A Comparison of Sources of Uncertainty for Calculating Sprinkler Activation

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ABSTRACT

Treatment of uncertainty is an important consideration when performing a quantitative risk assessment (QRA) for the purpose of performance-based fire safety design. It has been noted in New Zealand that the outcome for fire QRAs is sensitive to uncertainty in the effectiveness of fire safety systems, including sprinkler systems. This paper considers the uncertainty in sprinkler activation time and the heat release rate (HRR) at the time of sprinkler activation for two scenarios; one where a set of sprinkler experiments in a room is modelled and the second which considers a more general design case for the same room. The relative importance of aleatoric (natural) and epistemic (model) uncertainties is shown to depend on the scenario being modelled. Twelve sources of uncertainty were quantified based on literature data and ranked for the scenarios considered. A new probabilistic-deterministic design tool for making risk-informed fire safety decisions is used to calculate output distributions for the two parameters considered and the sources of uncertainty are ranked in terms of sensitivity for output uncertainty. It is found that fire growth rate tends to be more important than the model uncertainty associated with the deterministic zone model engine for the scenarios considered, and uncertainty in the fire location becomes more important than the model uncertainty in design cases where there is greater uncertainty. Uncertainty in sprinkler response parameters and the ambient interior temperature provided the least contribution to the output uncertainties.

KEYWORDS: sprinklers, risk, uncertainty, Monte Carlo, probabilistic.

INTRODUCTION

A consequence of moving from a prescriptive to a performance-based building regulation paradigm is a shift in uncertainty. A prescriptive-based code specifies how a building should be designed and built, but not the intent of the code or the level of risk that society will accept for that building, so there is minimal uncertainty in how a building should be built to meet the regulatory requirements but substantial uncertainty in the intent of the regulation. A performance based approach increases certainty in the regulatory intent by stating it directly but allows more flexibility and thus uncertainty in how a building is designed to meet the intent [1].

One approach to evaluating the fire risk of building designs in a performance-based environment is the use of engineering tools and judgment to perform a quantitative risk assessment (QRA). The objective of a QRA is to provide a measure of the probability and consequences of scenarios that are perceived to pose a threat to people, property, and the environment [2]. The three key fire risk analysis elements have been defined by Hall [3] as being explicit treatment of probability, well-defined measures of severity, and explicit consideration of uncertainty. Explicit consideration of uncertainty is noted as being the most difficult. This study looks at the uncertainty in predicting the activation time of a sprinkler for the purpose of a fire QRA.

There are many different sources of uncertainty, and many may be nearly impossible to quantify. The large number of taxonomies for uncertainty indicates that there is a large degree of uncertainty in even classifying uncertainty [4]. The classification system considered in this study was developed by the Danish Energy Agency for the purpose of QRA [5]. This system classifies uncertainties as resource uncertainty, assumption and decision uncertainty, model uncertainty (commonly known as epistemic uncertainty) and input uncertainty (also known as aleatoric uncertainty).

Resource uncertainty includes big-picture factors such as uncertainty in project management and quality control, the quality of available research, and available analytical methods. For example, a certain type of

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sprinkler might be specified by the designer, but if a sprinkler with different response parameters is installed by mistake then the sprinkler will not respond as predicted by the designer. Resource uncertainty is not considered in this study and is difficult to quantify but it can significantly influence the performance of a fire safety design.

Decisions and choices made in selecting models and assumptions include uncertainty. For modelling fire, a variety of models are available, ranging from simple correlations to zone and field models. Decision uncertainty can become more of an issue with a more complex model. A simple hand calculation based on one input parameter will have less decision uncertainty than a more complex zone or field model. An example of decision uncertainty within a zone fire model is the choice of plume air entrainment and ceiling jet submodels. The *a priori* simulations of the Dalmarnock fire test [6] demonstrate how decision uncertainty can affect the outcome of a prediction when there are a large number of degrees of freedom in the model. Several modellers were given a set of input data and produced substantially different results using the same two computer fire models, FDS and CFAST.

Epistemic uncertainty is the uncertainty in the modelling processes employed, and is a function of the model. A key consideration for the selection and use of a fire model is the accuracy of the model. However, the principles of 'consistent level of crudeness' [7] apply: if the certainty in the input parameters to the model is low, then the accuracy of the model itself is less important.

Aleatoric uncertainty considers natural variability. Aleatoric uncertainty depends on the situation being considered. Some of the input parameters for a specific fire that is being reconstructed will be known with much more certainty than in the case of a building fire safety design QRA. For instance, the point of origin and geometry of the room of origin may be known in a reconstruction, and depending on extent of damage, the relevant material properties of the fuel and surrounding materials can be measured. In the case of building fire safety design, the geometry of the building and the contents can change over the lifetime of the building and thus should be factored into the modelling scenario.

Typically fire models are verified by comparing model predictions with experimental measurements. The goal of experiments is to minimise the aleatoric uncertainty, i.e. control the input parameters as closely as possible. In this situation, the fit of the model to the experimental data can be improved by increasing the complexity of the model; for example, by going from a zone model to a field model or from a simpler field model to a more refined field model. Increasing the complexity of the model allows it to be adjusted to fit the results more closely. However, this is not representative of the use of a model within a design or reconstruction context. In order to provide benefit to society, a fire model must either be able to provide additional information or insight into a real-world fire scenario beyond what can be observed, whether it is to reconstruct a past fire or to consider risks from future fires. Any real scenario has less information available and less control of input parameters than an experimental fire; that is, there is more aleatoric uncertainty. The verification data provides useful information on the model uncertainty, because aleatoric uncertainty is minimised. If the aleatoric uncertainty in the scenario that is being considered is greater than the model uncertainty, then the accuracy of the model is likely sufficient for the intended purpose.

