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Abstract

This study chronicles the development and integration of a smoke detector activation algorithm that describes the response time of a smoke detector into a Large Eddy Simulation (LES) fire model. Although the activation algorithm could be used with any CFD smoke movement model, the results here address specifically its application to the Fire Dynamics Simulator (FDS). The fire model predicts the smoke concentration and velocity adjacent to the detector while an algorithm based on characteristic velocity-based lag times describes the transport of smoke into the sensing chamber of the smoke detector. An Underwriters Laboratories Standard 217 fire test, as well as experimental data from two experimental multi-room compartment fires, were used for comparison and validation of the accuracy of the algorithm. A series of benchmark studies in a numerical wind tunnel provided a mechanism to establish the sensitivity of the model to the different input parameters. The algorithm was found to be very accurate in determining detector activation times for both high and low-velocity smoke flows. Additionally, it was found that the algorithm provides more accurate smoke detector activation times than other correlations based on optical density or temperature. The activation algorithm will be included in the next release of FDS (version 5.x).

Keywords: Smoke detection, Detector delay time, FDS, Smoke detector response, Smoke detector activation Algorithm

Disclaimer

Combustion Science & Engineering, Inc. (CSE) makes no warranty, expressed or implied, to users of the smoke detector activation algorithm and accepts no responsibility for its use. Users of the algorithm assume sole responsibility for determining the appropriateness of its use in any particular application; for any conclusions drawn from the results of its use; and for any actions taken or not taken as a result of analysis performed using these tools. Users are warned that the algorithm is intended for use only by those competent in the fields of fluid dynamics, thermodynamics, heat transfer, combustion, fire science, and smoke detection, and is intended only to supplement the informed judgment of the qualified user. The software package is a computer model that may or may not have predictive capability when applied to a specific set of factual circumstances. Lack of accurate predictions by the model could lead to erroneous conclusions with regard to fire safety. All results should be evaluated by an informed user. Throughout this document, the mention of computer hardware or commercial software does not constitute endorsement by CSE, nor does it indicate that the products are necessarily those best suited for the intended purpose.

Contents

Chapter 1

1 Introduction

Early detection of fire plays an important role in the life safety of building occupants. The ability to accurately predict the performance of fire detection systems is an integral part of the analysis associated with fire safety design and fire reconstruction. Traditionally, smoke detection systems are designed and installed based on prescriptive requirements. While studies have shown that the presence of functional smoke detectors in residential settings can significantly reduce the number of injuries and fatalities associated with fire (e.g. Mallonee *et al.*, 1996; Ahrens, 2004), there are potential detector locations in a given residence that can cause significant delays in the activation of a smoke alarm. This delay can result in serious injury or death. Therefore, a performance-based smoke detection system design will require an accurate method for determining the time to activation and optimum detector placement in unique building geometries.

The two most prominent types of fire detectors are thermal (e.g. sprinklers and heat detectors) and smoke detectors. Plume and ceiling jet correlations (maximum temperature and velocity) coupled with a thermal lumped-mass model of the convective heat transfer have been used to predict the response of sprinklers and heat detectors (Stroup and Evans, 1988). This model has been incorporated into fire analysis tool suites (e.g. FPETool) as well as zonal-type fire models (e.g. FAST). In addition, since 1990, NFPA 72E has incorporated a method for the spacing of heat detectors (in the form of look-up tables developed from modeling estimates) based on the fire growth rate and size, the detector's thermal response characteristics (i.e. Response Time Index or RTI), and the ceiling height.

Smoke detector activation schemes have also previously been incorporated into zone models (e.g. FPETool and FAST) (Upadhyay and Ezekoye, 2005). The most simplistic and practical method for the modeling of smoke detector activation treats the detector as a very sensitive thermal element (i.e. with no thermal lag) and uses a weak correlation between the temperature rise and smoke obscuration at the location of the detector. The critical increase in temperature above ambient assumed for smoke detector activation is 11.1°C (20°F) (Heskestad and Delichatsios, 1977). This method ignores many of the factors that affect smoke detector activation such as the response characteristics of the detectors as well as the characteristics of the smoke. There has been significant criticism levied on the technical basis and accuracy of such an approach, which has left substantial doubt as to its validity (Beyler and DiNenno, 1991; Schifiliti and Pucci, 1996; Luck and Sievert, 1999; Schifiliti, 2001; Cholin and Marrion, 2001; Mowrer and Friedman, 1998; Gottuk *et al.*, 1999; Wakelin, 1997).

A more accurate methodology to predict the activation of smoke detectors is needed. The technique should be able to model the transport of smoke as well as estimate the local conditions (i.e. velocity, temperature, smoke obscuration) at the smoke detector. Fire Dynamics Simulator (FDS) is one predictive tool that has been shown to effectively model fire and smoke transport in well-ventilated conditions, especially when the size of the fire is small compared to the compartment (i.e. when a fire detection system's response is most relevant). Previous versions of FDS did not include a smoke detector activation model.

A preliminary study was conducted to assess the ability of FDS to predict smoke detector activation (D'Souza *et al.*, 2002). The methodology for determining the conditions and time for smoke detector activation uses FDS to compute the flow field and smoke movement and a detector lag time is obtained from physics-based algorithms. The geometry of the space of interest is created in FDS. The smoke yield, which is a fraction of soot mass to total mass burned, is obtained from the fire protection scientific literature (e.g. Tewarson, 2002) and is an input into the model. The heat release rate of the fire is input into the model, as well as a value for the heat of combustion (needed to determine the mass burning rate) from the literature, and the resulting fire flows and smoke movement are modeled. The model calculates, as a function of time, the smoke density (g/m3) and the smoke velocity (among other variables) at all cells inside the computational domain.

D'Souza *et al.* preliminary work demonstrates that the FDS model can predict smoke detector activation with reasonable accuracy when used in conjunction with smoke detector lag correlations that correct for the time delay associated with low velocity smoke penetrating the detector housing (D'Souza *et al.*, 2002). While the work of D'Souza *et al.* (2002) found reasonable agreement between experimental and model results, this preliminary approach is still only a first order technique which takes the time for conditions outside of the detector to reach threshold limits as defined by UL 217, and then calculates the lag time at that discreet point in time. Since the FDS model calculates the flow field and smoke density transiently at the detector, the goal of this effort was to improve upon the D'Souza *et al.* methodology by not only incorporating the correlation into the model, but also utilizing the transient numerical solution of FDS. The use of this transient numerical solution instead of a point in time correlation will ensure that the model is calculating the smoke obscuration inside of the detector chamber (after the dwell and characteristic mixing lag times as described by Cleary et. al., 2000), and will therefore provide a more accurate and singular solution of the activation time, instead of a broader range of times.

Chapter 2

2 Model and Scenario Definition

2.1 Model Documentation

This section provides a short description of the smoke detector activation algorithm following the framework suggested by ASTM E 1355 (2004). It is intended to outline the major features of the model, its history, the underlying physical assumptions, and other relevant information. More detailed information about the algorithm itself can be found in the next chapter.

2.1.1 Name and Version of the Model

The name of the model is the smoke detector activation algorithm. It was designed to function in conjunction with Fire Dynamics Simulator (FDS), a model that solves the equations of fire-driven flows (McGrattan ed., 2005). The algorithm is written in Fortran.

2.1.2 Type of Model

The smoke detector activation algorithm is a model to predict the time to activate a smoke detector in the presence of a fire-driven flow. The algorithm is designed to use the output of a Computational Fluid Dynamics (CFD) model that provides the local velocity and smoke concentrations at the detector location. The algorithm solves the equations that account for smoke detector lag and activation. The algorithm is currently designed to be integrated with FDS (McGrattan and Forney, 2005).

2.1.3 Model Developers

The algorithm was created and developed by Combustion Science & Engineering, Inc. (CSE) with the support of the National Institute of Standards and Technology (NIST). The algorithm is theoretically based on the work of Cleary *et al.* (2000) and other foundational studies (e.g. Brozovsky, 1991; Newman, 1987; D'Souza *et al.,* 2002).

2.1.4 Model Uses

The algorithm was created to provide the fire protection engineering and fire investigation communities with an accurate tool to predict the activation of smoke detection devices in the presence of a fire-driven flow. This tool has uses that include:

- Fire Protection System Design – Determination of proper smoke detector location for consistent and timely fire detection and notification of building occupants
- Fire Investigation and Reconstruction – Reconstruction of time and/or conditions necessary for smoke detector activation for a given hypothesized fire scenario

2.1.5 Model Output

The algorithm utilizes the smoke concentration and velocity predictions at a prescribed location from FDS for a prescribed fire source to predict the smoke concentration inside the sensing chambers of typical smoke alarms. The smoke concentration and velocity from FDS provide the conditions outside the smoke alarm. The algorithm uses these conditions to predict the flow of smoke into the alarm and the conditions inside the sensing chamber of the alarm. The algorithm determines the smoke concentration within the alarm sensing chamber at each time step of the FDS calculation. During a simulation, FDS will save the history of the smoke concentration within the smoke detector in a separate data file (i.e. casename_smkdt.csv). When the smoke concentration inside the chamber meets the user-defined threshold for smoke alarm activation, the algorithm will no longer continue to calculate concentration within the smoke detector. In the companion visualization software, Smokeview (Forney and McGrattan, 2004), the visual locator for the prescribed smoke detector will change color and the user can view the contents of the output file to locate the time of detector activation.

2.1.6 Relevant Publications

It has been well established in the fire protection engineering community that smoke detectors present an entry resistance to smoke-laden flows. Entry resistance means that the smoke concentration outside the detector may not correspond to that at the sensor located inside the housing. Heskestad (1975) first proposed that this time lag (τ) could be a function of the free stream velocity (U) flowing past the detector, and a characteristic length L, which is the effective distance that the smoke has to travel through the detector. This approach is adequate at sufficiently high velocities, but it is lacking when the velocity is low (Cleary *et al.*, 1999). Different fire scenarios can lead to low velocity flows at the smoke detector locations where the simple approach of Heskestad will not apply. For example, in the case of ceiling jets, Brozovsky (1991) found that this approach did not hold for low ceiling jet velocities. Qualey *et al.* (2001) observed long detector activation times under smoldering fires that generated low velocities. In order to deal with the full range of velocity conditions, Newman (1986) mentioned that the dynamic response of a smoke detector model could be described as a first order conventional diffusion equation based on two apparent detector characteristic times.

The above studies highlight the point that it is important not only to establish the transport lag between the fire and the smoke detector but also to properly establish the transfer of smoke particles from the outside of the detector into the sensing chamber. None of the above studies has attempted to transiently resolve both processes in a simultaneous manner. This can only be done using a CFD approach, as it requires detailed local and temporal resolutions of the velocity fields close to the detector as well as a precise estimation of the local concentration of smoke. Some initial studies (D'Souza *et. al.*, 2002; Cleary *et al.*, 2001; Cleary *et al.*, 1999) have used CFD fire modeling to study smoke detector activation, but none of these studies transiently incorporated the time lag factor that accounts for the smoke entry resistance.

The smoke detector activation algorithm is integrated with FDS and the results are dependent on proper use of FDS. Each version of FDS and Smokeview is documented by three separate publications – the FDS Technical Reference Guide (McGrattan ed., 2005), the FDS User's Guide (McGrattan and Forney, 2005), and the Smokeview User's Guide (Forney and McGrattan, 2004). The User's Guides only describe the mechanics of using the computer programs. The Technical Reference Guide provides the underlying theory and algorithm details, plus a description of any relevant verification and validation studies.

2.1.7 Governing Equations, Assumptions and Numerics

Following is a brief description of the components and major assumptions of the smoke detector activation algorithm. Detailed information regarding the assumptions and governing equations associated with the model is provided in Section 3.1.

The activation algorithm module is currently designed to be incorporated into FDS and makes use of the flow field and species concentration predictions of that model. The methodology of determining the conditions and time for smoke detector activation uses FDS to compute the flow field and smoke movement and a detector lag time is obtained from scientifically determined algorithms. The geometry of the volume of interest is created in FDS. A smoke yield, which is a fraction of soot mass to total mass burned, is obtained from the fire protection scientific literature (Tewarson, 2002) and is input into the model. The heat release rate of the fire is input into the model, as well as a heat of combustion (to determine the mass burning) from the literature, and the resulting fire flows and smoke movement are modeled. The model calculates a smoke density (g/m^3) and a smoke velocity among other outputs at all cells inside the computational domain as a function of time.

In order to convert the smoke density from the FDS output into a smoke obscuration, information about the smoke particles must be known. Mulholland (2002) has reported K_m-factors (light extinction coefficients per unit mass) for several common materials, which facilitates conversion of the smoke density measurements into smoke light obscuration (percent obscuration per meter). Mulholland reports a K_m of 7.6 m^2/g is adequate for smoke produced during flaming of wood and plastics, and a K_m of 4.4 m^2/g is appropriate for smoke produced during pyrolysis of wood and plastics. The algorithm methodology takes the smoke density from FDS, and uses the applicable K_m value to determine a smoke obscuration level.

To activate the smoke alarm, smoke obscuration levels must reach minimum levels and the smoke must enter the detector, overcoming the flow resistance introduced by the housing. The flow resistance of the housing can cause a delay (or lag) in the activation of the alarm. Brozovsky *et al.* (1995) and Cleary *et al.* (2000), among others, developed correlations for determination of lag times of smoke detectors. The smoke detector lag time is based on the characteristics of the specific detector, and the velocity of the smoke at the detector location. As an example, Cleary *et al.* (2000) produced a lag time correlation for a particular ionization smoke detector with the form:

$$\delta t = \text{dwell time} = 2.5U^{-0.71}$$
$$\tau = \text{characteristic mixing time} = 0.76U^{-0.87}$$

where:

$$\Delta t = \text{Detector delay time} = \delta t + \tau$$
$$U = \text{Smoke velocity at detector location}$$

The dwell time is the time for the smoke to penetrate the housing of the detector and enter the sensing chamber. The mixing time is the time for the smoke to mix within the volume of the sensing chamber and be detected by the sensing mechanism. The dwell time and characteristic mixing time in series is the lag time between the arrival of sufficient smoke at the detector and the actual sounding of the alarm. The time for attainment of the necessary smoke obscuration is summed with the detector lag time from the correlations of Brozovsky *et al.* (1995) or Cleary *et al.* (2000) to determine a total detector activation time. Often, when the velocity of the gases reaches a velocity of approximately 15 cm/s, there is sufficient momentum of the smoke so that there is little or no lag time associated with the activation of the detector (Brozovsky *et al.*, 1995).

The governing standard for all single- and multiple-station smoke detectors is the Underwriters Laboratories Standard 217 (2005). To meet the requirements of the standard, detectors must alarm when local smoke levels of between approximately 23% and 56% obscuration per meter (7% - 17% obscuration per foot) are reached during full-scale fire tests. Hence, the relationship between smoke density and obscuration must be determined to use the effectively use the output of FDS for smoke alarm activation. D'Souza *et al.* (2002) used a methodology that takes the calculated smoke density from FDS, and uses both K_m values to determine a comprehensive range of smoke obscuration levels, which therefore leads to determination of a range of times to attainment of smoke detector activation conditions considering the range requirements of UL 217 (23% – 56% smoke obscuration per meter). Therefore, this methodology determines the broadest reasonable range of times for attainment of the conditions necessary for smoke detector activation.

A key assumption of the activation algorithm is that the smoke obscuration listed on the back of the detector is the necessary smoke obscuration inside the housing to attain an alarm. The smoke obscuration sensitivity listed on the back of the smoke detector is that which was obtained in the UL 217 smoke box test (UL 217, 2005). It is assumed that the smoke box test is run at such a high velocity that while the smoke obscuration that is listed on the back of the detector is the smoke obscuration measured outside the detector at alarm, it is equivalent to the obscuration inside the smoke sensing chamber at alarm. This assumption is reasonable because the high velocity makes the lag time negligible. The default activation smoke obscuration inside the detector is set to 3.28 %/m (1%/ft), which is a common sensitivity of residential detectors from the smoke box. However, the algorithm continues to calculate the smoke obscuration inside of the smoke chamber even after the activation threshold is reached. Therefore, if for some reason, the user feels that this assumption is not valid or needs modification, the necessary obscuration for activation of the smoke detector can be modified via the input file, or the smoke obscuration inside the chamber can be post-processed to determine an activation time based on a different activation threshold.

2.1.8 Limitations of the Model

An accurate prediction of the activation time of a smoke detector requires a proper description of the velocity flow field and smoke concentration in the area of the smoke detector. Hence, the predictions from the algorithm are inherently dependent on the quantities and properties that affect the CFD predictions, including the input variables and calculation techniques. Important variables include but are not limited to grid resolution, material properties such as smoke generation rate and heat release rate and sufficient detail in the geometry.

The algorithm uses experimentally determined constants to characterize the smoke entry lag-time for typical smoke alarms. Hence, the user is responsible for either supplying these constants for the smoke detection device under consideration or properly selecting values for these constants from other sources. Default values, obtained from measurements presented in the literature, are included in the code but must be reviewed for appropriateness by the user.

Typically, the response of smoke alarms, per most standard codes, is characterized by measurements of local smoke obscuration (UL 217, 2005). A similar approach is used by the activation algorithm. The algorithm utilizes the smoke obscuration level indicated on an alarm (typically approximately 1%/ft) as the value inside the sensing chamber needed for alarm. Hence, the algorithm does not predict or monitor particle concentration, which is the actual mechanism that causes alarm activation. Particle concentration is difficult to predict due to limited information and models of particle generation, agglomeration and coagulation. Most standard tests do not distinguish the sensitivity of different types of smoke alarms (e.g. photoelectric or ionization) to different fire conditions. Similarly, the algorithm will not differentiate between smoke alarms of differing sensing technology, since the alarm threshold is based on the internal smoke obscuration (independent of the type of detector).

As mentioned above, an important limitation of the model is its dependence on accurate resolution of the smoke density and velocity at the detector location. If inaccurate computations of the smoke density and velocity are input into the algorithm, inaccurate estimations of the smoke detector response could result. Since the transport of the smoke is highly dependent on the velocity, the velocity is the ultimate dependent variable that FDS must accurately resolve for the algorithm to be successful. Of critical importance for accurate determinations of velocity in FDS is the user selection of the grid size. Since when a fire grows, it creates a ceiling jet, the smoke detector is located on the ceiling or sidewall in order to be located in the ceiling jet flow of the smoke. In order for FDS to properly determine the velocity at the smoke detector, the determination of the velocity that is input into the algorithm must, likewise, be determined for the ceiling jet flow.

