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Improving cable tray fire modelling with AI techniques

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Abstract. Modelling cable tray fires remains a complex issue, and existing models such as the FLASH-CAT model still have limitations due to the lack of information on certain input data. This paper discusses improvements in cable tray fire modelling by finding appropriate input data using an artificial intelligence (AI) technique. An AI-driven expert system was developed to assess missing data from a fire test database of 29 large scale cable tray fire experiments in open atmosphere. The expert system quantifies the dependencies between input and output data, helps identify influential parameters and refine model inputs. It also guides modelling efforts by identifying areas for model improvement. In this way, the applicability of an expert system in obtaining reliable input data for simulation tools to simulate a real fire scenario that has already been tested is demonstrated. Cable tray fire simulation results show improved accuracy compared with the use of default values for uncertain parameters.

1. Introduction

Cable tray fire modelling remains a complex issue as highlighted by a recent cable benchmark exercise conducted for a realistic cable fire scenario in an electrical system of a nuclear power plant [1]. Given the multitude of parameters involved in the definition of such a fire source, no theory has yet been put forward on how to model all the aspects of the problem, even for simple, open atmosphere conditions. Some approaches in the form of experimental studies [2],[3] and more recently [4],[5] have nevertheless been carried out and an empirical model referred to as FLASH-CAT [3] (short for flame spread over horizontal cable trays) was developed by the NIST for horizontal cable tray fires in open atmosphere. It is a relatively simple model for predicting the growth and spread of a fire within a vertical stack of horizontal cable trays. To perform representative simulations, it is necessary to have all the parameters involved in the definition of cable trays. Unfortunately, in practice this is not the case, either because some parameters have not been measured, or because they are too difficult to measure. In this case, default values are used, leading to a deviation from experimental results. To overcome this difficulty, artificial intelligence (AI) techniques can be used to better interpret the deviations between experimental and numerical results and try to reduce them.

Artificial intelligence can be divided into two components: connectionist artificial intelligence and symbolic artificial intelligence. The first is characterized by machine learning and enables the development of models that cannot be formalized. To achieve good performances, these techniques require large databases. The second aims to represent knowledge and formalize reasoning.

In this paper, we propose a method for using symbolic artificial intelligence (1) to help exploit sparse experimental data corresponding to cable tray fire tests, (2) to distinguish the deviation attributable to imprecision in the data from that due to a poor modelling, (3) to guide modelling work and identify the most relevant experimental measurements to be carried out.

2. Experimental data

The tests considered are large-scale experiments involving the combustion of horizontal cable trays in an open environment. The data have been performed within two projects, the OECD PRISME project steered by IRSN and the CHRISTIFIRE project performed at NIST and are described in publications and technical reports [3], [6]-[8]. The fire consists of a set of cable trays positioned horizontally one above the other, on which unpowered electrical cables are laid to form the combustible material. The generic experimental procedure consists in igniting the fire in the centre of the lower cable tray and following combustion until it is extinguished. Measurements are taken to determine the temporal evolution of the fire's heat release rate (HRR). The parameters of the experiments (see Table 1) concern the physical properties of the cables (type, cable mass per unit length), the dimensions of the cable trays (length, width, vertical spacing between trays), the arrangement of the cables (loose or tight), the number of cables on the trays, and finally the characteristics of the surrounding environment (presence of a side wall or ceiling). The variable of interest is the temporal evolution of HRR. This signal, similar for all tests with a growth phase, a maximum and then a decay phase is characterized by a set of three scalar quantities: the maximum heat release rate (HRR_{max}), the total heat released, corresponding to the integral of HRR (Total heat of combustion, THC), and the fire growth index (FGI), corresponding to the ratio between the maximum value of HRR and the time to reach it. The parameters are the cable type (Thermoset and Thermoplastic), the fuel mass per unit area, the number of cable trays, the cable tray width, the cable tray length, the vertical spacing between cable trays, the number of cables per cable tray, and the cable mass per cable tray.

