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A probabilistic model for fatality estimation of ship fire accidents

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ABSTRACT

Fatality estimation is beneficial for improving the safety of fireproofing in ship design and ensuring a quick response to fire accidents. This paper proposes a probabilistic method for fatality estimation of fire accidents caused by critical temperature and critical smoke in terms of comparing the available safe egress time and the required safe egress time. The kernel of this proposed method is first to derive the available safe egress time estimation equation by using fire dynamics simulator field model to simulate the fire development process and, to determine the required safe egress time equation given by the guideline of International Maritime Organization, which consider crowd behaviours, including waiting time at corridors, stairs and doors. The proposed method is applied to a real fire accident and the fatality rate is approximate to real scenarios. Consequently, this paper proposes a practical and holistic method for fatality estimation of ship fire accidents.

1. Introduction

Fire accident is an important type of maritime accidents and has a relatively high likelihood of occurrence among all types of maritime accidents besides collision and grounding. For example, Wróbel et al. (2017) discovered that 24% of maritime accidents from 2011 to 2015 were fire accidents by using 100 previous ship accidents based on several sources (e.g. European Maritime Safety Agency and the Government of Hong Kong); in Hong Kong, fire accidents account for 7% of all maritime accidents (Yip, 2008); in the Gulf of Finland, the fire accident rate is approximately 10% (Kujala et al., 2009). Moreover, as a type of non-navigational accident, fire accidents also have more serious consequences than other types of maritime accidents. Specifically, Roberts et al. (2013) discovered that 19% of fatalities are caused by fire from 501 accident records of bulk carriers. Weng and Yang (2015) concluded that fire accidents caused 132% more fatalities than other types of maritime accidents.

From the perspective of risk analysis, human fatality is often introduced to analyse the consequence of maritime accidents. Specifically, the Ministry of Transportation (MoT) of China issued criteria for defining minor, major and catastrophic consequences, and fatality is the key criteria to determine the severity of the consequences (Zhang et al., 2016). Moreover, in the SAFEDOR project, this criterion is used for risk analysis of maritime accidents (Guarin et al., 2009). Hence, to reduce fatalities and improve fire safety, many previous studies have focused on the evacuation of passengers and crewmembers (Cho et al., 2016; Chu et al., 2013; Ha et al., 2012). However, ship fire accidents cause more fatalities than other types of maritime accidents because they often occur unexpectedly and provide little evacuation time for passengers and crewmembers (Baalisampang et al., 2018a). Therefore, estimating the fatality rate of ship fire accidents has the following benefits. First, safety fireproofing designs can be carried out by introducing the fatality estimation model to further analyse the weakness of fire safety (Kang et al., 2017). Second, after introducing the fatality estimation model, the decision-maker will have a better understanding of fire accident development and countermeasures can be taken for fire safety management.

There are many studies that simulate evacuation in emergency situations, from micro approaches that simulate the movement of the crews, to macro approaches that incorporate human behaviour in the simulation process (Musharraf et al., 2018a; Olenick and Carpenter, 2003). These methods are widely used for human reliability analysis (Musharraf et al., 2014, 2018b) and can be used to find bottlenecks in ship structures. However, in practice, these methods cannot be used to predict the outcome of a fire in terms of the number of deaths (Hanea and Ale, 2009). The motivation of this paper is not only to consider human behaviour but also the ship structures and characteristics of the ship and the environment. To achieve this, a comparative perspective rather than an absolute perspective is used for the modelling process. Therefore, the human behaviours are derived from statistical data.

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However, although some uncertainties may exist in this modelling process, they will be further analysed in the discussion.

The available safe egress time (ASET) and required safe egress time (RSET) are generally used to estimate the fatality rate in building fires (Hanea and Ale, 2009; Hanea et al., 2012) from a comparative perspective. However, different from building fires where experiments can be performed to collect the ASET and RSET data, the estimation of ASET and RSET is a challenge for ship fires due to uncertainty. Studies have been carried out to address this challenge. For example, Salem (2016) utilized a Monte Carlo simulation to address the uncertainties for estimation of ASET, and Wang et al. (2013) focused on the uncertainty of ASET for a ship fire accident. Based on the above discussion, two scientific problems for fatality estimation due to ship fire accidents remain unaddressed in the literature. First, there is no probabilistic method that considers both ASET and RSET to estimate the fatality rate. Second, the ASET and RSET estimation methods are too complex due to the uncertainty, and the literature lacks a simplified quantification method to derive ASET and RSET.

