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Decision analysis of emergency ventilation and evacuation strategies against suddenly released contaminant indoors by considering the uncertainty of source locations

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ABSTRACT

In case hazardous contaminants are suddenly released indoors, the prompt and proper emergency responses are critical to protect occupants. This paper aims to provide a framework for determining the optimal combination of ventilation and evacuation strategies by considering the uncertainty of source locations. The certainty of source locations is classified as complete certainty, incomplete certainty, and complete uncertainty to cover all the possible situations. According to this classification, three types of decision analysis models are presented. A new concept, efficiency factor of contaminant source (EFCS), is incorporated in these models to evaluate the payoffs of the ventilation and evacuation strategies. A procedure of decision-making based on these models is proposed and demonstrated by numerical studies of one hundred scenarios with ten ventilation modes, two evacuation modes, and five source locations. The results show that the models can be useful to direct the decision analysis of both the ventilation and evacuation strategies. In addition, the certainty of the source locations has an important effect on the outcomes of the decision-making.

1. Introduction

In recent times, the occupants inside buildings and other enclosed spaces are being threatened by various incidents related to the release of hazardous contaminants, such as the accidental releases of toxic chemicals, and chemical/biological terrorism. When hazardous contaminants are suddenly released indoors, it is crucial to take proper actions to mitigate damages and protect indoor occupants. In the reference manual released by the Federal Emergency Management Agency (FEMA), five possible protective actions are suggested after the presence of an airborne hazard has been detected. These actions, in increasing order of complexity and cost, are evacuation, sheltering in place, personal protective equipment, air filtration and pressurization, exhausting and purging [1]. As a major component of these actions, emergency ventilation and evacuation can play vital roles in protecting occupants because the former is a major measure to control the dispersion of contaminant, and the latter is a critical factor to affect the spatial and temporal distribution of occupants.

Although much research has been devoted to the fire and smoke control strategies, only a few studies have been conducted on the strategies against suddenly released contaminant indoors. As an early investigation on the emergency ventilation to control the indoor contaminant dispersion, Zhai et al. [2] employed commercial computational fluid dynamics (CFD) software to predict chemical and biological agent (CBA) dispersion in an office building in order to find the best locations for CBA sensors and to develop effective ventilation systems. This study demonstrated that CBA dispersion could be effectively controlled by proper emergency ventilation strategies. However, this study did not provide a methodology to quantify the performance of ventilation strategies during a short period of time immediately after the contaminant was released.

To evaluate ventilation performance in a finite period of time, we have presented several indices, including Accessibility of Supply Air (ASA), Accessibility of Contaminant Source (ACS), and Integrated Accessibility of Contaminant Source (IACS) in our previous studies [3–5]. These indices have contributed to the decision-making

Abbreviations: AMG, algebraic multigrid; BEC, basic exposure cell; CBA, chemical and biological agent; CFD, computational fluid dynamics; EC, exposure cell; EFCS, efficiency factor of contaminant source; FVM, finite volume method; RANS, Reynolds averaged Navier–Stokes; SGEM, spatial-grid evacuation model; SIMPLE, semi-implicit method for pressure-linked equations.

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Nomenclature

BEC_i	ith basic exposure cell
$\overline{C_i}(t)$	equivalent concentration of EC_i at time t (mg/m^3)
$\overline{C}_i^j(t)$	volume-averaged concentration in the jth layer of EC_i at time t (mg/m^3)
$\overline{C}_{n,i}(t)$	volume-weighted-average concentration of n layers (mg/m^3)
$\overline{C}_R$	average exhausted concentration of contaminant under steady-state conditions (mg/m^3)
d^*	optimal decision alternative
d_i	ith decision alternative which is a combination of the ventilation and evacuation modes
D	decision space consisted of all the decision alternatives which are the combinations of the ventilation and evacuation modes
EC_i	ith exposure cell
$EFCS3(d_i, S_j)$	EFCS3 of the decision alternative d_i under the state of nature S_j
$EFCS3(\tau)$	Efficiency factor of contaminant source 3 (EFCS3) which reflects the influence of a contaminant source on all occupants over the time period τ
m	identifying number of the individual or the total number of decision alternatives
n	number of layers for an exposure cell or the total number of states of nature
N	total number of exposure cells
$P(d^*, S_j)$	maximum payoff for the combination of the optimal decision alternative d^* and the source location S_j
$PNC_i(t)$	number of occupants in EC_i at time t
S	state space consisted of all the state of natures which are defined as the potential locations of contaminant source
S_j	jth state of nature or jth source location
S_ϕ	contaminant source term [mg/(m^3 s)]
t	time [s]
$\vec{u}$	velocity vector [m/s]
U_m	velocity component of the occupant m in x direction [m/s]
w_j	weighted coefficient to reflect the differences of contact exposure along the height direction
$x(m, t)$	coordinate of the occupant m at time step t in x direction [m]
$y(m, t)$	coordinate of the occupant m at time step t in y direction [m]

Greek symbols

Γ_ϕ	contaminant diffusion coefficient in the air [m^2/s]
Δt	time step [s]
τ	a period of time [s]
ϕ	contaminant concentration [mg/m^3]

process involved with contaminant dispersion and emergency ventilation. However, these indices cannot describe the evacuation process of occupants, during which the occupant distribution is changing with time. As a preliminary study, we used the IACS index concept to numerically analyze the influence of the contaminant source location, occupant distribution and air distribution on the emergency ventilation strategy [6]. However, the evacuation process was neglected in the study due to the inherent limitations of IACS.

To better evaluate the performance of emergency ventilation by considering the evacuation process, we presented a new concept of efficiency factor of contaminant source (EFCS) [7]. The EFCS is a set of indices, including EFCS1–EFCS3, which reflects the occupants' relative exposure to a contaminant immediately after the contaminant is released from multiple aspects. The principal advantage of EFCS over IACS is that it successfully takes into account the temporal development of occupant distribution during the evacuation process. By using EFCS3 as an evaluation index, we proposed a procedure for determining the optimal ventilation and evacuation strategies against a contaminant being released at different indoor locations, and thoroughly discussed the effects of source location, ventilation mode, and evacuation mode on the exposure to indoor occupants [8]. However, the study is based on the assumption that the locations where the contaminants were released are completely known. Therefore, it was neglected that the risks of the ventilation and evacuation strategies due to the uncertainty of source locations.

The previous studies have confirmed that an expected optimal combination of ventilation and evacuation strategies could adversely impact the indoor occupants and cause higher casualties if the decision maker fails to determine the source location correctly [6,8]. To ensure the ventilation and evacuation strategies are effective in protecting indoor occupants, decision makers should be able to correctly determine the source location in short period of time. Technically, this objective can be achieved by an online contaminant source identification system that identifies source characteristics (e.g., location, release time and strength) based on the measurements from a small network of contaminant sensors. Several ongoing preliminary studies are making progress in identifying the sources of airborne contaminant in indoor environments [9–15]. Although the current studies have resulted in methods to determine the source location, these methods cannot ensure that the source location can be correctly identified with complete certainty in wide range of real-world indoor environments where various environmental disturbances exist. Furthermore, there has been no report of the application of contaminant source identification system in a real building. The current progress in research and technology suggests that there is still a long way to go to make the source identification system a reality. Therefore, at the present stage, it is more practical for us to investigate how to rationally reduce the risks associated with the decision-making process for which ventilation and evacuation strategies to implement in the likely chance that the source location is known with a high level of uncertainty.

The purpose of this study is to provide a framework for determining the optimal combination of emergency ventilation and evacuation strategies against a suddenly released contaminant indoors by considering the uncertainty of source locations. The issues related to fire/smoke dispersion are not the case of this study, since the fire/smoke control strategies are different and established elsewhere. To cover all possible situations, we classify the certainty of source location as complete certainty, incomplete certainty, and complete uncertainty. According to these classifications, we present three types of decision analysis models including models under certainty, risk, and uncertainty. These models incorporate the EFCS3 index [7] to evaluate both the effects of ventilation and evacuation strategies on protecting indoor occupants against a certain source location. A decision-making procedure based on these models is proposed. Moreover, one hundred scenarios, which are the combinations of ten ventilation modes, two evacuation modes, and five contaminant source locations, are studied numerically to demonstrate the applications of the models.

