DATA ASSIMILATION BASED NUMERICAL SIMULATIONS TO ASSIST REAL-TIME SMOKE CONTROL MANAGEMENT IN LARGE SPACES

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Abstract
The work presented in this paper illustrates the concept of numerical simulations for real-time 'Numerical Fire Forecast' (NFF), applied to smoke control management in large spaces. The numerical calculations performed within the Inverse Zone Modelling framework are based on a series of full scale experiments conducted using the Japanese Building Research Institute (BRI) fire test facility. The experimental set-up consists of a large space of 720m^2 floor area and 26.3m ceiling height, equipped with shafts and fans to study different smoke control options. The measurements include the smoke layer interface (from thermocouples, photometers and visual observation), the smoke layer temperature at different heights (using thermocouples) and the mass flows of air and hot smoke through mechanical and natural vents. In the case of natural filling (i.e. no mechanical or natural venting), the assimilation of smoke layer height data within a 30 s window results in more than 4 minutes lead time of the forecast, with a good level of confidence. Predictions are given in terms of smoke layer height and upper layer temperature. The steady-state value of the methanol fire (Q_c = 1300 kW) has been estimated after 30 s with less than 10% error. Widening the assimilation window does not improve the forecast. When mechanical ventilation is activated after the assimilation process with a sufficiently high exhaust rate, the forecast shows with a relatively substantial positive lead time, safe levels of smoke interface height.

Introduction
Fire Safety Engineering is a multi-disciplinary science, which aims at designing fire-safe buildings with appropriate solutions to preserve property and, most importantly, human life. Therefore, before the construction (or the renovation) of a building, architects, fire engineers and regulators need to consider a given set of fire scenarios in order to examine different options and choose the most appropriate one(s). For this purpose, a large amount of tools have been developed across the years in order to provide an answer to various questions that arise when studying the complex phenomenon of a fire. These questions are often related to the integrity of the building (fire resistance of the structure), fire and smoke spread, and evacuation. The tools used range from simple engineering hand-calculations to the more sophisticated computational fluid and solid mechanics.

Many fire simulation tools have been developed to provide guidance in a priori studies. The level of complexity already reached in these tools and the required computational resources render their use for real time predictions impossible. Subsequently, fire fighters have to rely on their intuition and experience as to the decisions and actions to take in real fire situations. It is in this context that the concept of sensor assisted fire fighting has emerged [1]. The main idea consists of using real-time information (provided by the sensors) to steer a fire model that is simple enough to be able to produce a forecast of the situation with a reasonable lead time. The technique used is called Data Assimilation (DA); it has been relied upon in many fields of geosciences, and most importantly in weather forecast [2].

The feasibility of Numerical Fire Forecast (NFF) has been first examined in [3-4]. The authors used Inverse Zone Modelling (IZM) to predict the upper layer temperature, the smoke layer height and the heat release rate in a closed compartment fire with floor leaks. Fire Dynamics Simulator (FDS) data acted as source for data assimilation in the zone model in order to dynamically estimate the fire growth rate, the plume entrainment rate, and the delay time. Positive lead times were obtained.

In the work presented here, we continue to examine the NFF concept (within the IZM framework) by applying it to smoke control in an atrium, based on the experimental data presented in [5].

The article is organized as follows. First, the experimental set-up is presented along with the details of data collection. The following section provides a formulation of the zone model. Then, the data assimilation model is addressed and the structure of the code described. Finally, the outcomes of the modelling are discussed in the results' section, before addressing the main conclusions and perspectives on future work.

Experimental configuration

The numerical calculations are based on a series of full scale experiments conducted using the BRI fire test facility [5] and intended to assess the quality of 'analytic theories for simple control problems' [6]. The experimental set-up consists of a large space of 720m^2 floor area (30m×24m) and 26.3m ceiling height equipped with shafts, fans and windows for natural ventilation to study different smoke control options. The source of the fire consists of 15 methanol pans, of 45 cm^2 each, put together on the floor. A smoke candle was placed at a corner of the fire source and the smoke generated was driven by the fire plume. The Heat Release Rate (HRR) obtained by converting the average mass burning rate is 1300 kW. The measurements include the smoke layer interface (from thermocouples, photometers and visual observation), the smoke layer temperature at different heights (using thermocouples) and the mass flows of air and hot smoke through mechanical and natural vents. More details can be found in [5]. The case examined in this paper is the natural filling case referred to as A-1 [5]. Afterwards, we illustrate that the method is also readily applicable when mechanical venting is achieved.

