may be included thus extending the approximate response surface $\overline{f}(x)$ as:

$$\overline{f}(x) = a + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} c_i x_i^2 + \sum_{i \neq j} \sum d_{ij} x_i x_j \tag{3}$$

This response surface with interaction terms is more accurate. However, more evaluation simulations are needed to determine the coefficients.

2.1. Multi-sub-model response surface framework

The framework for assessing the life safety risk in case of fire consists of different sub-models for determining the risk in a quantifiable measure. Depending on the scope, these sub-models will model fire ignition and spread, smoke spread, evacuation, toxicity analysis, fire brigade intervention, etc. in which they have to interact with each other. Therefore, a relation between these sub-models should be established. For example, output from the smoke spread model can be used for determining the visibility in evacuation models.

In Fig. 2, a sequential method of three sub-models is shown: smoke spread, evacuation and consequence analysis, is shown. A response surface is created for the smoke spread model. Based on a limited learning set a response surface of the CFD model is established which is then used to generate input data for the evacuation model. The results of the evacuation model are used for the consequence model. In the example provided below, the consequence model is an analytical model which does not need a response approach to determine the final output results. With regard to this paper, the focus is on response surface modelling for the CFD part, which relates to the first element in the chain shown in Fig. 2. In future research it is intended also to elaborate further on the inclusion of evacuation modelling, in interaction with smoke spread models, into the methodology. In particular, attention will be paid to the uncertainty propagation with respect to evacuation time and toxicity doses for analysing life safety of occupants in complex buildings [15].

2.2. Response surface model formulation in 2D

The response surface – here composed of a linear combination of second order polynomial functions – needs to predict the output for specific sub-models. In case of the smoke spread sub-model, the output is expressed in terms of concentrations, temperatures and radiation. For every 2D grid-location and every time step considered in the smoke spread model, the response surface method needs to predict a different outcome. This means that time and position (2D) are the three input variables for the response surface when using one response surface for all the results. However, by increasing the number of variables (time, place, fire-parameters, etc.), the complexity of the polynomials increases more than linearly. The addition of variables also leads to an increase in the number of parameters to be estimated and might even reduce the accuracy of the outcome. Therefore, the method is developed in such a way that, depending on the desired accuracy, a response surface can be created for:

- Every single time step or a group of time steps (i.e., multiple time steps are considered together). In the latter case, time becomes an additional parameter, i.e., interpolation is done over different time steps. This might reduce accuracy in strongly transient phases.
- Every single grid location at which the response surface is evaluated in a horizontal slice of the room. Using one response surface function for every location may give the impression that the correlation between the