2. Overview of decision analysis

Decision analysis refers to a broad quantitative field, overlapping operations research and statistics, which deals with modeling, optimizing and analyzing decisions made by individuals, groups and organizations [16–18]. The purpose of decision analysis is to assist decision makers in making better decisions in complex situations with uncertainty. It is a rational approach to decision-making that uses a formal model to represent alternative actions, potential states of nature relevant to the problem being analyzed, probability distributions of the states of nature, and expected payoffs to reach an optimal decision. In general, a decision problem includes the following main elements:

(1) Decision maker: the person(s) responsible for making a decision.
(2) Decision alternative: an action that may be taken by a decision maker. Decision alternatives must be mutually exclusive (clearly distinct among themselves) and, ideally, collectively exhaustive (cover all reasonable options). A set of all the available decision alternatives is called decision space. Determining a realistic decision space demands creativity and experience with the nature of the problem of concern. Decision alternatives are under the control of the decision maker.
(3) State of nature: an uncertain event which, if it occurs, partly determines the outcome of a decision. Similar to decision alternatives, states of nature must be mutually exclusive and, ideally, collectively exhaustive. A set of all the possible states of nature is called state space. Judgment and experience are indispensable in determining a realistic state space. In addition, the states of nature are uncontrollable by the decision maker.
(4) Payoff: the net result (gain or loss) of taking a particular decision alternative combined with a particular state of nature. In other words, the payoff is the consequence of a decision under a certain situation.
(5) Decision criterion: a standard adopted by the decision maker to determine an optimal decision.

With the above elements, a decision problem can be described by a payoff table or a payoff matrix. A general format of the payoff table is as follows.

The payoff table contains three parts including; decision alternatives, states of nature, and payoffs. As shown in Table 1, $d_i (i = 1, 2, \cdots, m)$ is the decision alternative, $S_j (j = 1, 2, \cdots, n)$ is the state of nature, and $P(d_i, S_j)$ is the payoff of the decision alternative d_i under the state of nature S_j. The payoff table should be used for the decision maker to find an optimal alternative according to an appropriate decision criterion. In addition, the outcome of a decision problem depends on two things; the decision alternative chosen by the decision maker and the uncontrollable state of nature which happens to occur.

Table 1
A payoff table in general format.

Decision alternative	State of nature			
	S_1	S_2	$\cdots$	S_n
d_1	$P(d_1, S_1)$	$P(d_1, S_2)$	$\cdots$	$P(d_1, S_n)$
d_2	$P(d_2, S_1)$	$P(d_2, S_2)$	$\cdots$	$P(d_2, S_n)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
d_m	$P(d_m, S_1)$	$P(d_m, S_2)$	$\cdots$	$P(d_m, S_n)$

3. Decision analysis models of emergency ventilation and evacuation strategies

3.1. Concepts to quantify the exposure risk of occupants

In this study, the objective of the emergency ventilation and evacuation strategies is to minimize the risk of exposure of indoor occupants to a potential contaminant over the duration of an emergency situation. Therefore, the outcome of a decision alternative is evaluated by the exposure risk to the indoor occupants. To quantify the risk of exposure, we will introduce two concepts, Exposure Cell (EC) and efficiency factor of contaminant source, in this section. The EC is a basis for defining the EFCS.

3.1.1. Concept of exposure cell (EC)

EC is an abstract spatial concept presented in our previous paper [19], representing the indoor spatial volume within which the occupant exposure is calculated, as shown in Fig. 1. An EC can be used to represent the volume occupied by a single occupant, which is called Basic Exposure Cell (BEC) and denoted by $\mathrm{BEC}_i \quad (i = 1, 2 \ldots N)$ or a part of the room denoted by $\mathrm{EC}_i \quad (i = 1, 2 \ldots N)$. Here, N is the total number of ECs.

To distinguish the occupant exposure based on different exposure routes, an EC can further be sub-divided into several layers. For exposure through inhalation, an EC may only have one layer (one-layer model) corresponding to the respiration region, as shown in Fig. 1a and b. For exposure through contact with the skin, an EC can be divided into several layers (multiple-layer model) along the height of the human body, as shown in Fig. 1c considering that the contaminant concentration, the exposed skin area, and the absorption rate of the contaminant by the skin are non-uniform along the height of a human body.

The contaminant concentration in the exposure cell EC_i at time t is represented by equivalent concentration $\overline{C}_i(t)$. The equivalent concentration is defined as a uniform EC concentration which provides the same total occupant exposure as the non-uniform concentration of the true exposure volume. The $\overline{C}_i(t)$ is suggested to be

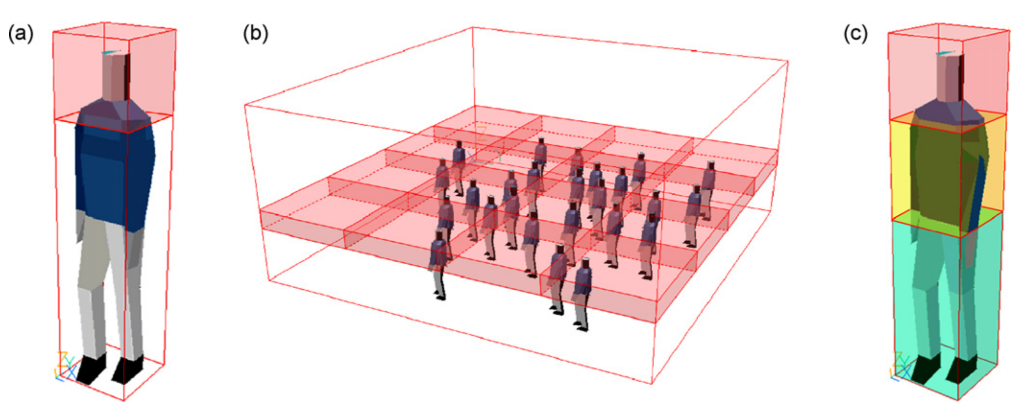


Fig. 1. Exposure cell and its layered model [8]: (a) basic exposure cell (one-layer model); (b) the room is equally divided into 16 exposure cells in the range of $Z = 1.4$–1.8 m (one-layer model); and (c) basic exposure cell (three-layer model).

calculated by:

$$\overline{C}_i(t) \approx \overline{C}_{n,}(t) = \sum_{j=1}^{n} w_j \overline{C}_i^j(t) \tag{1}$$

where $\overline{C}_i^j(t)$ is the volume-averaged concentration in the jth layer of EC_i at time t (mg/m^3), $\overline{C}_{n,}(t)$ is the volume-weighted-average concentration of all layers and n is the number of layers, the weighted coefficient, w_j, reflects the variation in contact exposure along the height of the occupant, and the sum of w_j equals 1.

In summary, the EC concept and its layered model provides a reasonable spatial discrete form to quantify the influence of contaminant on occupants for multiple exposure routes.

3.1.2. Concept of efficiency factor of contaminant source 3 (EFCS3)

The concept of EFCS was presented in our previous paper to quantify the influence of a contaminant source on the occupants during any period of time [7]. EFCS consists of three indices, including EFCS1–EFCS3. In this paper, we employed EFCS3 to evaluate the exposure risk to indoor occupants. The index is defined as:

$$\mathrm{EFCS3}(\tau) = \frac{\sum_{i=1}^{N} \int_0^{\tau} \overline{C}_i(t)\mathrm{PNC}_i(t)\ \mathrm{d}t}{\overline{C}_\mathrm{R} \sum_{i=1}^{N} \int_0^{\tau} \mathrm{PNC}_i(t)\ \mathrm{d}t} \tag{2}$$

where EFCS3(τ) reflects the influence of a contaminant source on all occupants over the time period τ, $\overline{C}_i(t)$ is the equivalent concentration of EC_i at time t (mg/m^3), $\overline{C}_\mathrm{R}$ is the average exhausted concentration of contaminant under steady-state conditions (mg/m^3), $\mathrm{PNC}_i(t)$ is the number of occupants in EC_i at time t.

On the right side of Eq. (2), the denominator is the total exposure dose of all the occupants assuming they are exposed to the concentration $\overline{C}_\mathrm{R}$. The numerator is the actual cumulative exposure dose of all the occupants. Therefore, EFCS3 is a non-dimensional index which indicates the relative risk of exposure to all the occupants throughout the emergency event. The lower value of EFCS3 corresponds to a better combination of response strategies.

For most ventilated indoor environments, the air flow is turbulent and the contaminant concentration is relatively low. In these cases, the effects of the contaminant characteristics on the contaminant dispersion as well as the effects of the contaminant dispersion on the air density and airflow field are trivial and can be neglected. Therefore, the gaseous contaminants in most indoor environments can be treated as passive gases. For passive gases, EFCS3 can be considered independent to the intensity and composition of the contaminant source. It is, however, primarily a function of the airflow pattern, occupant distribution, and contaminant source location. Therefore, EFCS3 can be used to evaluate the emergency ventilation and evacuation strategies without knowing the intensity and composition of the source.

3.2. Modeling the decision-making of emergency ventilation and evacuation

3.2.1. Decision alternatives

Our previous study [8] has concluded that the influence of contaminant on occupants can be significantly reduced by choosing a proper combination of the ventilation and evacuation strategies. Therefore, we define the decision alternatives as all the available combinations of the ventilation and evacuation strategies in this study.

