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Review

A Review of Modelling and Simulation Methods for Flashover Prediction in Confined Space Fires

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Abstract: Confined space fires are common emergencies in our society. Enclosure size, ventilation, or type and quantity of fuel involved are factors that determine the fire evolution in these situations. In some cases, favourable conditions may give rise to a flashover phenomenon. However, the difficulty of handling this complicated emergency through fire services can have fatal consequences for their staff. Therefore, there is a huge demand for new methods and technologies to tackle this life-threatening emergency. Modelling and simulation techniques have been adopted to conduct research due to the complexity of obtaining a real cases database related to this phenomenon. In this paper, a review of the literature related to the modelling and simulation of enclosure fires with respect to the flashover phenomenon is carried out. Furthermore, the related literature for comparing images from thermal cameras with computed images is reviewed. Finally, the suitability of artificial intelligence (AI) techniques for flashover prediction in enclosed spaces is also surveyed.

Keywords: flashover; artificial intelligence; CFD software; prediction; thermal vision camera; thermal image

1. Introduction

Enclosure or confined fires are situations that firefighters are used to handling. The consequences of this type of emergency can involve people and structures. A confined fire is one that takes place inside structures such as blocks of houses, garages, single-family homes and commercial establishments. The last International Association of Fire and Rescue Services (CTIF) study [1] suggests that 35% of fires (see Figure 1) located in several cities around the world are structure fires. These kinds of emergencies caused civilian (non-fire service) deaths, civilian fire injuries and property damage. Currently, the reported data about this phenomenon in Europe is very poor. This is because there is not a common database which involves all European countries and most of the fire services do not document such situations. An example of this is the study carried out by the European Fire Safety Alliance (EFSA), which only involves nine countries. Table 1 shows an overview of the results from research [2] carried out for EFSA related to residential fires.

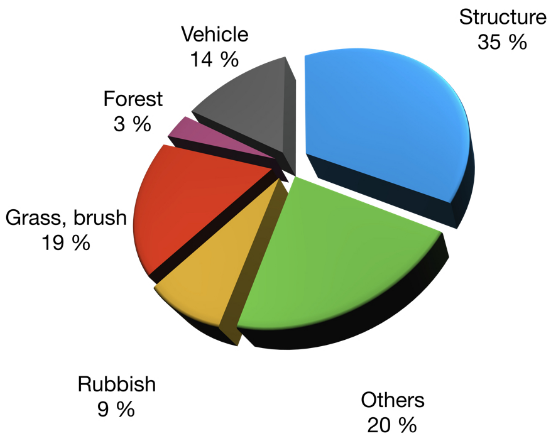


Figure 1. Distribution of fires by types. International Association of Fire and Rescue Services by Center of Fire Statistics of CTIF 2018 [1].

Table 1. Population, fatalities per capita per year and percentage of fatal fires in selected European countries [2].

Country	Population (Million)	Fatalities Per Capita Per Year (Approx.)	% Fatal Fires (Related to All Residential Fires)
Belgium (2014–2015)	11.4	0.6 per 100.000	0.5%
Denmark (2011–2012)	5.8	1.1 per 100.000	1.2%
Estonia (2013–2017)	1.3	3.7 per 100.000	4.6%
Finland (2011–2012)	5.53	1.4 per 100.000	
Netherlands (2011–2014)	17	0.2 per 100.000	0.6%
Norway (2016–2017)	5.3	0.5 per 100.000	1.3%
Poland (2011–2012)	38	1.3 per 100.000	
Sweden (2011–2013)	10	1.1 per 100.000	1.2%
UK (2014)	66	0.6 per 100.000	
Total	160.3		
Total Europe	742.9		

To compare these results with data from another continent the reader can refers to the National Fire Protection Association (NFPA [3]) statistics. According to NFPA, during the five-year period between 2010–2014, USA fire departments responded to an estimated annual average of 358,300 home structure fires. These kinds of emergencies caused an annual average of 2520 civilian (non-fire service) deaths, 12,720 civilian fire injuries, and US$ 6.7 billion in direct property damage. On average, seven people died each day in the US in home fires during this period. Currently it is very difficult to obtain accurate data to evaluate confined space fires in Europe, because there is no database available for this dangerous type of emergency. Furthermore, there is no data available on how this type of enclosure fire affects emergency teams, materials or victims.

In order to get some idea of the risk for people involved in these situations, Table 2 provides a more detailed breakdown of losses by occupancy in two types of buildings, family homes and buildings. 70% reported home structure fires and 84% of the fatal home fire injuries occurred in one- or two-bedroom family homes, including manufactured homes.

Table 2. Reported home structure fires by property use (NFPA [3]), 2010–2014 annual averages.

Property Use	Fires	Civilian Deaths	Civilian Injuries	Direct Property Damage (in Millions)
One- or two-family homes, including manufactured home [1]	250,500 (70%)	2100 (84%)	8440 (66%)	$5,438 (81%)
Other multi-family housing [2]	107,800 (30%)	410 (16%)	4280 (34%)	$1271 (19%)
Total	358,300 (100%)	2520 (100%)	12,720 (100%)	$6710 (100%)

[1] One or more bedrooms are considered; [2] dwellings, duplexes, manufactured homes (also called mobile homes), apartments, terraced-houses and townhouses. Other residential properties, such as hotels and motels, dormitories, barracks, rooming and boarding homes and the like are not included. One or more bedrooms are considered.

A compartment fire [3] is one that takes place inside an enclosed area, such as a house, in which two circumstances can occur:

- The enclosure is ventilated, the oxygen consumption is less than the available amount.
- The room is under-ventilated (lack of inlet air or lack of an outlet for the smoke). During the combustion process, oxygen levels in the enclosure decrease. No open vents or oxygen displacement by combustion gases can be the causes.

To understand the combustion process in the enclosure it is necessary to introduce the reader to fuel-controlled (FC) and ventilation-controlled (VC) concepts. If there is sufficient oxygen to consume the fuel pyrolysis gases released, this is known as an FC scenario. Conversely, if there is lack of oxygen to continue the reaction, this is a VC situation. Taking into account both enclosure situations (ventilated and under-ventilated), once the ignition in a material has occurred, there a several ways in which the situation may evolve. In a ventilated enclosure, if the fire dies after ignition, this can be because the energy released is not sufficient to further pyrolysis in the same material or in nearby materials. For that reason it is not possible for the fire to spread (FC). Alternatively, if the enclosure is under-ventilated, the lack of oxygen in early stages can result in a non-adequate mix with the fuel gases impeding the combustion process (VC). Another possibility is when the heat released from the flames is enough to generate new pyrolysis gases from new unburned material and sufficient oxygen is present to maintain the combustion process. Subsequently, fire reaches the growing stage, where fire can spread over the same surface as flames spread or reach other surface materials by radiation. In a ventilated confined space, all fuel can be burned and fire dies or a transition from FC to VC can take place causing the fire to die out due to lack of oxygen. In some cases, the fire can grow to become a fully developed fire after a transition stage known as flashover.

