MULTI-PARAMETER STUDY OF INTERACTIONS AND UNCERTAINTIES WITHIN CFD-BASED CONSEQUENCE ANALYSIS USING ELEMENTARY EFFECTS ANALYSIS

Hendrik Wahl, Goetz Vollmann, Markus Thewes,
Ruhr-University Bochum

ABSTRACT

In the course of an extensive CFD-study, which was carried out at Ruhr University Bochum, the authors set the focus on the analysis of consequences caused by fire incidents under the consideration of applied numerical models and coupled evacuation simulations. In doing so, the Austrian, the Swiss and the Dutch approaches for quantitative risk analysis of road tunnels were compared and the influence of deviations and variations of the determining factors and parameters was analysed.

Therefore, single parameters of common CFD simulations were classified regarding epistemic and operational uncertainties. While epistemic uncertainties are a common theme, the term "operational uncertainties" was here introduced for parameters, which are subjected to assumptions and simplifications chosen by the risk analysis user. Subsequently, parameter ranges were defined and implemented into an elementary effects analysis (EEA). Main advantage of this method is its characteristic of a stringent parameter screening combined with a global sensitivity analysis. Finally, a concept for the method validation was developed and applied to the results.

Keywords: Elementary Effects analysis, consequence analysis, CFD, egress model, aleatory uncertainties, epistemic uncertainties

1. INTRODUCTION

In the aftermath of the huge tunnel fires in the Alps, the European Union has committed itself to a high safety standard for federal road tunnels in general and TERN-tunnels in particular. Consecutively, uniform minimum safety requirements were defined in the EU-Directive 2004/54/EC (European Parliament and Council, 2004) and corresponding national regulations. If a specific tunnel deviates from those requirements or if it has special characteristics, the safety level shall be determined by means of a quantitative risk assessment and – as a result and if necessary – further measures have to be implemented for the purpose of risk mitigation and damage control. This is done on the basis of the technical risk definition, namely as the product of frequency and consequences of certain events within a quantitative risk analysis (QRA).

While some countries have developed standardized approaches for conducting such a QRA, none of the corresponding parameters and values needed for conducting it are standardized on a European level, resulting in a significant array of possible results using the different national approaches available for one and the same incident.

At Ruhr University Bochum, the authors have conducted a study comparing different European QRA approaches and determining the influence of uncertain parameters within the boundaries of selected standardized QRA methodologies. We present results from this study, showing differences between Dutch, Austrian and Swiss methodologies (read RWS (QRA-tunnels 2.0 - Gebruikershandleiding, 2012), ASFINAG (RVS 09.03.11 - Tunnel-Risikoanalyse, 2015) and ASTRA (ASTRA-Richtlinie 19004 - Risikoanalyse für Tunnel der Nationalstrassen, 2014)) and their impact on the calculation of possible consequences of an incident. Thereby, we laid a special focus on the interaction of different parameters within the calculation and the influence on the subsequent result.

After a short explanation of usually encountered uncertainties – with special regard to QRAs – we then introduce the Elementary Effects Analysis (EEA) and apply it onto the concept of a CFD-based consequence analysis. For this purpose, a model tunnel is defined, spanning a parameter space that includes uncertainties identified in comparison of different standardised approaches, literature and expert opinions. The publication concludes with a validation of the method and a discussion of the gathered results.

2. SOURCES OF UNCERTAINTIES

In statistics in general but also in risk assessment in particular, two types of uncertainties play a significant role in the assessment of procedures or systems. On the one hand, aleatory uncertainties describe an inherent physical fuzziness arising due to natural and unforeseeable variability and randomness of processes and actions. Such uncertainties obviously cannot be reduced, even with the availability of a substantial amount of data for the announced assessment. On the other hand, epistemic uncertainties specify model uncertainties, e.g. due to lack of knowledge or accompanying statistical uncertainties caused by noisy data or an insufficient basic population of the observed cohort. Such problems can normally be reduced by collecting more data or by a more precise assessment of the inherent mechanisms of the observed system.