It has been noted in New Zealand that QRA outcomes are highly sensitive to the effectiveness of the proposed fire safety systems, including sprinklers, smoke control systems, and passive barriers. The uncertainty in the performance of these systems have caused the regulator (the New Zealand Department of Building and Housing) to require the alternative performance-based solutions to have a 3:1 probability of being safer than the deemed-to-satisfy solution in the comparative probabilistic risk assessment [8].

A joint project between the University of Canterbury and the Building Research Association of New Zealand Limited (BRANZ) is currently underway to develop a risk-informed tool for use in time dependent fire QRAs. The new tool is a probabilistic-deterministic model where uncertainties are considered in the probabilistic component of the model, and a zone model is used for the deterministic time-based calculations.

In this study sources of aleatoric uncertainty are compared with the epistemic uncertainty in the fire plume excess temperature correlation used in the confined ceiling jet model embedded within the fire zone model when modelling activation of the nearest sprinkler. Two scenarios are considered: the first models a set of experiments conducted at the University of Canterbury, and the second considers the same room geometry but as a design scenario where the item ignited is a polyurethane foam upholstered chair or sofa and where the spatial location of the fire in the room is uncertain. The relative importance of the epistemic model uncertainty is compared between scenarios. Two output parameters are considered; the time of sprinkler activation and the heat release rate (HRR) at the time of sprinkler activation. The relative sensitivity of the model to each of the uncertain parameters is discussed.

MODEL DESCRIPTION

Probabilistic aspects and uncertainty in input and model parameters are considered in the new tool and propagated through the deterministic fire phenomena engine by the Monte Carlo approach. The computational efficiency of the zone model engine means that enough runs can be completed in a reasonable amount of time with currently available desktop computing resources to get a reasonable representation of the uncertainty distributions. The structure of the model can be seen in Fig. 1.

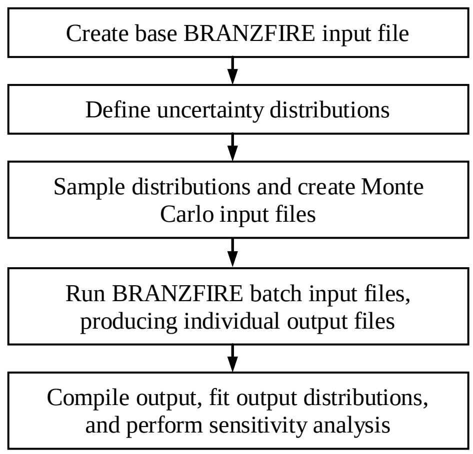


Fig. 1. Probabilistic-deterministic model structure.

Deterministic Model

The BRANZFIRE [9] two zone model is used as the deterministic model to calculate the sprinkler activation time. Details of how BRANZFIRE calculates the layer properties can be found elsewhere [9] [10]. In BRANZFIRE, plume air entrainment can either be calculated with Delichatios' or McCaffrey's correlations. McCaffrey's correlations are chosen for this study because they were used in the BRANZFIRE verification report [11]. BRANZFIRE predicts the ceiling jet temperature and velocity based on either Alpert's correlations [12] or the JET model [13], which includes the effects of the upper layer under a confined ceiling. The JET model is considered here because a previous study has indicated that it provides more accurate results in small rooms when compared with Alpert's correlations [10]. The LAVENT method from NFPA 204 [14] resolves the variation of the ceiling jet temperature and velocity with distance below the ceiling. The detector thermal response is modelled by Heskestad and Bill's differential equation [15]. The choices in submodels represent decision uncertainty.

Probabilistic Model

The commercially available software program @Risk [16] is used to sample input parameter probability distributions for use in the deterministic model. The Latin Hypercube sampling approach is used to ensure that the extreme values in the distributions are sampled adequately. The sampled values are written to BRANZFIRE input files, which are then run as a batch producing individual output files. The output data is then collected for analysis in Excel. The output from 5000 iterations was compared to 1000 iterations; the mean and variance was similar for the output distributions but the distributions were smoother with 5000 iterations. The maximum standard sample mean error is 0.9 % for both sprinkler activation time and HRR at the time of sprinkler activation with 5000 iterations. Pearson's correlation coefficient is used to compare sensitivity of the sprinkler activation time and HRR at the time of sprinkler activation to the sources of uncertainty, because of its ubiquity and ability to measure the degree of relation between the input and output as a standardised slope [17].

SCENARIOS

Two separate scenarios are considered to evaluate the relative uncertainty contribution of the parameters. The first scenario is based on specific sprinkler activation tests conducted at the University of Canterbury [18]. The second scenario uses the same room geometry as the first scenario but the uncertainty in the fire parameters is expanded.

Scenario 1

The first scenario is based on 3 tests out of a series of 10 where a single chair was burned in the centre of a room with the door open. The 3 tests are considered because they were repeat tests with the same ignition scenario, type of sprinkler, and ventilation conditions. The experimental room was 8 m long, 4 m wide, and 2.4 m high, based on the dimensions of the UL 1626 room [19]. The walls and ceiling were light timber frame with 10 mm painted gypsum plasterboard. No uncertainty is considered in the room geometry or the material properties of the room lining. Two Tyco TY3251 standard response, pendant, spray sprinklers with a nominal activation temperature of 68 °C were installed and located 2 m from the centre of the room. The sprinklers were oriented so the yoke arms were perpendicular to the flow. The sprinklers were pressurised with water to measure the activation time with pressure switches but no water supply was connected. A plan view of the experimental layout is shown in Fig. 2. The chair was comprised of cushion grade non-fire retarded polyurethane foam blocks (approximately 0.56 kg each), covered with acrylic fabric and backed by 10 mm plasterboard as seen in Fig. 3. The chair was placed on a load cell to measure the mass loss during the fire, and the heat release was calculated based on the mass loss measured by the load cell and an effective heat of combustion obtained from Cone Calorimeter tests. The interior temperature varied from 23 °C to 27 °C. A summary of the experimental results is shown in Table 1.