To address the two problems, this paper proposes a simplified probabilistic method to estimate the fatality rate from the perspective of both ASET and RSET. Specifically, when estimating the ASET, the critical smoke and critical temperature, which are the contributing factors of fatalities in fire accidents, are considered. The fire dynamics simulator (FDS) field model is used to predict the ASET considering several parameters to address the uncertainties in the estimation process (Wang et al., 2013; Salem, 2016). Flame acceleration simulator (FLACS) is another widely used method for fire development simulation (Yang et al., 2018; Dadashzadeh et al., 2013a). The difference between these two methods is that FDS uses large eddy simulation (LES) and even direct numerical simulation (DNS) and is not based on a RANS formulation, while FLACS is a RANS code (Mouilleau and Champassith, 2009; Yet-Pole et al., 2009). In previous studies (Dadashzadeh et al., 2013b; Vasanth et al., 2017; Baalisampang et al., 2017, 2018b; Dasgotra et al., 2018), both methods have been widely used for fire simulation, and while each method has its own merits, the results from either method are acceptable. Therefore, this paper will not discuss the advantages and disadvantages of the methods in detail and only states the reason why FDS is used. Moreover, when estimating the RSET, crowd behaviours including at the corridor, stairs, and doors are considered for evacuation time estimation.

The remainder of this paper is organized as follows. Section 2 proposes the framework for fatality estimation considering both ASET and RSET. Section 3 applies the proposed method for fatality estimation using an example of a fire accident occurring at a bulk carrier. Discussion is carried out in Section 4, where the limitations of the probabilistic model and the derivation of ASET and RSET are discussed. Conclusions are drawn in Section 5.

2. Development of fatality estimation model for ship fire accidents

2.1. Establishing a generic estimation framework for ship fire accidents

To estimate the fatalities of ship fire accidents, a fatality estimation framework is developed in a similar way to that life safety frameworks for building fires have been developed, namely, by using ASET and RSET (Hanea et al., 2012; Hanea and Ale, 2009; Kong et al., 2014). However, the derivation of ASET and RSET is different in ship fire accidents than in building fires. This framework is developed in three steps and shown in Fig. 1.

First, the ASET is derived using the FDS simulator, which is a widely used tool to simulate fire development for building fires. In this step, the ship cabin is constructed, and the parameters of the ship fire are defined. Finally, the critical temperature and smoke are derived, which can be used to obtain the critical time for fatality estimation using regression analysis.

Second, RSET is obtained using the guidelines issued by the International Maritime Organization (IMO). In this step, three types of human behaviours, crowding at doors, i.e., crowding in stairs and crowding in corridors, are considered. The response time, detection and alarm time are also modelled in this process.

