Fire Safety Journal 97 (2018) 19–28

Contents lists available at ScienceDirect

Fire Safety Journal

journal homepage: www.elsevier.com/locate/firesaf

Real-time forecasting of fire in a two-story building using ensemble Kalman filter method

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ARTICLE INFO

Keywords:
Real-time forecasting
Ensemble Kalman filter
Bootstrap method
Filter divergence

ABSTRACT

Accurate and reliable prediction of smoke development process is critical for building fire protection design. Although modern computers allow us to use sophisticated models, e.g. CFD, to simulate certain fire scenarios, the simulation time is often drastically longer than zone models. This paper applies a real-time forecasting method, Ensemble Kalman filter (EnKF) algorithm, to a zone model, CFAST, for the simulation of a full-scale fire experiment in a two-story building structure. The results of the CFAST simulation with and without the EnKF algorithm are compared to the experimental data. It shows that the EnKF algorithm can significantly improve the accuracy of the CFAST simulation of the smoke layer temperature and height. To solve the problem of filter divergence and further reduce the computational cost, a general statistical interference method, the bootstrap method, is added to the EnKF algorithm. It shows that the bootstrap method improves the accuracy with fewer ensemble members and less computing time, thus even achieving a real-time forecasting on a personal computer. A sensitivity analysis is also conducted in nine case studies for demonstrating practical engineering applications of the real-time forecasting process.

1. Introduction

In the modern society, corridor-style buildings are commonly applied by architectures. During fires, these spaces might become the major paths for smoke spreading inside the building [1,2]. A lot of previous studies, both experimental and numerical, have been done to investigate the smoke movement along the corridors. Wakamatsu [3] proposed a set of detailed formula on the smoke in the corridor of fire floor and the connected vertical shaft, He [4] investigated the smoke layer temperature and velocity along the corridors. Kim [5] used laser sheet for the visualization of the smoke spreading process in a corridor. Lee [2] found that the toxic gas products spread faster than the soot in a long corridor. Besides, the investigation on flame characteristics in corridor-like structures is now also a hot topic [6–8].

With the increasing computational power, numerical simulations nowadays have been widely used in fire research [9–13]. Olenick [12] conducted one survey for fire and smoke simulation models from seven countries in 2003 and found there were currently about 168 numerical programs, increasing rapidly from a total of 74 in 1992 [13], resulting from more knowledge about fire science and physics available, and growing computer resources. On the whole, these existing models can be classified into two categories: the zone models and the field models [14]. The field models are based on computational fluid dynamics (CFD), which discretizes a simulation domain into thousands or millions of grids, and calculates the conservations equations (e.g. continuity, mass, energy, momentum and species) among these grids [15] for obtaining plenty of detailed information. On the other hand, the zone model simply divides a compartment into two control volumes, the upper hot and the lower cold layers, each of which the physical states are assumed to be uniform. This assumption may have its limitations but former experimental studies have shown that it works well with enclosure fires under particular conditions [12]. Moreover, when compared to field models, due to its significantly lower computational costs, fewer inputs and thus easier implementation, the zone model is nowadays still developing prosperously. One of the most popular zone models is the Consolidated Model of Fire and Smoke Transport (CFAST) developed by the US National Institute of Standards and Technology (NIST) [16]. Plenty of researches were carried out based on this model. Bailey [17] proposed a

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https://doi.org/10.1016/j.firesaf.2018.02.007
Received 6 August 2017; Received in revised form 30 September 2017; Accepted 25 February 2018

Nomenclature

x	Model states
M	Forecasting model
K	Kalman gain
Q	Gaussian white noise
q	Number of ensemble member
y	Measurement (observation) model states
P^f	Forecasted error covariance
R^2	Ratio of variance and square of the mean

Greek Symbols

c	Control vector
w	Model error
a	Confidence factor (screening factor)
σ_a	Weighting factor
ε	Error covariance

Superscripts

f	Forecasted
a	Analyzed
o	Measurement (observation)
bs	Bootstrap resampled

Subscripts

t	Time, second
e	Entry of a bootstrapped sample

Abbreviations

RMSE	Root mean squared error
EnKF	Ensemble Kalman filter
CFD	Computational fluid dynamics
FDS	Fire dynamic simulator
HRR	Heat release rate

corridor flow sub-model to CFAST to improve the prediction accuracy of smoke flow in corridors. Hostikka [18] divided the whole space into several subzones to improve the zone model performance in long tunnel-like spaces. Zhang [19] added a sub-model to zone model to predict the pre- and post-flashover fires. Nishino [20] integrated a model which considered horizontal entrainment during the process of horizontally smoke spreading under the ceiling to further predict the smoke layer depth.