Table 1. Tests parameters

Institute	Name	Cable					Tray				Cable arrangement		Environment	
		Type	Ref.	D (mm)	Mass (kg/m)	(kg)	n (#)	w (m)	l (m)	h (m)	Number of cables (#/tray)		Wall	Ceiling
IRSN	PR2_CFSS_1	TP	PVC_1	13	0,235	138	5	0,45	2,4	0,3	49	Loose	Yes	-
IRSN	PR2_CFSS_2	TS	HFFR_1	20	0,57	219	5	0,45	2,4	0,3	32	Loose	Yes	-
IRSN	PR2_CFSS_4	TP	PVC_2	14,5	0,32	169	5	0,45	2,4	0,3	44	Loose	Yes	-
IRSN	PR2_CORE_1	TP	PVC_3	28	2	504	5	0,45	2,4	0,3	21	Loose	Yes	-
IRSN	PR3_CFP_S0	TP	PVC_3a	28	1,75	441	5	0,45	2,4	0,3	21	Loose	Yes	-
IRSN	PR3_CFP_S1	TP	PVC_3a	28	1,75	441	5	0,45	2,4	0,3	21	Tight	Yes	-
IRSN	PR3_CFP_S2	TP	PVC_3a	28	1,75	441	5	0,45	2,4	0,3	21	Loose	-	-
IRSN	PRF_BCM_S1	TP	#900	16	0,382	205	2	0,9	2,4	0,45	112	Loose	Yes	-
IRSN	PRF_BCM_S2	TP	#900	16	0,382	205	2	0,9	2,4	0,45	112	Loose	Yes	-
NIST	CF_MT_2	TP	701	14	0,366	116	3	0,45	2,4	0,3	44	Tight	-	-
NIST	CF_MT_8	TP	701	14	0,366	232	4	0,45	3,6	0,3	44	Loose	-	-
NIST	CF_MT_9	TP	701	14	0,366	116	4	0,45	3,6	0,3	22	Loose	-	-
NIST	CF_MT_16	TS	269	12	0,24	138	3	0,45	2,4	0,3	80/30/50	Loose	-	-
NIST	CF_MT_7	TS	16	19	0,671	377	7	0,45	2,4/3,6	0,3	36	Loose	-	-
NIST	CF_MT_17 *	TS	M		0,52	367	7	0,45	3,6	0,3	28	Loose	-	-
NIST	CF_MT_18 *	TS	M		0,52	489	7	0,9	2,4	0,3	56	Loose	-	-
NIST	CF_MT_20 *	TS	M		0,52	367	7	0,9	3,6	0,3	28	Loose	-	-
NIST	CF_MT_22 *	TS	M		0,52	734	7	0,9	3,6	0,38	56	Loose	-	-
NIST	CF_MT_23 *	TS	M		0,52	367	7	0,45	3,6	0,23	28	Loose	-	-
NIST	CF_MT_24 *	TS	M		0,52	367	7	0,9	3,6	0,23	28	Loose	-	-
NIST	CF_HW_1	TP	800	12,4	0,31	236	2	0,45	6,8	0,3	56	Loose	Yes	Yes
NIST	CF_HW_2 *	TS	802/803	15	0,43	234	2	0,45	6,8	0,3	40	Loose	Yes	Yes
NIST	CF_HW_3	TS	802	15	0,42	114	2	0,45	6,8	0,3	20	Loose	Yes	Yes
NIST	CF_HW_4	TP	800	12,4	0,31	118	2	0,45	6,8	0,3	28	Loose	Yes	Yes
NIST	CF_HW_6	TS	816	16,7	0,42	183	2	0,45	6,8	0,3	32	Loose	Yes	Yes
NIST	CF_HW_7	TS	812	16,3	0,54	110	3	0,45	6,8	0,3	10	Loose	Yes	Yes
NIST	CF_HW_8	TP	810	15,2	0,43	175	3	0,45	6,8	0,3	20	Loose	Yes	Yes
NIST	CF_HW_9	TS	824	5,1	0,08	112	2	0,45	6,8	0,3	103	Loose	Yes	Yes
NIST	CF_HW_10 *	TS	803/802	15	0,43	234	2	0,45	6,8	0,3	40	Loose	Yes	Yes

(*) More than one type of cable

Cable type : TP= Thermoplastic - TS= Thermoset

Cable ref. : Details are given in reference [1], [2], [3] and [4] ; M means several type of cables

3. Methodology and tools

3.1. Expert systems

An expert system for cable tray fires is developed to calibrate missing data. It is an artificial intelligence tool capable of reasoning from observed data and generic knowledge, using an inference engine [9]. This tool makes it possible to understand the behaviour of a process (here a cable tray fire) in a given situation. It is done by dynamically crossing the knowledge of the physical phenomena involved, contained in the knowledge base, with the knowledge specific to the experimental set-up. The propagation of the information takes place by means of an inference engine; the algorithmic part of the expert system based on the Bayesian Belief Network methodology [10]. As such, expert systems derive the most likely diagnosis or prognosis of a cable tray fire in negligible time.