3.2.2. States of nature

The contaminant source location, intensity and composition are primary factors which can greatly affect the number of casualties during an emergency, and are outside of the decision makers' control. If we set the objective for the decision-making as minimizing the casualty level, then the states of nature should be defined as all possible combinations of contaminant source locations, intensities and compositions, which will make the number of states tremendously large, and consequently make the decision problem unsolvable.

In this study, we set the objective as minimizing the relative exposure of the occupants to the contaminant. The payoff of a decision alternative under a certain state of nature is defined as the reciprocal of EFCS3. Since EFCS3 and the payoff defined are independent of the intensity and composition of the contaminant source, the states of nature can be redefined as just the possible contaminant source locations. As a result, the decision analysis models will be significantly simplified.

3.2.3. Payoffs of the decision alternatives under states of nature

The index EFCS3 is employed to quantify the payoff of a decision alternative under a certain state of nature. Since a greater value of EFCS3 indicates a higher relative exposure level, we define the payoff, which represents the gain of a decision, as follows:

$$P(d_i, S_j) = \frac{1}{\mathrm{EFCS3}(d_i, S_j)} \tag{3}$$

where EFCS3(τ, d_i, S_j) is the value of EFCS3 for the combination of the decision alternative d_i and the state of nature S_j.

The above definition shows that a lower the relative exposure level, results in a higher payoff, and thus a higher reward for the decision alternative. Although the defined payoff can reflect the relative exposure level, it cannot be used to determine the casualty rate without knowing the intensity and composition of contaminant source. Since many contaminants of concern have non-linear toxic load effects, a large reduction in relative exposure may not ensure that the casualty rate will be lower than a certain threshold. In practice, a certain threshold of casualty rate can hardly be reached solely by ventilation and evacuation strategies because there are a wide variety of contaminants which could be released indoors. Therefore, minimizing the generalized exposure risk can be a more practical way to protect occupants from a release.

3.2.4. Certainty of source location

In order to decide the most appropriate emergency ventilation and evacuation strategies, the decision makers should, at a minimum, be equipped with a basic contaminant detection system that is capable of detecting a sudden release, but is not able to identify the contaminant source location. In this case, the contaminant source location is completely unknown to the decision makers. Unfortunately, this is the situation in front of decision makers today.

Recent advancements in source identification studies make us optimistic that the use of an identification system can become a reality in the future [9–15]. As a realistic expectation, the results of the identification system may be best expressed in a probability form to take into account the uncertainties due to a variety of environmental disturbances. In this case, the contaminant source location is incompletely certain to the decision makers. On the other hand, as an idealistic expectation, the source location may be identified with complete certainty in some particular indoor environments by a highly robust identification system. In this case, the contaminant source location is completely certain to the decision makers.

In summary, we can classify the certainty of source location as complete certainty, incomplete certainty, and complete uncertainty. According to the different certainties of source location, we will present three types of decision analysis models that are decision analysis under uncertainty, under risk, and under uncertainty in the following sections.

3.3. Decision analysis model under certainty

The decision analysis model under certainty is based on the assumption that the information of source location is completely certain. The goal of the decision makers is to determine an optimal decision alternative d^* from the decision space which satisfies the following equation under the source location S_j:

$$\max_{d_i \in D} P(d_i, S_j) = P(d^*, S_j) \quad (4)$$

where d^* is the optimal decision alternative under the source location S_j, $P(d^*, S_j)$ is the maximum payoff value, and D is the decision space.

3.4. Decision analysis model under risk

If the information of source location is incompletely certain, the model to make an optimal decision of emergency ventilation and evacuation is called the decision analysis model under risk. In this case, decision-making process can only be based on the experience or the probability results of the source identification to set or presume the relative likelihood of the possible source locations. It is just an optimal decision with statistical context, and the decision maker therefore needs to take a risk to achieve the desired outcome of a specific decision alternative. The decision analysis model under risk can be solved by a variety of approaches, which are distinguished by the decision criterion in use, as reported in [20–22]. In this study, we employed a commonly used expected value criterion for demonstrating the application of decision analysis model under risk. Here the probability of state S_j is assumed to be p_j. The expected payoff of a decision alternative can be calculated as follows:

$$E(d_i) = \sum_{S_j \in S} p_j \times P(d_i, S_j), \quad \forall d_i \in D \quad (5)$$

where $P(d_i, S_j)$ is the payoff for the decision alternative d_i under the state of nature S_j, and S is the state space.

The expected value criterion chooses the decision alternative with the maximum expected payoff. The first step is to calculate the expected value of the payoffs for each of the possible decision alternatives, and then select the optimal decision alternative d^* from decision space which satisfies the following equation:

$$\max_{d_i \in D} E(d_i) = E(d^*) \quad (6)$$

where $E(d^*)$ is the maximum expected payoff.

3.5. Decision analysis model under uncertainty

Suppose that the source location is completely uncertain, which represents the worst case situation, and then the model to determine an optimal combination of emergency ventilation and evacuation strategies is called the decision analysis model under uncertainty. In the following, five commonly used decision criteria will be introduced and their applicability to solving the decision analysis model under uncertainty will be discussed.

3.5.1. Model based on maximax criterion

The maximax criterion, also called optimistic criterion, chooses the alternative with the maximum of maximum payoffs. This criterion assumes that the best outcome will occur for any choice of the decision alternatives. This criterion chooses the "best of the best". But it does not provide protection against the potentially worst case outcome for each alternative. The decision maker who adopts this criterion is always full of optimism and willing to accept risk and seizes an opportunity with only the best result in mind. With the maximax criterion, the objective of decision-making process is to determine the optimal decision alternative d^* which meets the condition as:

$$\max_{d_i \in D}\{\max_{S_j \in S} P(d_i, S_j)\} = P(d^*, S^*) \quad (7)$$

The above objective can be accomplished by the following two steps:

Step 1: For each decision alternative (a row in payoff table, see Table 1), determine the maximum payoff.
Step 2: From these maxima, select the maximum payoff. The decision alternative leading to this payoff is the ultimate choice for the decision maker.

3.5.2. Model based on maximin criterion

The maximin criterion, also called the pessimistic criterion, maximizes the minimum payoff. This criterion assumes that the worst outcome will happen no matter what alternative is selected. From the conservative viewpoint, the decision maker estimates the minimum returns for the alternatives and picks the maximum among them or the "best of the worst". Thus, it provides a way of avoiding the worst outcome. With maximin criterion, the objective of decision-making process is to determine the optimal decision alternative which satisfies the following equation:

$$\max_{d_i \in D}\{\min_{S_j \in S} P(d_i, S_j)\} = P(d^*, S^*) \quad (8)$$

The above objective can be accomplished by the following two steps:

Step 1: For each decision alternative (a given row in the payoff table, see Table 1) determine the minimum payoff. This represents the worst possible outcome if that decision alternative were chosen.
Step 2: From these minima, select the maximum payoff. This decision may be pessimistic but is also conservative and less risky, since the least negative is chosen from the potential negative outcomes. The decision alternative leading to this payoff is the chosen decision.

3.5.3. Model based on Hurwicz criterion

The Hurwicz criterion attempts to find a middle ground between the extremes posed by the maximax and maximin criteria. Instead of assuming total optimism or pessimism, the Hurwicz criterion computes the weighted sum of the maximax and maximin evaluations by introducing a coefficient of optimism, $\alpha \in [0, 1]$.

$$H(d_i) = \alpha \max_{S_j \in S} P(d_i, S_j) + (1 - \alpha) \min_{S_j \in S} P(d_i, S_j), \quad \forall d_i \in D \quad (9)$$

Then, choose the maximum of the weighted sum.

$$\max_{d_i \in D} H(d_i) = H(d^*) \quad (10)$$

The Hurwicz criterion is a compromise between the maximax and maximin criteria. The coefficient α reflects the decision maker's tolerance towards risk. A cautious decision maker will set $\alpha = 0$ which reduces the Hurwicz criterion to the maximin criterion. An adventurous decision maker will set $\alpha = 1$ which reduces the Hurwicz criterion to the maximax criterion. But it is difficult to determine the appropriate α for decision makers, since it varies from person to person. Therefore, it is a subjective criterion.

3.5.4. Model based on Savage minimax regret criterion

The Savage minimax regret criterion focuses on avoiding the regret, opportunity cost or loss resulting when a particular state of nature occurs and the payoff of the selected alternative is smaller than the payoff that could have been attained with that particular state. The regret corresponding to a particular payoff $P(d_i, S_j)$ is defined as:

$$R(d_i, S_j) = \max_{d_i \in D} P(d_i, S_j) - P(d_i, S_j), \quad \forall d_i \in D, S_j \in S \tag{11}$$

where $\max_{d_i \in D} P(d_i, S_j)$ is the maximum payoff attainable under the state S_j.