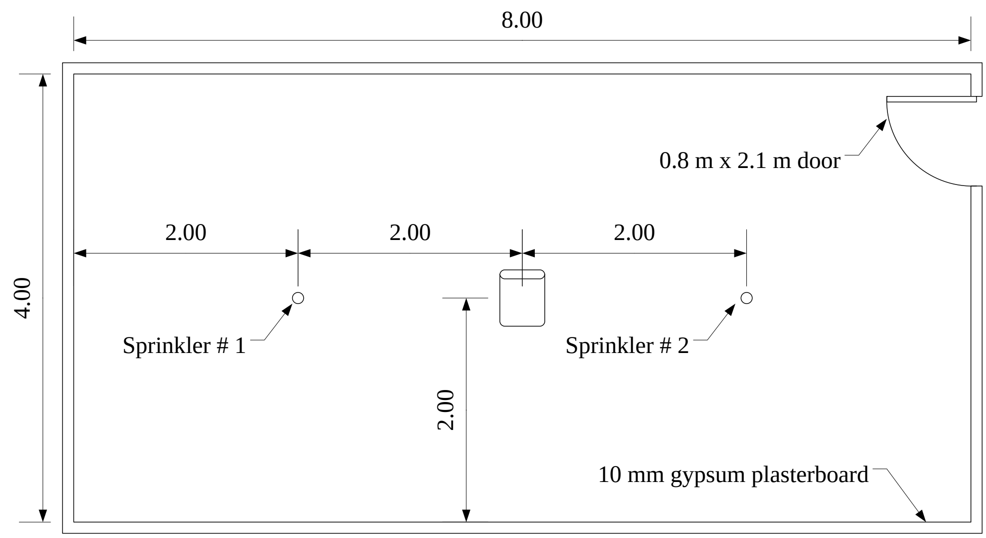


Fig. 2. The layout of the experimental room (extracted from Bittern [18]). Dimensions in metres unless otherwise stated.

Scenario 2

The second scenario considers the same room geometry as Scenario 1, but the fire parameters have much more variability, as could be expected under real-world conditions. The room geometry is considered to be known with no uncertainty, and the door is considered open. The location of the fire is uncertain. The fuel item is a piece of furniture with polyurethane foam cushioning, but it is uncertain if it is a single-seat chair, two-seater or three-seater sofa.

Table 1. Experimental results for Scenario 1 [18].

Experiment	Sprinkler	Sprinkler activation time (s)	HRR at sprinkler activation (kW)	HRR growth rate α (kW/s²)
4	1	226	125	0.0024
	2	226	125	0.0024
5	1	216	129	0.0028
	2	211	126	0.0028
6	1	266	116	0.0016
	2	272	125	0.0017
Mean		236	124	0.0023
Standard deviation		26	4.4	0.0005

Fig. 3. Upholstered chair configuration considered for Scenario 1 (extracted from Bittern [18]).

SOURCES OF UNCERTAINTY CONSIDERED

The sources of uncertainty that are quantified are summarised in Fig. 4. The ambient temperature is modelled as a normal distribution with mean 25 °C and standard deviation 1 °C to match the range in the experiments. The maximum and minimum sampled values for all the distributions that are not truncated have been checked to make sure that no unrealistic extremely improbable values were included.

Fire Location and Sprinkler Geometry

For Scenario 1, the fire location is considered to be in the centre of the room as per the experiments. In the experimental tests, a firelighter was ignited with a propane torch in the centre of the interface between the seat and the back. However, air movement, uneven flame spread, and turbulence could have shifted the centreline of the plume over the duration of the fire, so the radial distance of the plume from the sprinkler is assumed to be normally distributed over the 400 mm width of the chair. In the experiments, the top of the seat cushion is located 0.75 m vertically from the floor. Due to the geometry of the chair, the base of the fire for modelling purposes could move as the fire progressed, spreading upward or progressing downward as the chair burned. Therefore a normal distribution with a mean of 0.75 m and a standard deviation of 0.05 m is used for the fire height parameter.

