QUANTIFYING ERROR AND UNCERTAINTY IN CFAST 2.0 SMOKE LAYER HEIGHT PREDICTIONS

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ABSTRACT

In this paper, the model error associated with predictions of smoke layer height with the smoke transport model CFAST 2.0 is evaluated for four different scenario configurations. The evaluation is made with a statistical analysis methodology based on a comparison of experimental measurements and model predictions. With quantitative knowledge of the model error future predictions from the two-zone model can be adjusted so that the error is taken into account. The suitable method of adjustment depends on how the uncertainty is treated in a specific application. For example, this can be done either by using conservative adjustments or by treating the uncertainty in the predictions as a stochastic variable.

1. INTRODUCTION

A number of papers addressing model error have presented comparisons of, for example, the smoke transport model CFAST 2.0 with experiments. The results are, however, reported qualitatively as the model "overpredicted the temperature in the upper layer" and "gives conservative estimates of fire environment" by Luo et al. [1]. Peacock et al. [2] use words such as "favourable, satisfactory, well predicted, successful, reasonable, systematic deviation exists" or "show obvious similarities" to discuss comparison with experimental data. Some attempts have also been made at quantitative comparisons [2,3], with quantitative specification of the error as a single term or as an interval of variation of the error during the fire scenario. If a single term is used for the error in the whole scenario, the representation of the error will be inaccurate for many predictions. To express the error as an interval that applies for all predictions in the whole scenario have practical draw backs. The estimate of the uncertainty in the error will be too large, which will make adjustments of the predicted temperature difficult. Up until now very little work has been focused on studying how the error varies during a scenario and how this can be modelled even with simplistic approaches. One reason is that there is no general agreement on how to address the issue in practical terms. In several fire model evaluation guidelines [4,5], it is clear that it is not possible to evaluate the use and limitations of smoke transport models *per se*. Instead, they provide a methodology for the evaluation of smoke transport models for a specific application. The evaluation guidelines recommend comparison with experiments in order to quantify model error and model uncertainty, but do not describe how to perform the comparison quantitatively. There is no generally accepted protocol for addressing uncertainties in a model confidence study using a quantified approach.

2. OBJECTIVE

The objective of this paper is to report on a quantitative analysis of the predictive capability of the two-zone model CFAST 2.0 used for smoke layer height predictions. The approach taken is based on a statistical quantitative comparison of model predictions and experimental measurements to quantify the model error and the uncertainty in the model error.

In this paper, the type of prediction model analysed is presented very briefly since it is well-described in the opened literature. Some comments are presented on the model error and how to characterise the error. The scenario configurations from which the data have been collected are presented and, finally, the results with a discussion and conclusions.

3. BACKGROUND

As a general background, a very brief presentation of the two-zone model is presented together with the definition of the term model error used in this analysis.

3.1 The Prediction Model

Extensive overviews of the fire and smoke transport models available have been presented in a number of papers and reports [6-8]. In this paper, the analysis is limited to the two-zone model

CFAST 2.0. This type of model is commonly used in fire safety engineering applications and is well described in the literature. Even if there are updated versions of the computer model available, version 2.0 is used as an example since it is well known and used by many practitioners. Another reason is that the model is introduced to many students in most fire protection engineering programmes at university level. The model has also been found by practicing consultants to suit their requirements for many applications. Although new and more advanced models are developed, the two-zone model will probably still be used in design applications for several reasons: it is a cheap, readily available and computationally fast model.

In two-zone models, the fire room is divided into two control volumes, see Fig. 1. These are the upper smoke layer and the lower layer of "ambient" air. The zones are connected via a plume and openings to connecting rooms or the outside. The zones in a room are separated by an interface, and it is assumed that there is no exchange of mass across this interface, except for the fire room. The temperature within a zone is uniform, so there is no temperature profile within a zone. The fire is modelled as a mass- and energy-producing source. The smoke is assumed to fill the room from the top, and the interface will drop until steady-state conditions are attained or the room is totally filled with smoke.

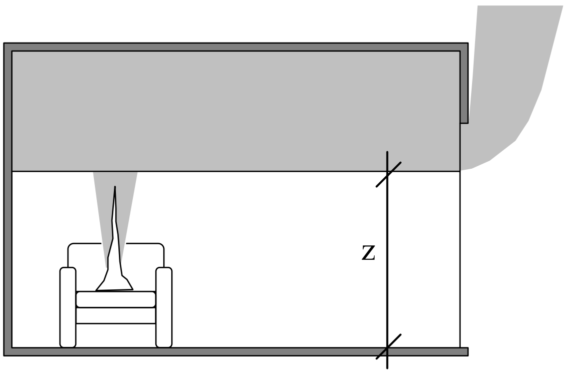

Fig. 1: Illustration of a two-zone model

The output from a two-zone model of a fire room is multi-variable and is often time dependent. In this study, the model output has been analysed in terms of the interface (smoke layer height), see variable z in Fig. 2. Predictions are made during the fire development for a certain time period from the time of ignition onwards, for a well-defined situation referred to as a *scenario*.

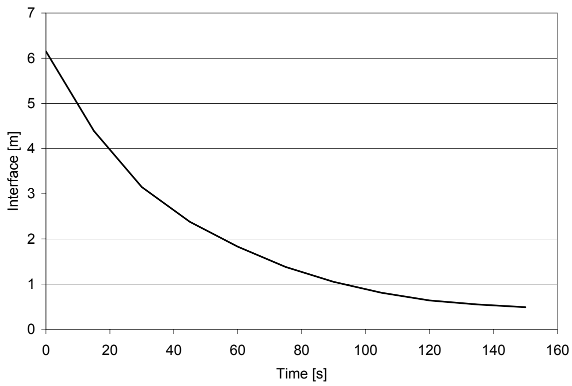

Fig. 2: Interface, z, as a function of time after ignition

3.2 The Model Error in Two-Zone Models

The error in the model predictions of a scenario will not be the same at each point in time. Neither will the error be the same for two different scenarios at the same time point. To express the model error as a constant error would be idealistic from an error-correction point of view, but does not seem to be an adequate assumption [9]. This would result in considerable uncertainty in the error itself.

Regarding predictions from the two-zone model CFAST, it has been concluded that the errors for a number of scenarios, i.e. a *scenario configuration*, have to be studied. It has been found that the error varies both within a scenario and between different scenarios [10]. Each scenario configuration represents a range of scenarios in which the variation in inter-scenario parameters affecting the model error is limited. From a practical standpoint, it is crucial to reduce the complexity of adjusting for the error. It is considered necessary to use the same adjustment model over the time frame of interest in a scenario for a specific application.

Once the error has been determined for a scenario configuration, this information can be used to take the model error into account, by adjusting the prediction. Since the information on the model error is derived for a certain scenario configuration, it is necessary that future model predictions that are to be adjusted are valid for the specific scenario configuration.