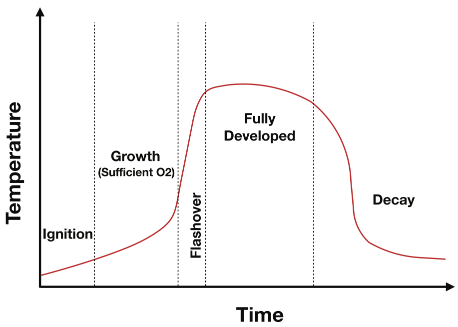
Flashover phenomenon, or also called generalised sudden combustion, can be defined as a transition phase from growth to fully developed stage (see Figure 2a). As a consequence, all combustible surfaces inside the enclosure, that were not involve in the fire, begin to burn. It occurs due to the radiation received from the smoke layer which can be up to 170 kW/m^2 [4]. Once all fuels are involved in the fire the fully developed stage is reached. As a result, firefighters can't stay inside the enclosure under flashover conditions, 80 kW/m^2 is the maximum supported radiation by their clothes according to NFPA 1971, Standard on Protective Ensemble for Structural Fire Fighting. In the Table 3 different radiation values are shown, and they can be compared to the maximum heat flux for a post-flashover case in order to get an idea of this phenomenon's power.

Table 3. Approximate radiant heat flux [4].

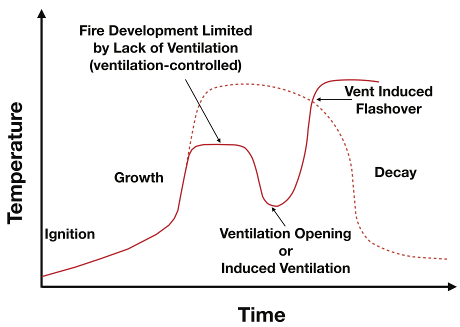
Approximate Radiant Heat Flux (kW/m^2)	Comment or Observed Effect
170	Maximum heat flux as currently measured in a post-flashover fire compartment.
80	Heat flux for protective clothing Thermal Protective Performance (TPP) Test. [1]
52	Fiberboard ignites spontaneously after 5 s. [2]
29	Wood ignites spontaneously after prolonged exposure. [3]
20	Heat flux on a residential family room floor at the beginning of flashover. [4]
16	Human skin experiences sudden pain and blisters after 5-s exposure with second-degree burn injury. [5]
12.5	Wood volatiles ignite with intended exposure [6] and piloted ignition.
10.4	Human skin experiences pain with 3-s exposure and blisters in 9 s with second-degree burn injury. [7,8]
6.4	Human skin experiences pain with a second exposure and blisters in 18 s with second-degree burn injury. [9,10]
4.5	Human skin becomes blistered with a 30-s exposure, causing a second-degree burn injury. [11]
2.5	Common thermal radiation exposure while fire fighting. [12] This energy level may cause burn injuries with prolonged exposure.
1.4	Thermal radiation from the sun. Potential sunburn in 30 min or less. [13]

[1] From NFPA 1971, Standard on Protective Ensemble for Structural Fire Fighting; [2] From Lawson, "Fire and the Atomic Bomb."; [3] From Lawson, "Fire and the Atomic Bomb."; [4] From Fang and Breese, "Fire Development in Residential Basement Rooms."; [5] From NFPA 1971, Standard on Protective Ensemble for Structural Fire Fighting; [6] From Lawson and Simms, "The Ignition ofWood by Radiation," pp. 288–292; [7] From NFPA 1971, Standard on Protective Ensemble for Structural Fire Fighting; [8] From Lawson, "Fire and the Atomic Bomb."; [9] From NFPA 1971, Standard on Protective Ensemble for Structural Fire Fighting; [10] From Tan, "Flare System Design Simplified," pp. 172–176; [11] From NFPA 1971, Standard on Protective Ensemble for Structural Fire Fighting; [12] From U.S. Fire Administration, "Minimum Standards on Structural Fire Fighting Protective Clothing and Equipment."; [13] From Bennett and Myers, Momentum, Heat, and Mass Transfer.

The NFPA [4] also defines flashover as the transient phase in the development of an indoor fire in which surfaces exposed to thermal radiation reach their ignition temperature almost simultaneously and the fire spreads rapidly throughout the space available within the enclosure.



(**a**)

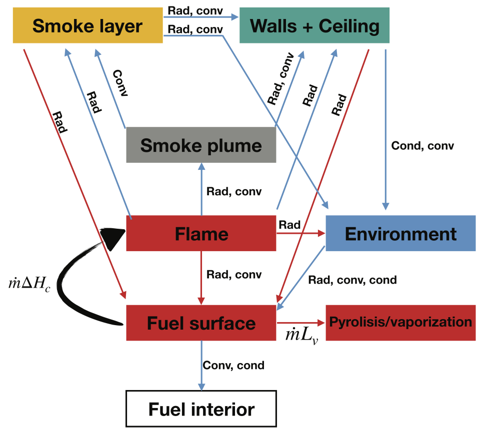


(**b**)

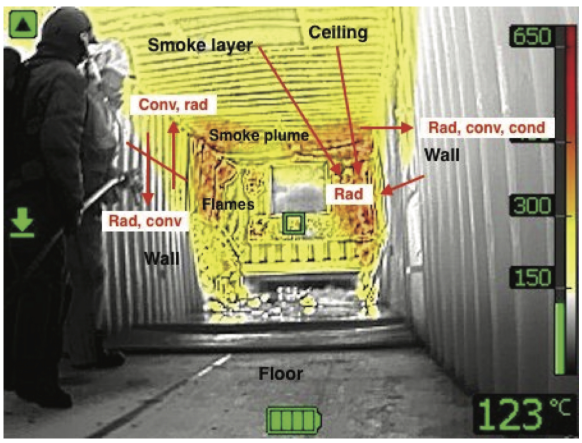
Figure 2. Flashover and ventilation induced flashover. (**a**) Flashover representation as a transition phase in the fire standard curve before the fully developed fire stage in an enclosure (**b**) Ventilation induced flashover representation.