Zone model formulation

Fire dynamics can be examined by several means that differ in the level of detail forsaken. The simplest way is the use of algebraic equations; the most sophisticated one is Computational Fluid Dynamics (CFD). The choice of zone modelling, which is an intermediate solution (in complexity), is motivated by the simplified physics that make it quicker to run compared to CFD models. Furthermore, it offers the advantage, over algebraic equations, of addressing transient events.

Zone modelling is often used to evaluate the life safety tenability of a fire environment [7]. Since its overall accuracy is closely tied to the input data, the DA technique will improve, in principle, the quality of the output thanks to a dynamic estimation of the model parameters.

The enclosure is divided into two distinct gaseous zones (hot upper layer and cold lower layer) as a result of thermal stratification due to buoyancy. The fire source behaves as a 'pump' of enthalpy and mass towards the hot upper layer.

The zone model equations used in this work are formulated as follows. The mass of the hot upper layer increases due to smoke plume entrainment. The activation of mechanical venting will slow down this increase due to smoke extraction. The resulting conservation equation for the mass balance is therefore:

$$\frac{d\left(\rho_u V_u\right)}{dt} = \dot{m}_p - \dot{m}_{ex} \tag{1}$$

where ρ_u is the upper layer density, V_u the upper layer volume, t the time, $\dot{m}_p$ the plume mass flow rate, entering the upper layer at its bottom side, and $\dot{m}_{ex}$ the mechanical exhaust rate from the upper layer.

The mass entrainment for a single point source fire, assuming an axisymmetric plume, is expressed as [8]:

$$\dot{m}_p = C \times \left(\frac{\rho_a^2 g}{C_p T_a}\right)^{1/3} \times Q_c^{1/3} \times h^{5/3} \tag{2}$$

where C is the entrainment rate, ρ_a the ambient density, g the gravitational acceleration, C_p the specific heat, T_a the ambient temperature, Q_c the convective heat release rate (expressed in kW) and h the smoke free height (i.e. the height, measured from floor level, of the bottom of the smoke layer).
A more general expression for plume entrainment has been developed in [9] in order to account for example for the fire location (axisymmetric plumes, wall plumes or corner plumes), but we illustrate below that expression (2) suffices for the purpose of the present paper.

The mechanical exhaust rate is expressed as:

$$\dot{m}_{ex} = \begin{cases} \dot{V}_{ex}\,\rho_u & if\ t \geq t_{ex}, \\ 0 & otherwise. \end{cases} \tag{3}$$

where $\dot{V}_{ex}$ is a prescribed constant volumetric rate and t_{ex} is the activation time of mechanical venting.

Gathering different losses (burning efficiency and heat losses to walls and ceiling) into a single loss coefficient α_{loss} [7], the energy equation in the zone model is given by:

$$\frac{dE}{dt} = \alpha_{loss}\, Q_c - \dot{m}_{ex}\, C_p \left(T_u - T_a\right) \tag{4}$$

where T_u is the upper layer temperature. Choosing the reference level for energy E equal to zero at ambient temperature T_a, the energy contents in the upper layer is expressed as:

$$E = \rho_u V_u C_p \left(T_u - T_a\right) \tag{5}$$

The upper layer volume V_u is:

$$V_u = A\left(H_0 - h\right) \tag{6}$$

where the variable A is the floor area, and H_0 the ceiling height.
The initial conditions are $T_u = T_a$ ($\rho_u = \rho_a$) and $h = H_0$ ($V_u = 0$).