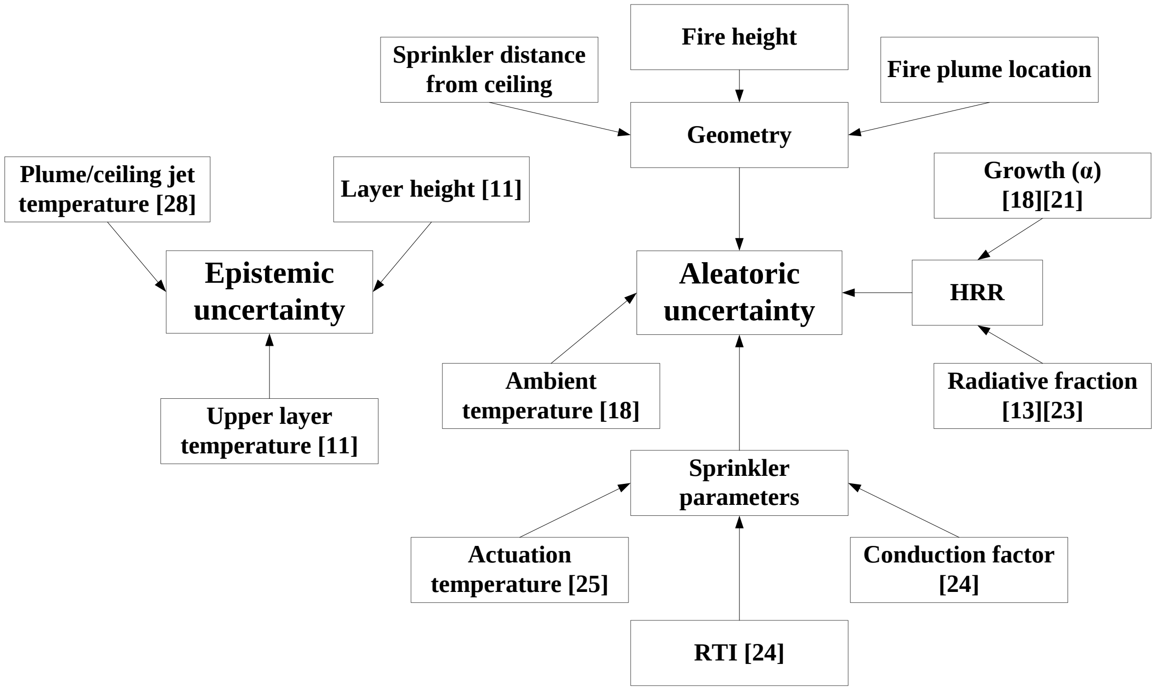


Fig. 4. Quantified sources of uncertainty categorised as epistemic or aleatoric uncertainty.

In the experiments, the sprinklers were located so that the centre of the glass bulbs were located 20 mm below the ceiling. Since the sprinkler bulbs have a length of approximately 20 mm, but the sprinkler response parameters are modelled at a point location, a normal distribution with a mean of 20 mm and a standard deviation of 5 mm is used for the bulb depth from the ceiling and truncated at 0 mm to prevent negative distances.

For Scenario 2, the fire location is unknown. As an initial approximation, the plume centerline is allowed to be located anywhere within the floor area with equal probability. Realistically, this is an over simplifying assumption because room contents are not randomly located but it provides a reasonable amount of uncertainty for the current analysis. For example, the probability of a large piece of furniture blocking a single doorway into a room is low. Work is currently underway at BRANZ to develop probability distributions for typical locations for furnishings in rooms.

As upholstered furniture fires are only considered for Scenario 2, the fire height from the floor is taken to be a discrete distribution with probabilities of 0.3 at a height of 0 m representing floor level, 0.4 at a height of 0.5 m representing seat level, and 0.3 at a height of 1 m representing the top of the seat back. The probability that the fire would start on the seat level was estimated to be slightly higher than at the floor or top of the seat back. A summary of the distributions used to model the fire location and sprinkler geometry uncertainty is shown in Table 2.

Fire Heat Release Parameters

The BRANZFIRE model predicts the upper layer development and plume and ceiling jet conditions as a function of the fire heat release rate. The heat release history of a fire can be characterised as having five states: incipient, growth, flashover, fully developed burning, and decay. There is a large amount of uncertainty in the incipient time; depending on the ignition scenario it can vary from fractions of seconds to several days. During the incipient time, the heat release and fire products are minimal and there is very little risk to occupants, other than perhaps sleeping or otherwise incapable of self preservation occupants in the compartment of fire origin. For the purposes of this study, the incipient phase of the fire is ignored due to the relatively large ignition source used. Sprinklers are designed to activate during the growth period of the fire so the flashover, fully developed burning, and decay phases of the fire are not considered in this study.

Table 2. Distributions used to model fire location and sprinkler geometry uncertainty for the two scenarios considered (μ – mean, σ – standard deviation).

Scenario 1			
Parameter	**Distribution type**	**Distribution parameters**	
Radial distance	Normal	μ = 2 m	σ = 0.1 m
Fire height	Normal	μ = 0.75 m	σ = 0.05 m
Sprinkler distance below ceiling	Normal	μ = 20 mm	σ = 5 mm
Scenario 2			
Parameter	**Distribution type**	**Distribution parameters**	
X and Y fire plume location (dist. from centre = $(X^2+Y^2)^{½}$)	Uniform	Minimum = -2 m	Maximum = 2 m
Fire height	Discrete	$P(H$ = 0 m) = 0.3, $P(H$ = 0.5 m) = 0.4, $P(H$ = 1 m) = 0.3	
Sprinkler distance below ceiling	Normal	μ = 20 mm	σ = 5 mm

A common and generally accepted design method of describing the increase in heat release rate during the growth period of the fire as a function of time for fuel controlled room contents fires is the αt^2 model. In this study, the fire intensity coefficient α was used to characterise the growth rate rather than the growth time t_g which represents the time required for the HRR to reach 1055 kW (both approaches are described in NFPA 72 [20]). Small fuel packages such as those used in the experiments modelled in this research will not reach 1055 kW so the fire intensity coefficient method was chosen, although the growth time can be calculated if desired. For Scenario 1, the range of growth rates is relatively easy to quantify because the model is representing a set of experiments where the HRR was calculated from the mass loss rate and effective heat of combustion. In the set of experiments, uncertainty in the mass measurement and heat of combustion contribute to uncertainty in the HRR. The load cell used in the experiments had a resolution of 5 g (error was not reported) and the Cone Calorimeter effective heat of combustion measurements ranged from 20.3 MJ/kg to 22.3 MJ/kg. Figure 5 shows the heat release curves for the experiments, as well as αt^2 heat release rate growth curves selected to approximate the mean and 95 % confidence limits. A log normal distribution was used for the αt^2 growth parameter for Scenario 1. This choice of distribution corresponds with a previous study by Frantzich [21] who also used a log normal distribution for the fire growth rate, designed to account for fast and slow fires with a mean of 0.02 kW/s² and standard deviation of 0.01 kW/s².