This definition of regret allows the decision maker to transform the decision matrix into a regret matrix. The minimax criterion suggests that the decision maker looks at the maximum regret of each strategy and selects the one with the smallest value, which can be mathematically described as:

$$\min_{d_i \in D} \max_{S_j \in S} R(d_i, S_j) = R(d^*, S^*) \tag{12}$$

This criterion is a better decision criterion than maximax or maximin and, arguably, Hurwicz as well. Although it employs the minimax logic, the values over which it operates (the regret) contain more information than the nominal payoffs, leading to a more informed decision than was possible with any of the three previous models. Nevertheless, it still fails to incorporate all of the available information and therefore falls short of being a rationally acceptable criterion.

3.5.5. Model based on Laplace insufficient reason criterion

The Laplace insufficient reason criterion postulates that if no information is available about the probabilities of the various states of nature, it is reasonable to assume that they are equally likely. Therefore, if there are N states, the probability of each is $1/N$. This criterion also suggests that the decision maker calculates the expected payoff for each alternative and select the alternative with the largest value. The use of expected values distinguishes this approach from the criteria that use only extreme payoffs. This characteristic makes the decision-making similar to that under risk. The procedure of decision-making with this criterion refers to Section 3.4.

3.6. Procedure of the decision-making

According to the three types of decision analysis models for emergency ventilation and evacuation, the procedure of decision-making can generally be divided into the following three stages:

Stage 1: Pretreatment

In this stage, all of the scenarios, which represent the different combinations of decision alternatives and states of nature, should be simulated and the payoffs calculated. This time-consuming stage should be accomplished before any event and the resulting payoff table should be stored for rapid access by the emergency ventilation system.

Stage 2: Selection of decision analysis model

After the contaminant release indoors is detected, the decision makers should select a proper decision analysis model according to information about the source location. For the completely certain, incompletely certain, and completely uncertain source location situations, the corresponding decision analysis models are the model under certainty, under risk, and under uncertainty, as previously defined.

Stage 3: Implementation of emergency ventilation and evacuation

According to the payoff table constructed in Stage 1 and the decision analysis model selected in Stage 2, an optimal decision alternative can be determined in real-time. After the optimal decision alternative is selected, the corresponding emergency ventilation and evacuation strategies should be implemented immediately to minimize casualties.

4. Case study

4.1. Case setup

In this study, a three-dimensional room ventilated by a ventilation system with multiple ventilation modes was taken as an example to demonstrate the application of the presented decision analysis models. The room was an isolated building consisting of one large room, all sides of which were exposed to ambient conditions. The ambient air pressure was one standard atmospheric pressure, and the ambient temperature was 20 °C. For simplicity, we assumed that all the four walls, the ceiling, and the floor were well insulated and represented adiabatic boundaries.

Fig. 2a shows the three-dimensional sketch of the room, which contained four supply air inlets (SA1–SA4), four return air outlets (RA1–RA4), one smoke exhaust (EA), four pillars (P1–P4), and two doors (D1, D2). Each supply air inlet was 0.4 m × 0.4 m in size, and each return air outlet was 0.8 m long × 0.5 m wide. The smoke exhaust outlet was 0.8 m (X) by 0.5 m (Y) in size. Each pillar had an 0.8 m × 0.8 m cross-section. The two doorways (D1, D2), each 1.6 m wide by 2.4 m high, were designated as a normal and emergency exit, respectively.

Fig. 2b illustrates five possible locations (S1–S5) for a single gaseous contaminant source. The source had a volume of 0.1 m (X) × 0.1 m (Y) × 0.1 m (Z). The initial coordinates for the sources to be released are listed in Table 2.

Fig. 3 illustrates the schematic of the ventilation system serving the room. The ventilation system was designed to provide three basic ventilation strategies: normal ventilation, smoke exhaust, and antiterrorist ventilation. The normal ventilation strategy was meant to meet the requirements of thermal comfort and indoor air quality (IAQ) under ordinary conditions; the smoke exhaust strategy was intended to remove smoke when a fire breaks out, and the antiterrorist ventilation strategy was aimed to provide better protection to the occupants during an indoor contaminant release. Table 3 summarizes the operating states of the dampers and fans for the three ventilation strategies. By turning on or off different dampers and fans, the system can be switched to different ventilation strategies. When the antiterrorist ventilation strategy was adopted, the return air outlets (RA1–RA4) would act as exhaust air outlets.

Each ventilation strategy can have several ventilation modes with different inlets or outlets activated. We specified 10 ventilation modes during emergency incidents for the purpose of demonstration. Table 4 summarizes the operating states of the inlets and outlets for all of the ventilation modes. The antiterrorist ventilation strategy included seven ventilation modes, V1–V7; the smoke exhaust strategy only included one mode, V8; and the

Table 2
Locations of the five possible contaminant sources.

Source locations	Coordinate of starting point		
	x [m]	y [m]	z [m]
S1	8.8	14.4	0.1
S2	8.8	1.5	0.1
S3	3.1	14.4	0.1
S4	3.1	1.5	0.1
S5	5.6	8	0.1

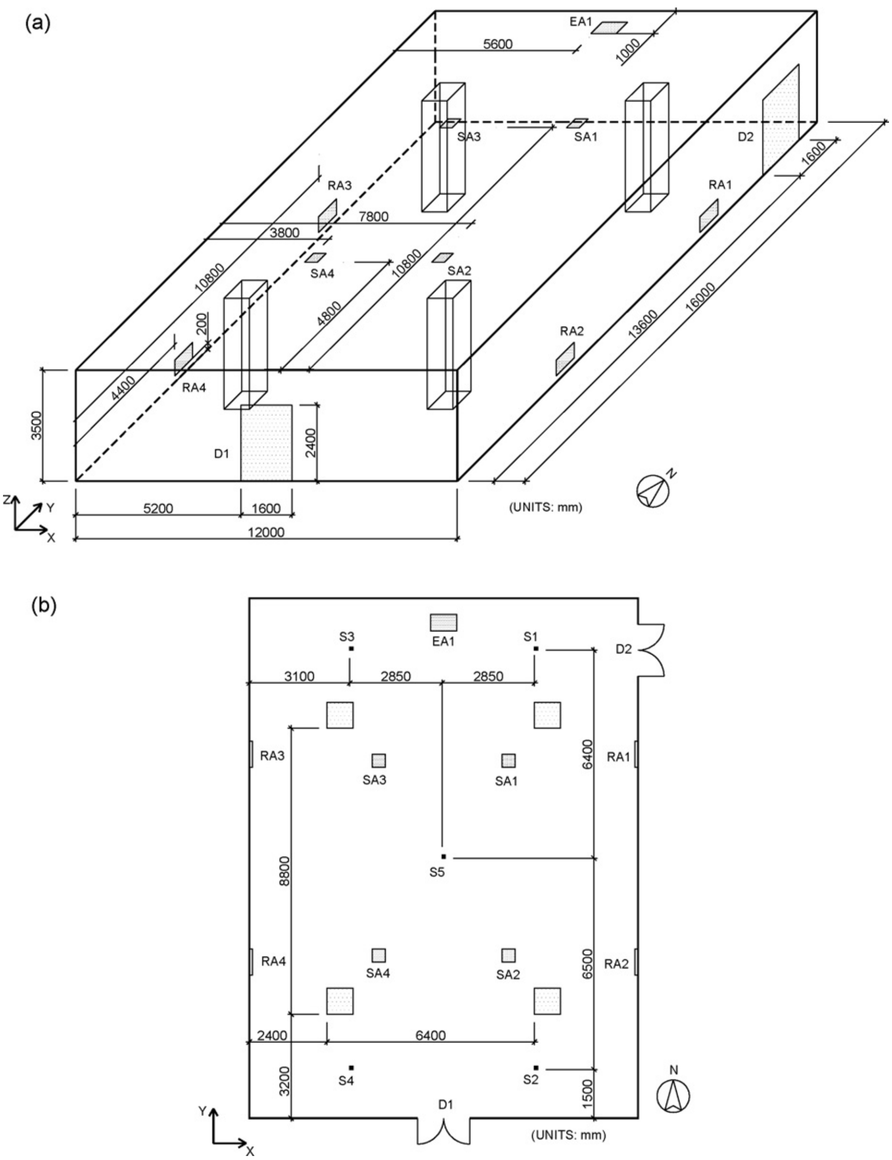


Fig. 2. Schematic of the ventilated room [8]: (a) three-dimensional sketch map and (b) plane layout.