Equations (1) to (6) are discretized in time using a Forward Difference Formula (FDF). The following set of equations is obtained:

$$\dot{m}_{p,n} = C\left(\frac{\rho_a^2 g}{C_p T_a}\right)^{1/3} Q_c^{1/3}\, h_n^{5/3} \tag{7a}$$

$$\dot{m}_{ex,n} = \begin{cases} \dot{V}_{ex}\,\rho_{u,n} & if\ t_i \geq t_{ex}, \\ 0 & otherwise. \end{cases} \tag{7b}$$

$$\left(\rho_u V_u\right)_{n+1} = \left(\rho_u V_u\right)_n + \Delta t\left(\dot{m}_{p,n} - \dot{m}_{ex,n}\right) \tag{7c}$$

$$E_{n+1} = E_n + \Delta t\left[\alpha_{loss}\, Q_c - \dot{m}_{ex,n}\, C_p\left(T_{u,n} - T_a\right)\right] \tag{7d}$$

$$T_{u,n+1} = T_a + \frac{E_{n+1}}{\left(\rho_u V_u\right)_{n+1} C_p} \tag{7e}$$

$$\rho_{u,n+1} = \frac{\rho_a T_a}{T_{u,n+1}} \tag{7f}$$

$$V_{u,n+1} = \frac{\left(\rho_u V_u\right)_{n+1}}{\rho_{u,n+1}} \tag{7g}$$

$$h_{n+1} = H_0 - \frac{V_{u,n+1}}{A} \tag{7h}$$

where subscript n refers to time and Δt is the time step.

Data assimilation model

The main idea behind the concept of Data Assimilation (DA) is to incorporate observed information into a model in order to produce an accurate image of the true physical state and be able to make a forecast of its evolution in time. This technique is widely used in weather forecast.

In our application, the Zone Model is referred to in DA terms as the ‘assimilating model’. The set of discretized equations (7a) to (7h) constitutes the forward integration model or the so called ‘model operator’. The zone model being chosen (mainly for its simplicity and efficiency in well defined cases), the control variable(s) and the observations must be defined. As our main objective, in the long term, is to be able to use information from video camera to produce a fire forecast, we have chosen in this application to use only smoke layer heights as observations, without including the information on the temperature. A temperature forecast will nevertheless be produced along with the smoke layer height descent profile. Then, during the definition of the control variable(s), it must be ensured that the problem is mathematically well-posed. For example, in this case, with the unique information on the smoke layer height profile, it is not possible to estimate more than one model parameter. The only model invariant (i.e. parameter to estimate) in our formulation is Q_c, which represents the one-dimensional model state. The other model parameters are set to constant values ($C = 0.21$, see [5-8], and $\alpha_{loss} = 0.4$, see [7]).

The objective is therefore to find the value of Q_c that minimizes the cost function:

$$J(Q_c) = \sum_{i=1}^{N} \left(\hat{h}_i - h_i\right)^2 \tag{8}$$

starting from an initial guess, Q_c^0. The variable N denotes the number of observations, $\hat{h}_i$ the observed value of h at time t_i, and h_i the calculated value at time t_i. Note that, in general, Q_c can vary with time. In the present paper, we restrict ourselves to a situation where Q_c is steady.

By using a gradient-based method and linearizing the forward model around the initial guess [4], the system to be solved becomes:

$$Q_c^{k+1} = Q_c^k + \frac{\sum_{i=1}^{N} \left(\frac{\partial h_i}{\partial Q_c}\right)^k \left(\hat{h}_i - h_i^k\right)}{\sum_{i=1}^{N} \left(\left(\frac{\partial h_i}{\partial Q_c}\right)^k\right)^2} \tag{9}$$

The algorithm of the calculations is given as follows:

Algorithm

Let $Q_c = Q_c^0$

i. *Consider an assimilation window (i.e. N observations).*
ii. *From the specified initial conditions, compute h(t), with a forward integration model.*
iii. *Compute the derivatives in (9).*
iv. *Update the value of Q_c with (9).*
v. *Return to ii, using the updated value for Q_c, and repeat until a convergence criterion is met ($Q_c^{k+1} = Q_c^k \pm 1kW$ here).*
vi. *After the collection of more observational data, the process from i to v may be repeated with a wider assimilation window.*

The main questions that are open at this stage are:

- How to estimate the initial guess? and
- What model to use to compute the derivatives?