The way the velocity is treated corresponds to an average value. If the detector is at node n, then,

$$\overline{U}^2 = \frac{1}{4}\left[\sum_{i=1}^{3}(u_i(n-1)+u_i(n))^2\right] \tag{1}$$

This will introduce a cell size dependency on the velocity and if the area of interest is within a boundary layer, then it will neglect the viscous effects at the wall.

The problem has to be evaluated to establish if the manner in which it is postulated corresponds to the assumptions. The assumption associated with Equation (1) is valid if $y >> \delta_B$ and $y << \delta_F$, where y is the cell size depth, δ_B is the boundary layer thickness and δ_F is the characteristic thickness of the ceiling layer. δ_F could be established in a preliminary fashion using correlations, but for more complex geometries, will have to be extracted from the CFD simulation (see Figure 1).

The smoke detector height, δ_D, is of the order of 25 mm and its length, d, is of the order of 100 mm. The cell size to be used also has to be comparable at least to the height of the detector.

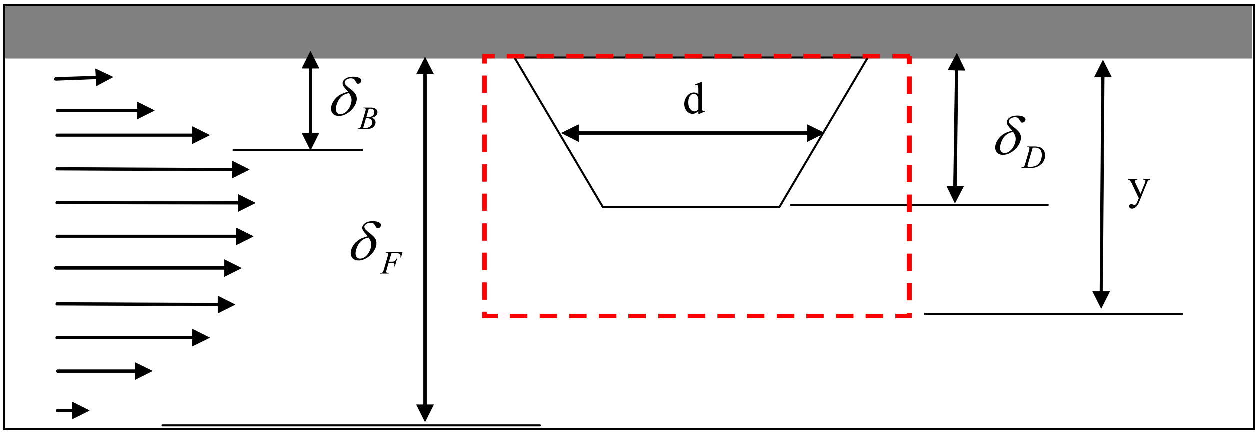

Figure 1 - A schematic of the ceiling jet boundary layer impinging on a smoke detector, and the necessary cell size estimates.

An estimate of the boundary layer thickness is presented below as Figure 2. This plot shows that for the relevant dimensions; the boundary layer thickness (δ_B) is less than half the typical height of a smoke detector for a wide range of velocities. Thus, the average value within a cell (per Equation (1)) containing a smoke detector will provide a reasonable estimate of the velocity. As a reference, exaggerated characteristic length scales (d) of 0.01 m and 1 m have also been presented. This plot shows that even for those length scales, the boundary layer thickness will only cover the entire height of the detector for very low velocities. Under these conditions the precision of the algorithm will decrease and the model will use a higher than real velocity and could lead to under-prediction of the activation time.

The boundary layer thickness equations used are as follows (Munson *et al.*,1994):

$$\begin{cases} \delta_B = \dfrac{0.664}{\mathrm{Re}_x^{\ 1/2}} & for \quad \mathrm{Re}_x < 5000 \\ \delta_B = \dfrac{0.370x}{\mathrm{Re}_x^{\ 1/5}} & for \quad \mathrm{Re}_x > 5000 \end{cases} \tag{2}$$

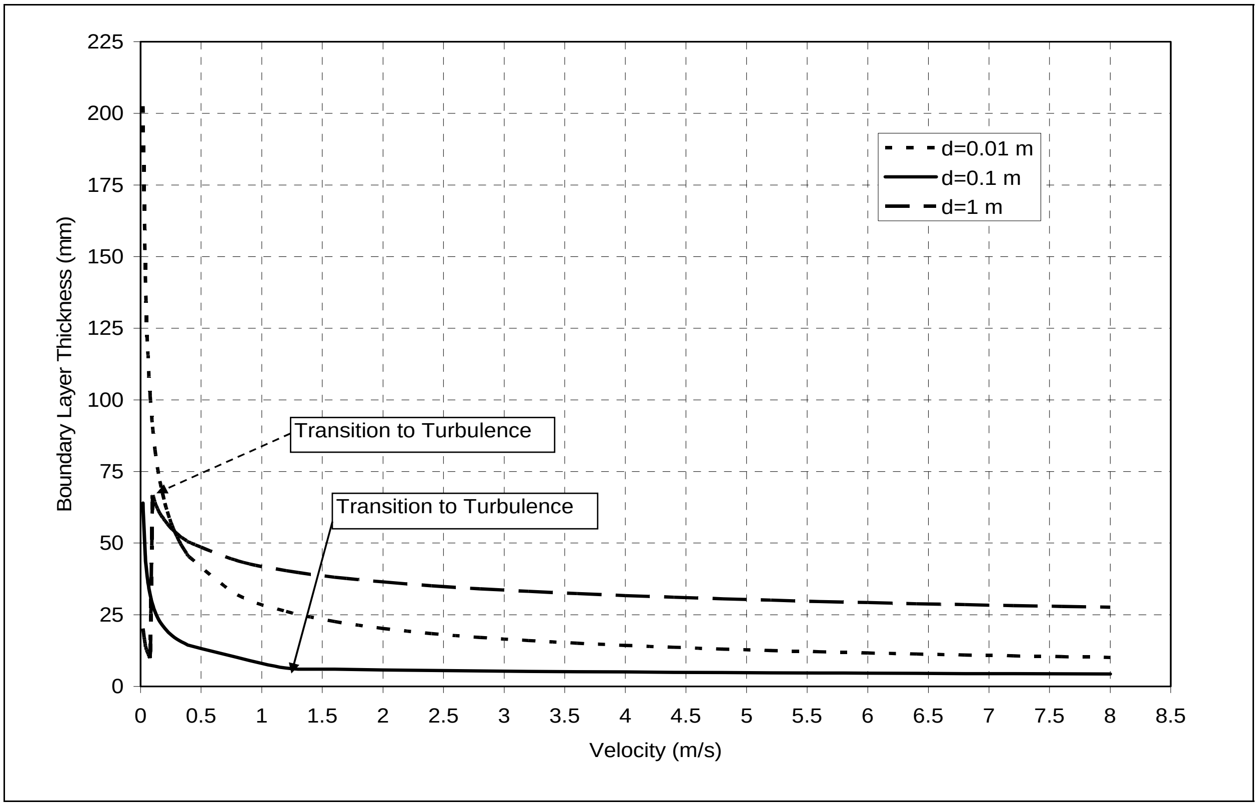

Figure 2 - An estimate of boundary layer thickness as a function of velocity.

Therefore, the user must take care to ensure that the cell size in the area of the smoke detector is adequate to properly estimate the ceiling jet flow velocity without being adversely affected by averaging in the lower boundary layer velocity or the velocity at depths below the ceiling outside of the ceiling jet.

2.1.9 Input Data Required to Run the Model

In addition to the general requirements needed for running a model in FDS, the algorithm requires additional input data. As with FDS, all of the input parameters required by the algorithm to describe a particular scenario are conveyed via a text file created by the user. This file includes the definition of the physical location(s) of the smoke alarm(s), the constants defining the lag-time of the alarm(s) and the sensitivity of the smoke sensor (input as a percent obscuration value per meter). The user must determine which entry-lag model to be used, the Cleary model (2000) (with four constants) or the simpler Heskestad model (1975) (which is dependent on a characteristic length). If the Cleary model is used, the four constants (defining the dwell and mixing times) are input. If the Heskestad model is used, the characteristic length of the smoke alarm is input. Default input values are provided, but must be reviewed by the user for appropriateness.

2.1.10 Property Data

As with any CFD simulation involving fire-induced flows, proper description of the properties of the materials involved, both those involved in the combustion process and those defining the geometric space, is critical for accurate predictions. Specific properties that influence the flow field and smoke generation are of particular importance to these simulations. Property data is available from numerous sources in various handbooks, in literature provided by the manufacturer, or from bench-scale measurements.

2.2 Scenarios for which the Smoke Detector Activation Algorithm has been Evaluated

This section provides a description of the scenarios or phenomena of interest that have been included to evaluate the smoke detector activation algorithm. It is the responsibility of the user to demonstrate the applicability of the model for scenarios that have not yet been validated.

2.2.1 Description of Scenarios or Phenomenon of Interest

The smoke detector activation algorithm is suited for determination of smoke alarm activation for a wide range of thermally-driven fluid flow scenarios, including flaming and smoldering fires. The algorithm is applicable for fire protection design studies and for forensic reconstruction analysis.

Fire protection design studies that utilize the algorithm will typically involve determining the smoke movement and alarm placement in an existing building or a building under design. A "design fire" is prescribed either by a regulatory authority or by the engineers performing the analysis and the properties of the smoke movement in the building are determined, allowing for the algorithm to determine alarm activation times. FDS is used to predict the transport of heat and combustion products throughout the room or rooms of interest. Factors that affect smoke movement, including ventilation equipment, often are necessary to be included in the simulation.

Fire forensic reconstructions require the model to simulate a fire based on information that is collected after the event. In many cases, there is interest in determining when a smoke alarm activated (or would have activated if in place and operational). The algorithm, in conjunction with FDS, provides a tool to calculate the conditions that a smoke alarm would encounter and the effect of different fire scenarios on activation times.

2.2.2 List of Quantities Predicted by the Algorithm upon which Evaluation is Based

The algorithm will provide predictions of the obscuration within the smoke alarm based on the detector's characteristics, providing a prediction of the time of alarm activation.

2.2.3 Degree of Accuracy Required for Each Output Quantity

The degree of accuracy for each output variable required by the user is highly dependent on the technical issues associated with the analysis. The type of analysis that is being undertaken will also influence the desired accuracy. The accuracy of the results from the algorithm is directly tied to the fidelity of the numerical solution from FDS, which is mainly dependent on the resolution of the computational grid.

Chapter 3

3 Theoretical Basis for the Model

This chapter presents the theoretical basis for the smoke detector activation algorithm. There are two basic types of smoke detector sensing technologies that are commonly used in residential and industrial applications: ionization and photoelectric. Although, the sensing chambers of these detectors use different principles of operation to sense the particles of the smoke, for modeling purposes, both can be thought of as a sensing chamber with an entry passage, which exhibits some flow resistance. This assumption is valid because smoke detector response is calibrated in an identical manner for both ionization and photoelectric detectors. According to UL 217 (2005), detector response should fall within a specified range under the specific conditions of the test. Since the flow field is at a relatively high velocity for the duration of the test, the evolution of the response with this parameter is not accounted for. Therefore, given a smoke concentration (or optical density) outside the detector, the response of the detector can be established through this calibration procedure. Extrapolation of the external smoke concentration (or optical density) to other scenarios is nevertheless not possible because the velocity fields can vary drastically.

3.1 Smoke Detector Model

The influence of the local smoke velocity on detector response has been established using a two characteristic parameter smoke detector model. This model uses a first-order differential equation to predict the concentration of smoke within the detector chamber. This form of the model was originally proposed by Heskestad (1975) and updated by Cleary *et al.* (2000) and others. The current study has implemented this model into the fire modeling code, Fire Dynamics Simulator. A brief review of this procedure is described below.

The Heskestad (1975) proposed model of entry lag into smoke detectors took into account a dwell time, which was described as the time for the smoke outside of the detector to penetrate the small entry channels of the smoke detector geometry and reach the sensing mechanism, sounding an alarm. Heskestad characterized this dwell time as the time for smoke at a velocity of U to traverse the entry channels of the detector. He proposed the use of a characteristic length, L, to simulate the extra length the smoke has to travel through the detector to the sensing mechanism. Therefore, he defined the lag time, τ, as L/U and used a single parameter model, as shown in Equation 3.

$$\frac{\partial Y_{\mathrm{o}}}{\partial \mathrm{t}} = \frac{\{Y_{\mathrm{e}}(\mathrm{t}) - Y_{\mathrm{o}}(\mathrm{t})\}}{\tau} \qquad (3)$$

The idea for Heskestad's formulation was that at activation, the internal smoke mass fraction would lag behind the external smoke mass fraction by a time τ, defined as L/U. This was intended to allow an engineer to determine when activation would occur based on the exterior smoke mass fraction from a zonal model or simple calculation. The problem with this formulation is that while it is accurate at activation, it is not as accurate transiently. Upon arrival of smoke, the smoke mass fraction instantly begins rising in the chamber, albeit reduced by a multiplicative factor of $1/\tau$. So while Heskestad intended to describe a dwell time, he actually formulated his equation based on a mixing time, as will be explained below.

This model was then refined by Newman (1986) and Cleary *et al.* (2000), among others, to take into account that there was a lag time associated with the smoke penetrating the housing, but there was also a characteristic mixing time for the smoke to mix within the sensing chamber and actually be detected by the sensing mechanism. The equation was formulated to be a transient description of the smoke mass transport. The two characteristic parameters that describe the smoke detector activation are termed the dwell time (δt) and the characteristic mixing time (τ). Both parameters are a function of the mass flow of smoke into the model detector, which is assumed to scale with the Reynolds number. According to Cleary *et al.* (2000), the smoke flow rate ($\dot{m}$) caused by the pressure drop across the entrance though an effective area, A, is treated as a control volume moving along a distance, L. The plug flow region empties into the sensing chamber volume, V (See Figure 3).

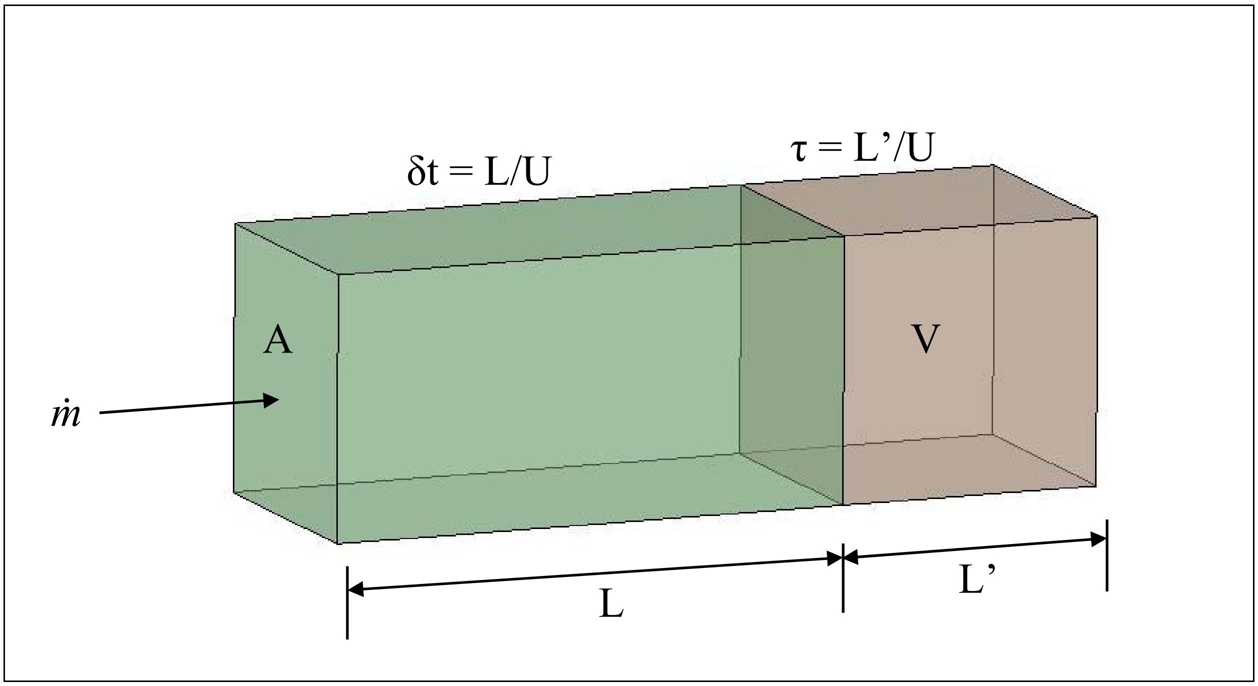

Figure 3 - A simplified smoke detector model, where *V* is the sensing chamber volume (*V=AL'*), *A* is the effective area of the detector, $\dot{m}$ is the smoke flow rate into the detector and *L* is the characteristic distance representing smoke entry resistance.

Thus, $\dot{m} = Au\rho$ and the Reynolds number is given below:

$$\mathrm{Re} = \frac{Lu}{\upsilon} \tag{4}$$

The dwell time (δt) can be defined as the mass of the smoke within the detector divided by the mass flow rate of smoke (Equation (5)). Cleary *et al.* (2000) showed that the dwell time lag could be represented following a power law dependence on velocity:

$$\delta t = \frac{L A\rho}{\dot{m}} = L \cdot u^{-1} \approx \alpha_1 u^{-\beta_1} \tag{5}$$

Cleary has found that the dwell time is not necessarily proportional to the smoke velocity (U) to the -1 power. The characteristic mixing time τ can be defined as the ratio between the mass of smoke in the sensing chamber divided by the mass flow rate (Equation (6)). In this case it is a function of the characteristic distance, L'. The mixing time can also be described by a power law dependence on velocity:

$$\tau = \frac{\rho V}{\dot{m}} = L' \cdot u^{-1} \approx \alpha_2 u^{-\beta_2} \tag{6}$$

where ρ is the density of the smoke. $\alpha_1, \alpha_2, \beta_1, \beta_2$ in Equations (5) and (6) above are proportionality constants that account for the detector geometry. As shown in Figure 3, the change in the mass of smoke in the sensing chamber volume should equal the difference in the mass fraction as it passes though the distance L. From this, the following equation is obtained:

$$\begin{cases} \rho V \dfrac{\partial Y_o}{\partial t} = \dot{m}\{Y_e(t-\delta t) - Y_o(t)\} \text{ when } t > \delta t \\ \dfrac{\partial Y_o}{\partial t} = 0 \text{ when } t < \delta t \end{cases} \tag{7}$$

and by combining with Equation (6) above

$$\begin{cases} \dfrac{\partial Y_o}{\partial t} = \dfrac{\{Y_e(t-\delta t) - Y_o(t)\}}{\tau} \text{ when } t > \delta t \\ \dfrac{\partial Y_o}{\partial t} = 0 \text{ when } t < \delta t \end{cases} \tag{8}$$

where "e" represents the entrance of the model detector and "o" represents the sensing chamber. Y_e is the mass fraction of smoke outside of the model detector, and Y_o is the mass fraction of smoke inside of the sensing chamber. If the initial mass fraction of smoke in the sensing chamber is zero, the mass fraction of smoke in the sensing chamber at any time t can be obtained by solving Equation (8):

$$Y_o(t) = \exp\left(-\int_0^t \frac{1}{\tau(t')} dt'\right)\left\{\int_0^t \left(\frac{1}{\tau(t')} \cdot \exp\left(\int_0^t \frac{1}{\tau(t')} dt'\right) \cdot Y_e(t'-\delta t)\right) dt'\right\} \tag{9}$$

where t'=t/τ and dt'=dt/τ .