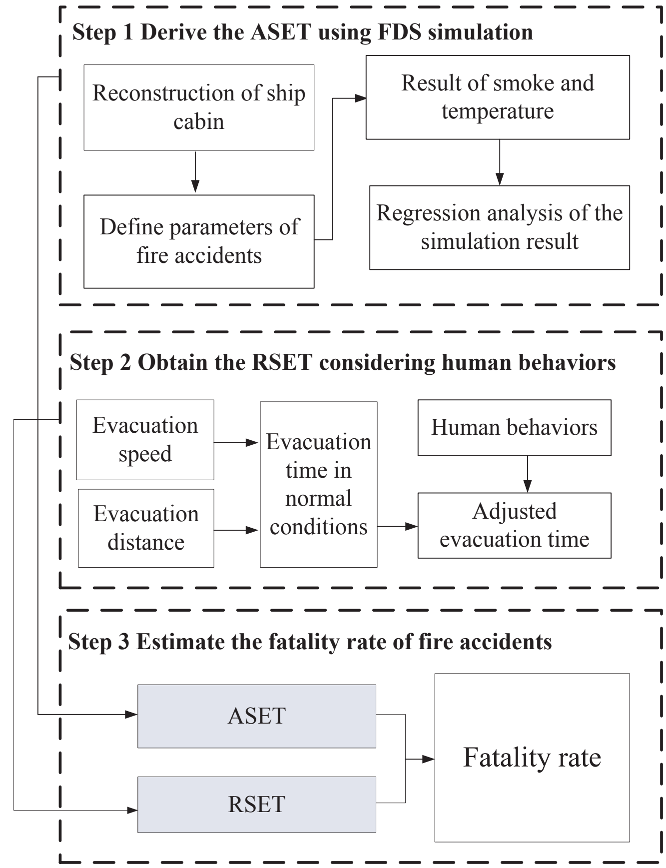


Fig. 1. Fatality estimation framework for ship fire accidents.

Third, the fatality rate is determined by comparing the ASET and RSET. If $ASET < RSET$, the crewmembers or passengers will not have enough time to escape the ship fire accident and the probability for fatalities is high. If $ASET > RSET$, the probability of fatalities is low.

2.2. Prediction of ASET using FDS

Time is a critical factor for emergency response to maritime accidents (Shi et al., 2014; Wu et al., 2018). The initial accident will develop into secondary accidents and have serious consequences if the optimal response time is missed (Mazaheri et al., 2014; Wu et al., 2017a). Moreover, from statistical data (Jasionowski, 2011), such as the accident of the MV Estonia ferry (1994) and MV Rocknes (2004), there is only 10 min or less for evacuation. Similarly, time is the most significant factor and is limited in ship fire accidents. In practice, there are two indices to define the $ASET$: (1) the time when the critical height of the smoke layer is reached (t_{smo}) and (2) the time when the critical temperature is reached (t_{temp}). In practice, the ASET is equal to the minimum of these two indices (Hanea et al., 2012; Kong et al., 2014), and is written as $ASET = min(t_{smo}, t_{temp})$.

FDS is suitable for simulating fire accident development due to two advantages (McGrattan et al., 2010). First, the ship fire has the characteristics of a low Mach number and a buoyancy-driven flow, which makes FDS especially suitable for ship fire simulation (Khan et al., 2017; Zhao et al., 2017; Kang et al., 2017). Second, FDS can simulate smoke spread and temperature change for fire accident development (Su and Wang, 2013), which is required for estimating ASET. The procedure of using this tool for fire development modelling can be

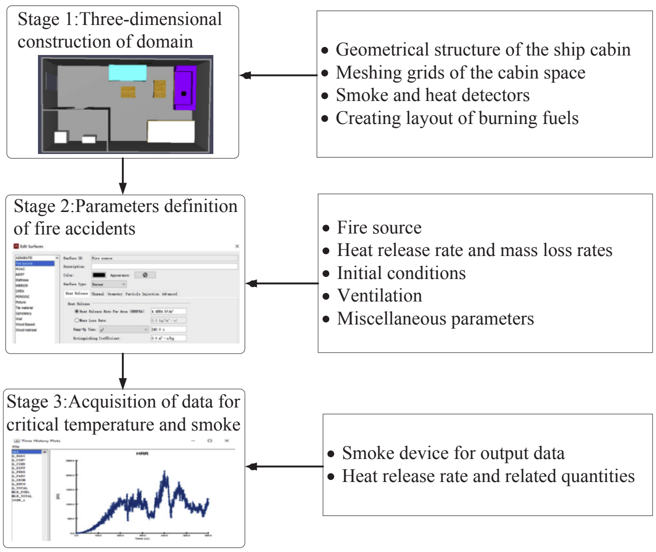


Fig. 2. Modelling process of fire accident development using FDS.

divided into three stages, which are the three-dimensional construction of the domain, defining the parameters of the fire accident and acquisition of data for critical temperature and smoke. A detailed description of the fire development simulation is illustrated in Fig. 2.

In the first stage, the 3D structure of the domain is constructed. This process includes the geometrical structure of the cabin, developing a meshing grid of the cabin, installation of heat and smoke detectors to obtain the simulation result and defining the layout of different types of fuels.