The way in which the error is taken into account depends on the application in which the prediction is to be used. In fire safety design, uncertainty is normally dealt with using conservative values for input data [11]. The uncertainty associated with the model prediction can be taken into account in a similar way, but is seldom addressed in practical applications. There may sometimes be a need to treat uncertainty as a stochastic variable, i.e. a statistical distribution. The possibility of visualising the result and studying the impact of the uncertainty on the final result in uncertainty analysis may call for stochastic treatment.

For a single prediction at a single point in time, the error, ε_{model} can be defined according to Fig. 3. When a comparison is made between experimental measurements of a variable under certain conditions of interest, e.g. the interface, and predictions of the same variable, data are collected at several time points during a scenario. The measured interface, z_m, and predicted interface, z_p, at each time point are together called a data point, and several data points thus represent a fire scenario, see Fig. 4. For each data point (i), there will probably be a measurable error, which can be expressed according to equation (1).

$$\varepsilon_i = z_{pi} - z_{mi} \tag{1}$$

where z_{pi} represents a deterministic model prediction and z_{mi} the corresponding measurement at the same point in time.

To analyse the error, the functional dependence of the error on the predicted interface for a scenario configuration is investigated. The objective is to determine:

$$\left.\begin{array}{l} \varepsilon_{model} = z_p - z_m \\ \varepsilon_{model} = g(z_p) \end{array}\right\} \quad z_m = z_p - g(z_p) = f(z_p) \tag{2}$$

To be able to express a certain degree of variation in the error (ε_{model}), the error for a specific scenario configuration is divided into a systematic and a random part, see equation (3).

$$\varepsilon_{model} = \varepsilon_{systematic} + \varepsilon_{random} \tag{3}$$

This is illustrated in Fig. 5 for a single prediction within a scenario configuration.

The systematic part can be accounted for and the random part will result in an uncertainty in the adjusted prediction. Model uncertainty is defined as the variation in model error, i.e. the random or uncertain part of the error. If a large proportion of the variation of the error for a given scenario configuration can be explained by the systematic part of the error, it can be reduced by suitable adjustments.

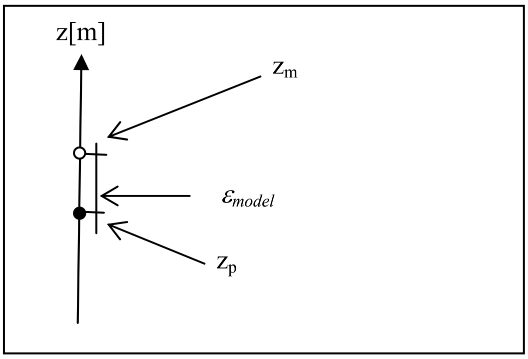

Fig. 3: Definition of the model error for a single prediction and measurement

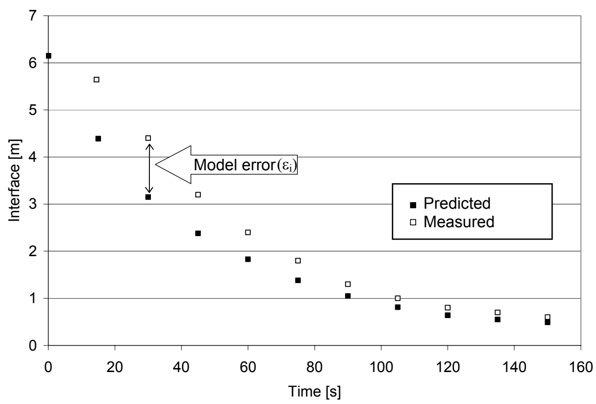

Fig. 4: Data from a fire scenario used to illustrate the variation of the error within a scenario

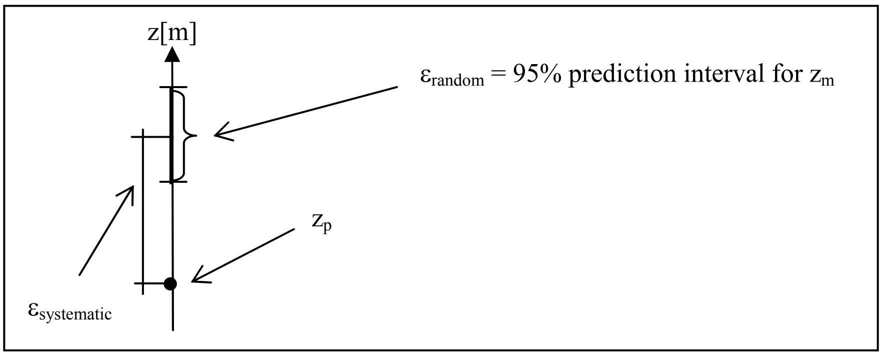

Fig. 5: Definition of the model error for a specific scenario configuration, i.e. as a combination of a random and a systematic error for each model prediction

4. METHOD

In order to explicitly analyze the error in CFAST predictions in quantitative terms, a methodology that earlier has been used to analyze the model error in temperature predictions for the same smoke transport model with promising results [12] is chosen. In this paper, only a brief overview of the method is presented, but a more extensive description is presented by Lundin [10] where limitations and assumptions are discussed in detail.

4.1 The Statistical Evaluation Method

The statistical method quantifies the systematic and random parts of the model error for the growth phase of the scenario configurations, where two-zone models have been used to predict the interface. It is achieved with a statistical analysis based on regression analysis.

The error in a model prediction is assumed to consist of a bias, i.e. a systematic part, and a random part referred to as the uncertainty or variability in the model prediction. The bias has been found to be dependent on the size of the predicted value, while the uncertainty is assumed to be independent of the predicted variable, i.e. the interface.

4.1.1 Variation of the error within a single scenario

A single data point will give no information on the variation of the error within a scenario. Fig. 4 shows that the size of the error varies significantly during a scenario and indicates that it will be of little value to determine the model error for a full scenario based on a single observation. Fig. 4 also indicates that it may not be appropriate to assume that the variation of the error between the predictions is totally uncertain, i.e. can only be described as random variation. There seems to be a systematic influence, causing the error to grow with descending interface and/or increasing time, which must be investigated further. If a systematic functional relation can explain a substantial part of the variation in the error between measurements and predictions within a scenario, i.e. the random error, will be small. The variation originates from the fact that the predictive capability of the model varies for the range of possible model output, i.e. output variables. The effects of the approximations and the appropriateness of assumptions are not constant. This uncertainty is referred to as the uncertainty in the error within a scenario and expressed as the variance of the error within a scenario, $V(\varepsilon_i)$.

4.1.2 Variation of the error between scenarios

If two different scenarios are compared at a certain point in time, the size of the error is likely to be different. An additional variation in the error will be introduced when several scenarios are studied. If only a single scenario is used to quantify the model error, information of this source of uncertainty in the error will be excluded. The variation in the error between scenarios can be divided into two different sources. The first source is differences in scenario-specific conditions or parameters, which depend on how the scenario configuration has been defined. If two scenarios are identical except for the value of a single input parameter that does not vary during the scenario, the size of the model error can be affected. The model accuracy is then affected by the value of this scenario-specific parameter. Examples of such parameters are the room height or the rate of heat release, or where a door is closed respectively open.