The determined mass fraction of smoke in the sensing chamber $Y_o(t)$ can be converted to obscuration per meter (or smoke optical density) or optical density using classical techniques (Drysdale, 1998). The optical density is defined as

$$OD = -\ln(\frac{I}{I_O}) = \kappa_m \rho Y_S L_P \tag{10}$$

The smoke obscuration percentage per meter is given below:

$$OPM = (1 - \frac{I}{I_0}) \times 100 = (1 - \exp(-\kappa_m \rho Y_s)) \times 100 \tag{11}$$

where the product $\kappa_m \rho Y_s$ is termed the extinction coefficient and L_P is the path length in meters. κ_m is a constant of proportionality termed the specific extinction coefficient (m^2/g) and ρY_s is the smoke mass fraction (g/m^3) (Drysdale, 1998). The specific extinction coefficient κ_m is a function of the wavelength of light (λ); smoke aerosol size distribution; structural properties and optical properties. For most flaming fuels, the value of 7.6 m^2/g can be used (Mulholland, 2002; Mulholland, 2000). Y_s can be calculated by establishing the external mass fraction using LES fire modeling and for the internal mass fraction in the sensing chamber of the detector by Equation (8) or (9). Thus, the obscuration (%/m) outside the detector (point e) can be obtained by Equation (12). The obscuration (%/m) within the sensing chamber (point o) can be calculated by Equation (13).

$$OPM_e(t) = (1 - \exp(-\kappa_m \rho Y_e(t)) \cdot 100 \tag{12}$$

$$OPM_o(t) = (1 - \exp(-\kappa_m \rho Y_o(t)) \cdot 100 \tag{13}$$

It is important to note that the thresholds for this work are purely based on obscuration per meter, and consequently on the relationship between this parameter and the smoke mass concentration. The response of smoke detectors has been found to depend also on other chamber type (e.g. ionization) dependent variables such as the total number of smoke particles and the characteristic particle size and charge of the smoke passing through the sensing chamber (Newman, 1989). Furthermore, dependencies on the fuel originating the smoke have also been made evident in the literature (e.g. Wolin *et al.*, 2001). Despite the shortcomings associated with the different variables affecting detector performance, optical techniques still present themselves as being the most attractive. The validity of these methods relies on them being directly associated with the explicit calibration and testing procedures followed by UL 217 (2005).

3.2 Large Eddy Simulation (LES) Fire Model

The Fire Dynamics Simulator model (a LES-based CFD model) is used within this study to model the transport of smoke from the fire to the detector. In the FDS code (McGrattan ed., 2005), a simplified low Mach number equation for fire and smoke transport calculation is used. In this approach, the acoustic waves have been filtered, but the flows are allowed to remain compressible. Hence, the time step can be increased to drastically reduce computation times. These simplified compressible flow equations are more computationally efficient for modeling fires and smoke. A Large Eddy Simulation (LES) approach has been used to deal with turbulence. LES solves the large eddy motions by a set of filtered equations governing the three dimensional, time-dependent motions. The small eddies are modeled independently from the flow geometry. Currently, the Smagorinsky model is used for the small eddy flow field (McGrattan et. al., 1998; McGrattan ed., 2005).

In the current version of FDS, a simplified mixture fraction-based combustion model has been implemented. The model uses a state relationship for both reactants and products, which can be derived by an ideal reaction of a hydrocarbon fuel; and the reaction rate is calculated from a steady-state flamelet equation. Finally, the heat release rate can be calculated using the local oxygen consumption rate and the appropriate heat of combustion. Thermal radiation intensity is solved by the radiative transport equation. A more detailed model description and associated sub-model validations can be found in the literature (Zhang *et al.*, 2002; Zhang and Roby, 2003; McGrattan *et al.*, 1998; McGrattan ed., 2005; Baum *et al.*, 1997; Baum *et al.*, 1998; Emmerich and McGrattan, 1998).

3.3 The Implementation of the Smoke Detector Model

At the smoke detector location, it is assumed that the LES grid resolution can reasonably capture the size of the smoke detector. Thus, the mass fraction of smoke and velocity at that location can be determined from the predictions by FDS. The mass fraction inside of the sensing chamber is then determined through the smoke detector activation algorithm by solving Equation (8) numerically instead of solving Equation (9), which requires far more computing power, as will be explained later in this report.

In order to obtain a solution for Equation (8), a simple predictor/corrector Runge-Kutta scheme is used. This scheme is currently used in FDS for sprinklers and heat detectors. The calculated Y_o is converted to the obscuration (%/m) using Equation (13). It is assumed that when the obscuration (%/m) in the sensing chamber is larger than the operating sensitivity of the detector provided by the manufacturer, the smoke detector will activate. While the model will include default settings which will reflect industry standard critical variables of smoke detectors, the model input will allow for input of the operating sensitivity of the smoke detector, as well as input of the mixing and dwell time lag coefficients of a specific detector as defined in the theory presented by Cleary *et al.* (2000).

As explained above, the Cleary *et al.* (2000) lag time theory includes two components, the dwell time and the mixing time, while the Heskestad (1975) theory includes only one component, a dwell time (mathematically equivalent to the Cleary mixing time τ) based on a characteristic length, L. The ODE that describes the smoke movement, Equation (8), is applicable in both cases, and hence has been programmed into the algorithm in FDS to utilize either method. To utilize the Cleary *et al.* two-parameter model, the user inputs all 4 lag time coefficients ($\alpha_1, \alpha_2, \beta_1, \beta_2$) to describe the dwell time and the mixing time, and the algorithm solves Equation (8) numerically. If the user does not have enough information about the detector, or if the user feels that the expected fire conditions warrant use of the simpler Heskestad model, the user instead inputs a characteristic length, L. The activation algorithm automatically sets $L=\alpha_2$ and sets β_2=-1 when using the Heskestad model. Referring back to Equation (6), this sets the mixing time (Heskestad's dwell time) equal to the Heskestad total lag time of U/L. In addition, α_1 is automatically set to 0 making the Cleary dwell time, δt, equal to 0 (see Equation (5)). By doing this, Cleary's mass transport equation, Equation (8), is reduced to Heskestad's mass transport equation, Equation (1). Therefore, utilizing these substitutions in Equation (8), the user can seamlessly use the Heskestad (1975) or Cleary *et al.* (2000)

methodologies when using the algorithm in FDS. The user should note that the while the Cleary *et al.* formulation is intended to be a transient lag time correlation, the Heskestad formulation is not. Therefore, if the user is calculating the response of the smoke detector based on the Heskestad formulation, while the activation time may be reasonably accurate depending on the velocity magnitude, the actual buildup of the smoke in the chamber over time will most likely not be reasonably accurate.

3.4 Review of the Theoretical Development of the Model

ASTM E 1355 (2004) requires that the theoretical basis of the model be reviewed by one or more recognized experts fully conversant with the physics of smoke detection, but not involved with the production of the model. The activation algorithm has been reviewed by experts from within CSE and also by the fire protection community through published work and presentations (Olenick *et al.*, 2005; Olenick *et al.*, 2006). The technical approach, assumptions, and validity of the model's underlying theory have been presented in the peer-reviewed scientific literature and at technical conferences cited in the previous section (e.g. Cleary *et al.*, 2000; Keski-Rahkonon, 2002; Heskestad, 1975; Bjorkman et al, 1992; Newman, 1986; Newman, 1987; Newman 1989).

Chapter 4

4 Mathematical and Numerical Robustness

ASTM E 1355 (2004) describes methods to evaluate the mathematical and numerical robustness of deterministic fire models. This process, often referred to as model verification, ensures the accuracy of the numerical solution of the governing equations. The methods include comparison with analytical solutions, code checking, and numerical tests.

The mathematical and numerical robustness of the activation algorithm implementation in FDS has been tested through comparison of the predictions with alternative methods of calculations. The original form of the algorithm (Equation (3)) was first proposed by Heskestad (1975) and has been utilized and refined by others (Newman, 1989; Cleary *et al.*, 2000). This algorithm has been rigorously tested by these researchers and others against experimental data and has been refined and subsequently accepted in the scientific literature. Therefore, the correctness and robustness of the algorithm itself has not been investigated as part of this work as that has already been accomplished by other researchers.

While the robustness of the actual algorithm itself has not been independently determined as part of this work, the robustness of the implementation and coding of the algorithm in FDS must be confirmed. As coded in FDS, the algorithm numerically integrates Equation (8) utilizing a predictor/corrector Runge-Kutta numerical scheme. Results to date have shown that the robustness of this approach is adequate, as will be discussed below. Direct solving of the analytical exact solution to Equation (8), listed above as Equation (9), was considered. Trapezoidal Gaussian and Simpson's Rule integrations (Press *et al.*, 1992) were coded into FDS and the model was run for many verification scenarios. It was found that the presence of the characteristic mixing time integral inside of another integral caused excessive run times and the final solution was not always in agreement with hand calculations. This is because the number of iterations of the larger integral and smaller integral created excessive run times and if the number of iterations was reduced to make the run times reasonable, a fully-converged solution of the algorithm was never found. Therefore, the method used to solve the exact solution (Equation 9) was not acceptable. For these reasons, the solving of the exact analytical solution was abandoned and instead, the ODE (Equation (8)) is simply numerically integrated. This procedure resulted in small increases in run times and an accurate result. Early versions (beta versions) of the algorithm coded into FDS before the date of this report suffered from the issues with the exact solution described above and, consequently, versions of the FDS code with compile dates before the date of this report should be not be used for smoke detector activation calculations.

In order to ensure that the coding of the algorithm in FDS is correctly solving Equation (8), a test of the robustness of the coding was undertaken. For this test, FDS with the incorporated smoke detector activation algorithm was used to model a simple corridor with detector stations situated at three locations down the corridor. A small fire, to ensure relatively low velocities, was input in the model and the response of the smoke detectors was simulated. Baffles were also put on the ceiling of the corridor to further slow the smoke velocity. The velocity and smoke density at the smoke detector locations were also recorded to a file. A picture of the simple FDS model is shown as Figure 4 below.

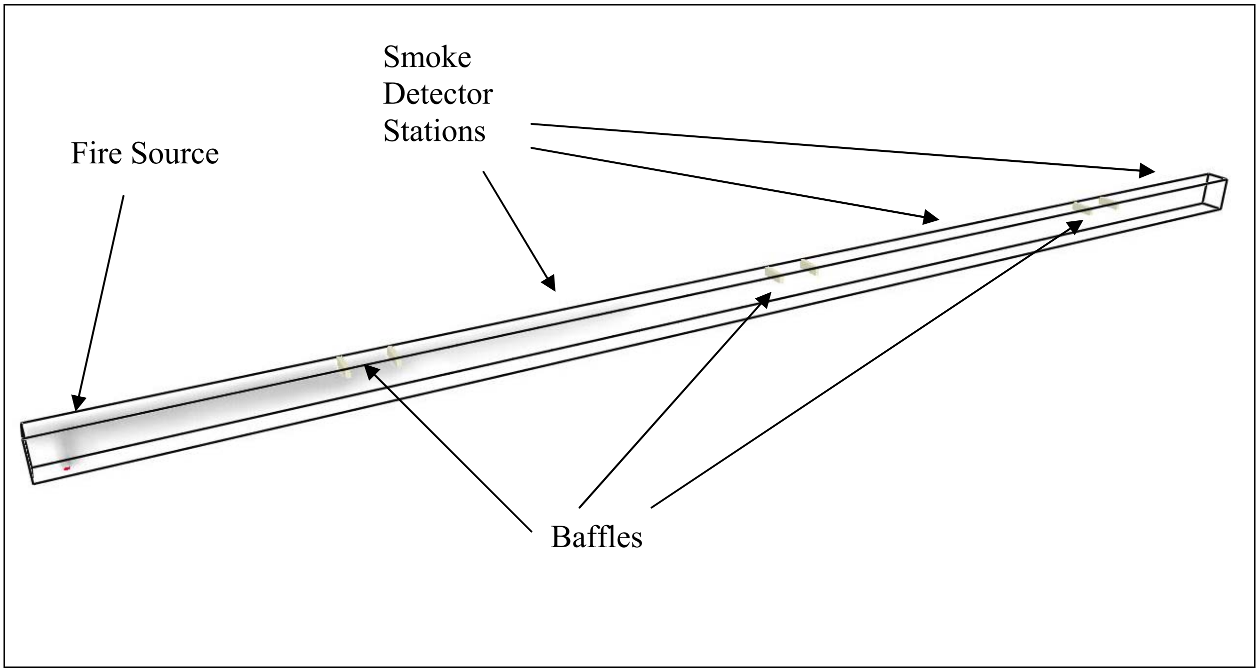

Figure 4 - The FDS corridor model utilized for robustness evaluation.

The algorithm was then independently coded into MATLAB (Version 7.0, 2004). Unlike the FORTRAN coding in FDS, where linear interpolation has been included in the code, MATLAB has toolboxes that do the interpolation automatically as well as automatic ODE solvers. The smoke density and velocity data from the FDS model was input into the MATLAB coding and the response of the smoke detectors was again simulated, this time by the MATLAB code. The response of the smoke detectors between the MATLAB coding and the FDS coding was compared to ensure that the FDS coding of the algorithm agrees with the MATLAB coding of the algorithm.

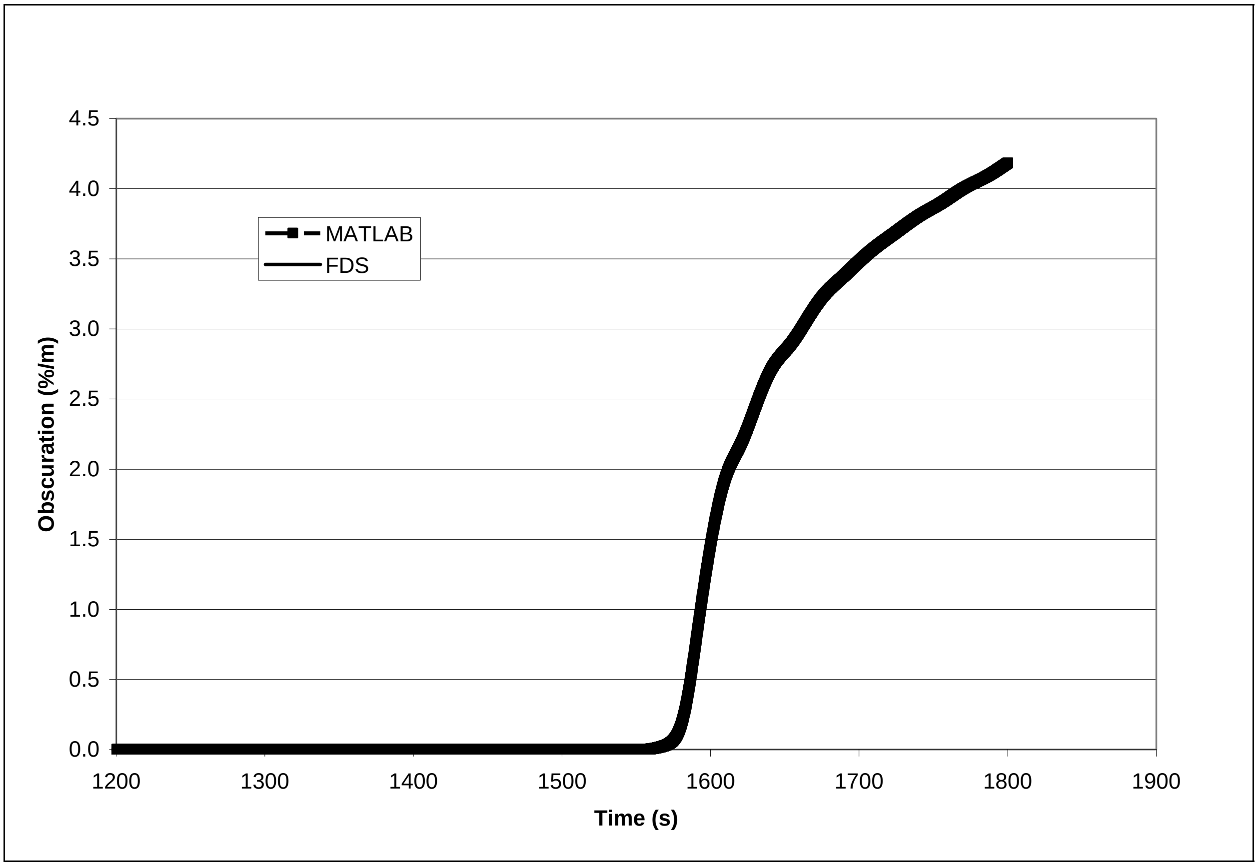

Figure 5 - The results of MATLAB and FDS coding of a smoke detector located at Station 3. The results overlap each other.

The comparison was undertaken with several different detector configurations, some of which included a mixing time but no dwell time and others utilized both time scales. Figure 5 above shows the comparison for a detector at Station 3, the station farthest from the fire source, where the velocity was relatively low. The detector had a large dwell time and a large mixing time so that both lag time aspects of the algorithm could be rigorously tested and verified. As can be seen in Figure 5, the results are almost identical. These results provide confidence that the coding in FDS is correctly solving the algorithm. While not shown above, hand calculations further verified that the results from the models were correct. Further, despite the differences in coding methods between FDS and MATLAB and the fact that MATLAB has some automatic solvers and linear interpolators, the answer is unchanged between the models. Therefore, the user can be confident that the algorithm has been robustly coded into FDS.