In the second stage, after constructing the ship cabin, two significant parameters are specified in the modelling process, which are heat release rate (HRR) and density of critical smoke. The first significant parameter specified is HRR. In the fire accident development period, the HRR can be treated as a function of squared time (t^2) and can be written as $Q = \alpha t^2$ (Wang et al., 2013), where Q is the HRR of the ship fire (kW), t is the ignition time of the fire (s), and α is the fire growth rate (kW/s^2). From this equation, the contributing factor for HRR is fire growth rate, and from Kong et al. (2014), this growth rate is defined as four categories using linguistic terms, as listed in Table 1. The second significant parameter is the density of toxic gases (Qu et al., 2013). There are two species of toxic gases to human beings, CO_2 and CO. In the early stage of fire development, CO_2 is the main product as there is sufficient oxygen for burning. CO is the main product when there is insufficient oxygen in the closed cabin. The rates of toxic gases (CO_2 and CO) are different for different fuels in the ship cabin. This can be estimated by referring to the SFPE Handbook for fire protection engineering (Hurley et al., 2015).

In the third stage, the simulation result of smoke and temperature spread can be obtained using FDS. Since there are two species of toxic gases in fire effluents, the ASET can be rewritten as $ASET = min\,(t_{CO}, t_{CO_2}, t_{temp})$, where t_{CO} is the time when the concentration of CO reaches the threshold limit for humans, and similarly, t_{CO_2} is the time when the concentration of CO_2 reaches the threshold limit for humans (becomes toxic to humans).

Table 1
Categories of fire growth rate (Kong et al., 2014).

Category	Fire growth rate (kW/s^2)	Time when Q reaches 1055 kW(s)
Slow	0.0029	600
Medium	0.0117	300
Fast	0.0469	150
Ultra-fast	0.1846	75

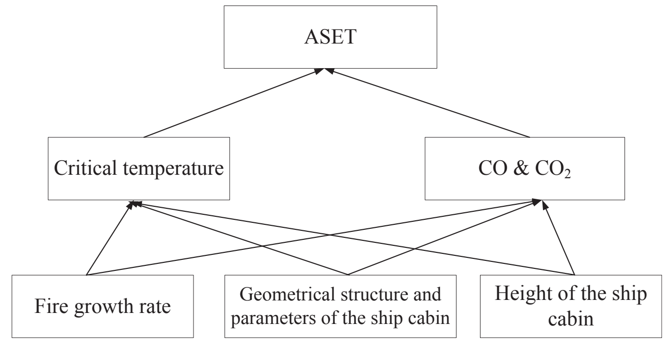


Fig. 3. Influencing factors of ASET for ship cabin fire.

Moreover, based on the data of smoke and temperature spread, the regression method can used to obtain the function of t_{CO}, t_{CO_2} and t_{temp}, and is introduced for fatality estimation in ship fire accidents in this paper. Hence, the influencing factors of the ASET can be summarized as shown in Fig. 3.

2.3. Derivation of evacuation time in normal conditions

RSET is another factor to discuss and define. Since this paper focuses on the time caused by critical temperature and critical smoke, which are discussed in Subsection 2.2, only the time required for evacuation of ship fire accidents is considered. In other words, the time required for response to secondary accidents (e.g., abandon ship due to flooding after fire accidents) is not considered. The key factor to define the RSET is the evacuation time for passengers and crewmembers. Previous studies in the literature focused on this factor (Lee et al., 2004; Kim et al., 2004; Sarvari et al., 2017).

To determine the RSET, the evacuation time in normal conditions (ETNC) should be determined. The ETNC is determined to be equal to the evacuation distance (ED) divided by the evacuation speed (ES). This problem can be transformed to determine the ED and ES. The first node is evacuation distance, which is related to the horizon, vertical and evacuation locations. The relationship can be simplified as follows. Suppose the height of each deck is the same and the upper deck is positive while the lower deck is negative. The main deck is assumed to be 0, and the other decks can be defined as shown in Fig. 4. The evacuation distance is the horizon distance plus the weighted vertical distance, where the weights are the deck number (n). The horizon and vertical locations are assumed to be random in the corridor and stairs, respectively. The other node, evacuation speed, is determined from the guidelines of IMO, and the initial speed in the corridor, stairs descent and stairs ascent is 1.2, 1.0, and 0.8 m/s, respectively (IMO, 2016). Based on these definitions, the ETNC can be derived using Table 2. Note that the evacuation location is not determined because it is one of the input parameters, and this type of input parameter varies in different scenarios and should be specified according to the ship conditions.