Flashover can occurs in two different scenarios related to the enclosure configuration and it depends on the fire is located inside a structure with constant air supply or not. The first one known as a fuel-limited fire is shown in the Figure 2a. In the growth stage there is enough oxygen to maintain the combustion process. If amount of fuel involved is sufficient therefore the energy level necessary for the occurrence of flashover can be reached followed by the full developed phase. Then, as the fuel is burned away, the energy level begins to decay. Once the fully developed phase is achieved, in most cases the fuel mass release rate becomes so high that the air supply rate becomes insufficient to consume all released pyrolysis gases (fuel-controlled to ventilation-controlled) [5] and the energy level begins to decay. On the second one (see Figure 2b), classified as under-ventilated situations, flashover stage can be reached after a fire dynamics change. It can be produced as a consequence of an induced ventilation or opening a vent in the structure such as door or window. Furthermore, due to the high quantity of radiation necessary to reach the flashover stage a minimum amount of fuel is necessary to produce it. In addition, the value of the energy generated by indoor fires with a single opening through which the air inlet and gas outflow are channelled can be approximate using the Kawagoe equation [6].

Currently, fire services use thermal image cameras (TIC) in different types of emergencies related with fire and rescue [7]. Furthermore it can provide value real-time information during a enclosure fire. However, the prediction of this phenomenon is not easy and on many occasions it could be a problem for firefighter teams who risk their lives in this situations. The focus of this review is on certain types of fires in confined spaces where flashover phenomenon is likely to occur [4]. In these emergencies, firefighters try to anticipate this situation by reading enclosure fire dynamics (e.g., see Figure 3) tracks. Sometimes this is not possible due to the rapid response multitasking nature of the emergency and the corresponding stress that these situations generate for the firefighter. Attempting a prevention of the flashover phenomenon described in this paper, the firefighter handling the TIC normally tries to monitor the temperature of the hot gas layer to detect changes in the environment. However, this method is not very accurate because flashover depends on multiple factors such as compartment configuration, fuel and ventilation, among others, and most importantly, the human factor. Another reason is that temperature acquisition with a TIC does not work in the same way when a smoke layer is present. This is because the temperature shown by the camera is the reflection temperature and not the inside temperature of the smoke layer. For instance, carbon particles or water vapour can reflect the visible light interfering in the image acquisition process. On the other hand due to the long wave of infrared light it is not easily reflected by smoke layer particles.



(a)



(b)

Figure 3. Enclosure effects on heat transfer in a fire container. (**a**) Schematic overview: Blue arrows indicate heat transfer, which is not used in the fire process; 'rad' refers to radiation, 'cond' refers to conduction and 'conv' refers to convection. The curved arrow refers to the mass flow rate of combustible gases [5]. (**b**) Thermal image of enclosure effects in a fire container during a firefighting training at San Vicente Fire Station, Alicante, Spain.

In view of the previous discussion, it is worthwhile mentioning the potential for using AI to predict this phenomenon. For this reason, this paper reviews work which has applied AI in similar situations. Through AI techniques, which focus on the study of intelligent agents, a device can take actions that maximise the chances of successfully completing a task based on environment perception. Nowadays AI techniques, such as flame detection [8,9], fire spread [10], fire and smoke classification [11], flashover occurrence [12,13], thermal interface location in a single compartment fire [14] or temperature and velocity profiles [15] among others, have been proven to predict certain fire-related situations. Different approaches have been used to research fire prediction, the most commonly adopted approach is artificial neural networks (ANN). ANN are computing systems usually used to find complex relationships between a source (input) and a target(output). Furthermore, research about fire science including this technology can be found. For example, in image recognition, they might learn to identify images containing fire by analysing example images and using the results to detect fire in other images [16]. Related to image dataset, convolutional neural networks (CNN) seems to be more effective to find highly accuracy patterns. It is noteworthy to mention that it is very difficult to find a useful data set of real flashover emergencies. To address this interesting point, this paper reviews research that used synthetic data obtained from simulations.

The main contribution of this manuscript is to conduct a review of the literature related to the modelling and simulation of enclosure fires with respect to flashover phenomenon. This is very important to be aware of the transcendence of the phenomenon as well as to analyze how technological innovation can contribute to predict it.

The outline of this paper is as follows. Firstly, research related with flashover modelling and simulation techniques is reviewed. Secondly, the cutting edge technology for comparing synthetic images with real images from thermal imaging cameras is revised. Third, the models that have been developed to predict flashover are reviewed. Fourth, we include a results and discussion section, where the key points of each section are treated. Conclusions and future lines of work can be consulted in the last section.

2. Modelling and Simulation of Flashover Phenomenon

This section provides a recap on the research related to flashover phenomenon and Computational Fluid Dynamics (CFD) techniques that simulate this situations.

2.1. Flashover Modelling

Physical and chemical causes determine the appearance of this phenomenon. In this line, research have been carried out to know what is happening inside the enclosure. For this reason is interesting to list previous most relevant work in this area to introduce the reader. Starting with Ingberg's research in 1928 [17] many studies in enclosure fires have been carried out in the last decades on compartment fires. Table 4 shows relevant studies about enclosure fires since 1928 to the present. Specially those related to flashover phenomenon.

Table 4. Relevant work about fire dynamics in enclosures.