Chapter 5

5 Model Sensitivity

A sensitivity analysis considers the level to which uncertainty in input parameters influence model results. In the case of the activation algorithm, the input parameters are limited to the transient predictions of velocity and smoke concentration at the smoke detector location (provided by FDS) and the coefficients that provide the description of mixing and lag times of the detector.

As described in the Technical Manual (McGrattan, 2005), FDS typically requires the user to provide several dozen different types of input parameters that describe the geometry, materials, combustion phenomena, *etc.* Among these many parameters, those that will directly impact the predictions from the activation algorithm include grid resolution, heat release rate, and smoke generation properties as they will directly influence velocity and smoke concentration predictions. Hence, care must be exercised by the user to properly prescribe these features of the model to ensure accurate prediction of smoke detection.

The coefficients that describe the lag time of a given smoke detector will also influence the predicted activation characteristics. The coefficients are typically determined experimentally; however, the influence of the uncertainty of these coefficients due to any experimental error on the predicted detector activation time has not been explored at this time.

The predicted activation time is also sensitive to the lag time model used. Currently, both the Heskestad (1975) and Cleary *et al.* (2000) models have been implemented in the code. As expected, the choice of models can have a major impact on the activation times, especially when the flow velocities are low. Figure 6 shows the prediction of smoke detector activation time as a function of flow velocity for the two different lag time models. The smoke concentration outside the detector was maintained at 4%/m, and the internal smoke concentration required for activation was set to 3.28%/m (or 1%/ft). For flow velocities above 0.15 m/s, both models indicate similar lag times. However, for low velocities (less than approximately 0.15 m/s), the choice of lag model can have a significant effect on activation time predictions. This velocity range can be indicative of a smoldering fire or of a relatively small fire in a large volume. It has been generally recognized that the Heskestad model will under predict smoke alarm activation times for these circumstances (e.g. Newman, 1987).

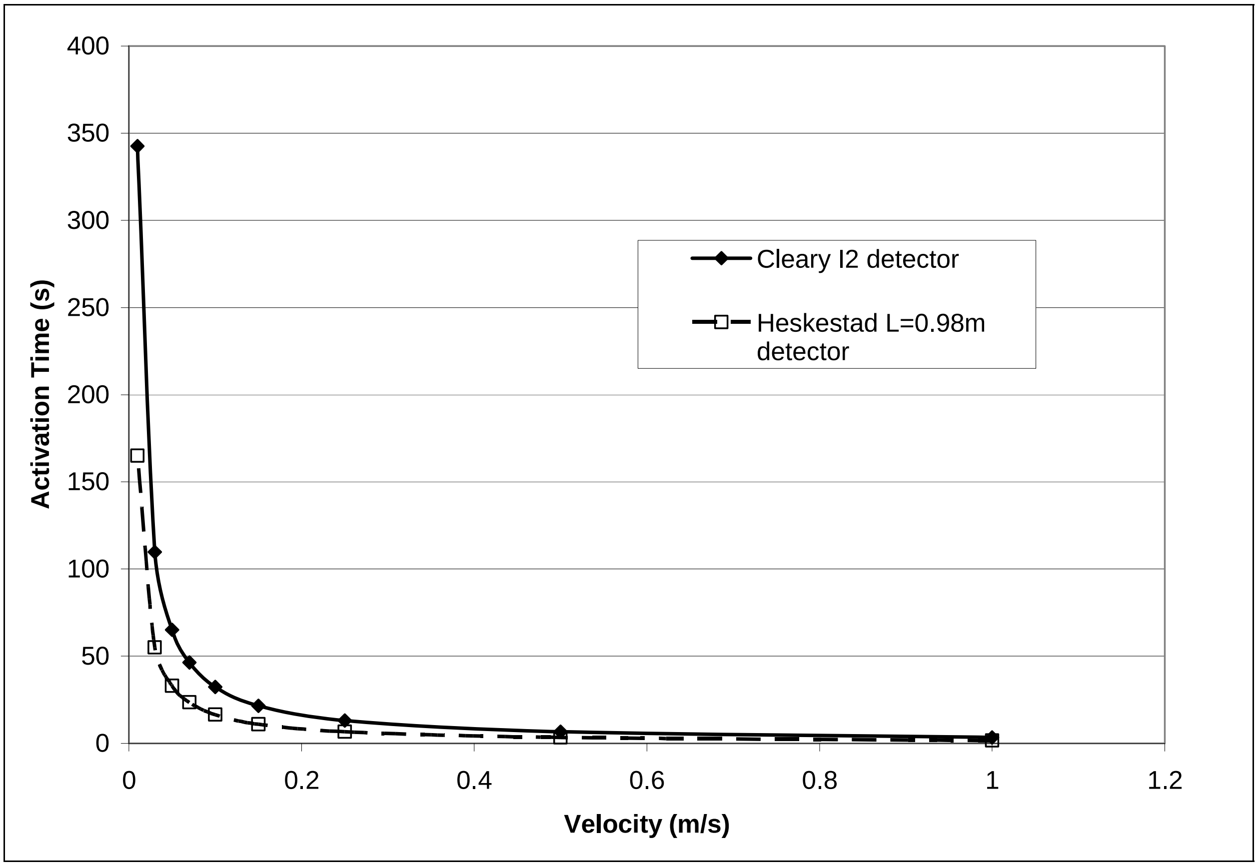

Figure 6 - Predictions of smoke detector activation time as a function of flow velocity using the lag time models of Heskestad (1975) and Cleary *et al.* (1999). The exterior smoke concentration was assumed to be 4%/m and a smoke concentration of 3.28%/m inside the detector was required for alarm activation.

As a further test of the sensitivity of both the Heskestad and Cleary *et al.* lag time models, the same conditions were maintained (4% smoke obscuration, 3.28% activation obscuration), but this time, the relevant lag coefficients were varied by 10%-20% in both directions. For example, for a Cleary I2 detector, the value of β_1 is -1.1. For the β_1 +20% detector, all of the other coefficients are unchanged from a Cleary I2 detector, except that β_1 is -1.1+((0.2)*-1.1)=-1.32. The characteristic length (L) of Heskestad and all four Cleary *et al.* coefficients ($\alpha_1, \alpha_2, \beta_1, \beta_2$) were varied by 10%-20% to determine the sensitivity of the activation time to these parameters under this controlled scenario. As can be seen in Figures 7 through 11, the activation time is most sensitive to the β_1 coefficient (Cleary dwell time exponent) and least sensitive to α_2 (Cleary mixing time coefficient and Heskestad characteristic length). It should also be noted that at relatively high velocities, as would be expected, the selection of the values of the coefficients has little effect on the activation time calculations since there is little, if any, velocity driven lag time.

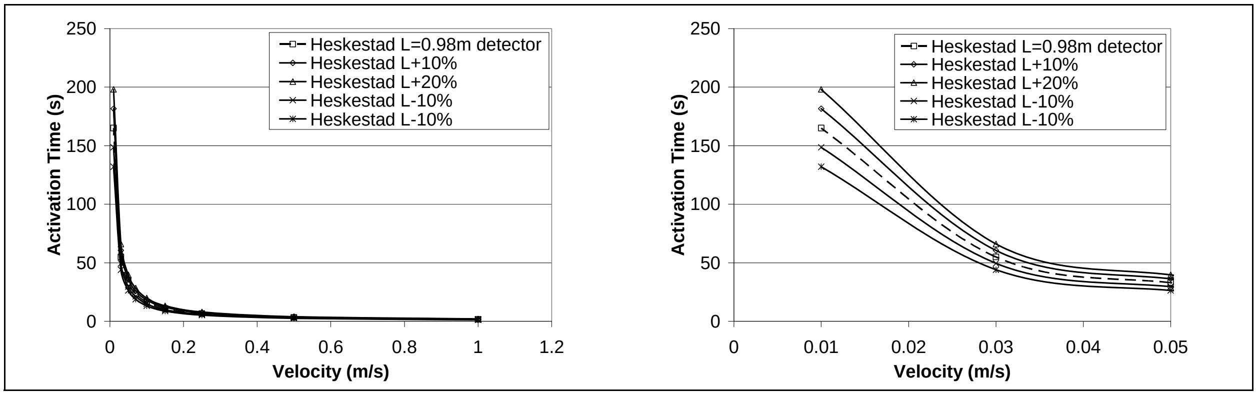

Figure 7 - Predictions of smoke detector activation time as a function of flow velocity when the Heskestad (1975) characteristic length, L, is varied. The full range of expected velocities is depicted on the left and an isolated view of the low velocity regime is shown on the right.

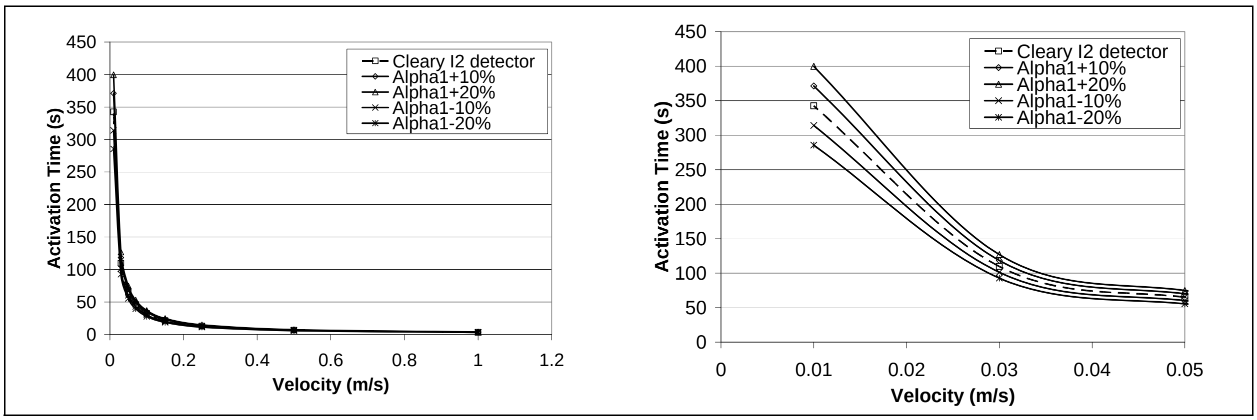

Figure 8 - Predictions of smoke detector activation time as a function of flow velocity when the Cleary *et al.* (2000) dwell time parameter, α_1, is varied. The full range of expected velocities is depicted on the left and an isolated view of the low velocity regime is shown on the right.

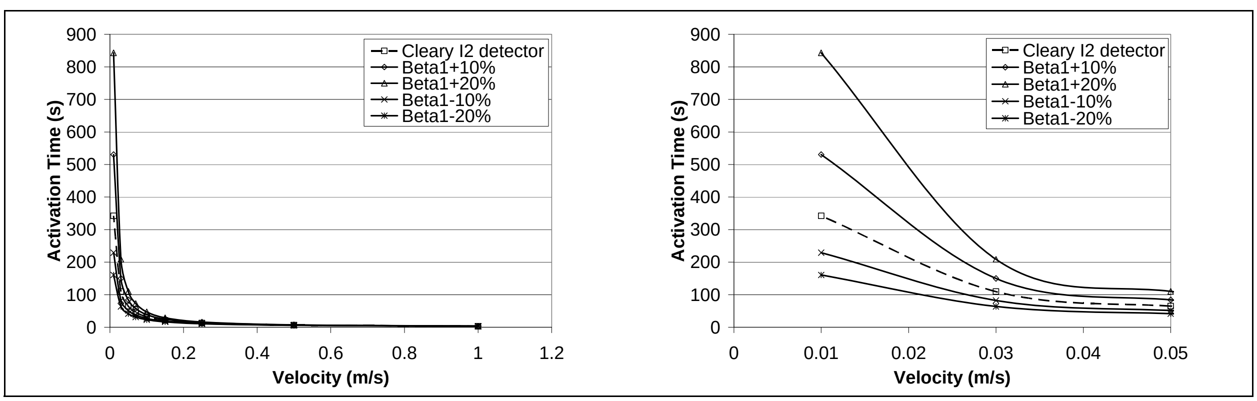

Figure 9 - Predictions of smoke detector activation time as a function of flow velocity when the Cleary *et al.* (2000) dwell time parameter, β_1, is varied. The full range of expected velocities is depicted on the left and an isolated view of the low velocity regime is shown on the right.

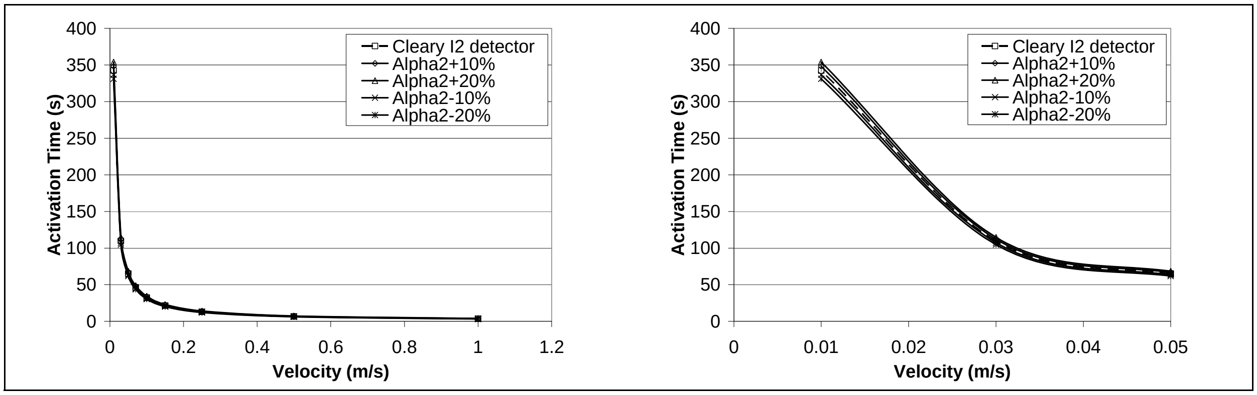

Figure 10 - Predictions of smoke detector activation time as a function of flow velocity when the Cleary *et al.* (2000) mixing time parameter, α_2, is varied. The full range of expected velocities is depicted on the left and an isolated view of the low velocity regime is shown on the right.

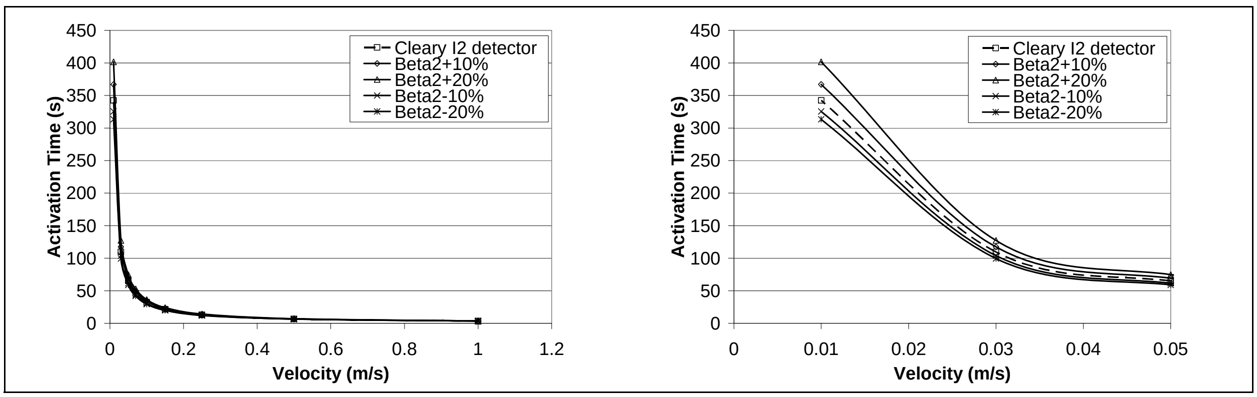

Figure 11 - Predictions of smoke detector activation time as a function of flow velocity when the Cleary *et al.* (2000) mixing time parameter, β_2, is varied. The full range of expected velocities is depicted on the left and an isolated view of the low velocity regime is shown on the right.

Chapter 6

6 Model Validation

Model validation is a process where the user simulates a controlled experiment and assesses the degree of difference between measured and predicted quantities. The assessment involves the model's input parameters, its mathematical formulation of the physical phenomena, and its interpretation of the measurements. In this chapter, validation work performed with the smoke detector activation algorithm in conjunction with FDS will be presented.

6.1 Underwriters Laboratories Standard 217 Fire Test

The accuracy of the activation algorithm is inherently dependent on the input variables to the algorithm, some of which come directly from the user and some of which are calculated by the fluid and smoke transport models within FDS. In this particular validation effort, the Underwriters Laboratories Standard 217 fire test (1985), utilizing polystyrene foam as the fuel, was used to determine the influence of the fluid and smoke transport models in FDS on the output of the algorithm.

The UL 217 fire tests provide a very strict and repeatable setup with multiple locations for photocell assemblies and smoke detectors. UL 217 test D (Polystyrene foam fire) was used for the validation assessment. Further details on this fire test are available in UL 217, 1985 edition, as the test has been removed from the standard in subsequent editions. To determine the heat release rate as an input for the fire model, oxygen consumption calorimetry was used to determine the exact heat release rate (HRR) profile of the polystyrene foam test sample used in UL 217 test D. The profile of the HRR was determined by burning a prescribed sample of the foam polystyrene type packing material under a collection hood with oxygen sampling. The polystyrene foam has a prescribed density between 24-32 kg/m^3, and contained no flame inhibitor. By monitoring the reduction of oxygen present in the hood exhaust, a measure of the heat release profile for the foam was determined as a function of time for the duration of the test:

$$Q_{foam} = \dot{m}_{oxy} \cdot \Delta Hc_{oxy} \tag{14}$$

where, $\dot{m}_{oxy}$ is the mass burning rate and ΔHc_{oxy} is a heat of combustion per oxygen consumed. The heat release rate is combined with a smoke yield for polystyrene foam estimated as an average from values in the literature for polystyrene and styrene.