Initial guess

The reference time for the calculations is the time of smoke detection at the ceiling. This calculation will allow, in the case of steady fire (considered in this study), to avoid the

uncertainties that may arise from taking into consideration the lag time during which the hot combustion products rise from the fire source to the detector [10].
In our calculations, the initial guess for the HRR corresponds to the minimum fire size needed for the plume to reach the ceiling height, H_0 [11-12]:

$$Q_c^0 = (Q_c)_{\min} = 1.06 \times 10^{-3} \times H_0^4 \times \left(\frac{dT_a}{dz} \right)^{3/2} \tag{10}$$

where dT_a / dz is the ambient temperature gradient (K/m). If this gradient is taken as 1 K/m in our calculations, the smallest size required for the fire to reach the ceiling is: $Q_c^0 = (Q_c)_{\min} = 507 kW$. It has been ensured, nevertheless, that considering an initial guess in the range 50 to 2000 kW converges rigorously to the same value of Q_c. This is shown below (see Fig. 2).

Computation of the derivatives
The derivatives in (9) are calculated numerically. If we introduce a perturbation, $Q_c^{'}$, in the HRR (taken here as $Q_c^{'} = 0.01 Q_c^0$), it generates a perturbation in the smoke layer height, $h^{'}$, calculated recursively and using the chain rule.

$$\dot{m}_{p,i}^{'} = \left(\frac{\partial \dot{m}_{p,i}}{\partial Q_c} \right) Q_c^{'} + \left(\frac{\partial \dot{m}_{p,i}}{\partial h_i} \right) h_i^{'} \tag{11a}$$

$$\dot{m}_{ex,i}^{'} = \rho_{u,i}^{'} \dot{V}_{ex} \tag{11b}$$

$$(\rho_u V_u)_{i+1}^{'} = (\rho_u V_u)_i^{'} + \Delta t \times \left(\dot{m}_{p,i}^{'} - \dot{m}_{ex,i}^{'} \right) \tag{11c}$$

$$E_{i+1}^{'} = E_i^{'} + \Delta t \left(\alpha_{loss} Q_c^{'} - \dot{m}_{ex}^{'} C_p (T_{u,i} - T_a) - \dot{m}_{ex} C_p T_{u,i}^{'} \right) \tag{11d}$$

$$T_{u,i+1}^{'} = \frac{E_{i+1}^{'}}{C_p (\rho_u V_u)_{i+1}} - \frac{E_{i+1} \times (\rho_u V_u)_{i+1}^{'}}{C_p (\rho_u V_u)_{i+1}^2} \tag{11e}$$

$$\rho_{u,i+1}^{'} = -\frac{\rho_a T_a}{T_{u,i+1}^2} T_{u,i+1}^{'} \tag{11f}$$

$$V_{u,i+1}^{'} = \frac{(\rho_u V_u)_{i+1}^{'}}{\rho_{u,i+1}} - \frac{(\rho_u V_u)_{i+1} \rho_{u,i+1}^{'}}{\rho_{u,i+1}^2} \tag{11g}$$

$$h_{i+1}^{'} = -\frac{V_{u,i+1}^{'}}{A} \tag{11h}$$

where the superscript ' denotes the perturbed values. Equations (11a) to (11h) are obtained by differentiating the discretized equations (7a) to (7h) with respect to the active variables that affect the cost function ($Q_c, \dot{m}_p, \dot{m}_{ex}, h, \rho_u, T_u, V_u \, and \, E$). The initial conditions are: $h_0^{'} = 0,\ \rho_{u,0}^{'} = 0,\ (\rho_u V_u)_0^{'} = 0, E_0^{'} = 0,\ T_{u,0}^{'} = 0.$

The derivative term (i.e. the observation operator) is therefore calculated as:

$$\frac{\partial h_i}{\partial Q_c} = \frac{h_i^{'}}{Q_c^{'}} \tag{12}$$

The technique used here is called the Tangent Linear (TL) technique. Details on TL coding are found in [13]. Other options to calculate the observation operator are the finite difference approximation or the adjoint modelling [13].