The other source is variation which arises from parameters that vary between experiments but is not taken into account in the model, i.e. humidity in fuel, external weather conditions etc. When two "identical" scenarios are evaluated at the same point in time, the predictions from the deterministic model are likely to be the same, although the measurements will probably differ, and therefore also the error. The difference is likely to originate from the uncertainty in reproducibility of the experimental measurements which is not captured by the prediction model or not known by the modeller.

By analyzing the size in the error for a number of scenarios, i.e. a scenario configuration previously described, the uncertainty in the error due to variation of scenario-specific parameters can be determined. When the error and uncertainty between scenarios is studied, it is difficult to find a systematic relation between the error and a specific parameter, since much of the variation originates from uncontrollable variation. The variation of the size of the error between scenarios is therefore treated as an independent random variation as a first approach, and the effect on the error from variation of both known and unknown scenario-specific parameters are added together. This uncertainty is denoted $V(\varepsilon_j)$.

4.1.3 Variation of the error for a scenario configuration

In order to determine the model error and the associated uncertainty in a way that makes the result of practical use, both the variation within a scenario and the variation between scenarios have to be taken into account. The resulting uncertainty of the error for a scenario configuration is a function of both uncertainties described previously, see equation (4).

$$V(\varepsilon_{model}) = f(V(\varepsilon_i), V(\varepsilon_j)) \qquad (4)$$

where ε_{model} is the error associated with the range of predictions defining a scenario configuration.

If part of the change in the size of the error during a scenario can be explained by functional dependence, i.e. as a systematic part, $\varepsilon_{systematic}$, between the error and other variables, the uncertainty $V(\varepsilon_{model})$ can be reduced. A benefit in such case is that if a prediction is made for a scenario that is similar to a previously defined and evaluated scenario configuration, it is possible to make adjustments for the error in the prediction. Using this approach, model uncertainty is defined as the variation in the model error for a specific scenario configuration that cannot be explained by the functional dependence, i.e. ε_{random}. The model error can then be described according to equation (3).

4.1.4 A quantified approach

The statistical method separates the two kinds of uncertainty and is based on the assumption that the predicted value itself has a strong correlation to the error, and can explain much of the variation of the error within a scenario through a simple relation.

In the analysis of the variation of the error within a single scenario, the functional dependence between ε_i and z_p is determined. This functional dependence is not assumed to be identical for different scenarios, but of the same type. Although the differential equations that constitute the model are complex, quantification using a statistical approach is simplified and is not concerned with the "true" relation. Since smoke transport models consist of several linked sub-models, the transparency is limited. The true relation is of concern for the model developer and involves very complex analysis. It is therefore not possible to quantify each error component in the model, so efforts here are limited to quantify the total model error, for some characteristic scenario configurations.

A linear relation is used to describe the dependence, see Fig. 6, which can be seen as a simple form of response surface. The objective is to describe the effect of the "true" mathematical relation that dominates. That part of the error not explained by the functional relation used in the statistical approach will result in a random error.

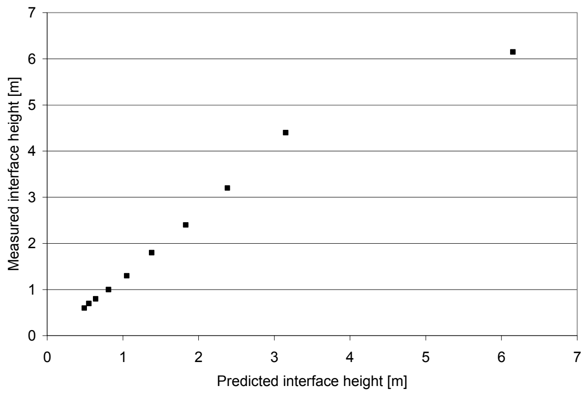

Fig. 6: Example of data points plotted to illustrate the potential linear relation between measured and predicted data

Since the interface data in a single scenario are correlated, the effect of scenario-specific parameters cannot be observed. Their effect on the error does not vary during a single scenario, as explained before. It is thus possible to isolate the dependence of the error within a scenario of correlated values, as a function of z_p. The uncertainty in the error between scenarios, ε_j, will be dependent on how the difference between scenarios affects the dependence between ε_i and z_p.

The statistical evaluation method is used to quantify both the error and uncertainty within a single scenario, ε_i and $V(\varepsilon_i)$, and the uncertainty in the error between scenarios, $V(\varepsilon_j)$. The regression model is a standard model included in most statistical textbooks and the intercept, α, bias, β, and residual variation, σ_ε, are calculated using standard statistical equations. A 95% prediction interval for the estimate of z_m based on an adjusted future prediction z_p can also be calculated with standard statistical equations. A prediction interval should not be mistaken for a confidence interval. A prediction interval describes the uncertainty in a single estimate of the variable represented on the y-axis, based on a single value from the x-axis. A confidence interval describes the uncertainty in the regression line, which can be seen as a mean value. Both uncertainties originate from the variation in the sample used in the regression analysis.

The final expression for the adjustment model for a scenario configuration with multiple scenarios is:

$$z_m \approx z_{adj} = \alpha^* + \beta^* \cdot z_p + \varepsilon \qquad (5)$$

The expression is stochastic, since α^* and ε contain uncertainties. Therefore the adjusted interface contains uncertainty and is expressed as a distribution based on both these uncertainties. They represent the random error. In a stochastic analysis, the expression in equation (5) can be used directly, but in many engineering applications a deterministic conservative value is of more use.

A conservative value can be derived from a prediction, with the adjustment model presented in equation (6). The distribution representing the model uncertainty is assumed to be normally distributed and a conservative value is derived from one of the bounds of the two-sided prediction interval. Which bound is used depends on whether a high or a low value is considered hazardous. The 95% bounds for a single prediction z_p are given by calculated with standard statistical equations [13] and are elaborated for the specific application by Lundin [10]:

$$I_{Zadj} = \alpha^* + \beta^* \cdot z_p \pm \lambda_{97.5\%} \sqrt{\left(\sigma_\alpha^2\right)^* + \left(\sigma_\varepsilon^2\right)^*} \quad (6)$$

The deterministic adjustment model, which gives a conservative estimate if low interface is regarded as hazardous, is:

$$z_{adj} = f\left(z_p\right) = \alpha^* + \beta^* \cdot z_p - \lambda_{97.5\%} \sqrt{\left(\sigma_\alpha^2\right)^* + \left(\sigma_\varepsilon^2\right)^*} \quad (7)$$

When the parameters are quantified the adjustment function for a scenario configuration can be expressed as:

$$\begin{aligned} z_{adj} = f\left(z_p\right) &= \left(\alpha^* - \lambda_{97.5\%} \sqrt{\left(\sigma_\alpha^2\right)^* + \left(\sigma_\varepsilon^2\right)^*}\right) + \beta^* \cdot z_p \\ &= U_{adj} + \beta^* \cdot z_p \end{aligned} \quad (8)$$

The 95% percentile for a normally distributed variable is given by $\lambda_{97,5\%} \approx 1.96 \approx 2$. For simplistic reasons the input needed for the conservative adjustment model can be reduced to two parameters, U_{adj} and β^*, once the statistical analysis for the scenario configuration has been performed, see equation (8).