Title	Source	Year	B and References
Tests of the Severity of Building Fires	NFPA	1928	Ingberg et al. [17]
Fire Behaviour In Rooms	Building research institute, Japan	1958	Kawagoe et al. [6]
Room flashover—Criteria and synthesis	Fire Technology	1968	Waterman et al. [18]
The Fire Resistance Required to Survive a Burnout	Fire Research Station	1970	Thomas et al. [19]
Experimental Study of Small Enclosure Fire with Liquid Fuel	Japan Natural Resources Panel on Fire Research and Safety	1976	Takeda, Nakaya & Akita et al. [20]
An Experimental Study of flashover Criteria for Compartment	Stanford Research Institute	1979	Martin & Wiersma et al. [21]
Flashover and Instabilities in Fire Behavior	Combustion and Flame	1980	Thomas, Bullen, Quintiere & McCaffrey et al. [22]
Estimating Room Flashover Potential	Fire Technology	1981	Babrauskas et al. [23]
Fire induced flows through room openings-flow coefficients	Symposium (International) on Combustion	1985	Steckler, Baum & Quintiere et al. [24]
Fires in compartments: The phenomenon of flashover	Royal Society	1998	Bishop & Drysdale et al. [25]
Defining flashover for fire hazard calculations	Fire Safety Journal	1999	Peacock, Reneke, Bukowski & Babrauskas et al. [26]
On the equations for flashover fire in small compartments	International Journal on Engineering Performance-Based Fire Codes	2001	Huo, Jin, Shi & Chow et al. [27]
Combustion and heat transfer in compartment fires	Numerical Heat Transfer, Part A: Applications	2002	Yeoh, Yuen, Chen & Kwok et al. [28]
Defining flashover for fire hazard calculations: Part II	Fire Safety Journal	2003	Babrauskas, Peacock & Reneke et al. [29]
On modelling combustion, radiation and soot processes in compartment fires	Building and Environment	2003	Yeoh, Yuen, Chueng & Kwok et al. [30]
Heat fluxes and flame heights in façades from fires in enclosures of varying geometry	Proceedings of the Combustion Institute	2007	Lee, Delichatsios & Silcock et al. [31]
An experimental study of the rate of gas temperature rise in enclosure fires	Fire Safety Journal	2011	Chen, Francis, Dong & Chen et al. [32]

Quantitative studies of flashover were first reported in the mid-1960s [18]; since then, more studies have attempted to formulate guidelines for the occurrence of flashover based on different simplifications [20]. Due to the complexity of this phenomenon and considering the flashover phenomenon at the beginning of post-flashover stage, a simplified approach is preferred (it is convenient to consider a specific model developed for this case) rather than a general one. A model for the estimation of room flashover potential was suggested by Babrauskas et al. [23] by determining experimentally the occurrence of this phenomenon when the upper gas layer temperature reaches 550–650 °C (823–923 K). The procedure suggests the simplest expedient for measuring mass loss rates, namely under free-burn conditions. It was concluded that the relationship between heat release rate and flashover potential is significant. Not only is the temperature of the gas layer related to the flashover occurrence but also heat flux at floor level is another factor to be considered. In research conducted by Peacock et al. [26] the experimental basis for working definitions of flashover was evaluated. Comparisons of available calculation procedures, ranging from simple correlations to computer-based fire models that can be used to estimate flashover were presented. It was concluded that flashover can occur when upper gas temperature is ≥600 °C or heat flux at floor level is ≥20 kW/m^2 depending upon on the materials and room simplified mass and energy balance. In this case, full-scale experiments were conducted in an enclosure $\leq 16\ m^2$ with a specified kind of fuel. In the same vein, the area and location influence of ventilation sources in the fire compartment (ventilation factor) was evaluated by Huo et al. [27]. The equation, which describes flashover, was studied to apply the results for a better design of small commercial establishments to improve safety. The authors relied on the two-layer model to explain that when the flashover occurs, the fire changes from fuel-controlled to ventilation-controlled. These methods—Kawagoe [6], Babrauskas [23], Thomas [22] and B. J. McCaffrey [33]—were also analysed and revealed different ways to find the value of the critical heat for the occurrence of flashover. In [27], ventilation factor was evaluated with an experiment using three different sizes of diesel pool fires. The experimental studies carried out by [27] were in a small compartment of length 4 m, width 3 m and height 3 m. The chamber was constructed with double layers of fire-rated and a 7 mm thick Gypsum board was used for the experimental study. The door measures were 1.6 m in width and 2.2 m in height. Their experiments were compared to results obtained from different equations proposed by [6,23,33,34]. This study concluded with an equation for calculating the critical heat release rate (HRR) for flashover occurrence in a small chamber, taking into account the ventilation factor for large openings.

Another key factor for the occurrence of flashover is HRR/time relation. Babrauskas et al. [29] concluded that this relation largely determines the occurrence of flashover. For this work an ISO 9705 [35] sized compartment vent was used (the test room dimensions were 2.4 m $\times$ 3.6 m $\times$ 2.4 m and it contained a single 0.8 m $\times$ 2.0 m high doorway), and experimental data were compared to computer simulations. Both have in common that shorter times increase the HRR at the onset of flashover for both a temperature-based and heat-flux-based definition of flashover. According to this study, for future research on room fires, apart from HRR value, the conditions and geometry of the fire plume, upper layer and compartment surfaces may be broadly defined for a deep knowledge of the pre-flashover phase. Regarding heat transfer importance in compartment fires, Yeoh et al. [30,36] concluded that the effect of the thermal radiation was decisive for flame temperature predictions. To reach this conclusion, different single-, two- and multi-compartment configurations were analysed and the authors highlighted the weight of wall heat transfer in enclosure fire predictions. Soot radiation was found to augment the radiation absorbed and emitted by combustion products.

2.2. Flashover Simulation

Previously, the problem of obtaining real data from this phenomenon and the possibility of using synthetic data if neural networks want to be applied to make a prediction has been commented. In this section research in this line is reviewed including those in which the flashover phenomenon has been simulated.

Confined fires have been extensively studied by the fire science community in order to improve numerical modelling techniques. Research oriented towards improving fire extinguishing systems, personal safety or material behaviour can be consulted among others. Related with flashover, full scale experiments are expensive due to the high quantity of materials and facilities involving. In addition to that they are very polluting for the environment, therefore most of these studies has been carried out in small structures. Subsequently, different numerical models were developed to have a deep knowledge of fires, having special relevance the application of computer simulation techniques. Furthermore, the information about real situations related to flashover phenomenon is very poor. Not all fire services document this kind of emergencies sufficiently and there are problems to obtain technical data related with real cases of these emergencies. Different scenarios can be simulated by varying enclosure and combustion parameters, number and dimensions of vents and environmental conditions. However, fire simulations must be employed in a responsible and acceptable way and users must have knowledge of the model and fire behaviour [37].