UL217 (1985) prescribes a strict test scenario in which smoke must reach each of the sampling locations within the test room in a specified concentration during a certain window of elapsed time. The smoke detectors must activate at some point during the test in order to be approved.

The fire test room, which is 10.9 m long by 6.7 m wide by 3.1 m high, is shown below in Figure 12. The test room has a smooth ceiling with no physical obstructions. The test is conducted with an ambient temperature between 20~25 °C. Two detectors are to be tested on a ceiling panel, and another two detectors are to be tested in a sidewall position, one on each side of the test chamber.

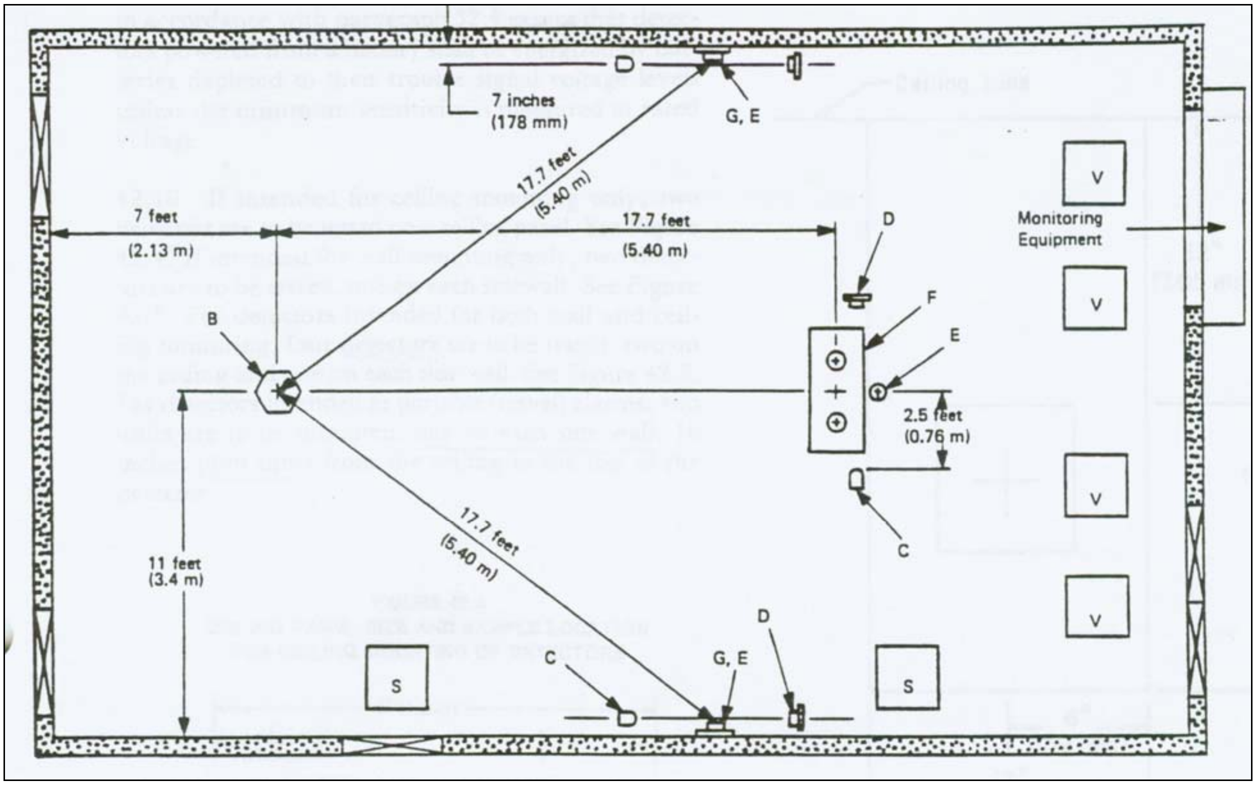

Figure 12. The test room for the UL 217 Fire Tests (reproduced from UL 217, 1985)

This setup was reproduced in FDS and the smoke alarm activation was modeled using the activation algorithm. The cell size utilized was approximately 3.0 inch cubes, which is smaller than the expected ceiling jet depth based on standard correlations, and is larger than the maximum expected depth of the boundary layer, as is discussed in Section 2.1.8 above. The fire test was modeled utilizing smoke detectors with generic lag time coefficients from the literature (I1 and I2 from Cleary *et al.* (2000) and Heskestad (1975) with an effective length of 1.8m) and the results for the various requirements for the buildup of smoke were compared with the model results. A screen capture of the model is shown as Figure 13 below and the results of the model are shown as Table 1.

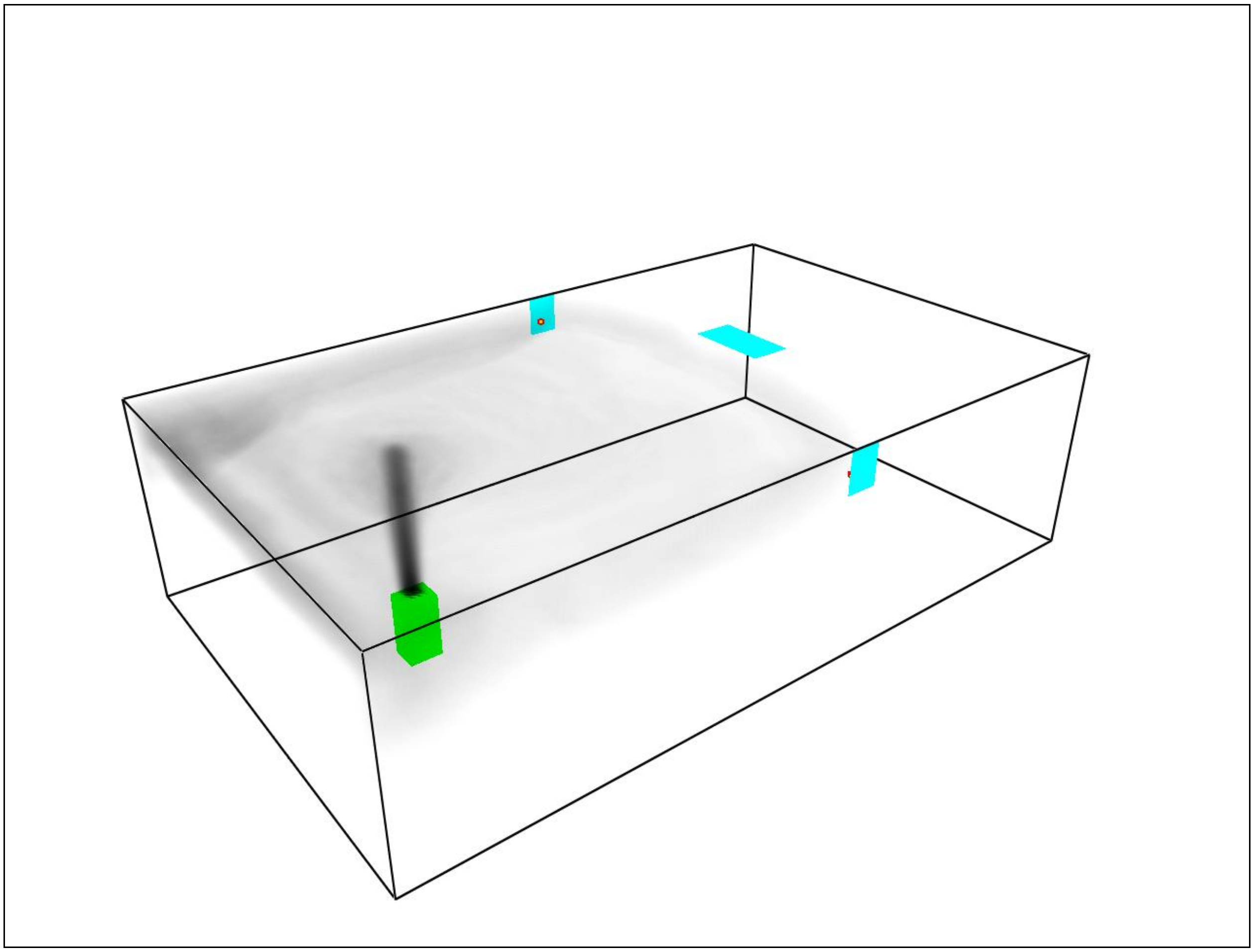

Figure 13 - The model test room for the UL 217 fire test validation. The locations of the smoke alarms are indicated by the rectangular patches.

Table 1 - The results of the UL 217 fire test validation using the smoke detector activation algorithm.

MODEL RESULTS		
REQUIREMENT	**Utilizing Flaming K_m**	**Utilizing Smoldering K_m**
Smoke buildup		
Starts 35-45 seconds at ceiling location	45.3-46.0s	45.7-46.1s
Starts 25-35 seconds at sidewall location	41.5-43.2s	41.7-43.4s
10%/ft (32.81%/m)		
Starts 70-90 seconds at ceiling location	67.4-68.1s	81.8-86.4s
Starts 60-80 seconds at sidewall location	51.6-53.4s	102.9->120s
After 10%/ft (32.81 %/m)		
Remains at 10-13%/ft (32.81-42.65%/m) at ceiling location	Both locations peak a little high (~18%/ft)	Occurred
Remains at 10-17%/ft (32.81-55.77%/m) at sidewall location	One station dips low (~7%/ft)	One station dips low (~6%/ft), other only quite low (~3%/ft)
All detectors activate during test	Occurred	

As can be seen from the summary of results presented in Table 1 above, the model performed reasonably well considering there were still some sources of error independent from the FDS model. First and foremost, as required by the standard, the smoke detectors in the model did activate during the time prescribed by the standard. Similarly, the rate of smoke buildup and the attainment of 10% obscuration/ft did match the test requirements. After attaining 10% obscuration/ft, the smoke level was to remain at the prescribed value for the duration of the test. The smoke levels in FDS generally dipped a little low, but were within a range that would be considered reasonable considering the potential input errors. The input errors in this model included the nature of the smoke yield of the polystyrene foam as well as the variability of the specific extinction coefficient (K_m) due to the fact that the material does not entirely burn in the flaming mode of combustion, but instead flames, smolders, and melts during combustion. Additionally, there is experimental error associated with the calorimetry techniques used to obtain the heat release rate of the polystyrene foam. When all of these potential error rates are taken as a whole, the results from the FDS model are acceptable and demonstrate that this technique is capable of properly modeling fluid and smoke transport for use by the algorithm.

6.2 Room-Corridor-Room Fire Test Validation

Replication of the UL 217 test D affirmed that FDS can reasonably simulate the smoke density and velocity as inputs for the activation algorithm. The activation algorithm must now be assessed against experimental smoke detector activation data to determine the level of accuracy the smoke detector algorithm can provide. As a first validation of the algorithm, a relatively small-scale test geometry was chosen. These tests were performed in a room-corridor-room geometry at Combustion Science & Engineering's laboratory facilities in Columbia, Maryland. In these tests, a mix of 75% heptane and 25% toluene was burned in a pan to create a highly repeatable fire source. Toluene is a highly sooting fuel when burned in a pool configuration (unlike the moderately sooty heptane) and the combination creates an environment which is detected quickly by a standard smoke alarms. Ionization detectors were placed on sidewall and ceiling locations in the room of origin, sidewall and ceiling locations in the connecting corridor, and on a ceiling location in the room remote from the fire source. Additionally, smoke density, velocity, and temperature measurements were made in order to log the relevant data associated with smoke detector activation. The fire pan was placed on a load cell in order to monitor the mass loss rate. The mass burning rate (and subsequent heat release rate) was relatively constant. More detailed information on the experimental procedure can be found in D'Souza *et al.* (2002). A screen capture of the model showing the test geometry is shown as Figure 14.

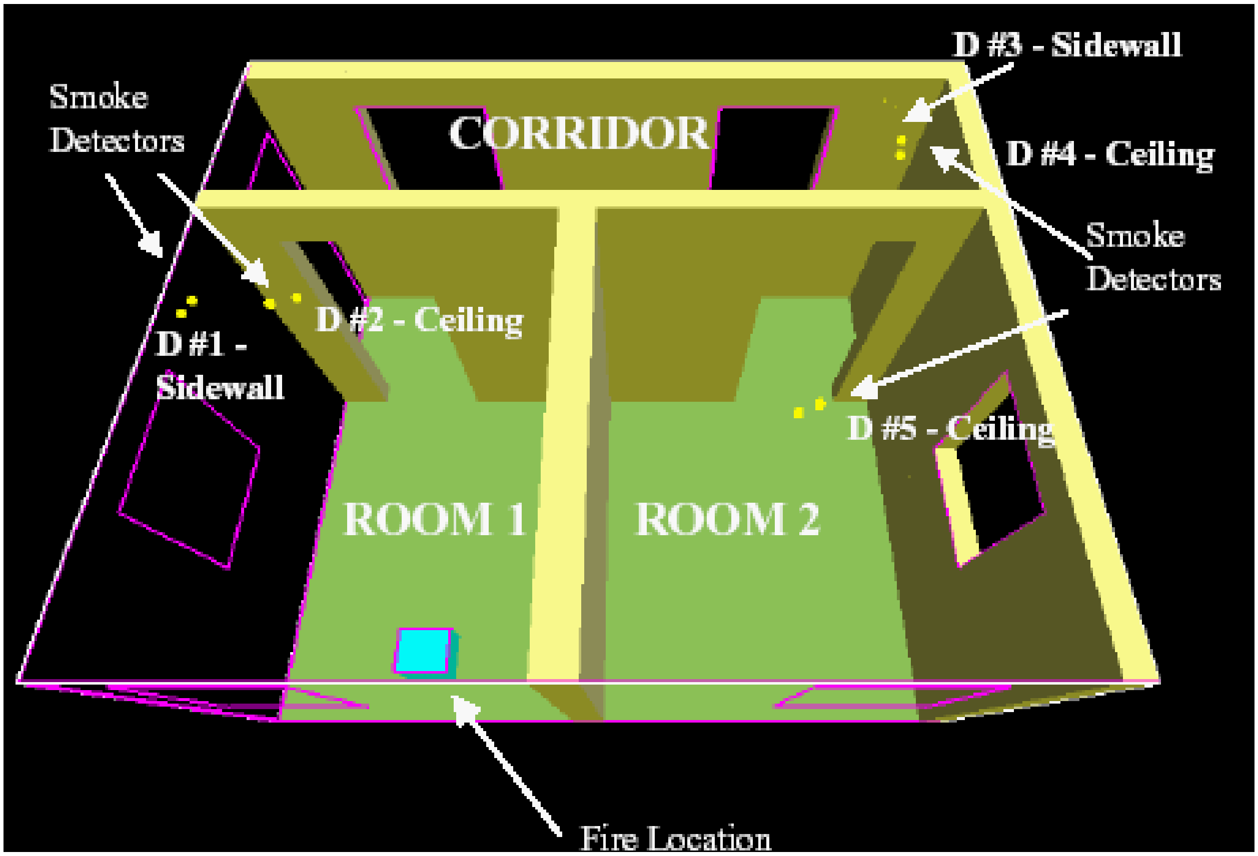

Figure 14 - Room-corridor-room test and model geometry.

The experiment was run three times for repeatability, and the experimental average smoke detector activation times were determined. Activation times ranged from approximately 10 seconds to over 70 seconds, depending on the location. The variation of activation time for a given alarm location was generally on the order of 5 seconds over the three tests. However, more significant variation was found for detectors #2 and #4 (both located on the ceiling). These results indicate the amount of real variation that can occur when modeling activation times. The model was run utilizing a calculated heat release rate for the fire and a weighted average smoke yield for heptane and toluene from the literature. The smoke detectors used in the test were not evaluated to determine the smoke lag time coefficients (via a wind-tunnel or NIST's Fire Emulator/Detector Evaluator (FE/DE)), which are necessary as inputs for the activation algorithm. Instead, values from the testing done by Cleary *et al.* (2000) were used as well as the default in FDS (Heskestad detector with L=1.8m) to determine how well the utilization of default and literature values could provide accurate results. The cell size utilized was approximately 3.0 inch cubes, which is smaller than the expected ceiling jet depth based on standard correlations, and is larger than the maximum expected depth of the boundary layer, as is discussed in Section 2.1.8 above. A screen capture of the model is shown as Figure 10 below and the results of the comparison between the model and the experimental results is shown are as Figures 15 and 16 below.

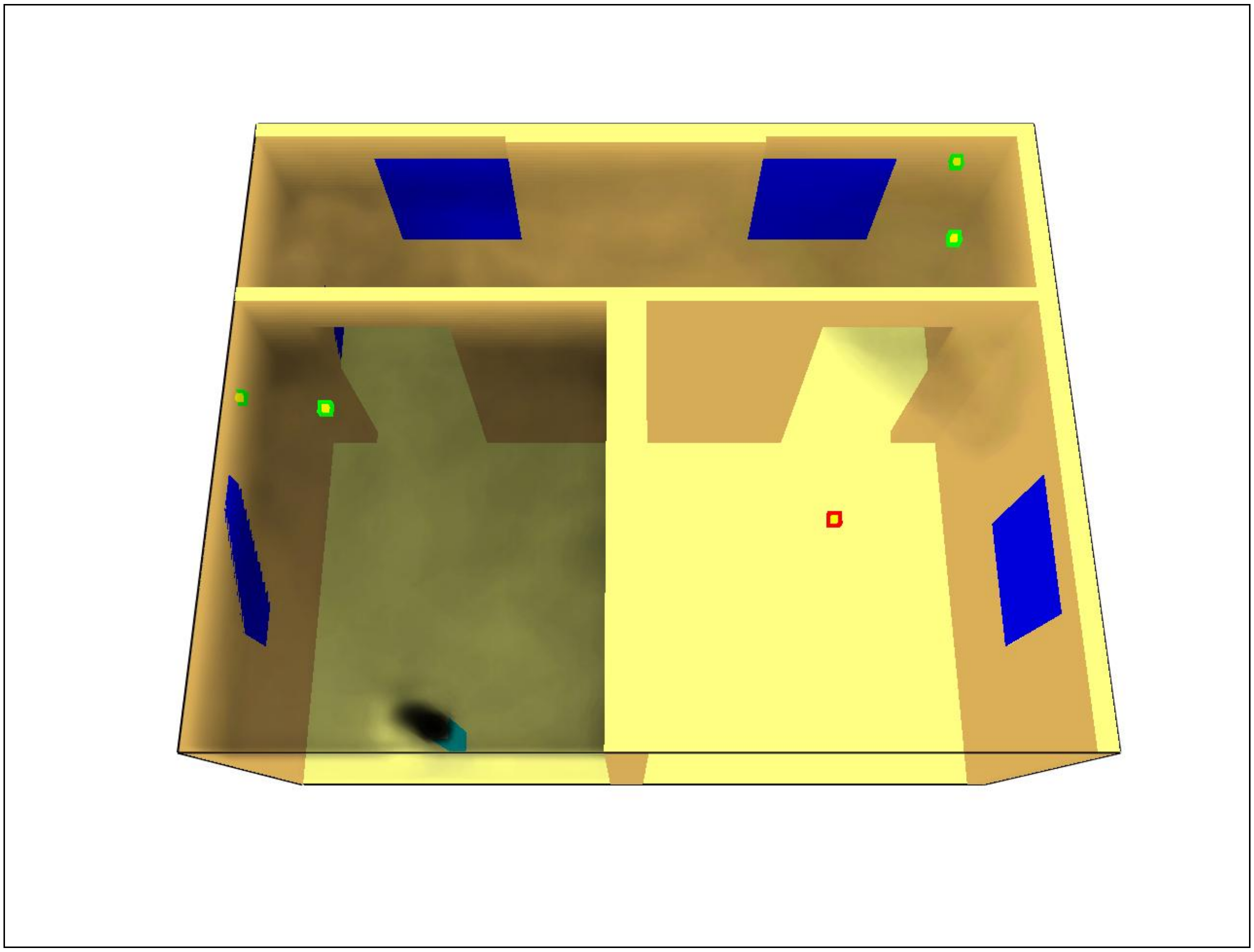

Figure 15 - Room-corridor-room model.