2.4. Estimation of waiting time considering human behaviour

Human error is a contributing factor to human fatalities in fire accidents (Akyuz, 2016; Soner et al., 2015; Wang et al., 2011), because different human behaviours in fires may cause chaos during evacuation. Hence, some studies have focused on this behaviour problem. Sarvari et al. (2017) systematically reviewed the emergency evacuation management for maritime transportation and stressed the importance of human behaviours in evacuation. Similar opinions are given in other studies (Lee et al., 2003; Roh and Ha, 2013). Ha et al. (2012) proposed a cell-based evacuation simulation model considering human behaviour on passenger ships. In that study, three types of human behaviours are considered: individual behaviours, crowd behaviours, and counter flow-avoiding behaviours. Similarly, Cho et al. (2016) developed a

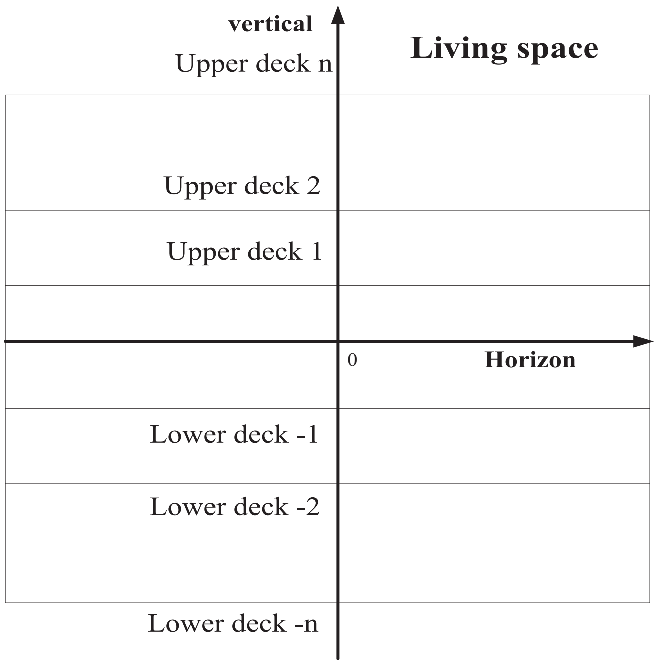


Fig. 4. Evacuation location and the definition of accommodation space.

velocity-based egress model considering the individual, crowd, and emergency behaviour for ship evacuation. Moreover, the moving characteristics such as the ship trim and heeling (Sun et al., 2018; Kim et al., 2004) and the layout of the ship (Chu et al., 2013; Park et al., 2004) are also important for evacuation.

From the above analysis, the passenger characteristics (e.g., age, gender), ship layout, individual, crowd, and emergency behaviour are the significant factors for ship evacuation. Since this paper intends to estimate the RSET from a probabilistic rather than a deterministic perspective, the human behaviours are simplified as follows. The IMO (2016) guideline provides two methods, a simplified evacuation analysis method and an advanced evacuation analysis method. The main difference between the simplified and advanced method is whether the passenger characteristics (e.g., age, gender) are considered. Since the modelling process is very complicated and since it is difficult to obtain detailed information of the passengers in the emergent situation when considering the passenger characteristics, the simplified method of IMO (2016) is applied in this paper. Moreover, since the passengers are asked to participate in training for evacuation after boarding the ships (Liou and Chu, 2016; Hanea et al., 2012), the moving characteristics are ignored since the passengers are trained and the moving characteristics will not be too different. Using the simplified method, the crowd behaviour can be categorized as crowding in stairs, crowding in corridors and crowding at doors.

The first human behaviour is crowd behaviour in corridors. This is simple to categorize because each deck is separate, and only the corridor density should be considered. From the IMO guidelines (IMO, 2016), the speed of a person is 0.67 m/s when the density flow is greater than 1.3 p/m/s, and the speed in the corridor is 1.2 m/s when the specific flow is less than 0.65 p/m/s. Therefore, the equation of evacuation speed in the corridor is listed in Table 3.