4.2 Modification of Data

Since most two-zone models neglect the transportation time for smoke from the base of the fire to the ceiling, and the smoke layer is thereby assumed to form directly, some modification of the data subject for analysis is necessary. If the dependence of the error and the predicted interface height are described by a linear relation, the impact of the assumption can be observed in the first part of the scenario, i.e. for high interface heights.

To reduce the effect of neglecting the transport time in the plume, the range of data analysed in a scenario was restricted by excluding data from the very first part of each scenario, so that the smoke layer stated to form in the experimental setup. Only predictions from 70% of the ceiling height and below were used in the analysis. This crude assumption is made based on observation of the measured and predicted data used in the analysis [15]. The effect of this restriction of the data is illustrated in Fig. 7, where the regression analysis for the original and modified data is presented. It has been observed that the effect is greatest in scenarios with high ceiling heights.

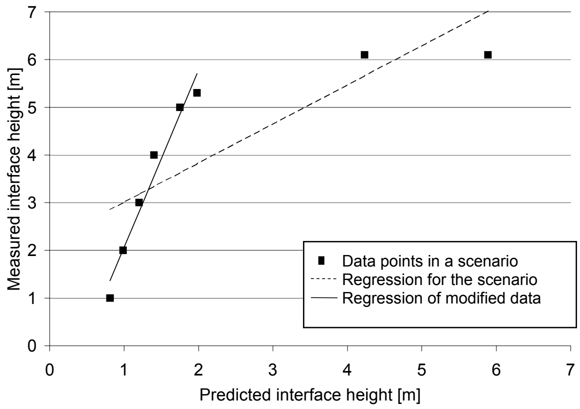

Fig. 7: Measured temperature plotted against predicted temperature, together with the regression line for the original data and the data in which predictions over 70% of room height were excluded [9]

Since the interface descends during the fire, the data point in the top-right corner of Fig. 7 represents the first data point in the scenario, the data point to the left of that point will be the second, etc. If the difference between the first and second data points is studied, it can be seen that the predicted height has decreased while the measured height is unchanged. This difference between predictions and measurements is due to the fact that the smoke transport time from the fire to the ceiling is neglected in the model. If the data points where the smoke filling process is not indicated by the measurements are excluded from the analysis, the linear model describes the data much better, according to the solid line in Fig. 7.

An alternative approach is to adjust the timescale for the predicted results, before the data is divided into data points since they are suspected to be displaced on the timescale. This can be done by defining each data point as ($z_{pi}(t_1)$, $z_{mi}(t_1+\Delta t)$). The parameter Δt is used to calibrate the curves before the analysis is performed. However, in following analysis the simplified approach where data before the smoke layer is formed in the experiments is excluded is used. The modification of the data is made manually before the statistical analysis is performed.

5. SCENARIO CONFIGURATIONS

The experimental data used for the statistical analysis consist of measurements of interface from full-scale scenarios. The measurements have been published in a number of scientific journals and these are summarised in a database which has been presented in previously published reports, e.g. [14]. The model predictions of the same scenarios by CFAST 2.0 are also included in the database [15]. The measured predicted data in the database are divided into scenario configurations referred to as scenario configurations A-D. The input data for the predictions, together with the corresponding interface vs. time data (z(t)) have been presented by Bragason [14]. A scenario configuration is defined by a number of scenarios, where one or more parameters vary within a certain range. Examples of such parameters are the height of the room, the number and size of ventilation openings, the numbers of rooms included, etc.

In the following sections, brief descriptions are presented of the scenario configurations analysed with the statistical method. For a more detailed description of the scenarios included in the scenario configurations, readers are referred to the original references, which are given in the description below.

5.1 Scenario Configuration A – Single Enclosure

Scenario configuration A involves smoke filling in a single room, with very limited openings. The floor area was 5.62 x 5.62 m^2 and the height 6.15 m. The only connection with the surroundings was an opening, 0.25 m high and 0.35 m wide, situated at floor level. The construction material was concrete, see Fig. 8 and Fig. 9.

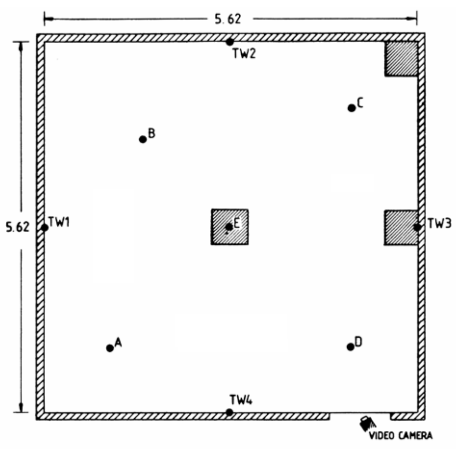

Fig. 8: Plan view of test room in scenario configuration A [16]

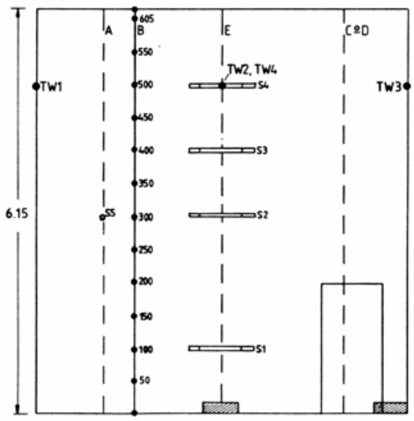

Fig. 9: Side view of test room in scenario configuration A [16]

A video camera recorded the smoke layer forming process. Squares of 1 meter were painted in black and white on two walls to make it easier to determine the smoke layer height by visual observations. Temperature was measured by thermocouples distributed over vertical lines with 50 cm spacing. Four lines; A, B C and D were placed near each corner of the room and one in the middle of the room (E) and four along the walls (TW1-TW4).

Data are available from five scenarios for scenario configuration A. The major difference between the scenarios is the rate of heat release. The fire was a typical pool fire with kerosene as fuel. Fire development was very rapid and the fire reached steady-state conditions after 30 to 60 s. The maximum rate of heat release could be changed by varying the size of the pool. The maximum rate of heat release varied between 30 kW and 390 kW. The original data was measured by Hägglund et al. [16].