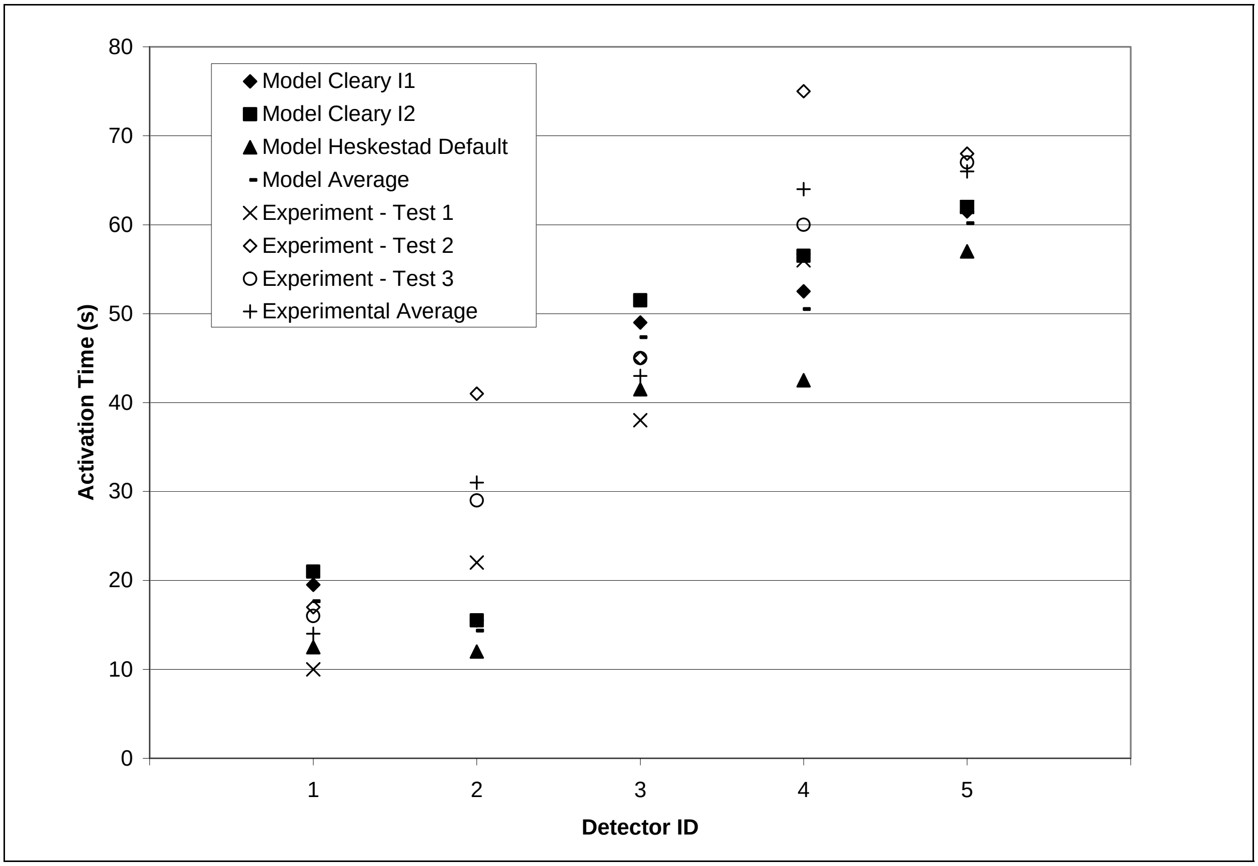

Figure 16 - Room-corridor-room model results compared with experimental results.

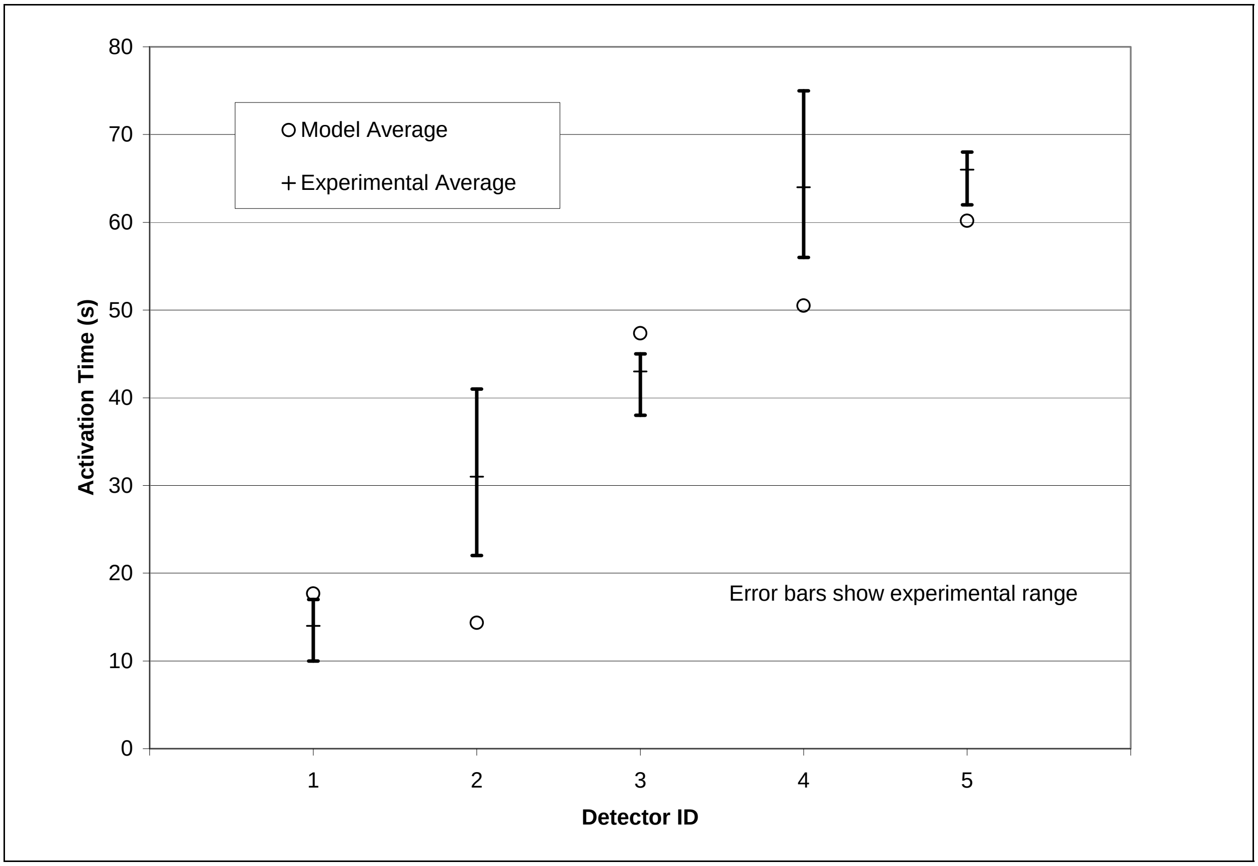

Figure 17 - Room-corridor-room average model results compared with average experimental results (subset of Figure 16).

As can be seen from the figures above, the model results agree reasonably well with the experimental data. Average values from the model were only 15-20% different than the experimental averages. There is also no consistent trend of under-prediction or over-prediction of the experimental values. This validation also shows that when the velocity slows as the smoke travels to the more remote alarms, the model is still successful in predicting activation time. This success is important as it is an indication that the algorithm velocity lag time correlations are accurately transporting the smoke into the sensing chamber and accurately accounting for the role of smoke velocity.

6.3 NIST 'Performance of Home Smoke Alarms' Test Validation

As a final validation of the activation algorithm and its incorporation into FDS, a fire test was modeled from the NIST 'Performance of Home Smoke Alarms' tests (Bukowski *et al.*, 2003). This test series is also known in the industry as the Dunes 2000 tests, as a tribute to similar tests that were conducted in the early 1970s (known as the Indiana Dunes tests (Bukowski *et al.*, 1975, Harpe *et al.*, 1977)). Test 5 was selected for the validation, since it was a flaming fire in a manufactured home geometry. Specifically, it was a flaming mattress fuel load ignited with a flaming source. A load cell was used to measure the mass loss rate of the mattress. In addition to the mass loss data, temperature (via thermocouples), velocity (via velocimeters), smoke obscuration (via photodiodes), and toxic gas measurements were recorded at locations throughout the structure. Figure 18 shows the geometry of the manufactured home with the locations of the sensing equipment. Figure 19 shows a snapshot of the FDS model.

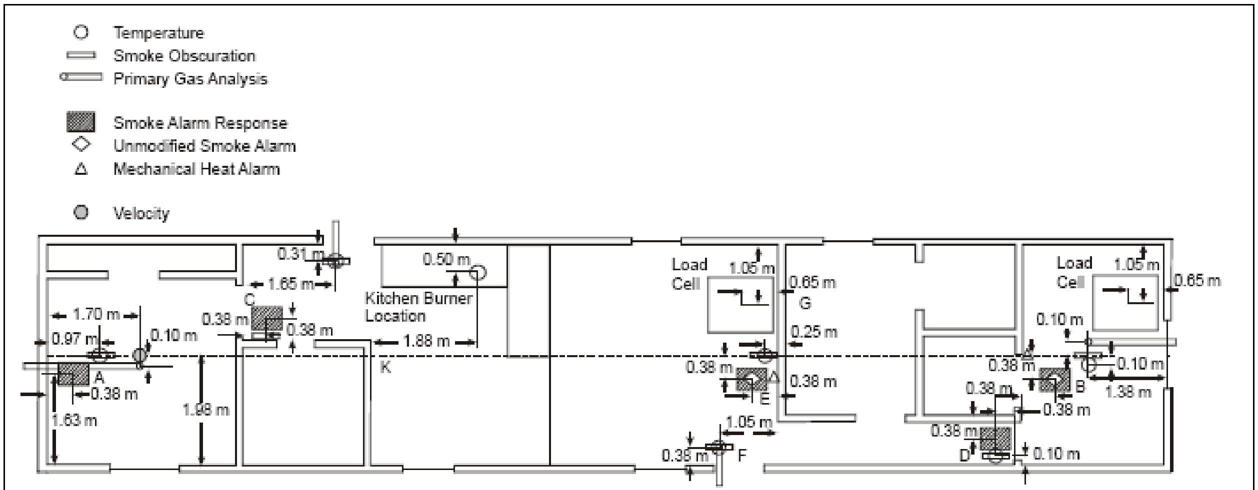

Figure 18 - Geometry of the Dunes 2000 manufactured home (reproduced Bukowski *et al.*, 2003)).

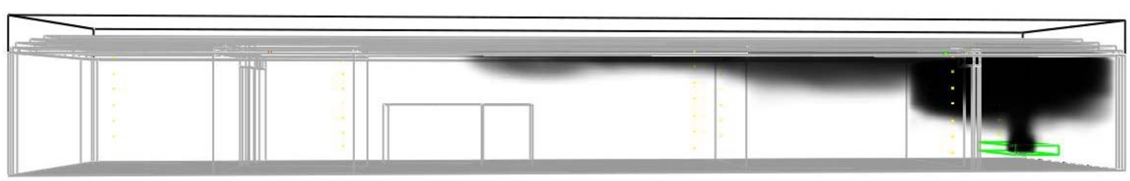
Figure 19 - Dunes 2000 manufactured home test 5 FDS model.

Smoke detector 'stations' were mounted at several locations in the residence. At each station, several ionization, photoelectric, and combination type alarms were installed. The alarms did not sound, but instead their internal chamber voltages were monitored and compared with calibrations in the FE/DE to determine when the alarms activated. A range of 'low', 'mid', and 'high' activation thresholds were determined by NIST for the alarms. The range of 'low' to 'high' is expected to bracket the entire range of potential activation times of the particular alarm, and the 'mid' alarm is expected to be the best approximation of actual alarm time. While the detectors were tested in the FE/DE to determine the 'low', 'mid', and 'high' activation thresholds, the detectors were not assessed to determine the lag time coefficients. Therefore, as was done with previous validations described in this report, generic lag time coefficients from the literature were used (I1 and I2 from Cleary *et al.* (2000) and effective length of L=1.8m Heskestad, (1975)). The cell size utilized was approximately 3.5 inch cubes, which is smaller than the expected ceiling jet depth based on standard correlations, and is larger than the maximum expected depth of the boundary layer, as is discussed in Section 2.1.8 above.

At each station, the experimental times were averaged and large outliers were removed if it became apparent that a particular detector was not operating like similar detectors at that station, or if there was a possibility of a data acquisition error. Figure 20 shows the data from all the tests before the outliers were removed compared with the model data. Figure 21 shows the data from the experiments after the outliers were removed compared with the model data. Finally, Figure 22 shows the data from the experiments after the outliers were removed averaged for the ‘low’, ‘mid’, and ‘high’ activation points compared with the averaged model data.

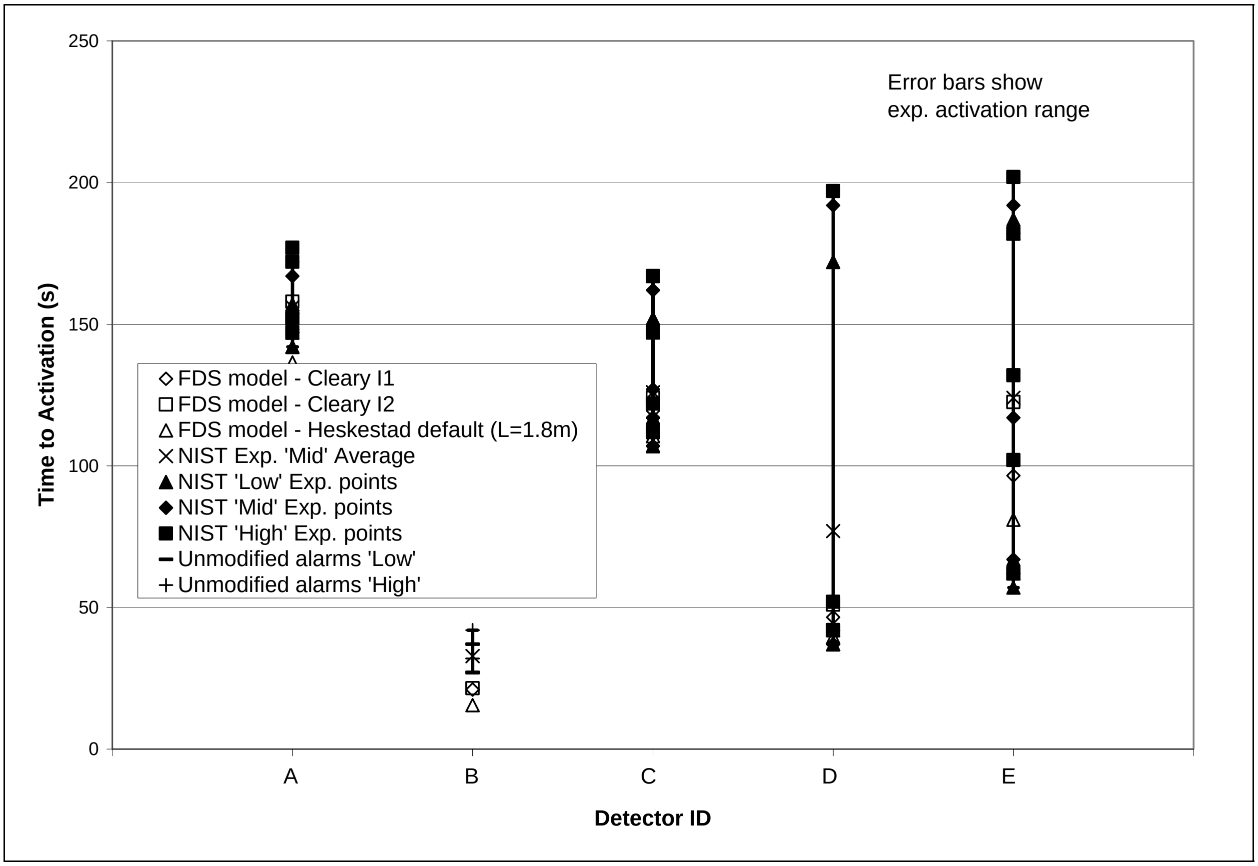

Figure 20 - All Dunes 2000 manufactured home test 5 experimental data (Bukowski *et al.*, 2003) compared with the model predictions.