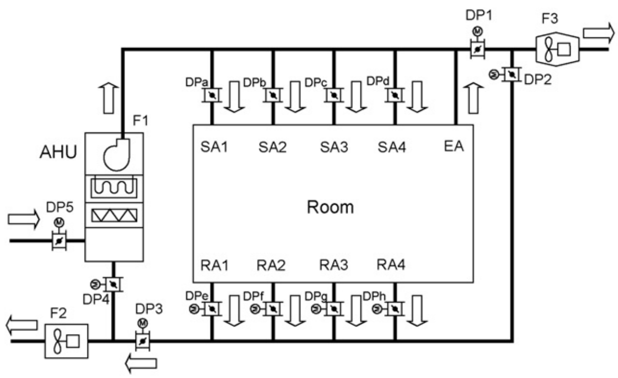
normal ventilation strategy included two modes, V9 and V10. Of the final two modes, V9 indicates that the normal ventilation mode remained unchanged when emergency occurred, while V10 represents that the ventilation system was shut down and all the air openings were closed during the emergency. For V1–V8, fresh air was supplied from exits D1 or D2 and the total airflow rate was $7200\,m^3/h$. The airflow rate for mode V9 was lower at $4032\,m^3/h$. The total airflow rate was distributed equally by the inlets or out-

Table 3
Operating states of dampers and fans for three ventilation strategies.

Ventilation strategy	Operating states of dampers			Operating states of fans		
	V1	V2	V3	F1	F2	F3
Normal ventilation	Closed	Closed	Open	On	On	Off
Smoke exhaust	Open	Closed	Closed	Off	Off	On
Antiterrorist ventilation	Closed	Open	Closed	Off	Off	On

Table 4
Descriptions of available emergency ventilation modes.

Ventilation modes	Openings in operation	Ventilation modes	Openings in operation
V1	RA1	V6	RA3, RA4
V2	RA2	V7	RA1, RA2, RA3, RA4
V3	RA3	V8	E1
V4	RA4	V9	O1–O4, RA1–RA4
V5	RA1, RA2	V10	–



F1–F3: fans; DP1–DP5, DPa–DPh: dampers; SA1–SA4: supply air inlets; RA1–RA4: return air outlets; EA: smoke exhaust outlet; AHU: air handling unit.

Fig. 3. Schematic of the ventilation system.

lets in operation. All the inlets and outlets were modeled as basic openings for simplicity.

There were 120 people randomly dispersed throughout the room before the evacuation. The heat generation of occupants was set as a convective heat source, which was completely penetrable to airflow and was distributed uniformly in the space below the height of 1.9 m with the rate of 4200 W. Two evacuation modes, mode A and mode B, were designated. For mode A, both the exit doors D1 and D2 were opened for evacuation. For mode B only the exit D1 was opened. Both doors were closed prior to the start of the evacuation. For simplicity, the effect of the moving occupants on the indoor airflow field was neglected and the air infiltration around the door was assumed zero when closed.

The application of the decision analysis models presented were demonstrated with 100 cases, representing all possible combinations of the ten ventilation modes, two evacuation modes, and five possible source locations. The five possible source locations corresponded to the five uncertain states of nature, while the combinations of the ten emergency ventilation modes and two evacuation modes represented the twenty available decision alternatives. These cases were named under the following rules. All the cases under source location S1 were denoted by "Case-S1-*-*", in which two asterisks were wildcard characters for representing ventilation and evacuation modes, respectively. All the cases with ventilation mode V2 were denoted by "Case-S*-V2-*", and all the cases with evacuation mode A were denoted by "Case-S*-*-A". In addition, all the cases with the combination of ventilation mode V2 and evacuation mode A were denoted by "Case-S*-V2-A", in which an asterisk represents all the possible source locations.

Fig. 4 illustrates the developing process of a typical case in this study. A contaminant was released at time t_0, and dispersed into the air. After the release, a certain period of time τ_0, which is called the pre-evacuation period, would be required to identify the release and to determine corresponding response strategies. At time t_1, the occupants were instructed to start evacuating while the ventilation mode was switched. After time t_1, the ventilation system was switched from the normal mode to an emergency mode. As a result, the flow field would transition from its steady-state in normal mode to a new steady-state in emergency mode. In this study, we specified the time t_0 and t_1 as 0 s and 30 s, respectively, for demonstration purposes. In each case, the contaminant was continuously released from time t_0 to t_2 with a constant emission rate of 300 mg/s, and was treated as a passive contaminant which has no influence on the airflow field.

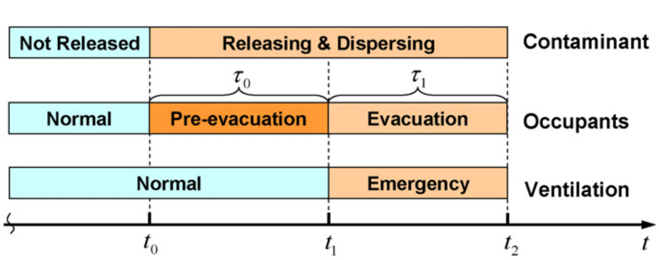


Fig. 4. Developing process of emergency events.

To quantify the exposure risk of occupants, we divided the room into many one-layer Exposure Cells, which encompass the occupants respiration zone (Z = 1.4–1.8 m) with volumetric dimensions of 0.8 m, 0.8 m, and 0.4 m for (ΔX, ΔY, ΔZ), respectively. The methods and tools used to simulate the indoor airflow, contaminant dispersion, and evacuation process will be introduced in the following two sections.

4.2. Simulation of contaminant dispersion

In this study, the indoor airflow and contaminant dispersion from time t_0 to t_2 were simulated by computational fluid dynamics (CFD), which is a powerful tool used to simulate the airflow and contaminant transport by using numerical methods and algorithms [23,24]. The governing equation for airborne gaseous contaminant transport in CFD modeling can be written as:

$$\frac{\partial \phi}{\partial t} + (\vec{u}\vec{\nabla}\phi) = \Gamma_\phi \vec{\nabla}^2 \phi + S_\phi \tag{13}$$

where ϕ is the contaminant concentration, t is time, $\vec{u}$ is the velocity vector, Γ_ϕ is the contaminant diffusion coefficient in the air, and S_ϕ is the contaminant source term. Similar governing equations can be written for other variables such as continuity, momentum, and energy to solve the airflow.

A commercial CFD program AIRPAK (http://airpak.fluent.com/) was used as a simulation tool, which is a customized version of the general-purpose program FLUENT (http://www.fluent.com/) tailored for indoor airflow computations. The reliability of AIRPAK has been validated on numerous occasions for indoor airflow and contaminant dispersion studies, as reported by Xu [25]. AIRPAK automates the mesh generation procedure, but allows users to customize the meshing parameters. In this study, hexahedral meshes were employed and systematically refined to ensure the solution was grid independent. The maximum sizes of meshes were set to be 1/20 of the room dimensions in the X, Y, and Z directions. Moreover, the mesh was refined around locations where the contaminant concentration and velocity gradients were expected to be high, such as areas adjacent to contaminant sources, inlets, and outlets.

To account for the turbulent flow indoors, an indoor zero-equation turbulence model was used, which adopts an algebraic expression of eddy viscosity directly in the near-wall region [26]. The Reynolds Averaged Navier–Stokes (RANS) equations, together with averaged energy and mass conservation equations were discretized by a finite volume method (FVM). The difference scheme is a second-order upwind scheme. A Semi-Implicit Method for Pressure-Linked Equations (SIMPLE) algorithm was adopted while momentum equations were solved on non-uniform staggered grids [23]. The discretized equations for each variable were solved by a point implicit (Gauss-Seidel) linear equation solver in conjunction with an algebraic multigrid (AMG) method (http://airpak.fluent.com/). Linear under-relaxation iteration was applied to ensure convergence.

Each CFD simulation was divided into two stages to reflect the impact of transitioning the ventilation mode at time t_1 on the indoor airflow field and contaminant dispersion. In the first stage, from time t_0 to t_1, the dispersion of contaminant was simulated based on the steady airflow field formed in the normal ventilation mode. In the second stage, from time t_1 to t_2, the transient development of the airflow field and contaminant distribution were simulated by taking the results at time t_1 as initial conditions. For all of the CFD simulations, the time step was set to 0.25 s.

4.3. Simulation of evacuation process

Many evacuation models have been developed to describe the evacuation pattern in buildings [27,28]. A review by Gwynne et al. [29] identified approximately 22 different evacuation models, which are currently available or under development. In general, these evacuation models can be divided into two categories: coarse network approach and fine network approach. Both types of approaches divide the space under study into many interconnected subregions. The resolution of this discretization is what distinguishes the two approaches.

The coarse network approach represents a space as several interconnected nodes and arcs. A node typically represents a distinct space in the building, such as a room, and an arc usually represents the actual connection of the building space. This approach describes the flow rates and average speeds of occupant groups by using mathematical equations for resolving the overall evacuation process. This approach cannot provide the exact position of each individual during the evacuation because the detailed descriptions of an individual's movement and the interaction between individuals are usually neglected in the model. Nevertheless, this approach is characterized by ease of operation and low computational cost, and thus is still suitable for fire safety design and assessment. There are several models of this type, including EVACSIM [30], EXITT [31], EVACNET [32], and CRISP [33].