After evaluating different existing techniques related to fire simulation (algebraic correlations, two Zone Models or Lumped Parameter Models [38] and CFD or Field Models) we have considered to review in this article the CFD models. Field Models approximate a space as a large number of discrete volumes. Furthermore it is capable to simulate complex confined fires scenarios and high quantity of research has been carried out to validate different CFD models. Considering the time spent to perform the simulations, most of the studies reviewed in this paper have used computational fluid dynamics techniques for their research including large eddy simulation (LES) technique (e.g., [30,39]). LES has the capacity of reducing the computational cost by ignoring the smallest length scales, which are the most computationally expensive to resolve, via low-pass filtering of the Navier–Stokes equations and to capture essential time-resolved information. Fire chemistry and soot formation and combustion processes has to be resolved to complete the fire model.

CFD software gives the possibility to obtain similar structured data to that of a vision thermal camera. For this reason and given its simulation accuracy the most relevant researches using this technology is reviewed in this section. Much research has been carried out to validate these tools comparing the results with real experiments or other kinds of models. In this line, in the following research [40] conducted by Chow et al., a comparison among zone and field models, about a common atrium building in Hong Kong, was carried out. The four zone models used for this study are: FIRST, CFAST, CCFM.VENTS model developed at the Building and Fire Research Laboratories (NIST, USA) and the NBTC one-room model of FIRECALC developed at CSIRO, Australia. The field model was a self-made fire field model based on computational fluid dynamics theories. While for a quick estimation of probable smoke layer thickness and temperature in a confined fire any of the above mentioned four models can be used, the author highlights the potential of computational fluid dynamics models over zone models to illustrate the simulations. Despite computing time being higher for this kind of simulation, the detailed analysis of the thermal environment was better. Furthermore, in order to validate different CFD models Yeoh et al., performs a series of experiments [28,30,36]. In one of them [28], two independent datasets (Lewis numerical results and Steckler experimental measurements) were used to successfully validate Fire 3D (CFD model), quantitative predictions about velocity and temperature fields in enclosure fires. Furthermore, a comparison among Steckler's experimental data [24] (which had been extensively used as a benchmark to validate various mathematical/computer fire models) and two other types of CFD software data simulations(ANSYS CFX-5 and FDS) were made to test ANSYS CFX-5 by Kumar et al. [41]. Some aspects of the simulations were compared and ANSYS CFX-5 CFD tool results agreed reasonably well with the measured fire data. The fire model provided reasonable predictions of the thermal flow fields under fully ventilated conditions. The time spent by ANSYS CFX-5 during the process was shorter compared to FDS. It was concluded that the understanding of the fire dynamics and advances made in numerical methods and computer hardware would have a significant impact on the performance of CFD fire models in the future. In addition, numerical simulations were carried out by Zhao et al. [42] to investigate the accuracy of fire dynamics simulator (FDS) in poorly ventilated fires with external flame. This study demonstrated the accuracy obtained with FDS software [43] to calculate and reproduce this kind of phenomenon. The results were validated with two methods, one of them based on temperature and the other one based on the volumetric heat release velocity. To carry out this study 32 simulations were accomplished for different opening geometries: 0.1 m $\times$ 0.2 m; 0.2 m $\times$ 0.2 m; 0.2 m $\times$ 0.3 m; and, 0.3 m $\times$ 0.3 m. The accuracy of the results obtained was discussed, comparing experimental data with empirical correlations. FDS proved to be capable of reproducing the neutral plane height for the various configurations with high degree of accuracy. Nevertheless, authors noticed some uncertainty at the level of the experimental data, since the HRR inside the enclosure could not be measured directly.

Several studies have carried out simulations of flashover with CFD techniques. As can be consulted in the previous paragraph, FDS has proved its capability to make accuracy simulations. Furthermore anyone can use this technology as it is a free software. On the following lines, research which have used this software to carry out flashover simulations is reviewed. Chow et al., conducted research [44] to evaluate the accuracy of FDS 3.01 in terms of simulating this phenomenon. Full-scale experiments to validate it were carried out in a compartment similar in size to the ISO-9705 room calorimeter. Necessary heat release rates were provided by gasoline pool fire of different diameters and ventilation factors, both of which were adjusted to produce the flashover in the enclosure. The criterion to determinate whether flashover occurs was to assume to be ≥550–600 °C adjacent to the ceiling and ≥20 kW/m^2 at floor level. After performing the full-scale experiments the results were compared with the simulated flashover fires, and they showed that FDS can be used to simulate flashover. Subsequently, in the work of Mackay et al., a series of computational models [45] using FDS 5 code were developed to design training activities on the flashover phenomenon for firefighters of the NSW (Australian) fire brigade. In this case the criterion to determinate the occurrence of flashover was ≥600 °C , taken adjacent to the ceiling but not heat release rate sensor was included in the real experiment. The full-scale experiment was conducted in a shipping container with dimensions 2.4 m by 12 m by 2.6 m, which is normally used by firefighters to perform their training. Wooden boards were used as a fuel and the experiments were carried out during a training day. The simulation results concurred with the qualitative experimental data. FDS produced higher temperatures of up to 100 °C, a fact that was expected since fire suppression was included in the experimental results. Another interesting approach [46] was provided by Yuen et al., a fire scene investigation—at aged-care facilities—was carried out using CFD techniques. The fire field model FDS 5.5.3 was adopted in this study and the simulations were compared with full-scale experimental data. For this research the flashover criterion was ≥600 °C, taken at around 10 mm below the ceiling and the approximate minimum heat release rate of 2175 kW by Thomas's criterion [22]. Six simulation cases were performed to investigate the possible ignition location that could result in the final state of the fire scene. The CFD results concurred with the experiments and the fire's development in the compartment room was described. Fire spreading and flashover were successfully modelled by FDS. Nevertheless, the author highlights that the problem of kinetic scarce data in the FDS pyrolysis model cannot fully represent the fire's complete behaviour. In light of this, an alternative method [47] was proposed by Evergren et al. to determine temperatures in the pre-flashover phase confined fires. After comparing the results obtained with the simulation software FDS the authors of this prediction model concluded that it is possible to predict temperatures in considerably less time compared to computer simulation software in confined fires in the pre-flashover phase.

Table 5 shows a summary of the references cited in this section related to fire modelling and simulation. The reader can see at a glance if the reference is related to modelling or simulation, as well as what are the most important techniques and software used for the simulations and deployment of TIC.

Table 5. Reference summary about modelling and simulation of flashover phenomenon.