However, standardized QRA approaches often will give its user a possible range of application for specific parameters. For instance, a specific approach might allow for a deviation of the amount of heavy goods transports within the tunnel between a minimal and a maximal amount. The user is then free to choose his value from in between this range and thereby he will also imply a range to possible consequences when conducting subsequent QRAs. In other words: Subjective assumptions and simplifications that the user of a standardized tool can apply during the assessment, will cause spreading of the results. This spread is than a function of the possible range of application.

With all that in mind and with regard to controlling the setup of this study, we specified the following definitions of uncertainties for further consideration:

- Epistemic uncertainties are understood as uncertainties in describing tunnel-specific input parameters, such as geometry, ventilation systems etc.
- Operational uncertainties describing input parameter depending on assumptions of model user

As one can see, there is no direct consideration of aleatory uncertainties (see definition above) since they are implicitly included within the operational uncertainties. For instance, results of fire tests might produce varying results under identical circumstances due to inherent aleatoric uncertainties. Since the user will apply these test results within the CFD-model we subsume such uncertainties also as operational ones.

3. METHOD OF ELEMENTARY EFFECTS ANALYSIS (EEA)

The EEA is a very strong and complex mathematical approach that was introduced by Morris (Morris, 1991) and further developed by Campolongo (Campolongo, Cariboni, & Saltelli, 2007). Generally, it is a screening method which enables its user to identify parameter impacts and is particularly applied for models that require substantial computational effort. Thus, the EEA represents a suitable alternative approach in cases where classic sensitivity analysis is limited due to the amount of possible parameters and their variation. For the purpose of this publication, we will only present the basic principle of the algorithm of the EEA and refer to (Morris, 1991) and (Saltelli, Tarantola, Campolongo, & Ratto, 2004) for further consideration.

3.1. Theoretical Basics

In contrast to classical sensitivity analysis, the elementary effects method only enables qualitative statements. Following effects of input x_i on a specific output y_i can be determined:

a) negligible
b) linear and additive
c) non-linear
d) involved in interactions with other factors

The method follows the One-Step-at-a-Time principle changing one parameter for each step while the others are fixed. A p-level grid as in **figure 1, left** discretizes a parameter space **Ω** with considered input parameters $x_{i(i=1,\ldots,k)}$. These are transformed by addition or subtraction of $e_i\Delta$ with e_i and thereby describe a zero vector with a unit as i^th component in a k-dimensional unit cube across p selected levels (see **figure 1, right**). Values of Δ lie in a range between 1/(p-1) and 1-(1/(p-1)) and each path through the parameter space describes a trajectory r.

Figure 1: Discretization of parameter space as p-level grid (left) and k-dimensional unit cube across p-selected level with k=3 as example (right) (Saltelli, Tarantola, Campolongo, & Ratto, 2004)

So-called Elementary Effects (EE) of a model outcome $y=y(x_1,\ldots,x_k)$ are determined by the following equation (1) for the i^th input factor in point x:

$$EE(x_1,\ldots,x_k) = \frac{y(x_1,x_2,\ldots,x_{i-1},x_i+\Delta,x_{i+1},\ldots,x_k) - y(x_1,\ldots,x_k)}{\Delta} \quad (1)$$

Sensitivity measures μ and σ are then defined, which allow a global assessment of locally changed input parameters within defined parameter ranges by summing up all EE of the i^th input factor. A further sensitivity measure μ* was introduced by (Campolongo, Cariboni, & Saltelli, 2007) due to problems of positive and negative effects cancelling each other out. Hence, the number of trajectories divides the whole sum of elementary effects. This improves parameter rankings but also provides a combined consideration of μ and μ* and enables statements about the range of elementary effects.