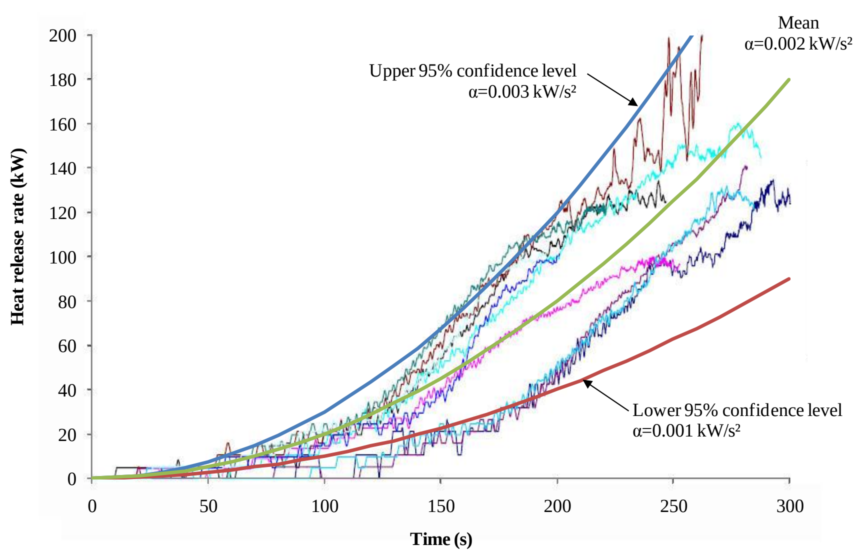


Fig. 5. Heat release curves from Bittern's experiments [18].

When considering the range of fires that a room may experience over a lifetime of use for design purposes, the fire growth rate uncertainty increases. Scenario 2 considers a design scenario where the item ignited is a piece of living room upholstered furniture containing polyurethane foam. The data for the variation in fire growth rate for polyurethane furniture was obtained from a meta-study by Young [22]. The fire growth data in Young's study was obtained from a range of experimental furniture fires in furniture calorimeters. Ignition sources ranged from cigarettes to gas burners, and the frequency for each ignition source was not based on statistics. Because the data analysed by Young was from the furniture calorimeter, compartment effects were not included, which may influence the growth rate although the effects are expected to be small in the early stages of fire growth of interest here. Therefore this distribution may not be ideal for real-world design scenarios. However, the range of fire growth rates is more realistic than selecting a single value and is useful for illustrative purposes.

The distribution of the fire growth rate constant from Young's study is shown in Fig. 6. A log normal distribution fit the growth rate from the study data reasonably well.

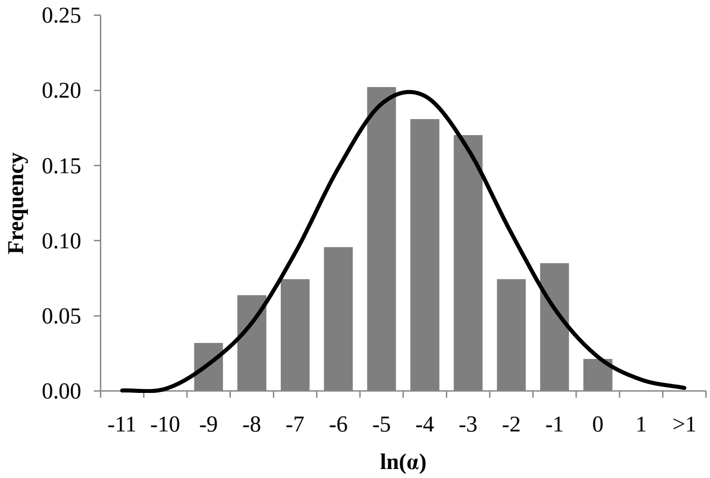


Fig. 6. Probability density of the logarithm of the heat release growth rate α, based on data from Young [22].

The radiative fraction of the heat release is another source of uncertainty, since the heat convected to the fire plume and ceiling jet is dependent on the amount of heat radiated from the fire. There are a range of values in the literature but no definitive study is available for upholstered furniture. Davis [13] [23] has estimated the uncertainty in radiative fraction to be ± 15 %, so a normal distribution is used with a mean of 0.3 and a standard deviation of 0.025. A summary of the distributions used for the fire heat release parameters can be seen in Table 3.

Table 3. Probability distributions for heat release rate parameters for both scenarios considered.

Parameter	Distribution type	Distribution parameters		Source
Scenario 1 α	Log-normal	μ = 0.002 kW/sec²	σ = 0.0005 kW/sec²	[18]
Scenario 2 α	Log-normal	μ = 0.09 kW/sec²	σ = 1.1 kW/sec²	[22]
HRR radiative fraction	Normal	μ = 0.3	σ = 0.025	[13,23]

Sprinkler Parameters

The sprinklers used for the experimental data were also used in a study to characterise the uncertainty in the response time index (RTI) and conduction (C) sprinkler parameters [24]. The sprinkler parameter study used the plunge test method under a range of wind tunnel temperature and velocity conditions in both parallel and perpendicular flow orientations.

Data on uncertainty in the sprinkler activation temperature was obtained from the study conducted by Khan [25]. A thermal liquid bath was used to slowly raise the temperature of glass bulb sprinklers until they activated. Standard response (5 mm diameter) glass bulbs of nominal 68 °C activation temperature were found to activate at a mean temperature of 72 °C with a standard deviation of 0.66 °C. A normal distribution with these parameters was used to model the activation temperature. A summary of the sprinkler parameter distributions is shown in Table 4.

Table 4. Distributions for the uncertainty in sprinkler parameters, used for both scenarios.

Parameter	Distribution type	Distribution parameters		Source
Response time index (RTI)	Weibull	$\alpha = 27.2$	$\beta = 96.6$	[24]
Conduction (C) factor	Normal	$\mu = 0.44\ (m/s)^{1/2}$	$\sigma = 0.01\ (m/s)^{1/2}$	[24]
Actuation temperature	Normal	$\mu = 72$ °C	$\sigma = 0.655$ °C	[25]

Model Uncertainty

Uncertainty in model predictions for the plume temperature, upper layer temperature, and layer height were considered because the JET model calculation for sprinkler activation time depends on these quantities. Estimates of the model uncertainty in calculating the layer height and upper layer temperature were made from the BRANZFIRE verification data [11]. The BRANZFIRE verification data includes comparisons to 62 kW to 158 kW fires in a 2.8 m by 2.8 m by 2.13 m tall room with various vent configurations using experiments reported by Steckler [26]. Figure 7 compares the BRANZFIRE model output to the experimental results cited in the verification report.