Authors & References	Modelling	Simulation	Research Techniques					Simulation Software			TIC
			Theoretical	Empirical		CFD	Other	FDS	ANSYS	Other	
				Reduce-Scale	Full-Scale						
Babrauskas et al. [23]	✓	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗
Peacock, Reneke, Bukowski, & Babrauskas et al. [26]	✓	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗
Yeoh, Yuen, Chen & Kwok et al. [28]	✗	✗	✓	✗	✓	✓	✗	✗	✗	✓	✗
Babrauskas, Peacock & Reneke et al. [29]	✓	✗	✓	✗	✓	✓	✗	✗	✗	✗	✗
Yeoh, Yuen, Chueng & Kwok et al. [30]	✗	✗	✓	✗	✓	✓	✗	✗	✗	✓	✗
Yeoh, Yuen, Lo & Chen et al. [36]	✗	✗	✓	✗	✓	✓	✗	✗	✗	✓	✗
Evegren & Wickström et al. [47]	✓	✓	✓	✗	✓	✓	✓	✗	✗	✗	✗
Zhao, Beji & Merci et al. [42]	✗	✓	✓	✓	✗	✓	✗	✓	✗	✗	✓
Mackay, Barber & Leonardi et al. [45]	✗	✓	✗	✗	✓	✓	✗	✓	✗	✗	✗
Chow et al. [40,41]	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗
Aravind Kumar, Kumar & Jain et al. [41]	✗	✗	✗	✗	✗	✓	✗	✓	✓	✗	✗
Yuen, Yeoh, Alexander & Cook et al. [46]	✗	✓	✗	✗	✓	✓	✗	✓	✗	✗	✗
Sudheer, Saumil & Prabhu et al. [48]	✗	✗	✓	✓	✗	✓	✓	✓	✗	✗	✓

3. Comparing Fire Dynamics Simulator Data with Thermal Camera Images

In order to create a useful dataset from simulated images with predicting purposes, is important to be sure that the image obtained is similar to images from the thermal image camera. To this end, some researchers who have used this method with good results are cited in this section.

To test thermal camera imaging acquisition data with CFD, Shudheer et al. [48] employed an infrared thermal camera for the temperature distributions measurement of gasoline open pool fires and numerical studies were conducted using FDS software. Centreline temperature distribution of numerical simulation and the temperature distribution from the experimental results were compared. Moreover, regarding the importance of validating FDS to simulate non-premixed flames, it is necessary to build a central plane temperature distribution and emissive power distribution from the radiometric thermal image. It is important to note that an infrared camera can only observe the total radiation intensity of the flame falling on to the sensor but not singularly the central plane and for this reason, it is necessary to do a conversion (see Figure 4) for comparing it with the simulation. Narrowband radiation model techniques and radiative transfer equations were used for this purpose in this research. Finally, numerical simulations were validated using the experimental measured heat flux and TIC radiation images. In this research area, comparative studies of measured and computed images were carried out in [49–51]. These studies focused on different flame types. Images rendered of radiation intensity were compared with measured images from TIC. The authors concluded that simulated and measured images display similar qualitative features. These studies suggest that is possible to acquire images from CFD software including camera parameters for obtaining similar images to TIC.

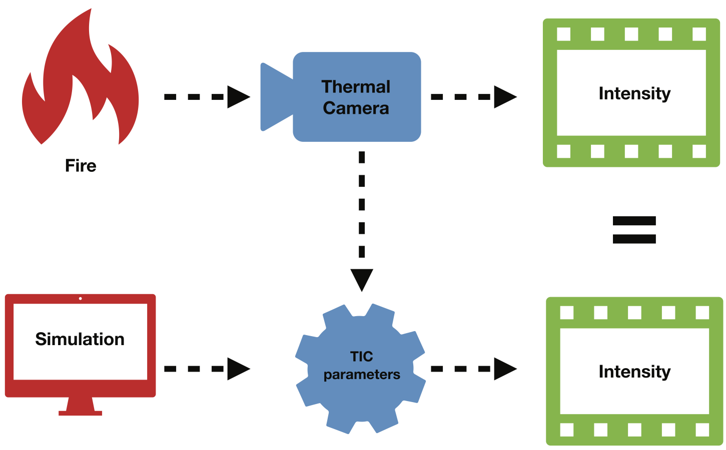


Figure 4. Image transformation.

4. Flashover Occurrence Prediction

Regarding the prediction of these phenomenon, most of the relevant studies shown below have been carried out using neural networks. Moreover, ANN has been used in research cited in this review to predict some physical aspects related to fires, even to predict the flashover phenomenon but not using TIC.

Research to perform flame detection using neural networks was conducted by Huseynov et al. [8,9]. Joint time-frequency analysis (JTFA) was used with a reduced time Fourier transform to extract relevant information. This study focused on the domain of the signal frequency, since the signals that a fire source emit can vary in amplitude and function depending on the distance, angle, presence of obstacles and other sources that are not flame generators (sun, wind, random modulation, bright lights, rain, fog, dust, etc.) that may look like flames in the eyes of an infrared sensor. In contrast to the time domain, the frequency of flickering of a flame remains relatively independent of the different environmental conditions. Due to the amount of several false positives that can occur, it was considered to use a multiple neural network instead of a large scale. This model was mounted on a digital signal processor (DSP, Texas Instruments (TI) F2812), reaching the conclusion that the response to the detection of a flame of this model is equal to or greater than some of the current detection systems. Another approach is the one given by Won-Ho Kim et al. [52]. His research is based on prediction by studying the neighbouring pixels of a video, provided by a TIC. The author proposes a flame detection system based on an algorithm optimised with a digital signal processor to optimise detection time, between 5 and 20 s.

Predicting parameters in compartment fires is an extremely fast alternative approach. In this line, several ANN's have been developed to do it instead of CFD techniques, which need more computational time to do the same work. In these cases, CFD techniques were used to validate ANN. In the following research, a novel ANN model GRNNFA, which is a fusion of the Fuzzy Adaptive Resonance Theory (FA) model and the General Regression Neural Network (GRNN) model, was developed to predict the locations of the thermal interfaces by Lee et al. [14]. To train and evaluate the ANN, experimental data obtained from Steckler et al. [24] were employed in a total of 55 experiments conducted by Steckler (with different fire locations, fire intensities and window and door sizes). Due to the diffusion and mixing effects of the fluid flow, the thermal height could not be determined precisely. For these cases, FDS was used to validate the ANN performing a simulation for the experimental data. When the simulations were compared with the experimental data, the authors noticed that FDS consistently under-predicted the experimental results of the thermal interface height. For this reason, the absolute difference was averaged, and this correction factor was applied for the neural network training. The predicted results by GRNNFA of the 55 cases were compared with the simulations results. It was found that the GRNNFA was able to predict the locations of the thermal interfaces well within the range envelope of the experimental results up to 94.5% accuracy (i.e., only 3 out of 55 samples was predicted outside the range envelope). The previous model was applied to five test cases that not appear in the experiments and the results were compared to FDS simulations. Subsequently, it was found that the difference between the predictions and simulations are well within the minimum error range. The key issue here is GRNNFA was able to capture efficiently the genuine, predominant characteristics of the fire phenomenon within seconds from limited samples. This ANN was applied to predict the flashover phenomenon in enclosure fires [13] based on the compartment geometry.