$$\mu = \sum_{i=1}^{r} \frac{|EE_i|}{r} \quad (2) \qquad \sigma = \sqrt{\sum_{i=1}^{r} \frac{(EE_i-\mu)^2}{r}} \quad (3) \qquad \mu_i{}^* = \frac{1}{r}\sum_{j=1}^{r}\left|EE_i^j\right| \quad (4)$$

3.2. Sampling

In this study, a recent approach named "Enhanced Uniformity Sampling" (eSU) by Chitale et. al. (Chitale, Khare, Muñoz-Carpena, & Dulikravich, 2019) is applied. In a first step, the eSU approach generates a sample of first and last trajectory points. In doing so, the frequency of each parameter is the same and the points are unique. This requires a so-called "building points by levels"-approach with a constant step size Δ as in **figure 2**.

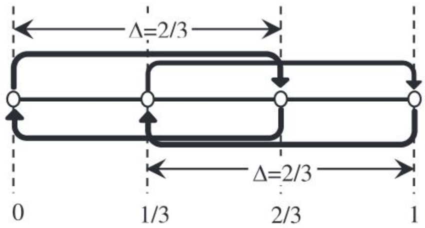

Figure 2: Parameter levels and constant step size for randomly selected parameter in unit parameter space (Khare, Munoz-Carpena, & Martinez, 2015)

A fixed vector for all trajectories containing 1 to k-1 elements changes the intermediate points between the first and the last trajectory sample point: the change of the first parameter of the first trajectory point then generates the second one, changing the second parameter of the second trajectory point generates the third one, and so on.

Finally, the sampling procedure repeats step 1 and step 2 for a number of Q times with the purpose to obtain the highest spread possible. This is determined by means of an Euclidean distance, which is determined at the end of step 2, where $d_{i,j}$ is the distance between all two trajectories r. If the corresponding trajectories have the property of maximum Euclidean distance ($ED=ED_{max}$), the sample is chosen for EE analysis.

$$ED = \sqrt{\sum_{i=1}^{r} \sum_{j=1}^{r} d_{i,j}^{2}} \tag{5}$$

As mentioned before, within this paper we can only describe the method in general terms. The interested reader is referred to (Morris, 1991) and (Saltelli, Tarantola, Campolongo, & Ratto, 2004) for more details.

4. SENSITIVITY ANALYSIS OF INPUT PARAMETERS FOR CFD-BASED CONSEQUENCES ANALYSES

Standardized QRA approaches, such as the RWS, the ASFINAG (at least partially) and the ASTRA approach, can only be compared indirectly. For instance, the ASTRA-approach combines a sophisticated probabilistic algorithm – which differs substantially from the RWS and the ASFINAG-approach – with the application of typical Swiss baseline assumptions for specific parameters. Since the statistical foundations of the aforementioned assumptions rely heavily on the available statistical data of the ASTRA highway network, the application of this approach onto an artificial model tunnel – one that is not part of this Swiss road network and may have significant deviations in terms of physical constraints – would produce questionable results. This is of particular interest when these results are then compared to parallel applications of the Dutch and the Austrian approaches. Nonetheless, all three approaches are modelling physical phenomena using a specified set of parameters with predefined ranges for their values (see also chapter 2). With that in mind, one may not be able to reasonably compare all three approaches within one model tunnel but the influence of the approach-specific data samples on a coupled CFD-egress-model. For achieving this goal, one has to analyse the different approaches in terms of variable parameters and to collate and cluster them in reasonable groups. Subsequently, these groups are then used to vary the input variables of a generic CFD-egress-model. The identification of elementary effects can then help to reduce the "noise" of a specific standardized approach (read: influence of approach-specific assumptions) and to focus on the influence of the "signal" (read: influence of the applied range of values for specific parameters).

