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The modeling of fire spread in buildings by Bayesian network

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ABSTRACT

Fire spread modeling is very important to fire safety engineering and to insurance industries involved in fire risk–cost analysis of buildings. In this paper, the Bayesian network is introduced. The directed acyclic graph of a fire spread model is presented. When the fire ignition location is known, the fire spread model based on the Bayesian network from the compartment of fire origin to another compartment can be built, and the probability of fire spread can be calculated by making use of the joint probability distribution of the Bayesian network. A specific application for an office building is presented for a case without sprinkler and one with sprinkler installed.

1. Introduction

Fires in buildings pose a significant risk to building occupants and cause property damage. A lot of research has been conducted over the last decades aiming to understand the mechanism of fire ignition and growth as well as smoke movement to adjacent compartments. This body of research resulted in computer models that predict fire growth and smoke spread through a building, which can be used to design effective strategies to control fire growth and spread in a building to improve life safety and reduce property damage [1].

Mathematical models to simulate fire spread between compartments are particularly important for fire risk assessment of large buildings. There are two kinds of approaches that can be used to simulate fire spread, the deterministic and probabilistic methods. Deterministic models such as WALL2D [2,3] can be used to predict the time of failure of a wall when subjected to a fire attack. The results of these models can also used in a Monte-Carlo simulation to predict the probability of failure at different times.

Ramachanandran [4,5] summarized the studies of probabilistic approach model done over last decades. In the earlier studies, the epidemic theory [6,7], random walk theory [8,9], Markov process [10–12], percolation process [13,14] and probabilistic network [15,16] were used to model the fire spread. These models could successfully describe the fire spread process in building in some respects. But there are some disadvantages to simulate fire spread process using these models. The epidemic theory can not explain the fire spread to adjacent combustible materials or compartments, which can not be reached by the burning flame or the fire spread due to radiation. The random walk theory [8,9] and percolation process [13,14] can simulate the fire spread from a fire compartment to one of its adjacent compartments, and then from this fire compartment to another adjacent compartment. But they are not good at simulating the scenarios that fire may spread from a fire compartment to multiple adjacent compartments or fire spreads from multiple fire compartments to their adjacent compartments. The transition probability in Markov process [10–12] is not the probability of fire spread from fire compartment to the adjacent compartment. It only presents the probability of fire will spread from fire compartment to a compartment comparing to the other compartments, i.e. there are two similar compartments at the each side of a fire compartment, the transition probability of each compartment will always equal to 50%, no matter how long the fire lasts. In addition, the fire spread process from one compartment to multiple compartment or multiple compartments to adjacent compartments at the same time can not be described by Markov process.

Ling and Williamson [15] first presented a probabilistic network approach to study room-to-room fire spread and a network of fire spread in a building floor was presented. This model did not consider the barrier breach because of radiation and the network is complicated. If the fire initial change, a new network had to be developed. Platt et al. [16] developed a simple and clear model in which event tree was used to determine the probability of fire spread form fire initial compartment to other compartments. This model is very good to express the fire spread process for small buildings. But it is hard to develop a tree for

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Nomenclature

A	variables describing whether a fully developed fire occurs in compartment A or not
a	a fully developed fire occurs in compartment A
$\tilde{a}$	a fully developed fire does not occur in compartment A
A'	variables describing whether an ignition occurs in compartment A or not
$P(a\|b)$	the probability of fire spread from compartment B to compartment A.
$P(a'\|b)$	the barrier failure probability indicating that heat transfers from fire compartment B to adjacent compartment A and ignites the combustible materials in compartment A.
$P(a\|a')$	the probability of fire grows from ignition to fully developed fire.

large buildings. If the initial fire compartment changed, a new tree has to be developed even for same buildings which make this model difficult to be programmed. The digraph (directed graph) approach was used for the fire spread sub-model of the fire risk evaluation and cost assessment model (FiRECAM) [17]. To simplify the problem, all compartments of the same type such as rooms, corridors, stairwells in one floor are combined as a node of the network of buildings. The developed algorithm searches all possible pathways for fire to spread from one node to another.