Regarding flashover prediction, a new ANN model was developed by Lee et al. [12] using probabilistic mapping with maximum entropy (PEmap). It was employed as a binary classifier for predicting this phenomenon occurrence in single compartment fire and results were compared and verified against data obtained by Fuzzy ARTMAP (FAM). A computer package (FAST [53]) was used to introduce a flashover criterion (the temperature of the upper hot gas layer $\geq$600 °C) to predict flashover. Due to the impossibility of getting enough data of real emergencies, the training of the model was carried out through computer software simulations. Specifically, 375 simulations (190 samples of flashover and 185 non-flashover) were carried out to train the PEmap model, varying randomly different parameters of the compartment:

- Length of the compartment (varies randomly from 2 to 10 m)
- Width of the compartment (varies randomly from 2 to 10 m)
- Height of the compartment (varies randomly from 2 to 10 m)
- Maximum heat release rate (varies randomly from 10 to 6000 kW)

Subsequently, for different combinations of these room dimensions and the maximum heat release rate the occurrence of flashover was determined by FAST. Albeit the prediction results show that PEmap is an efficient classification tool for determination of flashover with a high degree of accuracy (96.8%), the neural network model was not implemented in any device, such as a thermal camera, to be tested in a real case.

In a previous study [14] the GRNNFA model was applied to predict the thermal interface location in a single compartment fire. The performance of this ANN was proven to be comparable of the CFD model, moreover, computational speed of the GRNNFA was faster than CFD model. GRNNFA presented some limitations as it restricts the results in the application area of the model. In addition, Yuen et al. [15] presented a modification of the original GRNNFA model for multi-dimensional prediction problems and it was used to predict the velocity and temperature profiles at the centre of the doorway in a single compartment fire. GRNNFA model was successfully applied to predict the velocity and temperature at the centre of the doorway in a single compartment fire and multi-dimensional environment. There were some problems with the application of this technique in the local region because the training samples in that region may not be sufficient to describe the general behaviour of the system. Finally, this model was applied to predict the flashover under the given fire parameters (length, width, height and maximum heat release rate). It is concluded that this model is statistically superior than the Fuzzy ARTMAP and PEmap models [54]. In a real flashover situation, it is not possible to introduce parameters of a confined space in a device like TIC. The reason is that not only is the speed of events one of the crucial factors, but also the impossibility to know the exact dimensions of the enclosure. Image recognition techniques could be a useful technology to solve this problem. Another approach to predict the location of the thermal interface in a fire compartment (HTI) is studied in the work of Lee et al. [55]. A neural network model based on probabilistic entropy (PENN) was used as an alternative to the CFD technique (computer simulation). Using this technology the network requires less computational time for a case study. PENN model is applied to the prediction of the HTI within a confined fire using real experimental data. The statistical analysis of the results positively demonstrates the accuracy of PENN model in a confined fire. Moreover, the computational time incurred in the prediction of the HTI is much better than CFD techniques. On the other hand, authors clarify that although the use of this technique is encouraging, new lines of research are needed to deepen the determination of the initial kernel radius, because these have been determined empirically for this study.

In a fire emergency time is crucial to prevent a dangerous situation. As a consequence, predictions should be done in real time. The following researches include real time applications techniques to predict certain situations related to confined fires. A small world network model to predict real-time fire spread on board naval vessels was developed by Kacem et al. [10]. Despite the fact that the purpose of this research is not the flashover prediction, it was taken in account to evaluate the fire compartment and decide if it will be crucial for fire spread to other enclosure. To determinate the occurrence of flashover the pyrolysis rate in the compartment was evaluated and the duration of the fully developed phase is calculated using empirical formulas for a fuel limited combustion and ventilated limited combustion. Finally, full-scale experiments in a multi-compartment fire container with mechanical ventilation and CFD simulation were conducted to validate the model and determinate the probability of spreading a fire in a specified configuration naval vessel. Despite pyrolysis rate is considered to predict the occurrence of flashover it cannot be considered for predicting these situations with TIC. Related to TIC Kim et al., proposed a method [56] for fire heading in smoke-filled indoor environments using thermal imaginary designed for SAFFiR (Shipboard Autonomous Firefighting Robot). It is based on a previous study [11] in which it was used a probabilistic classification for fire, smoke, their thermal reflections and hot objects using Bayesian theory. The key point is the fire and smoke classification, a clustered-based image technique is used to discriminate the two classes foreground (objects) and background, resulting in fast computation during real-time implementation. Despite this method being used inside an enclosure, another approach classifying smoke from an outside compartment with a thermal camera could provide some relevant information about the fire development. In a recent study [57] Conditional Generative Adversarial Networks were used to predict rapid fire growth (flashover) in real time. There are some visual signals that can warn firefighters about a possible flashover, like dark smoke, high heat and rollover. A standard body camera was used to analyse the colour video stream. Very dark fire and smoke patterns were enhanced applying generative adversarial neural networks. Previously image-to-image conversion techniques were applied using conditional adversarial networks in order to obtain a thermal image from a regular colour image. The neural network training and test was carried out using 30 and 10 videos provided by two different fire departments. As a result flashover was predicted as early as 55 s before it occurred. While this technology was developed from a colour image authors remarks it can be applied over thermal images from TIC's to predict flashover situations. Currently training and test datasets from real situations are limited. Only is possible analysed a few cases with simple configurations like fire containers. CFD software could be an interesting tool to generate datasets with different configurations and fuels in order to train neural networks from TIC's images.

Table 6 provides an overview of the references related with fire prediction cited in this section. The reader can detect at a glance if the reference is related with flashover phenomenon, which are the most important techniques used in the research, the software used for the simulations, infrared sensors and TIC employment.

Table 6. References summary about flashover occurrence prediction show in this section.