4.1. Required Settings and defined Parameter Settings

For defining feasible parameter settings, a generic tunnel is modelled within an FDS-boundary, using the following assumptions for the subsequent consequence analysis:

- naturally ventilated tunnel
- monotonous length profile
- jammed traffic within a uni-directional tunnel with two lanes
- fire takes place in the middle of the tunnel
- buses are not regarded in the egress model

According to the applied definition of uncertainties (see chapter 2) and the described setup of the study, the corresponding parameter groups of all three approaches were collated and combined with findings from literature and expert opinions. In case of a detailed consequence analysis, these parameters usually must be chosen individually. In standardised models, they are fixed or at least their range is limited. Nevertheless, an experienced user should be able to choose and adapt plausible values. That said, given values for minimum and maximum of each parameter were derived from literature, expert opinion or provided input files for the standardized consequence analysis. Table 1 shows the applied ranges of selected parameters of the analysis.

Table 1: Ranges for selected input parameter assigned to operational uncertainties

Category/ Parameter			**Minimum**	**Maximum**	**Step Size Δ**
Geometry	*Length (m)*		500	800	100
	L. Inclination (%)		0	4.50	1.50
	Tunnel Height (m)		5.00	6.50	0.50
	Lane Width (m)		3.25	4.75	0.50
Fire Load	*Production Rates (g/MJ)*	*CO*	3.00	3.60	0.20
		CO_2	83.00	87.00	2.00
		HCN	0.25	0.90	0.22
		Soot	1.00	2.50	0.50
	Time to maximum (s)		300	600	100
Evacuation Scenario	*Eye-level (m)*		1.50	1.80	0.10
	Width of emergency exits (m)		1.20	2.40	0.40
	Soot extinction coefficient for		0.06	0.12	0.02
	*Impeded egress velocity(-)**		0.10	0.40	0.10
	Occupancy rate (person)	*Passenger Car*	1.00	2.50	0.50
		HGV	1.00	2.50	0.50

*specific FDS+EVAC parameter, factor multiplied to unimpeded egress velocity

4.2. Application of EEA

Comparative statements about the considered approaches are achieved by applying the EEA to a model tunnel. For this purpose, at first, 36 Parameters including HRR and their defined parameter ranges were sampled according to the eSU procedure introduced in chapter 3.2. It was repeated 12 times (number of trajectories r), which is defined as a recommendable amount according to (Chitale, Khare, Muñoz-Carpena, & Dulikravich, 2019). However, the sampling results in 444 simulations required for the EEA ((36 input parameters + 1 basis vector) *12 trajectories), which represent the spanned parameter space defining the model tunnel.

In a second step, the model tunnel was implemented into a FDS environment, which is coupled with the complementary program code EVAC for evacuation modelling. It was applied for reasons of simplification and follows same basic principles as the considered approaches.

In order to ensure that a generic model is basically available that will also allow further research and validation, the authors developed a tool based on Microsoft Excel to generate input files for FDS+EVAC automatically in connection with configurations of the parameter sampling. Finally, the EEA algorithm – which is applied to a list of results of the 444 simulations (here number of fatalities) – delivers the sensitivity measures μ, μ* and σ for qualitative assessment of parameter impact and interactions as a result of a quantitative data analysis.

5. RESULTS

As introduced in chapter 3.1, the evaluation of sensitivity measures μ* and σ for corresponding input parameters provides a parameter ranking: if both values are low, the impact on the outcome is negligible, while high values of μ* and σ indicates a high non-linear impact with interactions to other parameters. No parameter interactions are observed when either μ* (linear) or σ (non-linear) only takes on a high value. **Figure 3** visualize these relations and provides a graphical approach to identify the impact and interactions.