The current paper uses a new method implemented in CFAST to achieve real-time predictions. This method combines the measurement information and the forecasting zone model, i.e. a technique called "data assimilation" as originated from the numerical weather prediction (NWP) [21]. In 1910, Robinson [22] stated that the accurate weather forecasting required two conditions, (a) accurate initial state and, (b) proper equation of atmospheric motion. Due to the multidimensional, macro-scale and complex properties of atmospheric motions, up to now, it is not possible to find the analytic solution to the control equations, but instead we have to use numerical solution, which is often subject to accumulated numerical errors with the simulation time. Under such a circumstance, by applying data assimilation method, the misfit between measurement and model states can be minimized by continuously assimilating available information from the measurement into the models, and calibrating model parameters to fit the dynamic simulated scenarios. Among many data assimilation methods, the Ensemble Kalman filter (EnKF) [23] is considered as one of the most promising candidates, which was developed from the Kalman Filter [24]. Based on the Monte Carlo approach, the problem of the estimation and prediction of the background error covariance matrix in the practical application is solved by using the set theory: EnKF expands the application fields of traditional Kalman Filter into broader domains including automatic control, radar positioning, machine learning, target tracking and so on.

Regarding the indoor environment and fire protection, Lin [25] applied EnKF to forecasting the indoor pollutant dispersion and some crucial parameters of EnKF were discussed. Huchuk [26] used EnKF to predict the effective resistance and capacitance values of an office space. Lin [27] utilized EnKF with CFAST to forecast the compartment fire, and proved the achievement of improved accuracy compared to the traditional CFAST. One common problem of implementing EnKF is that it updates all ensemble members by estimating the correlation between measurements and ensembles [28]. Besides, to reduce the computational cost, it is always desirable to use a smaller number of ensemble members [29], which often results in poor approximation of the Kalman gain matrix and thus a poor update of model states. As a result, common problems such as under-sampling [30], covariance underestimation [31], filter divergence [32] and spurious correlations [33] may also happen under different experimental conditions. To resolve these problems, different methods could be applied [28,29,32–37]. For example, to solve the spurious correction problem, which often occurs in applying EnKF to macro-scale experiments, Lin [37] used localization methods to cut down the overestimation of two faraway model states. However, proper localization method relies on the cutoff distance, which is difficult to be determined and often requires empirical knowledge [29].

Based on accessible computer resources to apply ensemble Kalman filter to forecast fire in real time, zone model, instead of field model, is selected as the forecasting model. Specifically, in the current paper, EnKF is applied to a zone model, CFAST (Version, 6.3.0), to predict the smoke layer height and temperature in a full-scale two-story building designed by NBS [38]. After which, an improved EnKF using a statistical interference method, called "bootstrap method", is introduced to solving the filter divergence and spurious correlation problems. Finally, a sensitivity analysis is evaluated to obtain a more effective and economical observation strategy for data assimilation.

2. Methodology

2.1. Basic theory of EnKF

Ensemble Kalman filter was initially originated from Kalman filter, which was found by R. E. Kalman to recursively solve the discrete-data linear filtering problem in 1960 [39]. In 1994, Evensen proposed an alternative data assimilation method, named ensemble Kalmam filter (EnKF), based on Kalman filter to extend its application field from linear or approximately linear to highly nonlinear dynamic systems [23,40].

In this study, a black-box wrapper code was programmed to connect the forecasting model (CFAST) and the data assimilation tool box (OpenDA) [41]. Since heat release rate (HRR) is the key governing parameter in the CFAST zone model [42], it was included as the model input among other predefined initial model states. The model outputs included the model states to be predicted, such as smoke layer height and temperature of both the lower and upper layers in corridors. The coupling procedure is as follows: CFAST is executed based on the input file (*.in), and sends the calculated model states at the next time step to OpenDA for the data assimilation process combining measurement information and predicted model states whenever a measurement datum is available. In general, the theory of EnKF can be divided into two steps: the forecasting and the analysis steps.

1) Forecasting step

Before applying this method, usually we need to discretize the