In this paper, the Bayesian network (BN) [18–20] is used to simulate the fire spread process. Bayesian network had been used in the fire risk assessment [21]. Bayesian network can overcome the disadvantages mentioned in previous models. But Bayesian network can not directly describe fire spread process. To build the fire spread model, a general fire spread network has to firstly be built according to the floor plan of a building. Once the fire initial compartment is known, a detail fire spread model using a directed acyclic graph (DAG) of Bayesian network to express the fire spread process from the fire initial compartment to any destination compartment in the floor can be constructed and the probability of fire spread from the initial compartment to the destination compartment can be calculated by marginalizing the joint probability distribution of the Bayesian network.

2. Fundamentals of Bayesian network

The Bayesian network model is a tool to manage uncertainty using probability. A Bayesian network is a graphical model that combines graph theory and Bayesian probability theory. Bayesian probability theory deals with the problem of reasoning under uncertainty.

2.1. The fundamentals of probability

If A is an event, $P(a)$ represents the probability that event A is true, and $P(\tilde{a})$ denotes the probability that event A is not true. Some basic axioms can be expressed as follows:

$$0 \le P(A) \le 1 \tag{1}$$

$$P(a) + P(\tilde{a}) = 1 \tag{2}$$

If event A and event B are mutually exclusive, the probability of the union of events A and B is

$$P(A \cup B) = P(A) + P(B) \tag{3}$$

If events A and B are not exclusive

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \tag{4}$$

where $P(A \cap B)$ is called the joint probability of events A and B. Usually $P(A \cap B)$ is shorten as $P(A, B)$.

The joint probability $P(A, B)$ can be derived by

$$P(A, B) = P(B|A) \cdot P(A) \tag{5}$$

where $P(B|A)$ is called the conditional probability, which is the probability that event B occurs given that event A has already occurred.

$P(A, B)$ can also be written as

$$P(A, B) = P(A|B) \cdot P(B) = P(B|A) \cdot P(A) \tag{6}$$

Rearranging above equation leads to the famous Bayes theorem

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{7}$$

2.2. The basics of Bayesian network

2.2.1. Definitions

The Bayesian network is based on a fundamental assumption—the probability distributions in BN are subjected to the Markov condition. A Bayesian network or Bayesian belief network consists of two components:

(1) A graphical structure, called directed acyclic graph $\boldsymbol{G}$ (DAG). $\boldsymbol{G} = (V, E)$ where V are the set of nodes representing random variables on which the Bayesian network is defined and E are the set of directed edges representing relations among the variables. Fig. 1 is an example of a DAG.
In DAG, the family notation is often used to express the relationships between variables. For $A \in V$, the parents of A, or $pa(A)$, are the set of variables from which there is an arrow going to Node A. The children of A are the set of variables which are reached by an arrow from Node A. The ancestors of A are the set of variables who are the parents of A, its parent's parents and so on. The descents of A are the set of variables who are the children of A, its child's children and so on. The nodes without parents are called root nodes. The nodes without children are called leaf nodes.
In Fig. 1, Nodes A and B are root nodes. Node E is a leaf node. The nodes C, D are the children of Node A, and Nodes A, B are called the parents of Node D. Nodes A, B, C, D are the ancestors of Node E, and Node E is called the descendant of Nodes A, B, C, D. Node C is a non-descendent of Node B, or $ND(B)$.

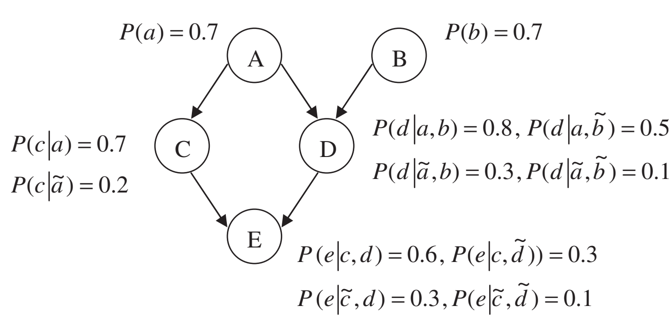

Fig. 1. An example of a Bayesian network.