Structure of the code

The calculation procedure addressed above has been implemented in a FORTRAN in-house code. The general structure of the code is the following:

- Program inputs
- Main loop: minimization of the cost function
    - Zone Model subroutine (ZM)
    - Tangent Linear Zone Model subroutine (ZM_TL)
- Program outputs

The required program inputs are: the maximum time of simulation, the time step, the height of the enclosure, its floor area, the ambient conditions, the exhaust rate of the mechanical ventilation and its activation time (if any), the plume entrainment coefficient, the heat loss fraction, the number of observations, the time for the initial observation, the time step between two observations and the values of the observations.

In the main loop of the program, the cost function is minimized in an iterative process until a convergence criterion is reached. During this process the ZM subroutine (Eqs. (7a) to (7h)) is called in order to provide the information on the smoke layer height and calculate the term $(\hat{h}_i - h_i)$ in Eq. (9). The derivative term is calculated using Eq. (12) by calling the ZM_TL subroutine in which Eqs. (11a) to (11h) are computed.

The program outputs are given in terms of the optimum value(s) for the model invariant(s) (in our case Q_c) and the subsequent forecast profiles of smoke layer height and upper layer temperature.

Results

Natural Filling

Figure 1 shows the experimental measurements of the smoke layer height obtained in [5] for the case of natural filling using thermocouple, photometer and visual observation. As discussed earlier, there is a lag time that corresponds to the travel time of hot products to the ceiling (where a detector is presumably placed). This is indicated in Fig. 1a. In order to avoid the uncertainty induced by the estimation of the lag time, the detection time is taken in the calculations as reference time. As to the uncertainties related to experimental measurements, a smoothed profile has been used by assuming an observation of *h* each 6 s (see Fig. 1b) Different algorithms have been developed to take into account the variations in the experimental data [14], but this will not be considered at this stage.

At 30 s after smoke detection, a first assimilation process is undertaken. The analysis conducted according to the algorithm described above leads to a HRR value of $Q_c = 1369\ kW$, which is within an error of less than 10% off from the true value (1300 kW). Figure 2 shows the convergence of Q_c starting from different initial guesses. The end value is reached very quickly for the wide range of initial guesses considered. Figure 3 shows the forecast of the smoke layer height after this first assimilation.

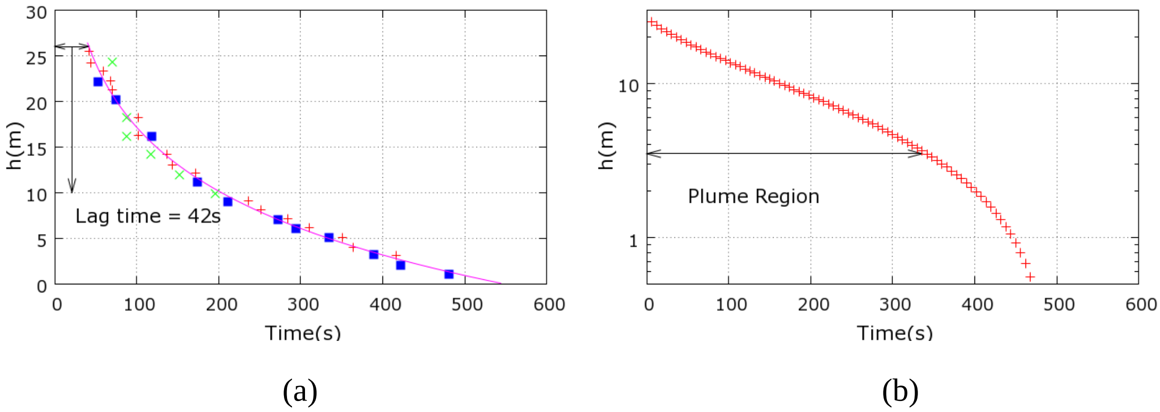


Figure 1. Experimental data of the smoke layer height in the case of natural filling [5]. (a) Thermocouple (+), photometer (×) and visual observation (■) measurements, and a smoothed profile (solid line). (b) Smoothed experimental data (given every 6 seconds) with no lag time in logarithmic. Arrow shows the extent of the plume region.