The fine network approach represents a space as an extensive network of nodes. Each node corresponds to a small area of the space. Such models can trace the trajectory of each individual and their response to environmental stimuli by considering their personal behavior. There are many models of this type, including buildingEXODUS [34], SIMULEX [35], SGEM [36,37], and Cellular Automata [38].

In this study, we simulated the evacuation process from time t_1 to t_2 using the fine network approach to obtain the detailed spatial and temporal distribution of occupants. The model employed is called a spatial-grid evacuation model (SGEM) since it represents the spatial layout of a space by a planar grid system [36]. The reliability of SGEM has been well-validated by comparing with field data of several fire drill exercises and was widely used in various practical projects [36,37]. The model calculates the position of each occupant by a Lagrangian approach as follows:

$$\begin{cases} x(m,t+1) = x(m,t) + U_{\mathrm{m}}\ \Delta t \\ y(m,t+1) = y(m,t) + V_{\mathrm{m}}\ \Delta t \end{cases} \tag{14}$$

where m is identifying number of the occupant; $x(m,\ t)$ and $y(m,\ t)$ are the Cartesian coordinates of the mth occupant at time step t, U_{m} and V_{m} are the velocity components of the occupant at time step t in the x and y directions, respectively, Δt represents the time step.

The trajectory of an individual can be determined by knowing the occupant's velocity vector and location at any time. The velocity vectors are calculated in two steps. First, the velocities of the occupants are calculated based on their locations and the crowd density at these locations. Second, the calculated velocities are adjusted by considering the inter-occupant influence and individual's behavior. For all of the simulations, the planar grids were set to 0.4 m by 0.4 m in size, which is slightly larger than the mean horizontal-projection area, 0.113 m^2, of an adult in general situations [39]. In addition, the time step was set to 0.25 s.

5. Results and discussion

5.1. Simulation results of contaminant dispersion and evacuation

Fig. 5 shows the contaminant distribution at three points in time for Case-S2-V3-A and Case-S3-V3-A. Both of these cases are employ ventilation mode V3 and evacuation mode A, thus the two cases share the same airflow pattern. It is shown that the contaminant distributions for the two cases were changing with time and quite different from each other. The area wherein the concentration was beyond 10 mg/kg was increasing even after 30 s for both cases. In addition, the area of concentration beyond 10 mg/kg for Case-S2-V3-A was larger than that for Case-S3-V3-A. The results indicate that the effect of ventilation mode V3 on S3 was better than that of V3 on S2 with regard to controlling the contaminant dispersion. Other results of contaminant dispersion are not provided here for brevity.

The calculated evacuation time for evacuation mode A was 126 time steps (31.5 s) and for mode B was 144 time steps (38 s). Fig. 6 shows the occupant distribution at three points in time for evacuation modes A and B. The occupant distributions resulting from the two modes were changing with time and quite different from each other. Thus, the effect of evacuation modes should be included when we evaluate the exposure risk of occupants during an emergency.

With the results of contaminant dispersion and evacuation, the payoff for each case, which is the reciprocal of index EFCS3, can be calculated by Eqs. (2) and (3). After the calculation of the payoffs, the decision payoff table was established as shown in Table 5. In total, there are 100 potential payoffs derived from the twenty decision alternatives combined with the five different states of nature. The decision alternatives were the independent combinations of the ten ventilation modes and the two evacuation modes, which were listed in the brackets of the first column of Table 5.

5.2. Optimal decisions under completely certain source locations

According to the decision analysis model under certainty presented in Section 3.3, it is quite easy to find an optimal decision alternative with Table 5. For a given source location, the decision makers can scan the column corresponding to the source location in the payoff table. The maximum payoff in this column is lead-

Table 5
Payoff table for the decision-making of emergency ventilation and evacuation.

Decision alternatives	States of nature				
	S1	S2	S3	S4	S5
D1 (V1, A)	31.04	61.15	939.67	40.33	188.52
D2 (V2, A)	21.74	83.57	925.15	33.59	186.07
D3 (V3, A)	25.07	54.81	1598.26	41.70	193.69
D4 (V4, A)	22.39	47.15	932.14	52.04	191.32
D5 (V5, A)	20.86	71.29	931.19	38.22	186.64
D6 (V6, A)	23.69	51.08	1435.17	46.37	193.08
D7 (V7, A)	22.18	60.39	1274.03	41.12	189.79
D8 (V8, A)	35.17	65.80	691.75	38.29	170.33
D9 (V9, A)	18.89	50.04	946.79	36.02	184.70
D10 (V10, A)	21.71	50.54	948.23	35.24	183.36
D11 (V1, B)	2358.88	202.11	8884.94	91.23	26.28
D12 (V2, B)	2345.22	1100.86	9006.57	88.49	22.83
D13 (V3, B)	2452.72	178.79	10164.87	91.27	26.16
D14 (V4, B)	2394.92	143.07	8970.22	310.35	23.18
D15 (V5, B)	2368.21	663.66	8901.55	90.10	23.69
D16 (V6, B)	2427.30	160.23	9598.77	220.24	24.00
D17 (V7, B)	2403.21	357.94	9621.86	172.24	23.78
D18 (V8, B)	2299.43	202.71	11327.47	87.04	26.31
D19 (V9, B)	2368.21	124.79	8955.76	91.67	21.41
D20 (V10, B)	2361.11	114.42	9041.59	93.99	22.43

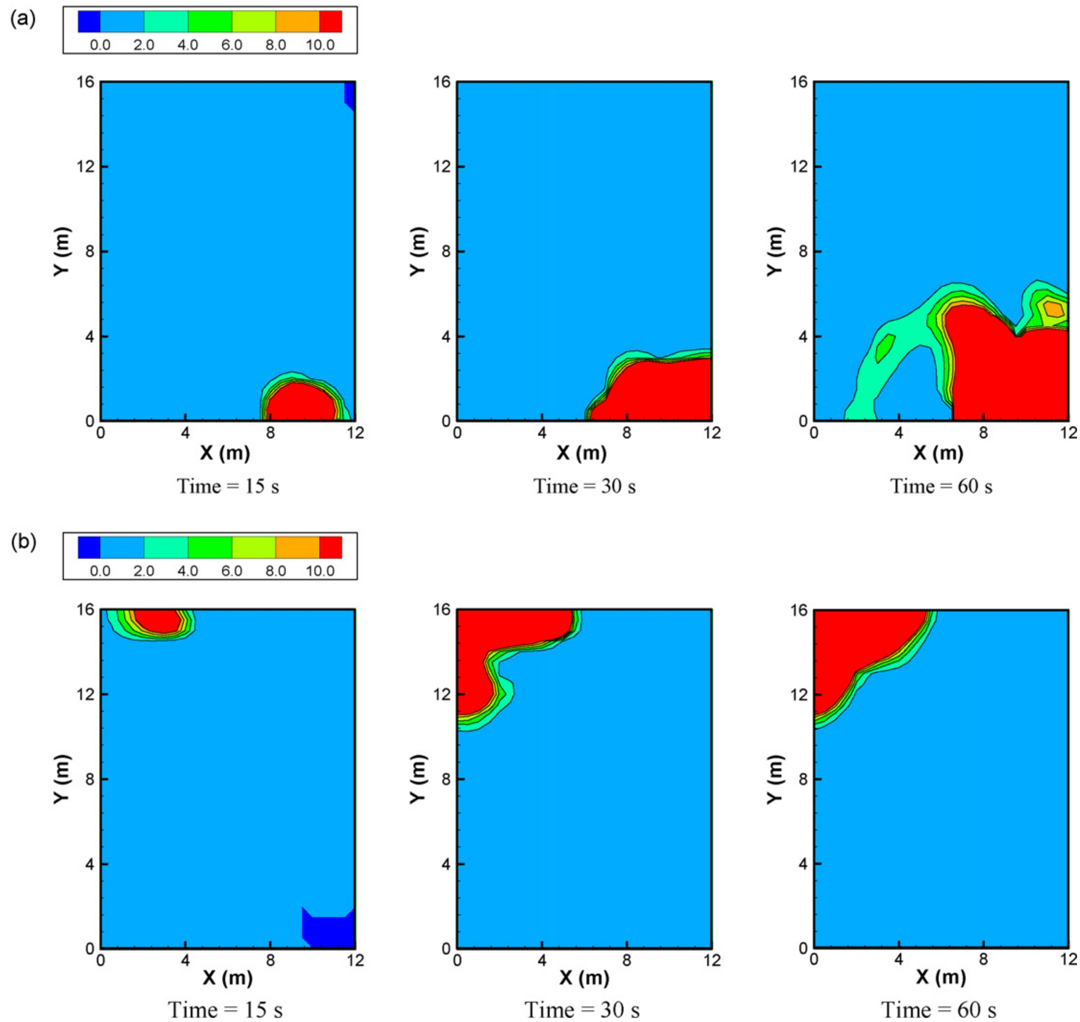


Fig. 5. Contaminant distributions at three points in time at horizontal plane $Z = 1.6$ m for two cases (concentration units: mg/kg): (a) Case-S2-V3-A and (b) Case-S3-V3-A.

ing to the optimal decision alternative, and the minimum payoff identifies the worst decision.