5.2 Scenario Configuration B – Two Rooms Connected by a Doorway

Scenario configuration B involves the spread of smoke from a small room to a large room, the two rooms being connected by a doorway. The smaller room was 3 x 4 m^2 in area and 2.6 m high. The adjoining room had a floor area of 5.6 x 5.6 m^2 and a ceiling height of 6.1 m. The rooms were connected by a doorway with a height of 2 m and width of 1 m. From the larger room, there was a 0.25 m high and 0.80 m wide opening to the outside at floor level. Both rooms were made of concrete, see Fig. 10.

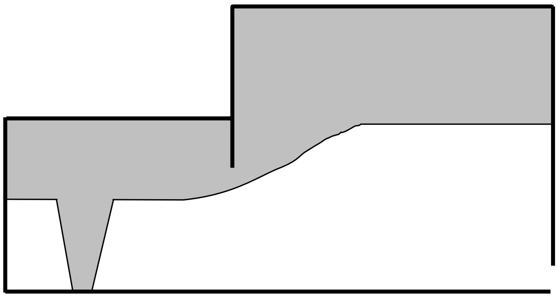

Fig. 10: Side view of test rooms in scenario configuration B

Data are available for two scenarios in scenario configuration B. The difference between the scenarios was the rate of heat release. The fire was a kerosene pool fire, exhibiting very rapid development. The fire reached steady-state conditions after 90 s. The maximum rate of heat release was varied by varying the pool area. The maximum rate of heat release varied between 330 kW and 670 kW. The original data were measured by Hägglund [17].

5.3 Scenario Configuration C – Single Room Connected to a Corridor

Scenario configuration C involves the spread of smoke from a small room to a corridor, which are connected by a doorway. The room in which the fire originated measured 4.2 x 3.3 m^2 and was 2.4 m high. The adjoining corridor had a floor area of 19 x 2.4 m^2 and the same ceiling height as the room. The doorway between the room and the corridor was 2 m high and 1 m wide. There was a 0.94 m high and 0.15 m wide opening to the outside at one end of the corridor. The construction was made of concrete, see Fig. 11.

Data from only two scenarios are available for scenario configuration C. The difference between the scenarios was the rate of heat release. The fuel was methane and the rate of heat release varied between 100 kW and 225 kW. The original measured data were presented by Rockett et al. [18].

5.4 Scenario Configuration D – Large-Scale Spaces

Scenario configuration D involves the spread of smoke in large spaces. The floor area measured 720 m^2 and the height was 26.3 m. A plan and section of the room are presented in Fig. 12.

Four scenarios were conducted in which the ventilation conditions were changed. The following conditions were evaluated: no smoke ventilation, natural ventilation and mechanical venting. The fire was assumed to be the same in all scenarios and consisted of a methanol pool fire. The total rate of heat release was measured to be 1300 kW. The original measured data were presented by Yamana and Tanaka [19].

6. RESULTS

The data from the scenario configurations where analyzed with the statistical evaluation method, which was written as a Matlab-routine [9] and has been used to perform the analysis results are presented in Figs. 13 to 20.

To visualise the results and predictive capability of CFAST 2.0 for the different scenario configurations, the data used in the analysis are plotted in a z_m vs. z_p graph, together with the linear functional relation. Different types of symbols are used for each scenario so that data points from the same scenario can be identified. A detailed description of each scenario is presented by Lundin where model predictions and experimental measurements for each scenario are plotted in interface height – time graphs [20].

Another graph illustrates the linear functional relation between these variables with the 95% prediction interval. The parameters determined in the statistical analysis can be used to adjust the predictions of a scenario similar to those defined as the scenario configuration.