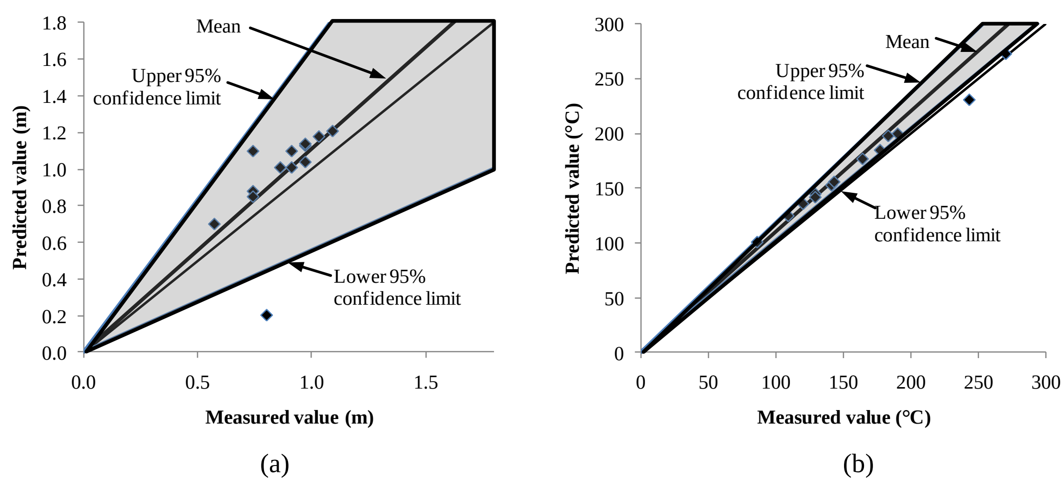


Fig. 7. Comparisons of BRANZFIRE model predictions to experiment data from Wade's verification report [11]: (a) layer height; (b) upper layer temperature.

From this data, distributions for the model uncertainty in layer height and upper layer temperature were produced. A multiplicative error likelihood model was used [27] because any error in layer height or temperature was assumed to accumulate as time progressed. The model calculations for layer height and upper layer temperature are multiplied by an uncertainty factor, which is sampled from the distributions and added as an input parameter to the input file.

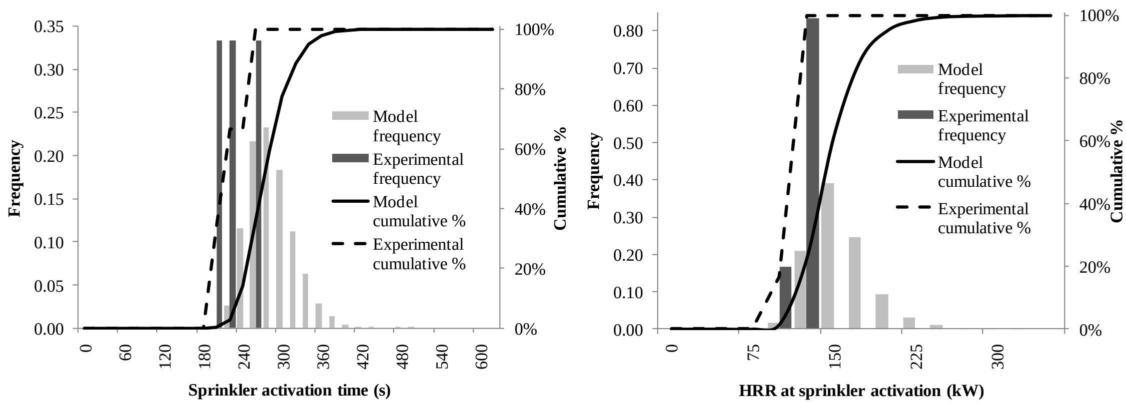
An uncertainty distribution for the plume temperature submodel output was estimated from the study by Sheppard and Meacham [28]. They found a 95 % confidence interval of ± 41.6 °C with a model similar to the JET model. As per Sheppard and Meacham's findings, an additive error likelihood model was used, where an uncertainty factor sampled from the distribution is added to the BRANZFIRE plume temperature calculation. Table 5 summarises the model uncertainty distributions used in this study.

Table 5. Distributions used for model uncertainty for both scenarios.

Parameter	Distribution type	Distribution parameters		Source
Layer height	Normal	μ = 111 %	σ = 28 %	[11]
Upper layer temperature	Normal	μ = 111 %	σ = 8 %	[11]
Plume temperature	Normal	μ = 0 °C	σ = 20.8 °C	[28]