A formal representation of the knowledge linking the input data to the output data is produced in the form of a causal graph to which the causal link is quantified using conditional probability tables. This formalism makes it possible to account for the generic information available on a cable tray fire. The quantification of conditional probability tables is based on a large calculation database and is independent of experimental conditions and results. The formalization of the reasoning is based on probabilistic reasoning, which makes it possible to cross generic information with contingent information. Probabilistic reasoning thus forms the algorithmic part of the expert system.

Generic information corresponds to the conditions specific to each experiment, including uncertainties. This information is used as input to the expert system, from which it identifies the most likely values of the parameters and their distributions. The originality of our approach lies in proposing a method that takes account of the dependencies that exist between the input data induced by the observations of the experimental results in a rigorous and systematic way.

The use of an expert system makes much easier to analyse the extent to which the experimental uncertainty can account for or, on the contrary, is insufficient to explain the discrepancies with the numerical model. This enables a richer exploitation of the experimental results and contributes to the identification of needs in terms of experiments to be carried out or numerical models to be developed.

3.2. Cable tray fire modelling

Cable tray fire is modelled with the SYLVIA software [11] which is a two-zone model developed by IRSN to predict the behaviour of mechanical/natural ventilation, fire development, hot gas and smoke propagation, and airborne contamination transfer in confined and mechanically ventilated enclosures.

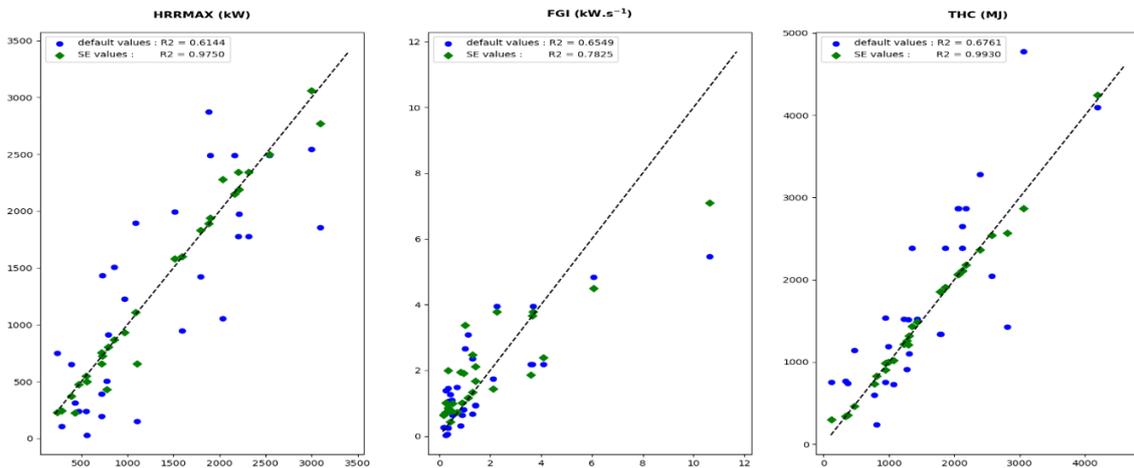
A FLASH-CAT-like model that simulates horizontal cable tray fire [3] was implemented in SYLVIA. Hypotheses used by the FLASH-CAT model suggest that the fire should propagate upward through the cable trays depending on an empirical timing sequence only based on the tray order in the stack model and assumes that, once ignited, the cables burn over a length that is greater than that of the tray below. The burning pattern has therefore an expanding V-shape as there is an increasing length of cable that initially ignites when fire propagates upwards and due to lateral propagation of fire. As the mass of combustible material at the centre of the V is consumed, a horizontal extinction front appears at the centre of the trays and the V-shape becomes an open wedge until the full length of cable is burnt. Since the computation time using SYLVIA is short enough to perform millions of calculations, our approach consists of building a database by performing a Monte-Carlo sampling. This Monte Carlo study is carried out by varying the input parameters of the simulation code. This database is made up of all the data corresponding both to the parameters and responses. It can then be interpreted as a numerical transcription of the generic knowledge carried by the SYLVIA software. Five parameters were considered in the present study, corresponding to uncertain input data of the cable tray fire model: the cable thermal inertia, the fuel mass fraction, the bench-scale HRR per unit of area, the ignition temperature, and the fire spread angle. Their discretisation is reported in Table 2. The parameters considered in this analysis are those used in the FLASH-CAT model. It should be noted that ignition HRR is not taken into account. The responses of interest are: HRR_{max} , FGI and THC. According to the number of parameters, their discretization and the number of realisations required to evaluate histograms of conditional probability tables, 740,000 SYLVIA calculations were performed to build the knowledge base (3 days of CPU time distributed over 60 cores).