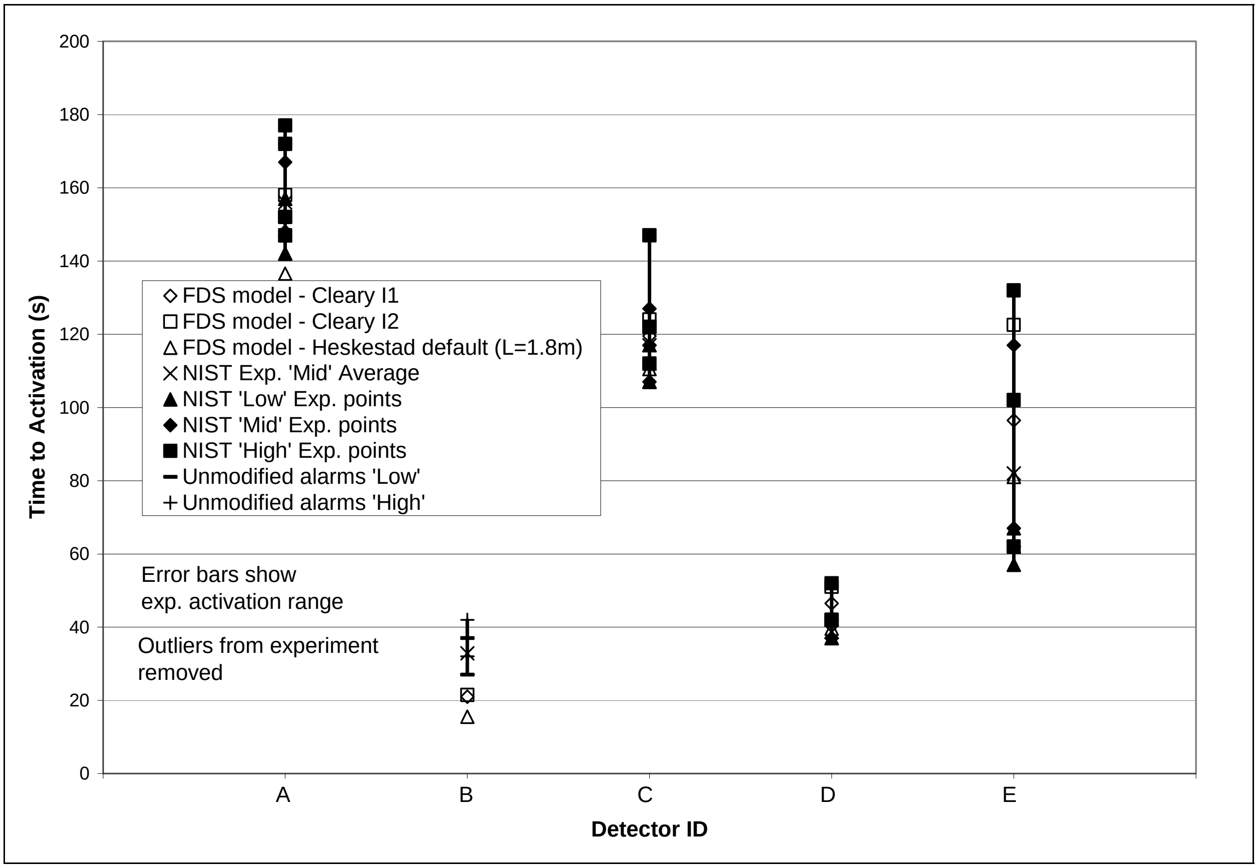

Figure 21 - Dunes 2000 manufactured home test 5 experimental data (Bukowski *et al.*, 2003) with the outliers removed compared with the model data.

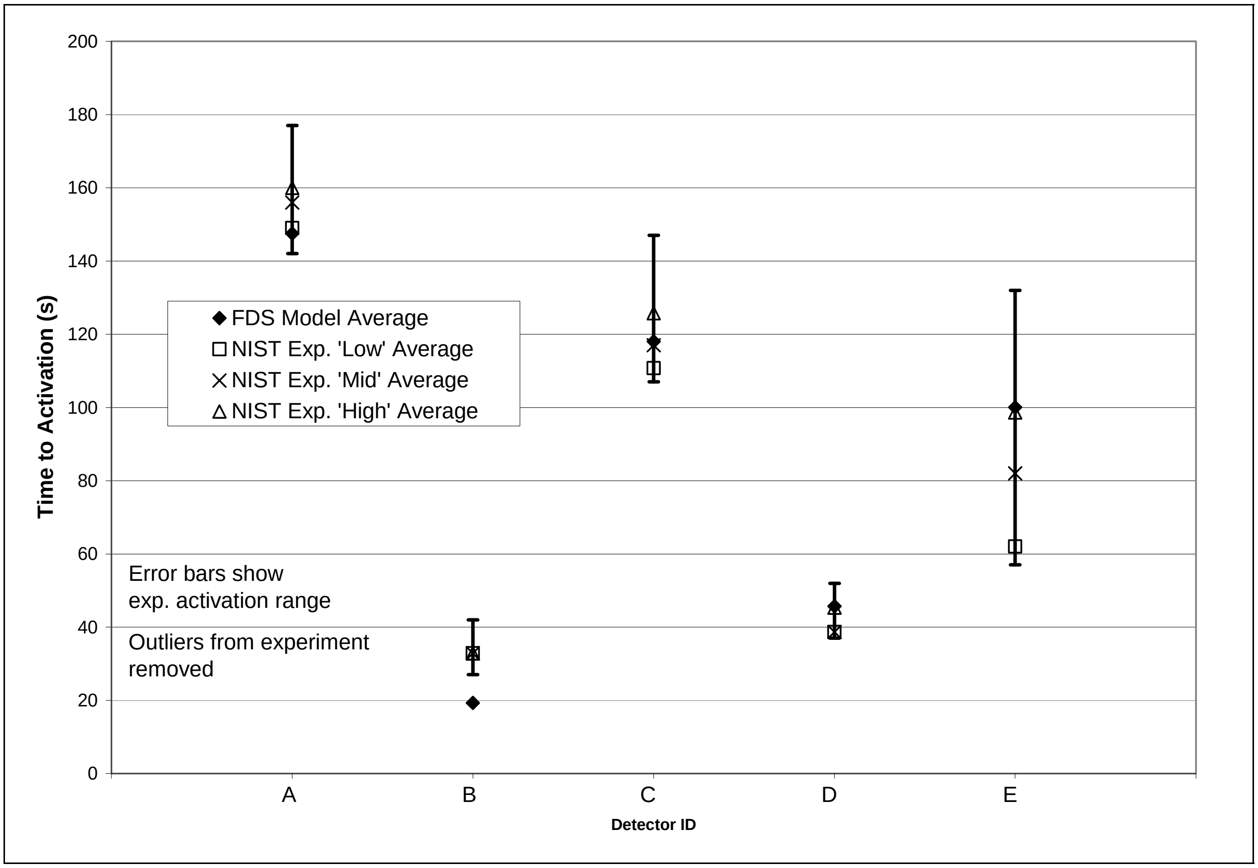

Figure 22 - Dunes 2000 manufactured home test 5 experimental data (Bukowski *et al.*, 2003) averaged after the removal of outliers compared with the averaged model data.

As is apparent from Figures 20-22 above, the activation algorithm and FDS model are accurately predicting the activation times of the smoke detectors, even for fairly complicated geometries in relatively large spaces as depicted in this validation. In fact, at 3 of the 5 detector stations, the model is almost exactly matching the average activation times of the 'mid' detector threshold, which is expected to be the best approximation of actual alarm time. This is particularly encouraging considering that the simulation results at the 3 detector stations furthest from the fire source (E, C, and A), the model still accurately predicted smoke detector activation considering the relatively slow velocity of the smoke. To highlight this, Figure 23 shows the temperature in the model, Figure 24 shows the velocity in the model, and Figure 25 shows the smoke obscuration in the model outside the detectors and the smoke obscuration inside the chambers of the three model detectors (Cleary I1, Cleary I2, and Heskestad L=1.8m) at Detector Station C. Figures 23-25 show the power of the activation algorithm in properly predicting smoke detector activation time utilizing FDS. Figures 24 and 25 show that even though smoke arrives at the detector at approximately 110 seconds after ignition and with a velocity of initially 0.15 m/s or less (and not much more over that critical velocity), the model smoke detectors do not activate until approximately 3-15 seconds later, at around 113-125 seconds, depending on the detector coefficients used.

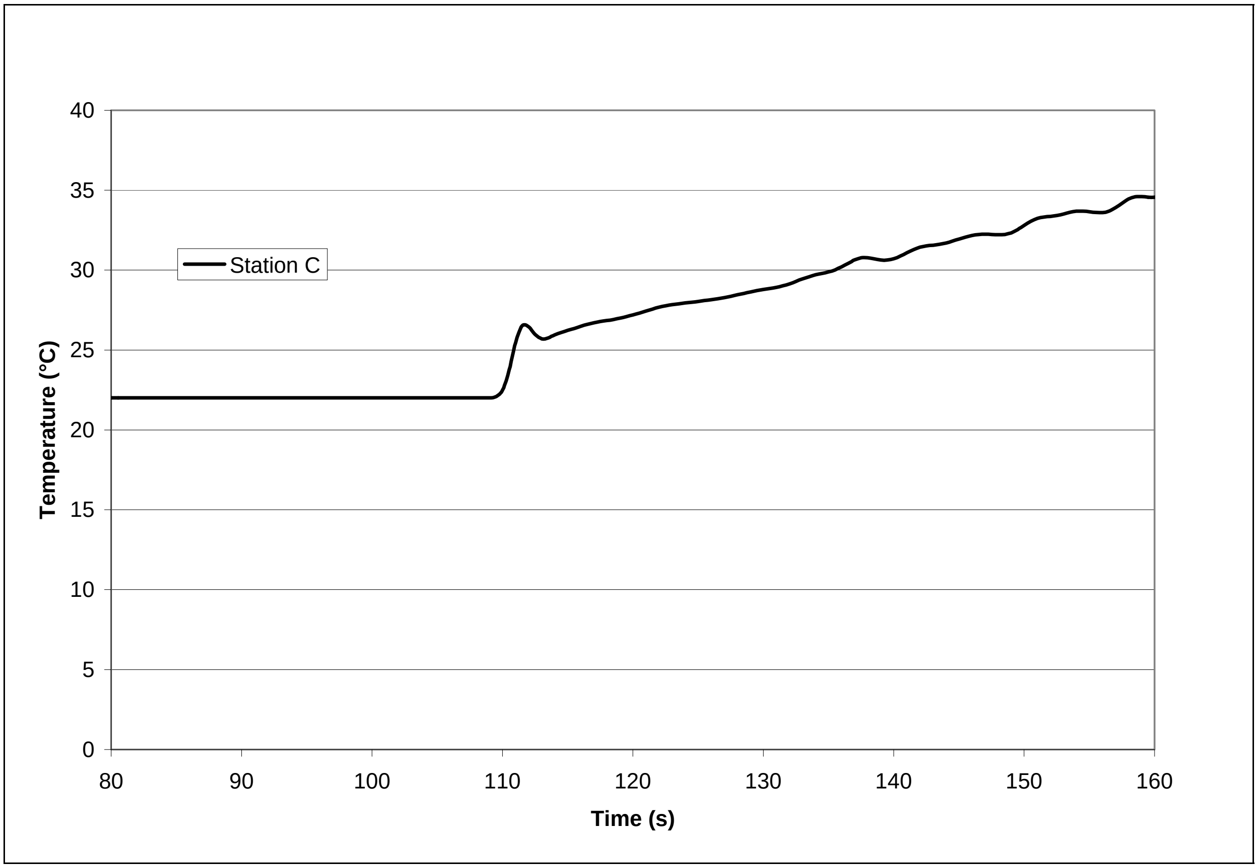

Figure 23 - Temperature in FDS model at Detector Station C.

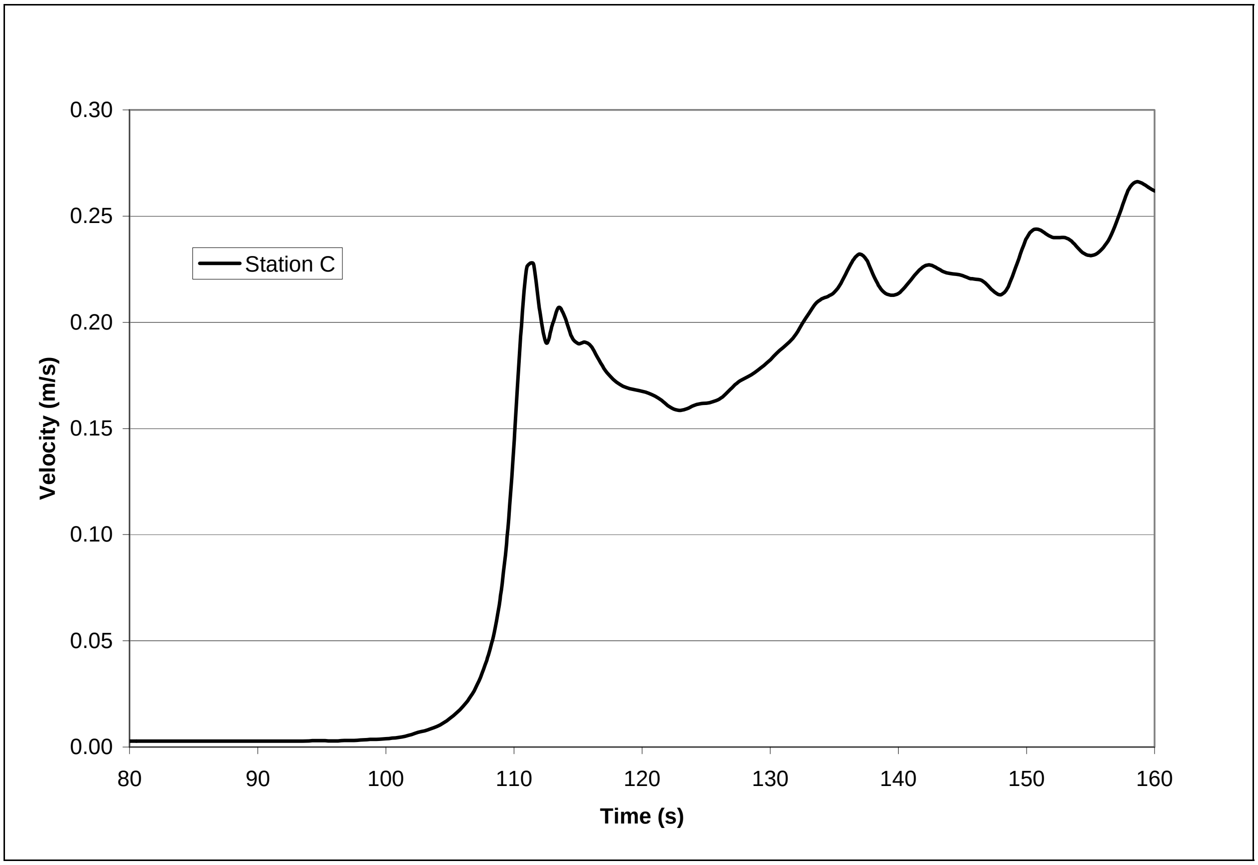

Figure 24 - Velocity in FDS model at Detector Station C.

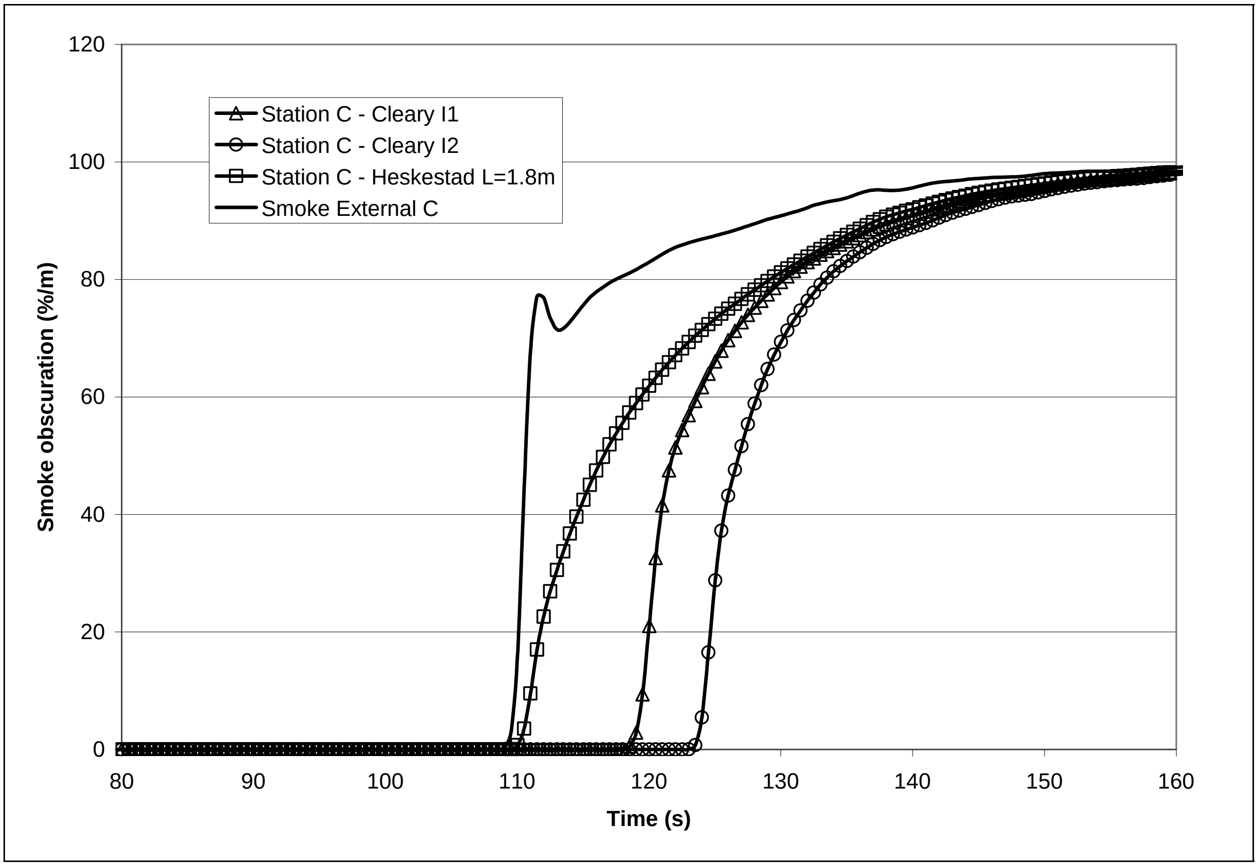

Figure 25 - Smoke obscuration inside and outside the detector in the FDS model at Detector Station C.