RESULTS AND DISCUSSION

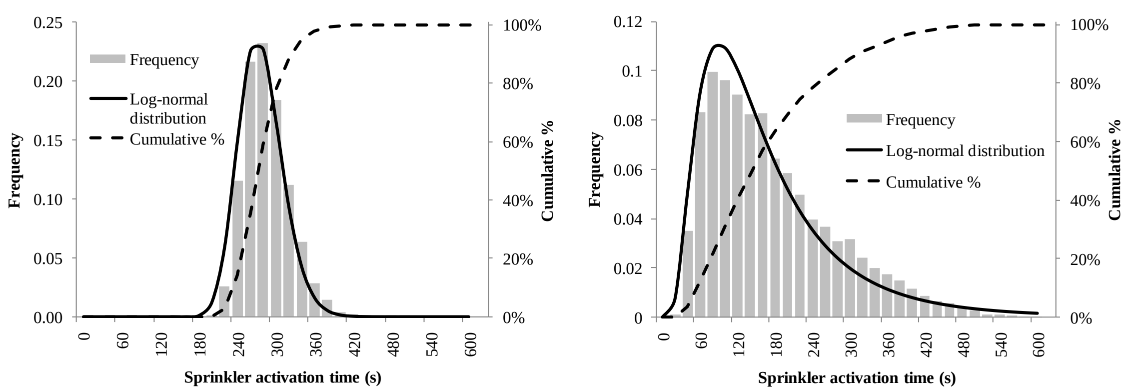
The modelled sprinkler activation time had a mean time of 276 s with a standard deviation of 35 s in Scenario 1. Compared to the experimentally measured sprinkler activation times [18], the mean time was 40 s longer and the standard deviation was 9 s greater in the model. The mean HRR at the time of activation from the model was 146 kW (compared to 124 kW experimentally) with a standard deviation of 29 kW (compared to 28 kW experimentally). The experimental statistics had a large margin of error due to the small sprinkler activation sample size of six, but the results matched reasonably well as shown in Fig. 8. The model tended to over-predict both sprinkler activation time and HRR at the time of sprinkler activation.



(a) (b)

Fig. 8. Comparison of experimental and model results: (a) sprinkler activation time ; (b) HRR at sprinkler activation.

The uncertainty in sprinkler activation time for the two scenarios can be seen in Fig. 9. Best-fit log-normal distributions are also plotted. There was significantly more uncertainty in Scenario 2 as expected.

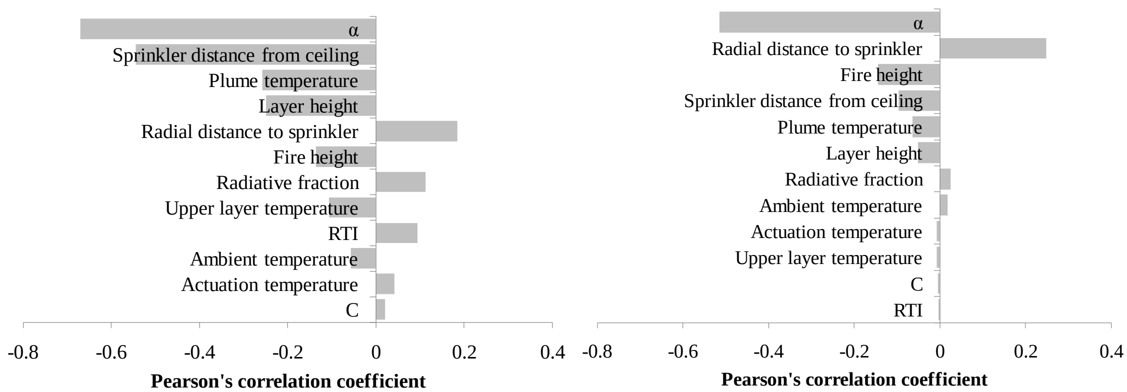


(a) (b)

Fig. 9. Sprinkler activation time distributions: (a) Scenario 1; (b) Scenario 2.

A tornado chart ranking the sensitivity of the modelled sprinkler activation time to the sources of uncertainty is shown in Fig. 10. For both scenarios, the heat release growth rate parameter α was the largest contributor to the uncertainty in the sprinkler activation time. A negative value for the Pearson's correlation coefficient indicates a negative relationship between the input and output parameter. As expected, if the fire grows faster (an increase in α), the sprinkler activation time decreased.

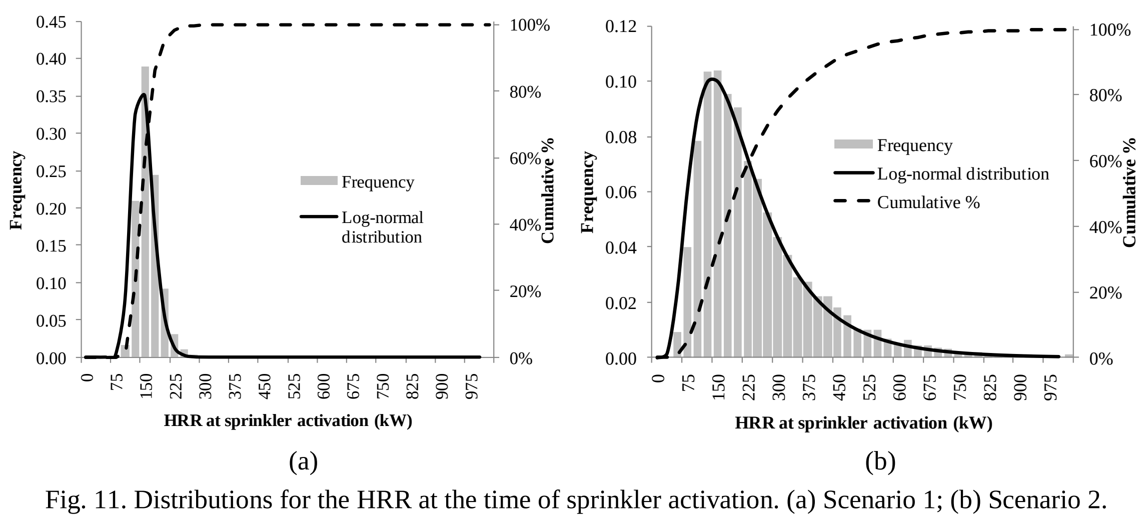
The sprinkler activation time was also sensitive to the distance of the sprinkler from the ceiling, due to the vertical distribution of ceiling jet temperature and velocity. The relative importance of the model uncertainty sources decreased as the uncertainty in α and the fire location increased from Scenario 1 to Scenario 2. The uncertainty in sprinkler parameters and the ambient temperature had little influence on the sprinkler activation time.



