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

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A B S T R A C T

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\textsuperscript{[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\textsuperscript{[2]}, performance-based\textsuperscript{[1,4]} or risk-informed\textsuperscript{[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\textsuperscript{[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\textsuperscript{[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\textsuperscript{[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.\textsuperscript{[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)\textsuperscript{[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
the response surface makes it possible to generate a (linear) interpo-
lation 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 appro-
priate 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

In the next section, the basic concept of surrogate modelling is
explained. Two methods are investigated: traditional Least Squares
(1S) 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]:

\[ y = f(X) \] (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 \( \bar{f}(x) \) by which the computational procedures can be simpli-
fied. An example can be a linear combination of second order polynomials:

\[ \bar{f}(x) = a + \sum_{i=1}^{n} b_{i}x_{i} + \sum_{i=1}^{n} c_{i}x_{i}^{2} \] (2)

in which \( x_{i}, (i = 1, \ldots, n) \) are the variables and the parameters
\( a, b_{i}, c_{i}, (i = 1, \ldots, n) \) are to be determined.

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
\( \bar{f}(x) \) as:

\[ \bar{f}(x) = a + \sum_{i=1}^{n} b_{i}x_{i} + \sum_{i=1}^{n} c_{i}x_{i}^{2} + \sum_{i<j}^{n} d_{ij}x_{i}x_{j} \] (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 quantifi-
able 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 in-
creases 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 de-
veloped 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

Fig. 1. Example of a response surface model.
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