Table 6 summarizes the maximum and minimum payoffs and their ratios given each source location. For each source location, the maximum payoff represents the best outcome and corresponds to the optimal decision alternative among all the available choices, while the minimum payoff represents the worst outcome and corresponds to the worst decision alternative. It is observed that the optimal decision alternative and corresponding payoff changed significantly with the source location. However, the optimal decision alternative for a given source location may not be the optimal one for another source locations. Therefore, the correct identification of source location is a critical pre-condition for the decision-making process.

Table 6
Maximum and minimum payoffs under five source locations.

Source location	Payoff		Decision alternative	Max/Min
S1	Max	2450.98	D13 (V3, B)	129.82
	Min	18.89	D9 (V9, A)	
S2	Max	1101.32	D12 (V2, B)	23.35
	Min	47.15	D4 (V4, A)	
S3	Max	11363.64	D18 (V8, B)	16.37
	Min	691.56	D8 (V8, A)	
S4	Max	310.37	D14 (V4, B)	9.24
	Min	33.59	D2 (V2, A)	
S5	Max	193.69	D13 (V3, A)	9.05
	Min	21.41	D19 (V9, B)	

In Table 6, the ratio of the maximum and minimum payoffs reflects the difference between the outcomes resulting from the optimal and worst decision alternatives. The minimum ratio is 9.05, which indicates that the occupant's risk of exposure was greatly reduced even under the worst case scenario. In addition, the results in Tables 5 and 6 are useful to analyze the impacts of the source locations, ventilation modes, and evacuation modes on the occupant's risk of exposure. The detailed discussion on these issues can be referred to our previous study [8].

With the decision analysis model under certainty and a correctly identified source location, the decision makers not only can determine the optimal decision alternative, but also can predict the outcome of the decision-making process. The decision-making process and its results exclude any uncertain factors or risks, and are independent of the subjective attitude or intuition of the decision makers. Therefore, this model can provide the decision makers with a completely objective method to determine the optimal emergency ventilation mode and evacuation strategy. However, the application of this model is based on the assumption that the source location can be correctly identified with complete certainty, which has a very lofty requirement on the source identification system. Unfortunately, this kind of identification system goes far beyond

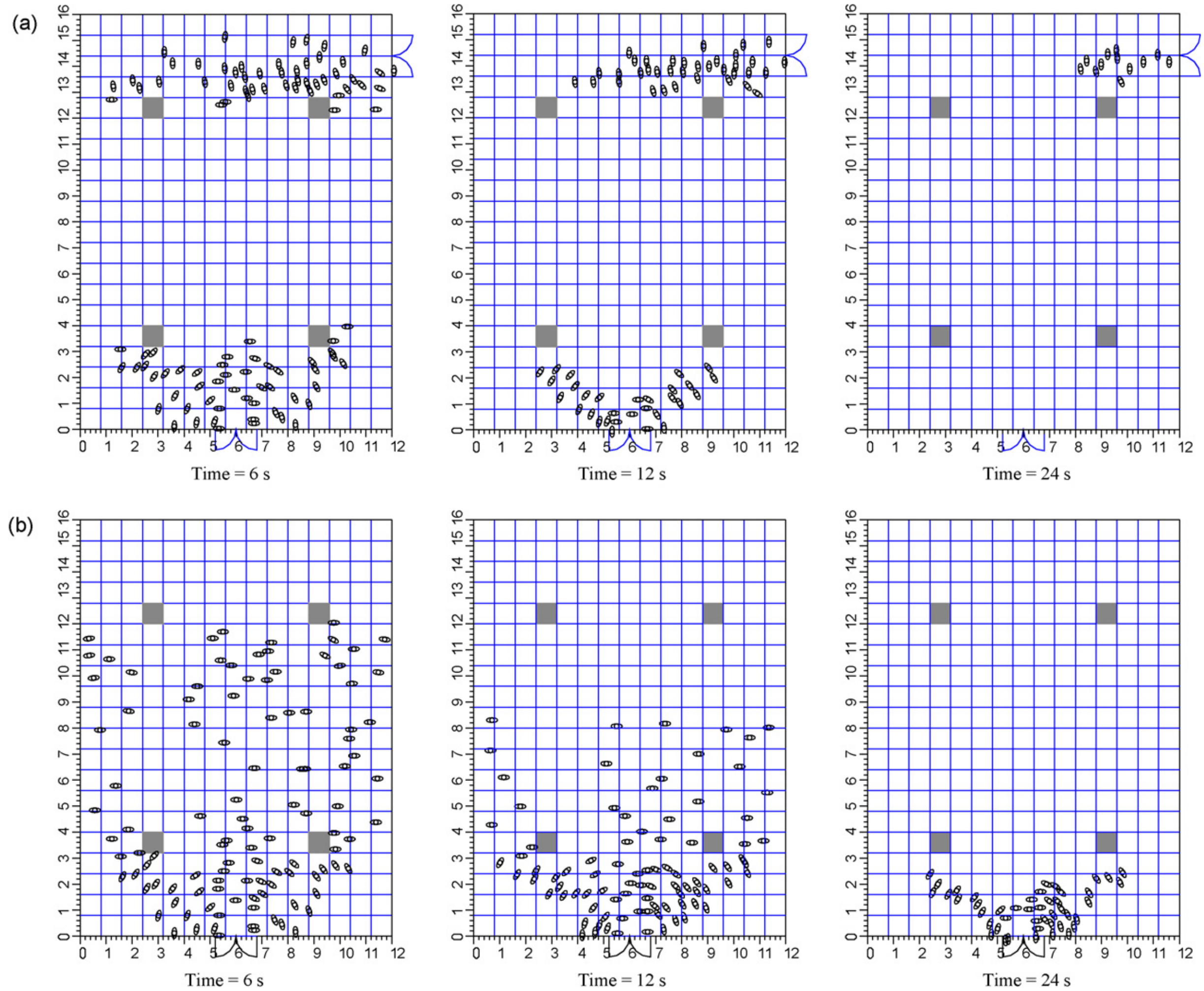


Fig. 6. Occupant distribution at three points in time under two evacuation modes: (a) mode A and (b) mode B.

the current technology. With the limitations of the current research on source identification, it is more realistic to make a decision with incompletely certain or completely uncertain information of source location.

5.3. Optimal decisions under incompletely certain source locations

To demonstrate the application of the decision analysis model under risk, we assumed the room of concern was equipped with a sophisticated source identification system. As a realistic expectation of the system, we assumed that the identified source locations were provided in a probability form to take prediction uncertainties into account.

Assuming a probability distribution of the possible source locations was given by an online source identification system after a release. The probabilities of locations S1 to S5 were 0.2, 0.1, 0.05, 0.2, and 0.45, respectively. In this study, a commonly used expected value criterion was employed to demonstrate the application of the decision analysis model under risk. With Eq. (5), the expected payoff of each decision alternative was calculated and listed in Table 7. With this table, the decision maker can easily determine that the optimal decision alternative was D18, a combination of ventilation mode V8 and evacuation mode B, which leads to the maximum payoff. The same procedure for determine the optimal decision alternative can be applied for other releases with different probability distributions of the source locations.

With the decision analysis model under risk and a probability distribution of the possible source locations, the decision makers can determine the optimal decision alternative and predict the expected payoff of the decision alternative. Since this model was solved on the basis of the probabilities of the possi-

Table 7
Expected payoff of each decision alternative by decision analysis model with expected value criterion.

Decision alternative	Expected payoff	Decision alternative	Expected payoff	Decision alternative	Expected payoff
D1	152.21	D8	132.51	D15	1013.77
D2	149.41	D9	146.44	D16	1036.27
D3	185.91	D10	146.37	D17	1042.68
D4	152.30	D11	966.31	D18	1075.78
D5	149.49	D12	1057.43	D19	961.88
D6	177.76	D13	1046.69	D20	964.64
D7	167.81	D14	1014.30	–	–

ble source locations, the uncertain factors or risks were involved in the decision-making process. Therefore, the optimal decision alternative and the corresponding payoff can be understood from a statistical viewpoint, which means that the decision makers take a risk by selecting a specific decision alternative whose outcome is only probable but not guaranteed. In addition, this model can be taken as an objective model since it excludes the subjective attitude or intuition of the decision makers throughout the process.