(a) (b)

Fig. 10. Tornado charts comparing sprinkler activation time sensitivity to sources of uncertainty: (a) Scenario 1; (b) Scenario 2.

Figure 11 shows the uncertainty in the HRR at the time of sprinkler activation time for the two scenarios. Scenario 2 has much more uncertainty than Scenario 1. Figure 12, which is a tornado chart ranking the sensitivity of the heat release rate at sprinkler activation to the quantified sources of uncertainty, shows that the major source of uncertainty for Scenario 1 is the sprinkler distance from the ceiling, due to the variation in temperature and velocity in the ceiling jet with height. The model uncertainty has a relatively large impact for Scenario 1, as the layer height uncertainty and the plume temperature uncertainty are ranked second and third, respectively. An increase in *α* causes the HRR to grow faster so as expected it has a positive effect on the HRR at the time of sprinkler activation, but the effect is offset by the tendency for the sprinkler to activate sooner. For Scenario 2, the uncertainty in *α* and fire location takes precedence, while the model uncertainties are of less consequence. For both scenarios, the uncertainty in sprinkler parameters and ambient temperature are the least influential on the HRR outcome.



(a) (b)

Fig. 11. Distributions for the HRR at the time of sprinkler activation. (a) Scenario 1; (b) Scenario 2.

For both output parameters considered in this study, the increase in uncertainty in the fire growth and location reduced the relative importance of the model certainty or accuracy. A more accurate but more complex and computationally expensive model will not provide more useful information for the model user if the model uncertainty is significantly less than the aleatoric uncertainty. An efficient model will provide a ‘consistent level of crudeness,’ balancing model uncertainty with aleatoric uncertainty. On the other hand, if the model inputs are well known for a specific situation, a complex model may well be justified.

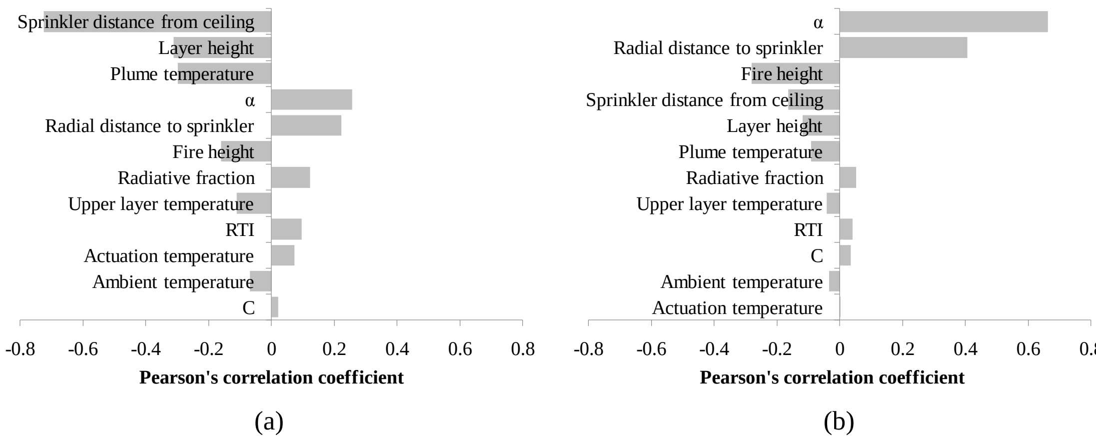


Fig. 12. Tornado charts comparing sensitivity to sources of uncertainty for HRR at the time of sprinkler activation. (a) Scenario 1; (b) Scenario 2.

Sources of Uncertainty Not Considered

There are many sources of uncertainty that are difficult to quantify. For instance, a number of assumptions are made in the BRANZFIRE zone model and associated submodels. As a zone model does not solve the momentum equation the combustion product transport time is assumed to be negligible. BRANZFIRE uses the LAVENT model for the vertical temperature and velocity distribution of the ceiling jet, and there is no data to indicate the level of uncertainty for these parameters. BRANZFIRE also makes the assumption of homogeneous temperature and combustion products in the layers, the effect of which is difficult to quantify. An advantage of using a field model is the ability to model these aspects, although other sources of uncertainty will come into play with field models, such as uncertainty in the turbulence models.

By using model verification data to create uncertainty distributions for the model, the uncertainty in many of these assumptions is included implicitly. It is expected that as a model is pushed beyond the situations for which it has been verified, the uncertainty in the model will grow and become impossible to quantify. Therefore, models should only be used within their limits where the uncertainty can be quantified and compared to the aleatoric uncertainty.

Other model input parameters, such as the thermal properties of the wall, ceiling, and floor linings, were modelled as single values and uncertainty was not considered because it was not expected to have a significant impact on the uncertainty of the outputs. Ventilation conditions could also be modelled as an uncertain parameter for the design scenario. In this case the door was modelled as being open all the time.

For the purposes of this study, all sources of uncertainty have been assumed to be independent. No correlations between parameters have been considered, due to a lack of data to support them. The uncertainty in the output variables would likely increase if correlations were included.

CONCLUSIONS

The importance of sources of uncertainty depends on the situation being considered. The accuracy of the model becomes less important as the fire and geometry parameters become less well defined. For the output and scenarios considered, uncertainty in the sprinkler response parameters provided little influence on the outcome. The BRANZFIRE zone model uncertainty was not the most influential source of uncertainty for the scenarios modelled, and became less important for Scenario 2 where the uncertainty in the fire growth and location was greater.

Model uncertainty should be considered when using computer fire models. While the increase in available computing resources allows more complex models to be used in probabilistic Monte Carlo simulations [29], a more complex model can introduce additional sources of uncertainty; particularly user decision uncertainty. In order to quantify the model uncertainty, the model must be used within reasonable parameters. If the model is used beyond its limits, the uncertainty in the output becomes unknown and should not be trusted. The model complexity should be matched to the level of certainty in the situation being modelled.

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