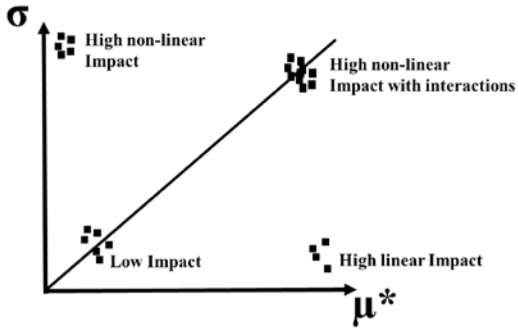

Figure 3: Approach to visualize graphical structures, according to (Chitale, Khare, Muñoz-Carpena, & Dulikravich, 2019)

Subsequent discussion about the obtained parameter ranking is based on the graphical approach. In addition, the authors present a method validation, especially for the purpose to identify if the selected number of trajectories is an appropriate choice for valuable statements.

5.1. Parameter Ranking

Figure 4 shows the diagrams representing the impact of corresponding parameters related to classified uncertainty groups. The diagram legend is structured hierarchically in descending order of influence on the overall result. In case of considerations for parameters assigned to the group of operational uncertainties, not all input parameters are visualized for reasons of clarity and visibility. The results are discussed below.

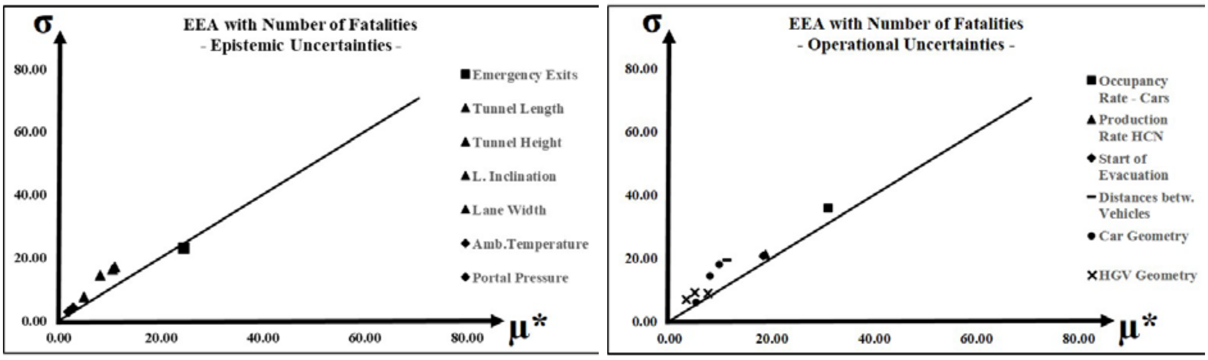

Figure 4: Parameter ranking for epistemic (left) and operational (right) uncertainties

In case of parameters describing tunnel-specific input parameters (group of epistemic uncertainties, see **figure 4, left**), the distance between emergency exits indicates the highest impact on the outcome (here fatalities), while the parameter 'Occupancy Rate of Cars' concerning to group of operational uncertainties (see **figure 4**, right) affects the system most. Nevertheless, all parameters show a non-linear behavior as well as interactions with other parameters. In this respect, the authors conclude with regard to a selection of parameters:

- Tunnel Geometry

Tunnel geometry affects the propagation of smoke, heat and toxic fumes significantly. Nevertheless, the results also show that the lane width has much less influence on the results of consequence analysis as tunnel height (ratio of 1:2) although similar bandwidths (1.5 m) are applied. Different number of lanes were not considered in the EEA.

- Occupancy Rate of Cars

In this study, the range was set between 1.0 and 2.5. Common values applied in considered approaches are between 1.0 (e.g. ASTRA, RWS) and 1.5 (ASFINAG). However, due to its dynamic character, the Dutch approach allows the model user to operate with a rate up to 3.0. The results show that such power given to the user could lead to high discrepancies which are not transparent in most approaches of risk analysis (black box problem).

- Production Rate

The production of HCN influences the system considerably, contrary to other production rates of CO, CO^2 and Soot (in part of non-listed lower impacts). During literature research it became apparent that there is no uniform scientific knowledge about the development of HCN during a fire. Since the production rate basically contains uncertainties resulting from natural variability within the highly complex combustion process, the scatter in the results illustrate the need for uniform benchmarks. Thus the influence signal could be significantly reduced and an important contribution would be made to the general standardization of the European safety level of road tunnels.