The second human behaviour is crowd behaviour in stairs, which can be divided into stairs ascent and stairs descent. The evacuation speed in the stairs is assumed to be the minimum of the evacuation speed ascent and speed descent, so the waiting time will be the maximum time between the time ascent and time descent. Similarly, the evacuation speed (ascent and descent) depends on the density of people at the stairs. The relationships among these nodes are summarized in Table 4.

The third human behaviour is crowd behaviour at doors. Since all crewmembers or passengers have to pass the door of the main deck, the waiting time at the door (WTD) should consider the evacuation of this deck and other decks. To calculate WTD, two steps are carried out. First, the probability of crowding (PR) at the door on the main deck is estimated. Using the main deck as an example, assume the distribution of each stair is normal, which can be achieved using equation $PR = \sum_{i=1}^{n} Normal(NPS_i, \rho_i)$, where ρ_i varies from the number of the deck because people need more time from the further deck to evacuate than the closer deck. Moreover, NPS_i stands for the number of people in the stairs, which is achieved by counting the people from the adjacent decks using equation $NPS_1 = if(-1 < EL < 1{,}1{,}0)$ for the first deck. Second, the WTD is equal to the probability of crowd multiplied by the number of people, which is written as $WTD = PR \times NP$.

2.5. Prediction of fatality rate for fire accidents using the Bayesian network

To estimate the probability of fatalities due to fire accidents, the Bayesian network is introduced in this paper. The Bayesian network is a widely used method for risk analysis and decision-making for maritime transportation. The advantages of the Bayesian network are as follows. First, this method can intuitively represent the relationship among multiple influencing factors due to the graphical structure (Eleye-Datubo et al., 2006; Wu et al., 2017b). Second, this method provides a probabilistic tool to quantify the relationship among these influencing factors (Fu et al., 2016) and can handle discrete and continuous variables (Cinicioglu and Shenoy, 2009). Last, some software, such as GeNIe (Montewka et al., 2014) and Hugin (Goerlandt and Montewka, 2015; Matellini et al., 2013), provide practical tools for Bayesian network modelling.

From the above analysis, the ASET and RSET can be determined using the above-established equations. The developed Bayesian network is simplified as follows. A sub-model is introduced to reduce the

Table 2
Quantitative relationships of the nodes for evacuation time in normal conditions.

Parent node	Child node	Equation	Description
Evacuation time in normal conditions (ETNC)	Evacuation distance (ED)	$ETNC = ED/ES$	Evacuation is equal to the evacuation distance divided by the evacuation speed.
	Evacuation speed (ES)		
Evacuation distance (ED)	Horizon (HZ) Vertical (VC) Evacuation location (EL)	$ED = if(and(-n \le EL \le n), HZ, HZ + n \times VD)$	Evacuation distance is the horizon distance plus the weighted vertical distance.
Horizon (HZ)	Corridor length (CL)	$HZ = uniform(0, CL)$	The crews are assumed to be randomly distributed in the corridor.
Vertical (VC)	Stairs length (SL)	$VC = uniform(0, SL)$	The crews are assumed to be randomly distributed in the corridor.
Evacuation speed (ES)	–	$ES = Triangular(0.8, 1{,}1.2)$	From the IMO guideline, the initial speed in the corridor, stairs descent and stairs ascent is 1.2, 1.0, and 0.8 m/s, respectively.

Table 3
Quantitative relationships of nodes for waiting time in corridor.

Parent node	Child node	Equation	Description
Waiting time at corridor (WTC)	Corridor speed (CS) Corridor length (CL) Evacuation speed (ES)	$WTC = CL/CS - CL/ES$	Waiting time exists when the CS is less than the ES in normal conditions.
Corridor speed (CS)	Density in corridor (DC)	$CS = \begin{cases} 0.65 \; if \; DC \leq 1.2 \\ 0.67 - (DC - 1.3) \times 0.53/0.65)) \\ if \; 0.67 < DC < 1.2 \\ 1.3 \quad if \; DC \geq 0.67 \end{cases}$	CS depends on the density of persons in the corridor.
Density in corridor (DC)	Number of people (NP) Corridor area (CA)	$DC = NP/(2n \times CA)$	People are assumed to be randomly distributed in the corridor of each deck.
Corridor area (CA)	Corridor length (CL) Corridor width (CW)	$CA = CL \times CW$	The corridors are treated as a regular rectangle.