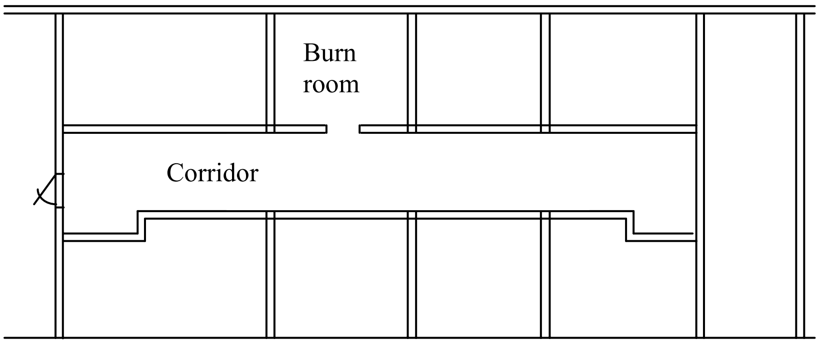

Fig. 11: Sketch of the geometry in scenario configuration C

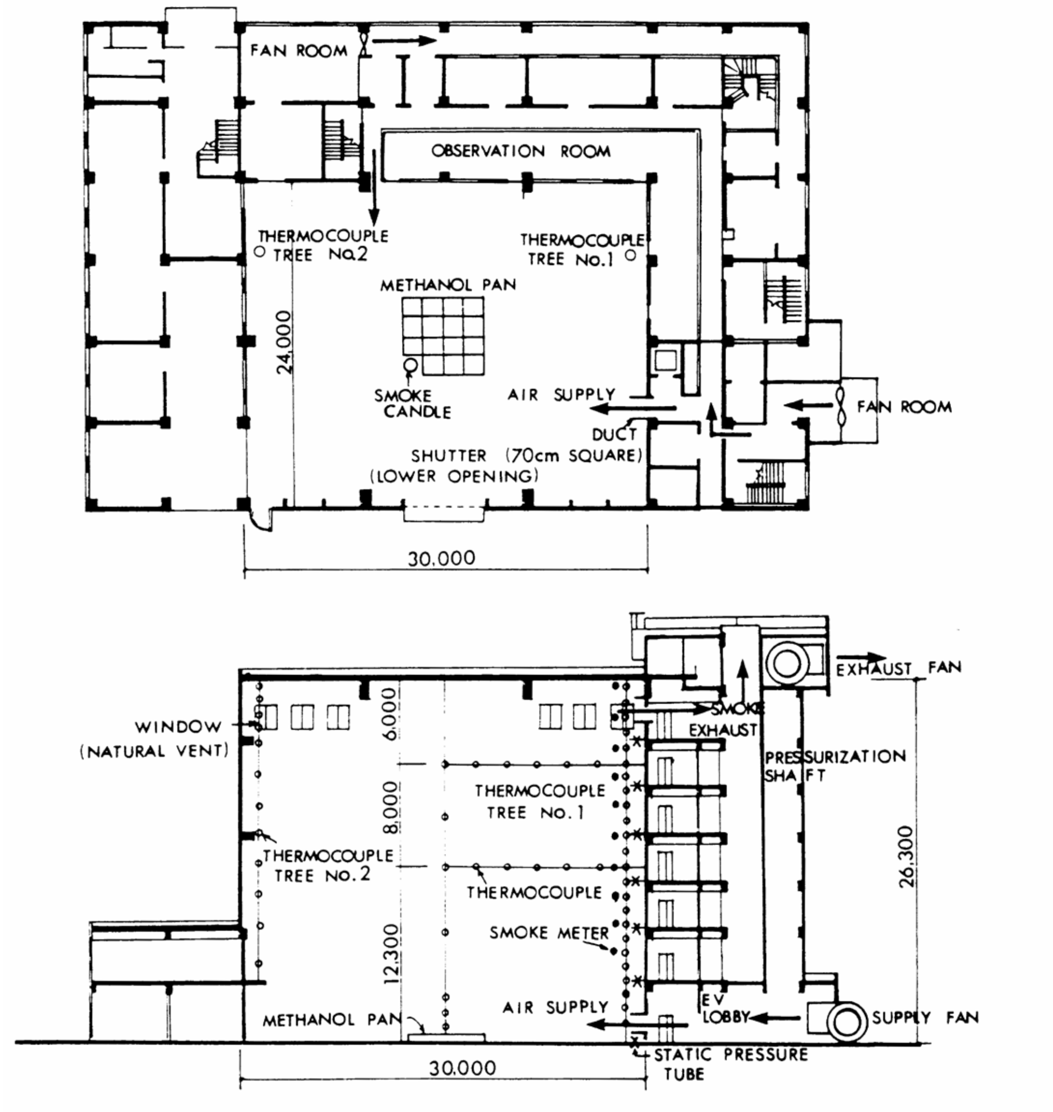

Fig. 12: Plan and section of the room where the experiments were conducted [20]

The results presented show that the assumption of a linear relation between measured and predicted interface can be a useful first approach to model the error. The regression parameters differ between the scenario configurations which indicate that the model error is sensitive to the scenario configuration layout, as assumed. There is also an obvious difference between the types of uncertainty that dominate in the different scenarios, both in size and importance. The parameters μ_α and β give an indication that there is a significant systematic error for all the scenarios. The predictive capability of the model can be seen as questionable if no account is taken of the error in the predictions.

If no consideration needs to be taken of the relation between the two main types of uncertainties separately in the analysis, a simplified form of adjustment model can be used, see equation (9).

$$z_{adj} = f(z_p) = \beta^* \cdot z_p + \left(\mu_\alpha - 1.96\sqrt{\left(\sigma_\alpha^2\right)^* + \left(\sigma_\varepsilon^2\right)^*} \right) \tag{9}$$

This is convenient in many fire safety engineering applications in which predictions from two-zone models are used as input in other models. There is only a real need to separate the uncertainties when the prediction model or a scenario configuration is evaluated and/or improved. When a suitable scenario configuration has been identified and the parameters determined by the statistical analysis, the parameters can be presented according to Table 1, to make it easier for the engineer to adjust the predictions, see equation (10).

$$z_{adj} = f(z_p) = \beta^* \cdot z_p + U_{adj} \tag{10}$$

Table 1 simplifies the use of the results from the analysis, since the amount of information is reduced. This simplification is a trade-off against the possibility of changing the percentile of the prediction interval used and of separating random and systematic errors.

Table 1: Scenario configuration-specific parameters for the simplified adjustment model

Scenario configuration	β	U_{adj}
A	1.7	-1.1
B	3.4	-4.0
C	1.9	-1.4
D	2.6	-11.6

An alternative to using the equations to adjust a model prediction is to use the graphs presenting the 95% prediction interval for the adjusted interface.

6.1 Scenario Configuration A – Single Enclosure

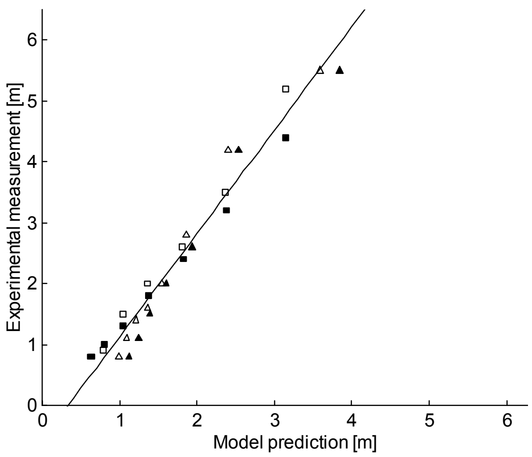

Fig. 13: Measured interface height plotted against predicted interface. The regression line is also shown

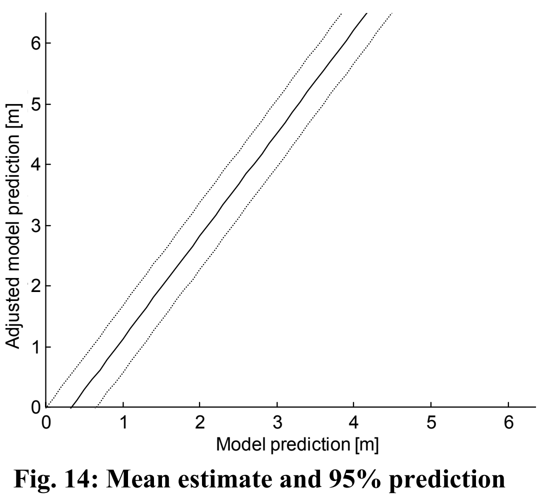

Fig. 14: Mean estimate and 95% prediction interval for the adjusted model prediction of the interface height

Parameters calculated with the statistical method:

μ_α = -0.57 m β = 1.7
σ_α = 0.12 m σ_ε = 0.25 m

6.2 Scenario Configuration B – Two Rooms Connected by a Doorway

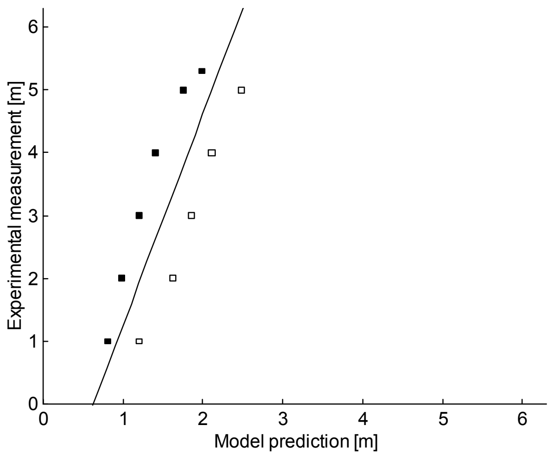

Fig. 15: Measured interface height plotted against predicted interface height. The regression line is also shown