Table 2. Parameter discretisation

Parameter	Discretisation
Thermal inertia of cables [$\text{kW}^2/\text{m}^4\text{K}^2$]	[0.2 ; 0.3] [0.3 ; 0.4] [0.4 ; 0.5] [0.5 ; 0.6]
Fuel mass fraction [-]	[0.1 ; 0.2] [0.2 ; 0.3] [0.3 ; 0.4] [0.4 ; 0.5]
Bench-scale HRR per unit area [kW/m^2]	[100 ; 150] [150 ; 200] [200 ; 250] [250 ; 300]
Ignition temperature of cables [$^{\circ}\text{C}$]	[200 ; 240] [240 ; 280] [280 ; 320] [320 ; 360]
Fire spread angle [$^{\circ}$]	[0 ; 15] [15 ; 30] [30 ; 45]

4. Simulation results

The expert system is used as a diagnostic tool. Only knowledge relating to the responses (experimental results through HRR_{max} , FGI and THC) is used as input data and the expert system informs us of the most likely values of uncertain parameters (cf. Table 2). This operation is repeated for all 29 fire tests. The results are shown in Figure 1 for each of the responses of the study, in the form of parity plots for calculations performed with default values of the uncertain parameters and calculations refined by AI.

**Figure 1:** Comparison between simulations and experimental data for the 3 responses

The use of default values for some input parameters led to deviations from experimental data for the 3 responses of interest (R^2 scores less than 0.68). The expert system informs us that of the five uncertain input parameters, one or more are influential on the responses of interest. The Pearson's correlation coefficients [12] were used to determine the degree of influence of parameters. Results are shown in Figure 2. For the THC response, the only influential parameter is the fuel mass fraction, the other parameters playing a role in the kinetics of the fire development. The five parameters have the same weight on the HRR_{max} response, which requires information on all the parameters for a good estimation of the instantaneous burning surface area. Indeed, the fuel mass loss rate plays a role on the position of the extinction front, the bench-scale HRR per unit surface, on the HRR level, the fire spread angle, on the ignition length of cables, and the thermal inertia of cables and the ignition temperature, on the fire spread velocity. In the original FLASH-CAT model, the fire spread velocity is a user input while in SYLVIA it is calculated. For the FGI response, the most influential parameter is the bench-scale HRR per unit surface which, in addition to playing a role in the HRR, also plays a role in the time to reach HRR_{max} , through the radiative heat flux from flames to the cable surface for the fire spread within the stack. In the original FLASH-CAT model a "minute rule" is used for the spread of the fire within the stack. In SYLVIA, thick targets, whose thickness corresponds to that of the cable sheath, are used for the spread of the fire within the stack. Targets exchange with the surrounding gas by convective and

radiative heat transfers and by conductive heat transfer in their thickness. The ignition of cables is then operated on a temperature criterion, corresponding to the temperature of the mesh in contact with the inner face of the target. In this way, the ignition of the cables is related to the thermophysical properties of the combustible, ambient conditions, and incident heat fluxes.