The reliability of the decision analysis model under risk is mainly determined by two factors: the decision criterion employed and the probabilities of source locations provided by the source identification system. In this study, the expected value criterion was used for demonstration purpose. This criterion is characterized by the ability to incorporate all of the available information, including the payoffs and probabilities of the potential states of nature. The decision criterion that is employed is a major factor which distinguishes different decision analysis models under risk. To make a better decision under risk, many researchers have investigated the improvement of the available decision criteria, as reported in [20–22]. Therefore, the improvement of the decision criteria under risk is beyond the scope of this paper. Nevertheless, advancements in the research area pertaining to decision criterion under risk can be easily incorporated in the framework of decision-making process presented in this study. Additionally, advancements in the studies on source identification may help us to obtain a reasonable estimate of the probabilities of the possible source locations. The use of a source identification system will provide a better foundation for sound decision-making.

5.4. Optimal decisions under completely uncertain source locations

As mentioned in Section 3.2.4, the research on the source identification of indoor airborne contaminants is still in its early stages, and there has been no publication of a source identification system used in a real-world indoor environment. Compared with source identification, contaminant detection is a mature technology and can be easily applied in various indoor environments. The decision analysis model under uncertainty is suitable for situations where the contaminant release was detected by a detection system but the contaminant source location was completely unknown.

To demonstrate the application of a decision analysis model under uncertainty, we employed the five decision criteria proposed in Section 3.5 to determine the optimal decision alternative by assuming that the source location was completely uncertain to the decision makers. Table 8 summarizes the optimal decision alternatives resulting from the different decision criteria. The optimal decision alternatives resulting from all of the criteria were exactly the same except that from the maximin criterion. Moreover, the results of the decision-making process were independent from changes in the coefficient of optimism α for the Hurwicz criterion. Note that these results only apply to the particular cases in this study and thus cannot ensure that the results of the decision-making process will not change with the different decision criteria for other cases.

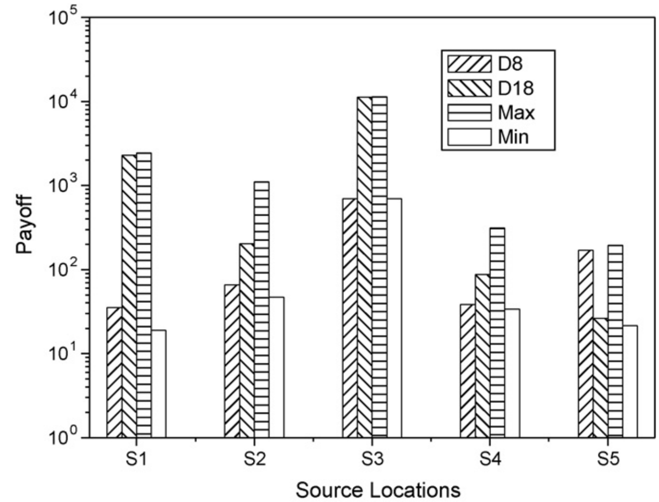


Fig. 7. Comparison of the decision payoffs of under uncertainty and the maximum and minimum payoffs for each source location.

The payoffs from alternatives D8 and D18 were further compared with the maximum and minimum payoffs under each source location, as shown in Fig. 7. The payoffs from alternatives D8 and D18 represent the two optional outcomes resulting from the decision analysis models under uncertainty. The maximum payoff given each source location can be taken as the outcome resulting from the decision analysis model under certainty in which the source location of a release was completely known. The minimum payoff under each source location represents the worst outcome of a contaminant release at the source location.

For each of the four source locations from S1 to S4, the payoff of D8 was much lower than the maximum payoff and slightly higher than the minimum payoff. For source location S5, the payoff from D8 was slight lower than the maximum payoff and much higher than the minimum payoff. In general, the decision alternative D8 resulting from the maximin criterion could not bring a large profit to the decision makers for releases at a majority of the source locations. The above results can be explained by reviewing the principle of the maximin criterion. The reason is that the maximin criterion is a pessimistic criterion which aims to avoid the worst outcome.

In contrast to decision alternative D8, D18 resulting from other decision criteria could bring a large profit to the decision makers for the releases at the majority of source locations. For each of the four source locations from S1 to S4, the payoff of D8 was slightly lower than the maximum payoff and much higher than the minimum payoff. Only for source location S5, the payoff of D8 was much lower than the maximum payoff and much higher than the minimum payoff. The above results may be due to the fact that the other criteria are more optimistic and will actively compete for an opportunity to get the best result. For the particular cases in this study, the payoffs of D18 are much greater than that of D8 under all source locations except source location S5. In addition, the payoff of D18 under location S5 is close to that of D8 with locations S1 and S4. Therefore, we suggest that D18 was a better choice in this case.

Table 8
Optimal decisions by the decision analysis models under uncertainty.

Decision criteria	Maximax	Maximin	Hurwicz				Savage	Laplace
			$\alpha = 0.2$[a]	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$		
Optimal decision	D18	D8	D18	D18	D18	D18	D18	D18
Ventilation mode	V8	V8	V8	V8	V8	V8	V8	V8
Evacuation mode	B	A	B	B	B	B	B	B

[a] α is the coefficient of optimism.

As demonstrated by the case studies, even if the source location is completely unknown, the decision makers can still reduce the risk of exposure to indoor occupants by a certain extent through use the payoff table (see Table 5) and the decision analysis model under uncertainty, which were prepared before the emergency. The decision analysis model under uncertainty can be solved with different decision criteria. The selection of the decision criterion depends heavily on the subjective attitude, intuition, psychology state, and risk tolerance of the decision makers. Therefore, the decision-making process under uncertainty is inherently a subjective method and the outcomes may be affected by the preferences of different decision makers. To accommodate the preferences of different decision makers, we suggest that a decision-making system be designed with several optional decision criteria.

Last but not least, the payoff of D18 was very close to the maximum payoff for each of the four source locations from S1 to S4. This indicates that the combination of ventilation mode V8 and evacuation mode B could provide fairly high protection to the occupants from the majority of possible source locations. Therefore, it is important to further investigate the combination of ventilation and evacuation modes which can adapt to releases at various locations. If such combinations of the ventilation and evacuation modes are available, then design of the emergency ventilation system and evacuation route can be simplified since fewer modes are considered. Moreover, the computational cost of decision-making can also be reduced since fewer cases require simulation.

6. Conclusions

In this study, the information of source location is classified as complete certainty, incomplete certainty, as well as complete uncertainty. According to this classification, three types of decision analysis models have been established, which are the model under certainty, under risk, and under uncertainty, respectively. This study provides a framework for rational response of the ventilation and evacuation strategies by considering the uncertainty of source locations when an emergency occurs. Furthermore, the models have been demonstrated by numerical studies of one hundred cases with different source locations, ventilation modes, and evacuation modes.

The objective of the decision analysis models presented is to minimize the relative exposure level of occupants. A distinct feature of these models is that the payoff, defined as the reciprocal of the index EFCS3, is independent of the intensity and composition of the contaminant source. By virtue of this feature, the state space of these models can be expressed as a set of possible source locations. As a result, the number of states of nature and the computational cost of the decision-making process can be significantly reduced. In addition, the models could be applied to direct both the strategies for ventilation transition and occupant evacuation since the decision alternative in the models is defined as the combination of these strategies.

The decision analysis model under certainty is suitable for the situations where the source location is completely known. This model can be used to determine the optimal emergency ventilation and evacuation strategies in a completely objective way. By using this model, the process and results of decision-making exclude any uncertainties, and are not affected by the subjective attitude of the decision makers. However, under current technologies, the source location can hardly be correctly identified with complete certainty in most indoor environments, which greatly limits the applications of this model in practice.

The decision analysis model under risk is applicable to the situations where the information of source location is incompletely certain. To obtain the information of source location, decision makers should be equipped with a sophisticated source identification system, which can provide the probabilities of potential source locations immediately after a release. This model can also be taken as an objective model. However, the decision maker needs to take on risk for the specific choice because the optimal decision is just a result of statistical data. The reliability of this model is mainly determined by the decision criterion employed and the outcomes of the source identification system. The advancements in the research on decision analysis under risk and source identification will contribute to sound decision-making under risk.

The decision analysis model under uncertainty can be applied to the situations where the contaminant release was detected by a detection system but the source location was completely unknown. The results of case studies indicate that, by using this model, the risk of exposure to indoor occupants can be reduced to a certain extent even if the source location is completely unknown. However, the decision-making under uncertainty is subjective and its results depend heavily on the subjective attitude of the decision makers. To satisfy the preferences of different decision makers, the decision-making system is suggested to be designed with several optional decision criteria. The further research on the combination of ventilation and evacuation modes which can adapt to releases at various locations will contribute to effective decision-making under uncertainty.

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