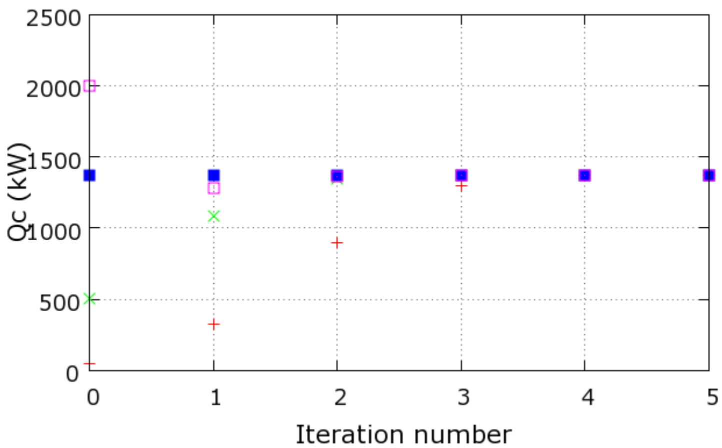


Figure 2. Convergence of the optimized value of Q_c for different initial guesses: (+) $Q_c^0 = 50\,kW$, (×) $Q_c^0 = 507\,kW$, (■) $Q_c^0 = 1369\,kW$ and (□) $Q_c^0 = 2000\,kW$.

If we define the lead time, in this application, as the time ahead of the event during which the forecasted smoke layer height is less than 0.5 m off the 'true' smoke layer height, Fig. 3 shows that the first assimilation results in a lead time of 257 s. We consider this very reasonable. The deviation, which takes place afterwards between the model and the experimental data, is due to the plume entrainment model (see Eq. (2)). The latter model holds only in the plume region, not in the intermittent region or the flame region (i.e. flame at the vicinity of the smoke interface). With Heskestadt's correlation, the flame length is indeed estimated as $L_f = 0.235 \times (1300)^{0.4} - 1.02 \times 0.093 = 4.0\,m$. This is in agreement with Fig. 1: from around 330 s, the smoke layer approaches the flame and the 'plume' formula is no longer accurate. Obviously, one cannot expect good forecasts anymore in such circumstances.

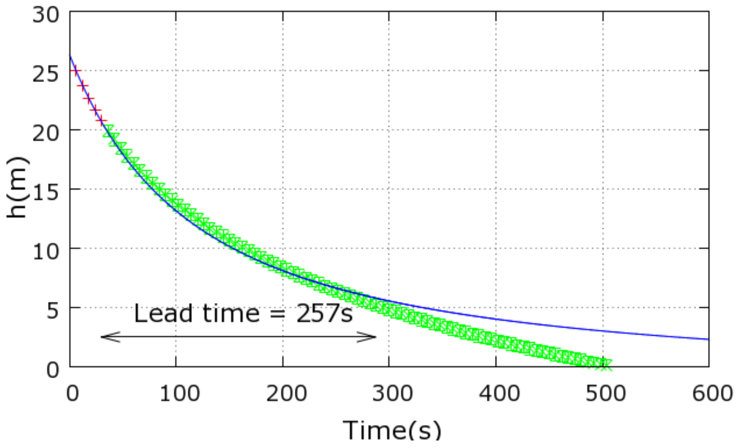


Figure 3. Forecast of the smoke layer height at 30 s after smoke detection (solid line). The assimilated data (+) is shown together with the data observed after assimilation (×) with an error bar of 0.5 m.