Authors & References	Flashover	Research Techniques		Simulation Software			Infrared Sensors	TIC
		ANN	Other	FDS	ANSYS	Other		
Huseynov, Boger, Shubinsky & Baliga et al. [8]	✗	✓	✓	✗	✗	✗	✓	✗
Huseynov, Baliga & Shankar et al. [9]	✗	✓	✓	✗	✗	✗	✓	✗
Kacem, Lallemand, Giraud, Mense, De Gennaro, Pizzo, Loraud, Boulet & Porterie et al. [10]	✓	✓	✗	✓	✗	✓	✗	✗
Lee, Yuen, Lo & Lam et al. [12]	✓	✓	✗	✗	✗	✓	✗	✗
Eric W.M. Lee, Y.Y. Lee, Lim & Tang et al. [13]	✓	✓	✗	✗	✗	✓	✗	✗
Lee, Yuen, Lo, Lam & Yeoh et al. [14]	✗	✓	✗	✓	✗	✗	✗	✗
Yuen, Lee, Lo & Yeoh et al. [15]	✗	✓	✗	✗	✓	✗	✗	✗
Kim et al. [52]	✗	✗	✓	✗	✗	✗	✗	✓
Lakhmi & Chee et al. [54]	✗	✓	✗	✗	✗	✗	✗	✗
Lee et al. [55]	✗	✓	✗	✗	✗	✗	✗	✗
Kim, Sung & Lattimer et al. [56]	✗	✓	✗	✗	✗	✗	✓	✓
Yun, Bustos & Lu et al. [57]	✓	✓	✗	✗	✗	✗	✗	✗

5. Challenges An Opportunities

Novel techniques used for modelling, simulation and prediction of flashover phenomenon in confined fires have been reviewed in this paper, identifying future opportunities and challenges. As far as modelling and simulation is concerned, the most recent studies of flashover have been reviewed. While the articles analysed describe a deep level of knowledge about this phenomenon, there are some issues that require further exploration.

Flashover research reveals some physical events which determine the beginning of this phenomenon, especially upper gas temperature ≥ 600 °C and heat flux at floor level ≥ 20 kW/m^2. Both factors have to be considered together to define the initial point of this transition phase to fully developed fire. Furthermore, ventilation factor has a vital impact on flashover occurrence. The location and size of the vents in the enclosure maintains a close relation to the development of this kind of phenomenon. Vent identification using computer vision techniques [7] in real time could provide valuable information to predict flashover. Furthermore, flashover is clearly determined by an HRR/time relation, which could be a key issue for prediction with ANN models.

The simulations reviewed from mathematical models reveal that nowadays computational fluid dynamics (CFD) simulation predominates over other analysed models. The detailed analysis of thermal environments, which can be used to train and validate ANN with certain accuracy, is one of the many advantages of this type of simulation. Various CFD software packages have been compared in different articles shown in this review. Notice in most cases FDS have been used to conduct research simulations. Not only have been FDS validated with acceptable scores but also ANSYS CFX software obtained similar results. In particular, the use of FDS is widely extended because it is a free and open-source software tool. Furthermore, flashover phenomenon has been widely simulated in most of the articles reviewed.

With regard to TIC, it is important to remark that according to the reviewed articles it is not possible to compare images from FDS simulations with thermal images obtained directly from TIC. Some transformations need to be done before this step, since the final image depends on the technical thermal camera parameters and conditions of the medium (scattering or non-scattering medium). This technique could provides the opportunity to compare images taken from emergencies real cases, where there are not sensors inside the enclosure, with images from simulations. A better approximation of simulation to the real case can be achieve which can be of great help for the fire investigation or firefighters training.

As for predictions using AI, this review shows that there are different lines of research that cover flashover. Different prediction models can be observed, with the predominant lines oriented to AI and neural networks. ANN models have been developed to predict fire, the location of the thermal interface in a fire compartment (HTI) or, when the flashover occurs. Furthermore, to the best of our knowledge, no document has been found that discusses AI in TIC to predict cases of flashover using datasets from CFD software. In fact, data sets used to predict flashover occurrence were based on simulation sensors information located inside the enclosure. For this reason, the identification of characteristic parameters which define a flashover situation using ANN trained with data from CFD software could be a big challenge. This technique could be used in other combustion processes in which real cases are very difficult to reproduce and could be interesting to predict a specific situation.

6. Conclusions and Future Work

Regarding to flashover phenomenon modelling, real complex scenarios with different vents and fuels have not been evaluated. Reduced-scale experiments with a simple configuration are used to study this kind of situation. However, to determine the occurrence of flashover, not only do gas layer temperature and heat flux radiation at floor level need to be considered but also ventilation factor and HRR/time. For this reason, other configurations of the enclosure should be analysed. In conclusion, flashover is well simulated using different CFD software.

The articles reviewed suggest that it is possible to obtain images from CFD software that are similar to a specific thermal imaging camera using its technical parameters. This should be taken into account for developing artificial intelligence technology based on TIC if CFD data want to be used to train ANN's. Programming and computer vision techniques can be used to conduct the mathematical calculations to achieve the final result.

Some research regarding flashover prediction using ANN was identified but to the best of our knowledge, research that predicts this phenomenon with TIC's using datasets from CFD software in order to train ANN's have not been found. Furthermore, thermal image cameras may be useful devices to predict flashover by fire services using ANN. Considering the research analysed, new prediction models can be developed focusing on real-time thermal images.

Taking into account the different areas studied and analysed in this review we conclude that flashover phenomenon is sufficient studied to be modelled and simulated using simple configurations. Furthermore, AI techniques have been used to predict its occurrence using sensors placed inside the enclosure. However, there are not any research which use data from CFD software to train ANN with flashover prediction purposes in TIC's.

We envisage future research on predicting flashover phenomenon with TIC's using datasets made from CFD software to train ANN's. This technology can prevent dangerous situations by warning firefighters, who handle thermal cameras, in real-time. Gas layer temperature, heat flux radiation at floor level, ventilation factor and HRR/time in the enclosure should be factored in. CFD techniques may be used to train the ANN model, and real experiments in a fire container may be a useful way to validate the final model. Furthermore, the study of this phenomenon using AI can help to delve into certain aspects that may not have been considered previously.

As future work, we plan to use other parameters from field models in order to create a dataset with thermal vision characteristics to train ANN models based on TIC. This will allow a breakthrough for the simulation and prediction of the flashover phenomenon.

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