Table 4
Quantitative relationships of nodes for waiting time in stairs.

Parent node	Child node	Equation	Description
Waiting time in stairs (WTS)	Stair ascent speed (SAS) Stair descent speed (SDS) Stair length (SL) Evacuation speed (ES)	$WTS = SL/\min(SAS, SDS) - SL/ES$	Waiting time exists when the stair speed (minimum between ascent and descent) is less than ES.
Stairs ascent speed (SAS)	Stair ascent density (SAD)	$SAS = \begin{cases} 0.8 \quad if \; SAD \leq 0.43 \\ 0.44 - (SAD - 0.88) \times 0.8 \\ if \; 0.43 < SAD < 0.88 \\ 0.44 \quad if \; SDU \geq 0.88 \end{cases}$	SAS depends on the density of persons in the stairs.
Stairs descent speed (SDS)	Stair descent density (SDD)	$SDS = \begin{cases} 1.0 \; if \; SDD \leq 0.54 \\ 0.55 - (SDD - 1.1) \times 15/19 \\ if \; 0.54 < SDD < 1.1 \\ 0.55 \quad if \; SDU \geq 1.1 \end{cases}$	SDS depends on the density of persons in the stairs.
SAD (SDD)	Stair area (SA) Evacuation location (EL) Number of people (NP)	$if\,(1 < EL \leq n,\, 1 \times NP,\, 0)/SA(SAD) if\,(-n < EL \leq 1{,}1 \times NP,\, 0)/SA(SDD)$	The density in the stairs depends on the ascent people or descent divided by the stairs area.
Stair area (SA)	Stair length (SL) Stair width (SW)	$SA = SL \times SW$	The stairs are treated as a regular rectangle.

nodes. In this paper, four sub-models are introduced (i.e., evacuation time in normal conditions, waiting time at corridor, waiting time at stairs, and waiting time at door). The associated intermediate nodes are included in the four sub-models. Specifically, the sub-model of waiting time at corridor includes the corridor area, density in the corridor, corridor speed, and waiting time in the corridor. The sub-model of waiting time at stairs includes stairs ascent speed, stairs descent speed, stairs ascent density, stairs descent density, stair area, and waiting time at stairs. The sub-model of waiting at the door includes a probability of the crowd and waiting time at the door. However, the input variables, which require further information from the specific fire accident, are excluded in the sub-model and are shown in purple.

When considering the RSET, the detection time, alarm time, and response time should be considered, which depends on the time of day and fire drills. Moreover, they are the parent node of the response time and the quantitative relationship can be defined as follows. From Hanea et al. (2012), the response time during daytime can be treated as a uniform distribution and defined as equation $RT_1 = uniform(30,60)$, while during night-time, the response time increases and is defined as equation $RT_0 = uniform(60,120)$. Considering that the passengers are required to participate in fire drills after boarding the ship and that they are not as familiar as the crewmembers with the procedures, the response time of the passengers is treated as 80% of the normal conditions and defined as $RT_1 = 0.8 \times uniform(30,60)$ and $RT_0 = 0.8 \times uniform(60,120)$. The graphical structure of the developed Bayesian network is shown in Fig. 5.

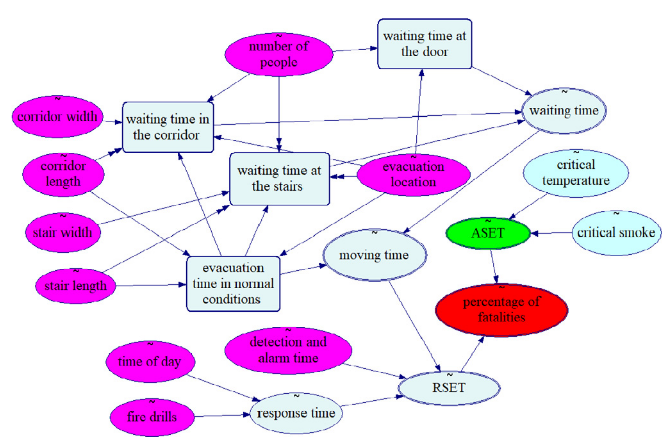


Fig. 5. Graphical structure of fatality estimation for fire accidents.