Figure 4 shows that, after a slight overestimation at the start of the calculation, the average upper layer temperature is well predicted, in between the measured profiles at 8 m and 24 m. The slope of the line is also in good agreement with the experimental data, indicating that a heat loss coefficient of $\alpha_{loss} = 0.4$ is suitable for these calculations.

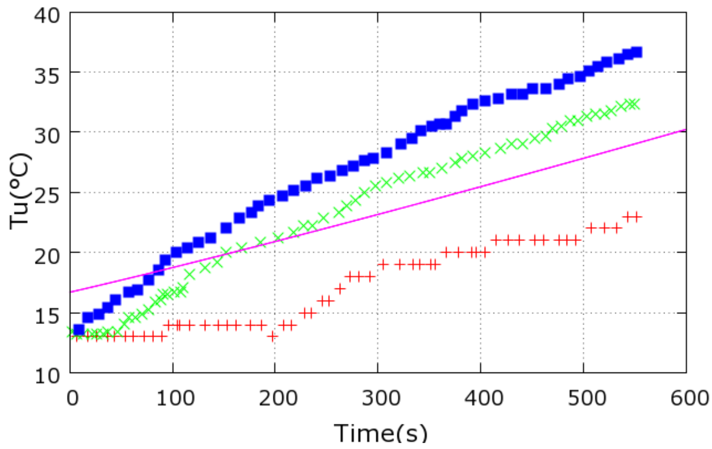
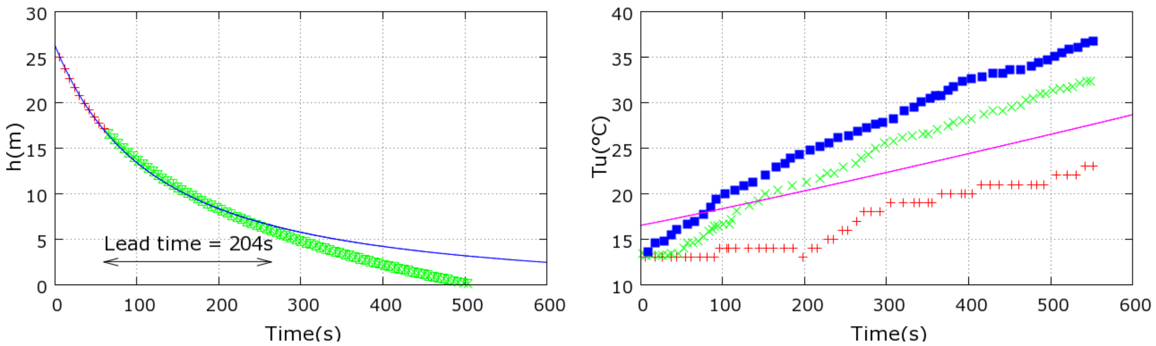


Figure 4. Forecast of the smoke (upper) layer temperature at 30 s after smoke detection (solid line) and measured profiles at different heights: 8 m (+), 16 m (×) and 24 m (■).

Data assimilation with the first 60 s after smoke detection, leads to a HRR value of $Q_c = 1234\,kW$, which is also within an error of less than 10% from the true value. There is no improvement in the lead time (Fig. 5). The reason is basically that the deviation is due to the fact that formula (2) does not hold in the flame region. Additional data, collected in the plume regime, does not remedy this issue. Therefore, in the case at hand, a 30 s-assimilation window is sufficient to estimate the HRR and the subsequent smoke layer height and upper layer temperature profiles, as long as the smoke layer interface remains in the plume region.



(a) (b)

Figure 5. Forecast at 60 s after smoke detection (solid lines). (a) Smoke layer height: (+) assimilated data, data observed after assimilation (×) with an error bar of 0.5 m. (b) Temperature at different heights: 8 m (+), 16 m (×) and 24 m (■).

Mechanical Ventilation

Mechanical ventilation was also examined in [5] in different cases. However, differences from natural filling are small: the mechanical venting as applied in the experiments is not very effective (not shown here). Therefore, we consider here a hypothetical case where an extraction rate $\dot{V}_{ex} = 50\, m^3/s$ is activated, 30 s after detection.