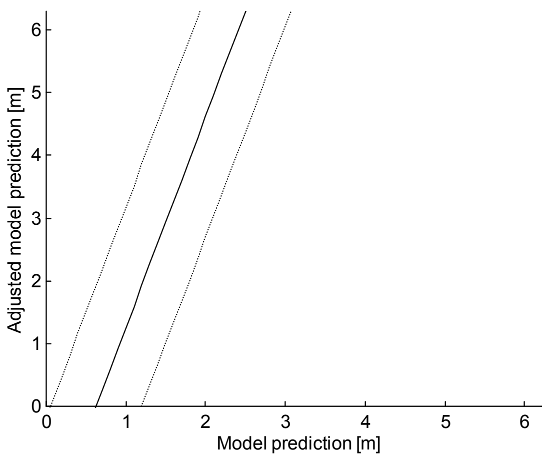

Fig. 16: Mean estimate and 95% prediction interval for the adjusted model prediction of the interface height

Parameters calculated with the statistical method:

μ_α = -2.1 m β = 3.4
σ_α = 0.94 m σ_ε = 0.28 m

6.3 Scenario Configuration C – Single Room Connected to a Corridor

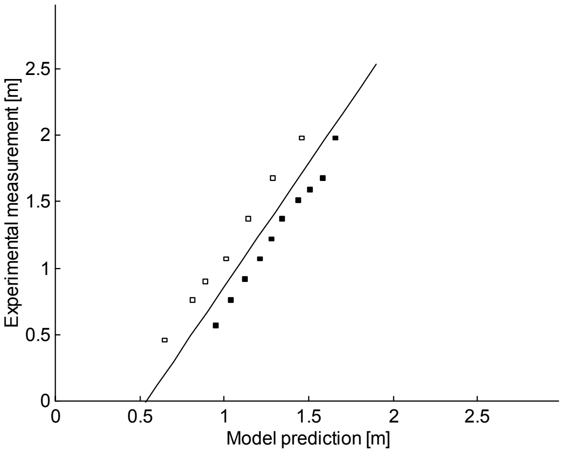

Fig. 17: Measured interface height plotted against predicted interface height. The regression line is also shown.

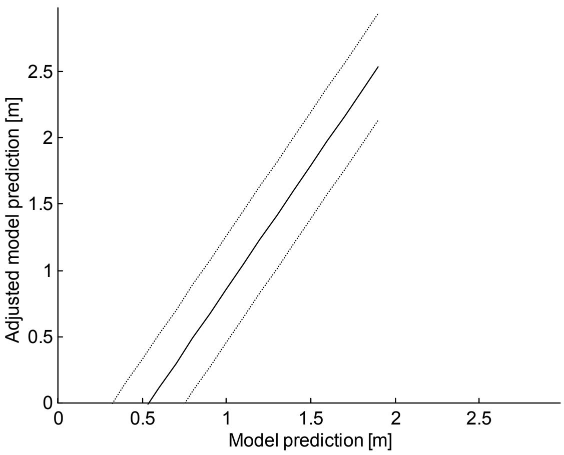

Fig. 18: Mean estimate and 95% prediction interval for the adjusted model prediction of the interface height

Parameters calculated with the statistical method:

$\mu_\alpha = -1.0$ m $\quad \beta = 1.9$
$\sigma_\alpha = 0.2$ m $\quad \sigma_\varepsilon = 0.036$ m

6.4 Scenario Configuration D – Large-Scale Spaces

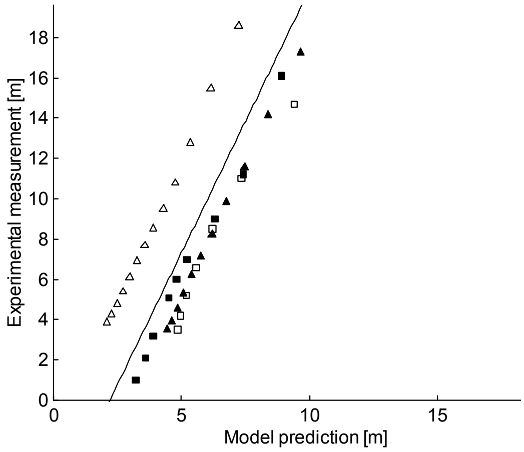

Fig. 19: Measured interface height plotted against predicted interface height. The regression line is also shown.

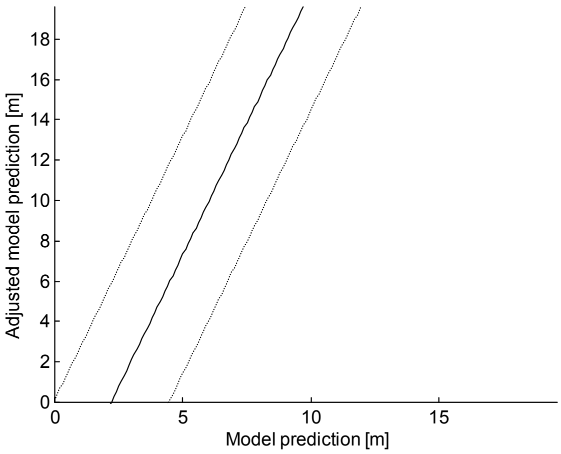

Fig. 20: Mean estimate and 95% prediction interval for the adjusted model prediction of the interface height

Parameters calculated with the statistical method:

$\mu_\alpha = -5.7$ m $\quad \beta = 2.6$
$\sigma_\alpha = 3.0$ m $\quad \sigma_\varepsilon = 0.46$ m

7. DISCUSSION

The analysis indicates that the interface height predictions at the beginning of scenarios are underpredictions, while CFAST 2.0 seems to overpredict the interface height at the end of the fire scenario. The point at which the predictive characteristics of the model changes is different for the different scenarios. In the following sections analysis and evaluation of the scenario configurations are discussed together with the limitations of the analysis.

7.1 Analysis and Evaluation of the Scenario Configurations

The results show that the predictive capability varies between the scenario configurations. The belief that the predictive capability varied for different types of scenarios has thus been proven. The need to define scenario configurations is confirmed since a general approach would result in a high degree of uncertainty in the error, i.e. high uncertainty associated with adjustment of the model predictions. The statistical methodology can effectively be used to evaluate the suitability of the prediction model for a certain scenario configuration. Alternative definitions of scenario configurations can also easily be evaluated by removing or adding scenarios and performing the statistical analysis again. The different scenario configurations considered in this study do not nearly cover the range of scenarios that is needed in practical applications, but can be used as a step in the quality control and verification of mathematical fire models example according to relevant standards [4,5]. An analysis of the situations normally modelled is required to derive suitable types of scenario configurations for practical applications and full-scale data for those configurations have to be derived. The range of each scenario must be limited by a maximum tolerable uncertainty in the adjustments, which is dependent on the scenarios used to represent the scenario configuration in the analysis.

It is difficult, in advance, to determine the optimal balance between accuracy and the range of applicability of a scenario configuration, i.e. how wide a range of different situations can be adjusted with the scenario configuration-specific adjustment model. With the statistical method, it is possible to evaluate the effect of the re-definition of a scenario configuration. Other actions taken to widen the range of applicability of the adjustment model or increase the accuracy of the adjustments can also be evaluated. The following are suggestions that can be evaluated in a sensitivity analysis with the statistical method, if the definition or re-definition of a scenario configuration is considered.