- Other Parameters

Parameters not listed in **figure 4** or are not mentioned in this discussion show a lower impact on the outcome of consequence analysis. Although parameters discussed above imply a higher uncertainty presumably due to applied ranges, they do not affect most of the other significantly. On the other side, specific parameter constellations can lead to cumulative effects.

5.2. Method Validation

The authors also dealt with a validation due to the fact that so far, no studies have been conducted using the EEA approach. For this purpose, two general concepts were pursued: firstly, the results of EEA were qualitatively examined in terms of logical coherence. However, no inconsistencies were indicated.
As a second step, a quantitative assessment was done to enable statements about the exploitation of the parameter space. Therefore, a new parameter sampling based on same applied ranges was generated with higher number of trajectories (r = 16). This resulted in 592 additional runs. A comparison between both method runs (initial vs. validation) indicates that within both runs most of the parameters affect the system in a similar manner with only small deviations. Nonetheless, some parameter categories show a differing overall impact on the system. One example is the tunnel geometry with the parameter 'Longitudinal Inclination' and 'Tunnel Height' that reveal twice as much influence on the CFD-egress-model during the second run. Nevertheless, a substantial amount of trajectories of at least r = 12 result in a sufficient parameter space exploitation and enable stable qualitative statements about their influences on the system.

6. CONCLUSION, OUTLOOK AND ACKNOWLEDGEMENTS

In total, the authors conducted 1036 CFD-simulations (444 for EEA and 592 for method validation) to identify the impact of common input parameters for CFD-based consequence analysis of road tunnels as well as to validate the introduced EEA approach.

The results have strongly indicated the need for more benchmarking in terms of QRA-related parameters and values, either with standardized approaches or detailed analyses. Here, a European effort of the scientific community seems feasible and necessary.

In particular, the applied method validation is a good complement to the EEA, as it can identify strong interactions between some parameters and allows statements that are more reliable and feasible.

The Authors would like to wholeheartedly thank the following persons for their support, their insight and open minded discussion during conducting the study: Niels Peter Hoj (Hoj Consulting, CH); Bernhard Kohl (ILF, A); Oliver Heger (ILF, A), Georg Mayer (BUNG, D) and – last but not least – Tineke Wiersma (RWS, NL).

7. REFERENCES

Bundesamt für Strassen ASTRA. (2014). *ASTRA-Richtlinie 19004 - Risikoanalyse für Tunnel der Nationalstrassen.* Bern.

Bundesministerium für Verkehr, Innovation und Technologie. (2015). *RVS 09.03.11 - Tunnel-Risikoanalyse.* Wien.

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivtiy analysis of large models. *Environmental Modelling & Software, Volume 22*, S. 1509-1518.

Chitale, J., Khare, Y. P., Muñoz-Carpena, W., & Dulikravich, G. S. (2019). An effective parameter screening for high-dimensional models.

European Parliament and Council. (2004). *Directive 2004/54/EC of the European Parilament and council of 29 appril 2004 on the minimum safety requirements for tunnels of the trans-European road network.*

Khare, Y. P., Munoz-Carpena, W., & Martinez, C. J. (2015). A multi-criteria trajectory-based parameter sampling strategy for the screening method of elementary effects. *Environmental Modelling & Software, Volume 64*, S. 230-239.

Morris, M. D. (1991). Factorial Sampling Plans for Preliminary Computational Experiments. *Technometrics, Vol. 33*, S. 161-174.

RWS Steunpunt Tunnelveiligheid. (2012). *QRA-tunnels 2.0 - Gebruikershandleiding.* Utrecht.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in Practice - A Guide to Assessing Scientific Models.* Chichester: John Wiley & Sons Ltd.