This is just after the 30 s-assimilation window, which was shown to be sufficient to estimate Q_c, h and T_u for natural filling (which is the case until the venting system is activated). Figure 6 shows that the option of 50 m^3/s exhaust rate will lead to a stabilization of the smoke layer height at around 12.7 m. The lead time in this case is probably higher than in the natural filling case, since the smoke layer interface remains in the plume region. Unfortunately, there are no experimental data to compare to.

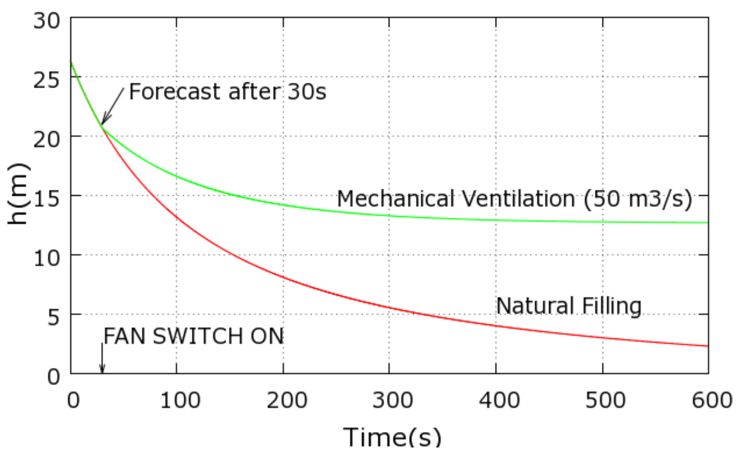


Figure 6. Effect of the mechanical ventilation option (with an exhaust rate of 50 m^3/s) on the forecast of the smoke layer height at 30 s after smoke detection.

This case illustrates therefore, how fire forecast could assist the smoke control management process in real time.

Discussion

In the version of the in-house code used for this paper, smoke layer height measurements are assimilated to find the HRR of the presumed steady fire and the related profiles of h and T_u. Ongoing research is undertaken to examine the possibility of assimilating more information of the fire in several geometrical configurations (e.g. doors, windows, ceiling vents...etc) and estimating more parameters like the entrainment coefficient C and/or the fire growth factor. It is important to note that the problem must be well-posed from both mathematical and practical standpoints. It is in this context that new algorithms are being developed in order to obtain valuable information on the fire (smoke, flame location, flame geometry) by video camera [14-17] and make reliable fire forecasts with a reasonable lead time.

Conclusions

The new methodology for fire forecast proposed in [3-4] has been applied in numerical simulations that can assist real-time smoke control management in an atrium. In this application, the assimilation of experimental data of the smoke layer height, in the case of natural filling, allowed to estimate the HRR of the steady fire after 30 s within a 10% error margin. A forecast of the smoke layer height and upper layer temperature has been produced with lead times in the order of 250 s. Widening the assimilation window did not lead to any improvement in this case, because the lead time was limited by a change in the configuration (plume versus flame), not by lack of assimilated data. An additional case with mechanical venting has also been examined to illustrate the possibilities offered by real time smoke management to quantify instantaneously the effect of different options with a positive lead time.

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Nomenclature

A floor area (m^2)
C plume entrainment coefficient
C_p gas specific heat (=1 kJ/kg.K)
E energy (kJ)
H_0 ceiling height (m)
J cost function (m^2)
N number of observations
Q_c convective heat release rate (kW)
T temperature (K)
V volume (m^3)
$\dot{V}$ volumetric flow rate (m^3/s)
g gravitational acceleration (=9.81 m/s^2)
h smoke layer height (m)
$\dot{m}$ mass flux (kg/s)
t time (s)
z elevation above the fire (m)
Δt time step (s)
α_{loss} heat loss coefficient

ρ density (kg/m^3)

Subscripts

a ambient conditions

ex mechanical extraction

i time index

p plume

u upper layer

Superscripts

ˆ observation data

' perturbed value

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