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Sensitivity analysis of fire models using a fractional factorial design

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ABSTRACT

This work presents a sensitivity analysis, conducted in the framework of the PRISME OECD programme, using fractional factorial design. Several field and zone computer codes have been used to study the influence of some factors characterizing either the fuel, or the compartment or the ventilation network on relevant responses for fire safety studies. More specifically, the effects of these factors on gas and wall temperatures, the concentration of oxygen in the room, total and radiative heat flux to the walls and the total pressure in the compartment were examined. The results have mainly allowed to organize in a hierarchy the importance of various factors on these responses. Along with this sensitivity study, three methods for generating samples were compared: the Monte-Carlo method, the full and fractional experimental designs. The results have shown that a fractional factorial design, composed of eight runs, gave the same information than a full factorial design, composed of 64 runs or than a Monte-Carlo method, composed of 200 runs.

1. Introduction

Sensitivity analysis is an essential part of any fire simulation project. The sensitivity of the simulation results, with respect to the physical input parameters, is needed to evaluate the justification of the conclusions in the light of the input uncertainty. The overall quality of the simulations, in turn, can be evaluated by a systematic validation and by studying the sensitivity to the numerical parameters, such as the numerical discretization or the turbulence model.

In case of several varying parameters, performing a thorough sensitivity analysis can be quite laborious. For the ease of interpretation, it may be temptating to change only one input parameter at the time but this may prevent one from perceiving the possible synergistic effects between the parameters. The classical methods of experimental design, such as full and fractional factorial design, should therefore be used to find the efficient yet comprehensive set of inputs giving good picture about the variability of possible simulation results. This variability is often investigated in the context of the probabilistic risk assessment, where the range of input values is treated as a random space. Numerical integration over a random space can be performed using a Monte-Carlo method, where a relatively large number of input values is chosen from the parameter space and deterministic simulations are carried out for all of them. The sensitivity of the simulation results to the input values can then be determined in terms of correlation coefficients, considering the internal parts of the input space.

The purpose of this work is to illustrate the use of fractional factorial design as a means of performing the sensitivity analysis for numerical fire simulations. Several field and zone computer codes have been used to study the influence of factors characterizing either the fuel, the compartment or the ventilation network on relevant responses for fire safety studies. The work has been carried out within the OECD PRISME programme of fire experiments. Concurrently to the experimental programme, the results of one test were used to perform a numerical fire simulation benchmark with the aim to validate the different fire models used by the current project participants. The exercise involved 12 organizations and six fire models detailed in Table 1. A description of the fire models and some references are available in [1] where the use of metric operators to quantify the differences between numerical results and experimental measurements was investigated in order to avoid qualitative comparisons.

The outline of the document is as follows. The first section presents a brief introduction to the sensitivity analysis (SA) and to the process of choosing a design of experiments (DoE). The objectives of the study are recalled in this part. The second section describes in detail the responses and the different input factors which have been selected for the construction of the sensibility analysis and DoE. A justification for using fractional design instead of full factorial design or Monte-Carlo methods is provided in the second part of this section. The last section presents the SA performed with a fractional factorial design.

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Table 1
List of participants and fire models.

Organization	Participant	Fire model	version
BelV	N. Notterman, F. Bonte	CFAST	6
CSN	J. Peco	FDS	4.06
DGA	C. Lallemand	OEIL	1.5.1
EdF	L. Gay	MAGIC	4.1.3
GRS	W. Klein-Hessling, M. Pelzer	COCOSYS	2.4 beta 5
iBMB	V. Hohm	FDS	5
IRSN	S. Suard	SYLVIA	1.4
JNES	T. Ito	FDS CFAST	4 6.1
Vattenfall & Lund University	T. Magnusson, P. Van-Hees	FDS	5.4.0
NRG	A. Siccama, P. Sathiah	FDS CFAST	4 6
Tractebel	E. Gorza	MAGIC	4.1.3
VTT	S. Hostikka	FDS	5.4.3

Because some user effects were highlighted in the early phase of the study, the final work presented here was only conducted for each fire model instead of each user.

2. Performing sensitivity analysis

The purpose of a SA study is to measure the influence of one or more input variables of a mathematical model (such as computer codes) on some selected output variables. It is performed by varying the values of the inputs in order to quantify the effect of these changes on the considered outputs. In this process input variables are called factors and output variables are called responses.

In the beginning of the analysis, the connection between inputs and outputs needs to be specified. In other words, the analyst has to choose a model to translate this connection and that will provide sensitivity measures to quantify the influence of each inputs. In most cases, a linear regression model is used but a second order or quadratic model is possible for certain specific applications. The unknowns of the model are the regression coefficients called β hereafter.

The choice of the simulations, necessary to determine the regression coefficients of the model, is crucial. This choice is often achieved following the theory of design of experiments (DoE). The goal of the DoE is to maximize the amount of information collected with a limited number of simulations. During the process, the variation range of each input is discretized. Among classical DoE, one can mention full factorial design where all contour of levels may be considered. In most of the cases, the input factors of the full factorial design are discretized in two levels, called "high" and "low". The DoE is then composed of two levels for all factors and thus requires 2^k runs.

Full factorial design may be feasible for small number of factor but becomes quite inpractical if the simulations are slow and there are many input factors to consider. In this case, it may be more convenient to use fractional factorial design where only a fraction of the full factorial design is used. This method is defined hereafter in Section 2.2.

Sometimes, the sensitivity analysis is conducted successively to a probabilistic simulation study using Monte-Carlo simulations. Accordingly, the responses obtained are saved for the SA but this method requires a lot of computations due to Monte-Carlo experiments. This method is commonly used for numerical integration where a relatively large number of simulations is performed at points that are chosen randomly within the space covering the range of factor variability. The points are chosen according to the joint probability density function of the random (input) variables. In general, the Monte-Carlo methods are further classified according to the method of choosing samples. The most straightforward method is called "simple random sampling" (SRS). It is easy to implement but may require a large number of samples to reach convergence of statistical estimator. Another sampling method is the "Latin hypercube sampling" (LHS) which is commonly used in probabilistic risk assessment applications [7]. LHS represents a class of "fully stratified" sampling methods, meaning that it gives equal consideration to all parts of the random space, regardless of the functional forms of the probability distributions [9].

2.1. Regression modeling

The regression model used for SA generally considers a pair of variables noted (X,Y) where X stands for the values taken by each factor and Y represents the response for a given simulation. The variable X is considered to be known without error and the variable Y is explained, in this study, as a linear function of X. The linear function is determined by minimizing the root mean square deviation. For more details on the theoretical basis of regression modeling and sensitivity measurement, the reader should refer to the book of Box et al. [2].

The simplest linear regression model with one predictor variable is expressed as

$$Y=\beta_0+\beta X+\epsilon \tag{1}$$

where X is the input factor or the predictor variable, β is the regression coefficient and ϵ represents the residual error of the model which is defined as the difference between the prediction obtained by the linear function and the value of Y observed ($\epsilon=Y-\widehat{Y}$). The coefficients β_0 and β are determined in such a way as to minimize the root mean square difference between Y and $\hat{Y}=\beta_0+\beta X$.

In the case of two input factors, the linear model can be written as

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\beta_{12}X_{12}+\epsilon \tag{2}$$

The terms X_1 and X_2 represent the main effects for the response Y whereas the term X_{12} in Eq. (2) represents the interaction effects between factors X_1 and X_2, ($X_{12}=X_1X_2$). For three input factors, the linear model is more complicated

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3$$