- Re-define the scenario configuration by excluding scenarios with substantially different scenario-specific parameters. This action will decrease the range of applicability, since the variation of the scenario-specific parameters is decreased, and the range of values that can be adjusted by analysis of the particular scenario configuration will thus be changed. This is appropriate if the parameter σ_α in the adjustment model is large.

- Add scenarios to the scenario configuration which have similar scenario-specific parameters to the scenarios included in the original definition. If the same definition of the scenario configuration is used and more scenarios are included in the type of scenario configuration, the uncertainty in the estimates with the statistical method will be reduced.

- Develop the model expressing the functional relation between the error and the predicted value in a more accurate way. In the development described in this study previously, the relation between the error and the predicted value is assumed to be linear. This seems to agree fairly well with the predictions of CFAST 2.0 for most scenario configurations, but improvements can be made and the assumption might not be valid for all smoke transport models. This is suitable if the parameter σ_ε is large.

- Increase the systematic part of the error by determining the variation between scenarios with a functional relation. The model error, ε, can be expressed as a function not only of the predicted value, but also of other parameters characteristic of a scenario, for example, rate of heat release. Such a study would require a greatly extended experimental database. This would reduce the parameter σ_α in the adjustment model.

- Reduce the uncertainty in measurements. Even if this uncertainty is not subject to analysis, it is included in the analysis results. A reduction in this source would reduce the final uncertainty.

7.2 Limitations

In the analysis, measured values are used to represent real values, which introduce error and uncertainty into the measurements as part of the quantified uncertainty. Another source of error and uncertainty is the fact that some conditions and variables can either not be controlled from scenario to scenario, or taken into account at all. Since a scenario configuration consists of several scenarios, this uncertainty has an effect on the analysis results.

It is concluded that, in practical applications, the error and uncertainty due to the prediction model used are only part of the problem. There are several other sources of error which must also be dealt with, e.g. the uncertainty associated with the modeller and the input data. This can also be a challenge when model uncertainty is evaluated. Part of the data used in the analysis consists of model predictions. In a recent code assessment exercise, one of the objectives was to compare simulations performed by different modellers using the same model. Modelling was carried out by professional engineers, and the differences in the results were significant [21]. In this work, efforts have been made to reduce the error associated with the modeller by using simple scenario configurations and an experienced engineer to perform the modelling exercises. However, it is recognised that error and possible variation due to the modeller cannot be totally excluded. Another example is error and uncertainty due to differences in input data used for modelling and the experimental data. If complex experiments are carried out, the measurement errors can increase. An example is the data presented by Reneke et al. [3]. During the scenario, the rate of heat release varied significantly and changed rapidly. This makes it difficult to get the correct data for the modelling exercise. Part of the error can therefore be caused by inaccurate data. It is difficult to separate the different types of error when the output data is studied and therefore one should be careful to draw conclusions about an isolated error component. Therefore, it is important to use simple scenarios where the experiments are performed under well-controlled conditions when the model error is analyzed.

Although no in-depth analysis of the analytical expressions in the prediction models was performed, it is concluded that the predictions at the beginning of the scenario were not suitable for modelling with the assumptions used in the two-zone models analysed. This is partly explained by the fact that the required transport time in the plume for the smoke to reach the ceiling from the floor is neglected in most two-zone models. The measured and predicted values in each data point are taken at the same time point. An alternative may be to adjust the time scale for the predicted results, before the data are divided into data points. A method that can be used if the time-interface graphs have similar shapes, but are displaced on the time scale, is to define each data point as ($z_{pi}(t_1)$, $z_{mi}(t_1+\Delta t)$). The parameter Δt is then used to calibrate the interface-time curves before the statistical analysis is performed.

8. CONCLUSIONS

The assumption that relation between predicted and measured interface height can be expressed as a linear model seems reasonable for many scenarios. A more sophisticated assumption might describe the relation more accurately, but this work should be seen as a first approach to quantify how the error varies during a scenario. By using the statistical method, additional knowledge of how the error varies within the first part of a fire scenario is generated for a specific smoke transport model.

The results from the statistical analysis provide quantitative information on the predictive capability of smoke transport models. They can be used as one approach when the uncertainty in the model output from smoke transport models are evaluated and assessed.

The quantitative output of the statistical analysis of a scenario configuration provides parameters for the adjustment model, resulting in an equation that can be used to make conservative adjustments to model predictions, within a specific scenario configuration. The adjustments for the possible predictions within a scenario configuration can also be presented in the form of a graph which can be used to derive conservative values. The conservative values are then used in deterministic analysis or design applications. The adjustments can also be expressed as a distribution that contains information on the uncertainty, and which can be used in probabilistic analysis, e.g. uncertainty analysis. A general adjustment factor for a smoke transport model cannot be derived, due to the variation in the predictive capability of the model in the different types of scenario configurations.

Analysis of the interface predictions made with the model CFAST 2.0 showed presence of both a systematic error and a random error, i.e. model uncertainty. The error varied depending on the scenario configuration. The interface seems to be underpredicted by the model.

Although the results show that the predictive capability of smoke transport models can be questioned, they also showed that the error in the prediction can be reduced or adjusted for. The "corrected" predictions in most cases are better estimates of the real interface than the original model predictions.

The scenarios investigated are chosen to fit fire safety design purposes, where evaluation of trial designs is one application where smoke transport models are used. This is a first step to analyze a limited number of scenarios that might be useful. It is important to continue to systematically evaluate scenarios of interest, and also to continue to evaluate the statistical method if it is found to be too limited or crude.

It is important to realise that these conclusions are not valid for future versions of CFAST or for other smoke transport models. They have to be evaluated, in order to derive basis for judgement on how to treat the model error and model uncertainty. By using the model applied in this paper, this can be done in a systematic way.

NOMENCLATURE

α	intercept of the regression line on the y-axis
β	slope of the regression line
ε	residual error for each data point in a scenario
ε_i	error within a scenario
ε_j	error between scenarios
ε_{model}	model error in a scenario configuration
ε_{random}	the random component of the model error for a scenario configuration
$\varepsilon_{systematic}$	the systematic component of the model error for a scenario configuration
$\lambda_{2.5\%}$,$\lambda_{97\%}$	percentiles corresponding to a prediction interval of 95%
σ	residual variance of the model errors
σ_α^2	residual variance of the intercepts in a scenario configuration
i	the number of a specific data points in a scenario
I_{Zadj}	prediction interval for the adjusted temperature
z	interface height
z_{adj}	adjusted interface height, a predicted interface height where the model error is taken into account
z_{mij}	measured interface height in data point *i (a single point on an interface height-time curve)* in scenario j
z_{pij}	predicted interface height in data point *i (a single point on an interface height-time curve)* in scenario j
U_{adj}	a part of the adjustment expression that is constant for each scenario configuration

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