Other predictive methods for determining smoke detector activation time have been published in the fire protection literature. Most notably is the temperature correlation (Heskestad and Delichatsios, 1977) and the optical density threshold method (Geiman and Gottuk, 2003). The temperature correlation, as described in Section 1, correlates smoke detector activation time with the time for a particular temperature rise at the detector. Values of this temperature rise have been suggested in the literature to be anywhere from 4°C – 13°C (Heskestad and Delichatsios, 1977; Geiman and Gottuk, 2003). The optical density threshold method of Geiman and Gottuk (2003) is a statistical post-processing method whereby when the smoke optical density reaches a certain threshold value at the smoke detector location for a given fire and detector type, the probability that the detector has activated by that time is given. For example, at a certain value of optical density for a flaming fire and an ionization detector, the threshold method will state that 80% of all detectors subjected to those conditions will have activated. Therefore, the method only provides a range from the start of the test and is not actually trying to approximate the actual activation time of the detector. A graphical comparison of the predictions made by the smoke detector activation algorithm with those of threshold method (Geiman and Gottuk, 2003) as well as the temperature correlation (Heskestad, 1975) is included as Figure 26. These other predictive methods are not as accurately predicting the smoke detector activation times, as can be seen in Figure 26. In fact, for the detectors located at station A (most remote from the fire), the optical density thresholds still do not accurately predict the activation time despite having wide error bars. This is because the threshold method does not explicitly account for smoke velocity. Further, the threshold method is under-predicting the activation time of the detectors at this location, thereby not erring on the side of a conservative answer from a design perspective.

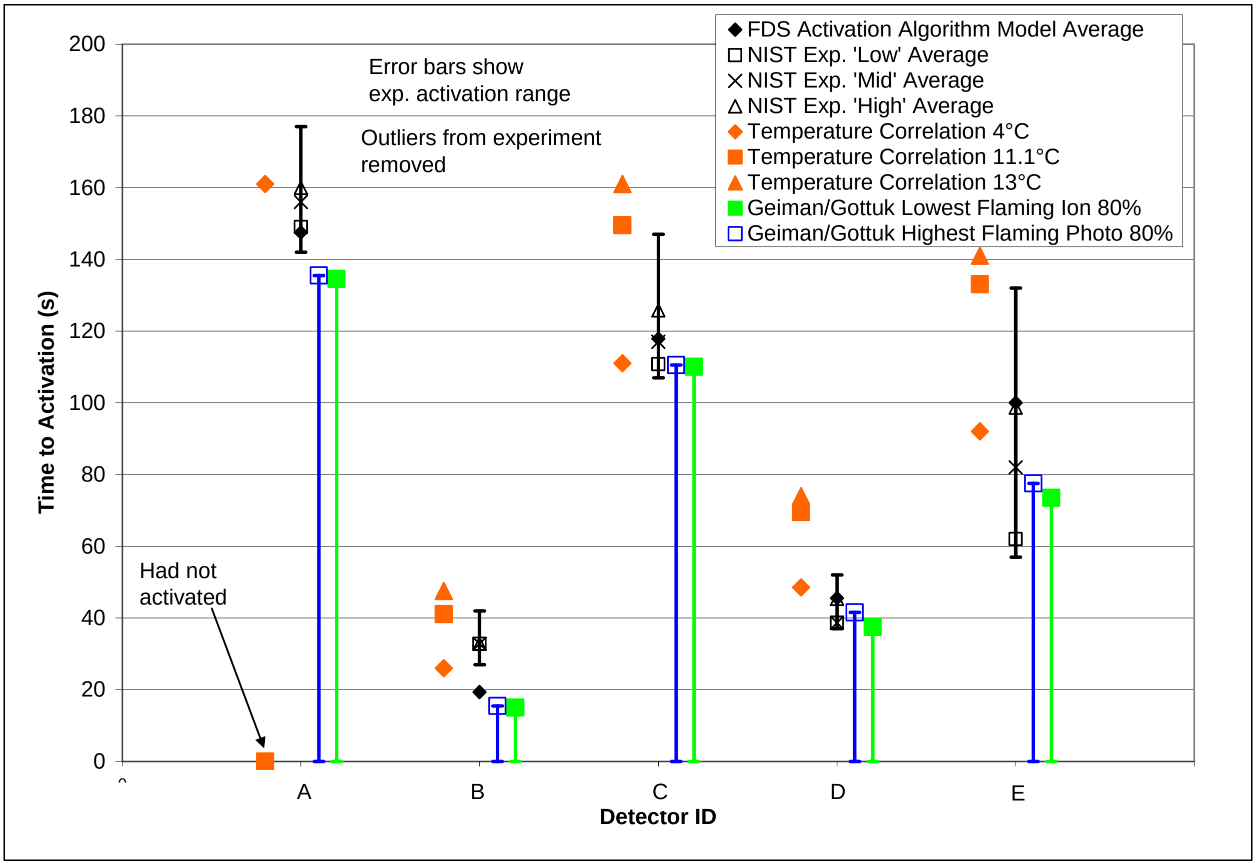

Figure 26 - Smoke detector activation predications of the smoke detector activation algorithm and other methods postulated in the literature.

Based on the analysis shown graphically as Figure 26, some standard smoke detector activation algorithms, working solely with an optical density criteria or a temperature correlation, are not predicting the smoke detector activation times as accurately as the activation algorithm integrated into FDS. Further, these methods could be under-predicting activation times on occasion, possibly leading to poor positioning of a detection device. Hence, the use of other correlations may not be conservative and could lead to an unsafe design. It is expected that differences in predictive capabilities between the activation algorithm and other methods of determining smoke detector activation time will be highlighted for the detectors that are greatly remote from the fire or for fires in an incipient state or that are relatively small in size (i.e. low heat release rate), which result in low flow velocities.

The above validations demonstrate that the FDS fluid flow and smoke transport model can be expected to accurately predict the smoke concentrations and velocities at a smoke detector location in a model within the expected range of errors of input variables into the FDS model. Further, from the two full-scale smoke detector activation model validations above, the activation algorithm can then be expected to accurately determine a smoke detector activation time within reasonable error rates, and as has been shown, will provide a more realistic and possibly more conservative estimation than other smoke detector activation time methods currently used in the fire protection profession.

Chapter 7

7 Conclusions

Early detection of fire plays an important role in the life safety of building occupants. The ability to accurately predict the performance of fire detection systems is an integral part of the analysis associated with fire safety design and fire reconstruction. The equations and numerical algorithm presented in this document describe a model for predicting the activation of smoke detectors in the presence of compartment fires. The smoke detector activation algorithm was designed to use the smoke concentration and velocity predictions of a computational fluid dynamics code, such as FDS, to predict the transport of smoke into detector housings. The algorithm properly accounts for detector lag due to the flow resistance of the housings and time required for mixing within the detection chamber.

The smoke detector activation algorithm has been validated against a number of fire scenarios and geometries. Included in these validation cases are the UL 217 fire test room, a multi-room compartment, and the NIST 'Performance of Home Smoke Alarms' tests. The algorithm and FDS model are accurately predicting the activation times of the smoke detectors, even for fairly complicated geometries in relatively large spaces. Other predictive methods for determining smoke detector activation time, most notably the temperature correlation and the optical density threshold method, were found not to be as accurate as the numerical techniques used by the activation algorithm for obtaining detector activation times.

An accurate prediction of the activation time of a smoke detector requires a proper description of the velocity flow field and smoke concentration in the area of the smoke detector. Hence, the predictions from the algorithm are inherently dependent on the quantities and properties that affect the CFD predictions, including the input variables and calculation techniques. Important variables include but are not limited to grid resolution, material properties such as smoke generation rate and heat release rate, and sufficient detail in the geometry. Hence, as the predictions of fire growth and smoke transport improve, the ability of the algorithm to predict smoke detector activation will also improve.

Chapter 8.

8 References

Ahrens, M., U.S. Experience with Smoke Alarms and Other Fire Detection/Alarm Equipment, NFPA, 2004.

American Society for Testing and Materials, West Conshohocken, Pennsylvania. *ASTM E 1355-04, Standard Guide for Evaluating the Predictive Capabilities of Deterministic Fire Models*, 2004.

Baum, H. R., McGrattan, K. B., and Rehm, R. G., (1997). "Three Dimensional Simulations of Fire Plume Dynamics," *Fire Safety Science – Proceedings of the Fifth International Symposium*, International Association for Fire Safety Science, pp.511-522.

Baum, H. R., McGrattan, K. B., and Rehm, R. G., (1998) "Large Eddy Simulation of Smoke Movement," *Fire Safety Journal*, Vol. 30, No. 2, pp. 161-178, March.

Beyler, C., and DiNenno, P., "Letters to the Editor," *Fire Technology*, v. 27, n. 2., 1991

Bjorkman, J., Kokkala, M. A., and Aloha,H., "Measurement of the Characteristic Length of Smoke Detectors", Fire Technology, v. 28, n: 2, May 1992.

Brozovsky E.L., A preliminary approach to siting smoke detectors based on design fire size and detector aerosol entry lag time. Master's Thesis, Worcester Polytechnic Institute, 1991.

Brozovsky, E., Motevalli, V., and Custer, R. P., (1995). "A First Approximation Method for Smoke Detector Placement Based on Design Fire Size, Critical Velocity, and Detector Aerosol Entry Lag Time," *Fire Technology* 31: 336-354.

Bukowski, R. W., Peacock, R. D., Averill, J. D., Cleary, T. G., Bryner, N. P., Walton, W. D., Reneke, P. A., and Kuligowski, E. D., Performance of Home Smoke Alarms: Analysis of the Response of Several Available Technologies in Residential Fire Settings. NIST Technical Note 1455, National Institute of Standards and Technology, 2003.

Bukowski, R.W., Waterman, T.E., and Christian, W.J., Detector Sensitivity and Siting Requirements for Dwellings. NIST GCR 75-51, National Institute of Standards and Technology, 1975.

Cholin, J.M. and Marrion, C., "Performance Metrics for Fire Detection," *Fire Protection Engineering*, n.11, 2001.

Cleary, T., Anderson, M., Averill, J., and Grosshandler, W., "Evaluating Multi-Sensor Fire Detectors in the Fire Emulator/Detector Evaluator", Proceedings of Interflam '99, 1999.

Cleary, T., Chernovsky, A., Grosshandler, W., and Anderson, M., (2000). “Particulate Entry Lag in Spot-Type Smoke Detectors,” *Fire Safety Science – Proceedings of the Sixth International Symposium*, International Association for Fire Safety Science, Interscience Communications, London, UK, pp. 779-790, 2000.

Cleary, T., Donnelly, M., Mulholland, G., Farouk, B., “Fire Detector Performance Predictions in a Simulated Multi-Room Configuration”, Proceedings of 12th Conference on Automatic Fire Detection, 2001

Drysdale, D., “An Introduction to Fire Dynamics”. Second Edition, John Wiley & Sons, 1998.

D’souza, V.,T., Sutula, J.,A., Olenick, S. M., Zhang, W., and Roby,R.,J., “Predicting Smoke Detector Activation Using the Fire Dynamics Simulator”. Proceedings of the 7th International Symposium of Fire Safety Science, 2002.

Emmerich, S. J., and McGrattan, K. B., (1998). “Application of a Large Eddy Simulation Model to Study Room Airflow,” American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc. Report SF-98-10-2, Atlanta, GA.

Fire Dynamics Simulator (Version 4.0) – User’s Guide. National Institute of Standards and Technology (NIST), NISTIR 6784. 2003.

Forney, G. P. and K.B. McGrattan. User’s Guide for Smokeview Version 4. NIST Special Publication 1017, National Institute of Standards and Technology, Gaithersburg, Maryland, July 2004.

Geiman, J.A. and Gottuk, D.T, “Alarm Thresholds for Smoke Detector Modeling”, Proceedings of the Seventh International Symposium for Fire Safety Science, 2003.

Gottuk, D.T., Hill, S.A., Schemel, C.F., Strehlen, B.D., Rose-Phersson, S.L., Shaffer, R.E., Tatem, P.A. and Williams, F.W., Identification of Fire Signatures for Shipboard Multi-criteria Fire Detection Systems,” Naval Research Laboratory Memorandum Report 6180-99-8386, 1999.

Harpe, S.W., Waterman, T.E., and Christian, W.J. Detector Sensitivity and Siting Requirements – Phase 2, NBS GCR 77-82, National Institute of Standards and Technology, 1977.

Heskestad, G. J., and Delichatsios, M. A., (1977). “Environments of Fire Detectors, Phase I: Effects of Fire Size, Ceiling Heights, and Material”, Volume II – Analysis Technical Report Serial Number 11427, RC-T-11, Factory Mutual Research Corp., Norwood, MA.

Heskestad, G. “Generalized Characteristics of Smoke Entry and Response for Products of Combustion Detectors”, Proceedings – 7th International Conference on Problems of Automatic Fire Detection, March 1975.

Keski-Rahkonen, O., “A New Model for Time Lag of Smoke Detectors”. Proceedings of the International Collaborative Project to Evaluate Fire Models for Nuclear Power Plant Applications, Gaithersburg, MD, USA, 2002.

Luck, H. and Sievert, U., “Does an Over-All Modeling Make Any Sense in Automatic Fire Detection/,” *AUBE ’99 Proceedings of the 11th International Conference on Automatic Fire Detection*, 1999.

Mallonee, S., Istre, G. R., Rosenberg, R., Reddish-Douglas, M., Jordan, F., Silverstein, P., and Tunell, W., (1996). “Surveillance and Prevention of Residential-Fire Injuries,” The new England Journal of Medicine, Vol. 335, No. 1, July 4th.

MATLAB, Version 7.0, The MathWorks, Inc., Natick, MA, 2004.

McGrattan, K. B., Rehm, R. G. and Baum, H. R., “Large Eddy Simulations of Smoke Movement”, Fire Safety Journal, 30(2), 1998.

McGrattan, K. B.(ed). “Fire Dynamics Simulator (Version 4) – Technical Reference Guide,” National Institute of Standards and Technology Report NIST Special Publication 1018, September, 2005.

McGrattan, K. B. and G. P. Forney. Fire Dynamics Simulator (Version 4), User’s Guide. NIST Special Publication 1019, National Institute of Standards and Technology September, 2005.

Mowrer, F.W. and Friedman, J., “Experimental Investigation of Heat and Smoke Detector Response,” *Proceedings of the Fire Suppression and Detection Research Application Symposium*, 1998.

Mulholland, G. W. “The Emission and Optical Properties of Smoke”, Recent Advances in Flame Retardancy of Polymeric Materials, Vol: III, Proceedings of 6th International Symposium of Fire Safety Science, 2000.

Mulholland, G. (2002). “Smoke Production and Properties,” *The SFPE Handbook of Fire Protection Engineering (3rd ed),* P. J. DiNenno (ed.), National Fire Protection Association, 2002.

Munson, B.R., Young, D.F., and Okiishi, T.H., Fundamentals of Fluid Mechanics, Second Edition, John Wiley & Sons, Inc., 1994.

Newman, J.S. “Prediction of Fire Detector Response”, presented at the SFPE Quantitative Methods for Life Safety Analysis Conference, March, 1986.

Newman, J. S., “Prediction of Fire Detector Response”, Fire Safety Journal, v. 12, 1987.

Newman, J. S., “Modified Theory for the Characterization of Ionization Smoke Detectors”. Proceedings of the Fourth International Symposium of Fire Safety Science. 1989.

Olenick, S.M., Roby, R.J., Klassen, M.S., Zhang, W., Sutula, J.A., Worrell, C., Wu, D., D'Souza, V., Ashley, A., Dubois, J., Torero, J.L., and Streit, L., "The Role of Smoke Detectors in Forensic Fire Investigation and Reconstruction," presented to the International Symposium on Fire Investigation Science and Technology (ISFI), June 26-28, 2006.

Olenick, S.M., Zhang, W., Carpenter, D. J., Roby, R. J., and Klassen, S. M., "Verification and Validation of a Smoke Detector Activation Algorithm for the Fire Dynamics Simulator (FDS)", presented to the NFPA Fire Protection Research Foundation Fire Suppression and Detection Research Application Symposium, Orlando, January, 2005.

Press, W. H., Teukolsky, S. A., Vetterling, W. T., and Flannery, B. P., Numerical Recipes in FORTRAN, Second Edition, Cambridge University Press, 1992.

Qualey, J. R. III, Desmarais, L. and Pratt, J., Response Time Comparisons of Ionization and Photoelectric/Heat detectors, NIST SP 965; 2001.

Schifiliti, R.P. and Pucci, W.E., "Fire Detection Modeling: State of the Art," Fire Detection Institute, 1996.

Schifiliti, R.P., "Fire Detection Modeling – The Research-Application Gap, *AUBE '01 Proceedings of the 12th International Conference on Automatic Fire Detection*, 2001.

Stroup, D.W., and Evans, D. D., (1988). "Use of Computer Models for Analyzing Thermal Detector Spacing," *Fire Safety Journal*, **14**, 33-45.

Tewarson, A., (2002). "Generation of Heat and Chemical Compounds in Fires," *The SFPE Handbook of Fire Protection Engineering (3rd ed),* P.J. DiNenno (ed.), National Fire Protection Association, 2002.

Underwriters Laboratories Standard 217, Standard for Single and Multiple Station Smoke Detectors, Third edition, Underwriters Laboratories, 1985.

Underwriters Laboratories Standard 217, Standard for Single and Multiple Station Smoke Alarms, Fifth edition, with updates though August 15, 2005, Underwriters Laboratories, 2005.

Upadhyay, R.R., and Ezekoye, O.A., "Smoke Buildup and Light Scattering in a Cylindrical Cavity Above a Uniform Flow", Journal of Aerosol Science, 36, 2005.

Wakelin, A.J., "An Investigation of Correlations for Multi-Signal Fire Detectors," Masters Thesis, Worcester Polytechnic Institute, Department of Fire Protection Engineering, 1997.

Wolin, S. D., Ryder, N. L., Leprince, F., Milke, J. A., Mowrer, F. W. and Torero, J. L., "Measurements of Smoke Characteristics in HVAC Ducts," Fire Technology, v. 37, n. 4, 2001.

Zhang, W., Hamer, A., Klassen, M., Carpenter, D., Roby, R., Turbulence Statistics in a Fire Room Modeled by Large Eddy Simulation, Fire Safety Journal, 37(8), 2002.

Zhang, W. and Roby, R., Large Eddy Simulation of Combustion in Compartment Fires, ASHRAE Transactions, 109, Part 2 (4647), 2003.