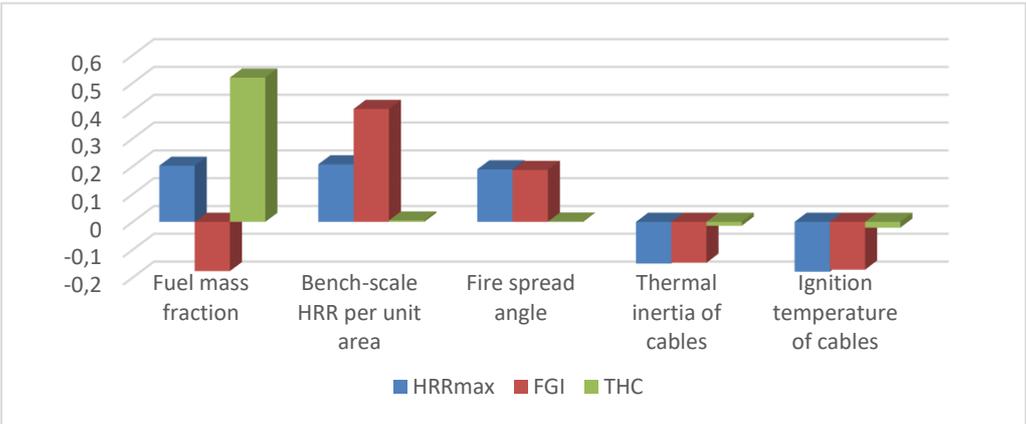


Figure 2: Influence of parameters on responses of interest

Using AI, new values are assigned to uncertain parameters. The R2 score increased from 0.61 to 0.97 for HRR_{max} and from 0.67 to 0.99 for THC. For the FGI response, even though the R2 score increased from 0.65 to 0.78, the expert system informs us that this response is poorly modelled and that improvements need to be made. Indeed, a uniform ignition of cables across the entire width of the cable tray is assumed (1D flame propagation) in the model. Depending on the width of the cable tray, the ignition of the cable may not be uniform along the entire length of the cable tray. In addition, in SYLVIA obstacles along an optical path (such as cable trays) are not considered in the radiative heat transfer from flames to the cable surface, resulting in an error in the ignition delay of cable trays.

To assess their physical relevance, the input data optimized by the expert system is compared with the default data. Figure 3 shows the results for 3 inputs, comparing the distribution of optimized values with the default value(s). For the fuel mass fraction, the value that best reproduces the experimental results may be significantly different from the default value. This indicates that this parameter may be the cause of modelling that is too far from experiment. The findings on the other two input quantities also indicate that the default values are probably too restrictive to reproduce the experiments.

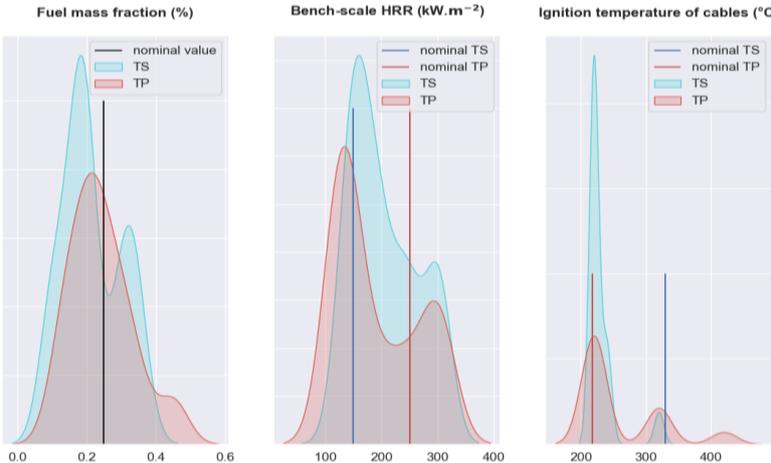


Figure 3: Comparison between the probability density functions of three input parameters (mass fraction, the bench-scale HRR per unit of area and ignition temperature) and their default values for thermoset (TS) and thermoplastic (TP) cables

5. Conclusion

Modelling cable tray fires remains a complex issue, given the multitude of parameters involved in defining such a fire source. To overcome the difficulty of obtaining reliable input data on cable tray fires, an AI-driven expert system was developed to analyse experimental uncertainties and guide modelling efforts by identifying areas for model improvement. Expert systems are powerful tools for improving the representativeness of simulations by identifying the most relevant parameters, as highlighted in this paper. The variability of the default values of the uncertain parameters was also highlighted, indicating that using the same default values to simulate all the fire tests is too restrictive to reproduce the experiments.

Expert systems based on Bayesian networks are ergonomic and comprehensible tools because they use symbolic AI based on formal reasoning that is easy to interpret. This is fundamental for modellers, who cannot be satisfied with experimental results alone. They need to understand the progression of phenomena that led to the result. In this way, expert systems act as a bridge between experimenters and modellers, ensuring a deeper understanding of modelling outcomes and driving further improvements in fire safety simulations.

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