3. Application of proposed model for fatality estimation

3.1. Scenario description of fire accidents

In August 2010, a fire accident occurred on the Yangtze River. At 10:00, a fire was detected in a cabin of the ship on the main deck; at that time, the fire was small, and little smoke was found. The ship was a bulk carrier with a total length of 150 m and a breadth of 26 m. Due to

Table 5
Detailed information of the fire accidents.

Factor/variable	Value	Factor/variable	Value
Time of day	Daytime	Corridor width	0.9 m
Detection and alarm time	Approximately 75 s	Corridor length	24 m
Number of decks	3	Stair width	0.9 m
Crew members	17	Stair length	3 m
Fatalities	1	Evacuation location	Main deck

many flammable materials in the cabin, the fire quickly spread to other cabins in the accommodation space. After evacuating the crewmembers, the fire was extinguished with the help of the firefighting department at 15:00. However, one crewmember died in the process. The fire caused one fatality and serious damage to the ship.

Moreover, from the investigation report, the fire occurred approximately 1 min before the fire was detected. There were only three decks in the accommodation space. There were 17 crewmembers on the ship. The ship parameters were as follows: the corridor and stair widths were approximately 0.9 m, the corridor length was approximately 24 m, and the stair length was approximately 3 m. Detailed information of the fire accident is included in Table 5.

3.2. Use of FDS for estimating critical conditions to estimate ASET

3.2.1. Three-dimension construction of accommodation space

To obtain the ASET using FDS simulation, the three-dimensional structure of the accommodation space should be constructed. The following four steps are used to achieve this in the FDS simulation software.

First, the number of meshing grids is defined. Define the accommodation space is 30 m long, 7.5 m wide and 2.1 m high. Note that the length of accommodation space (30 m) is a bit longer than the corridor (24 m), this definition is carried out in order to have an overall view of the fire development using FDS simulation. Moreover, the meshing grids should satisfy with fast Fourier transform. Specifically, as each grid is defined as 0.1 m, the grids should be 2 power to 300 in the length (30/0.1 = 300), 3 power to 75 in the width (7.5/0.1 = 75), and 5 power to 21 in the height (2.1/0.1 = 21) in the FDS. Therefore, the total number of meshing grids is to multiply them using equation $2^{300} \times 3^{75} \times 5^{21} = 47250$.

Second, the parameters of the ship cabin should be defined. In this paper, since the fire occurred in the living room of a cabin, the length is defined as 5 m. Fuel is another significant parameter and is specified. In this paper, a bed, sofa, tea table, desk, chair and shower room are defined, and their sizes are also defined. The majority of the furniture is constructed of wood. To simplify the modelling process, three assumptions are made. (1) The first assumption is that all the furniture is rectangular. (2) The small components of the cabin are ignored since the heat released by these components is small. (3) The fuels in the corridor are rare and the corridor is assumed to have empty fuels. Based on these assumptions, the cabin is developed and shown in Fig. 6.

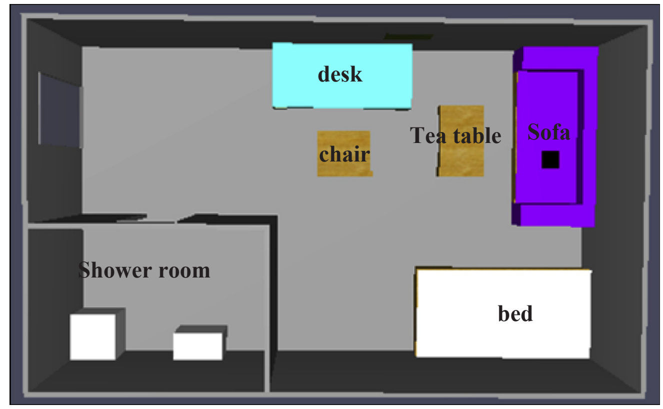


Fig. 6. 3D structure of ship cabin.

Third, the parameters of the fire accident should be defined. Note that two significant parameters should be carefully handled. (1) The HRR ($\dot{Q}$). $\dot{Q} = \varepsilon \times \dot{m} \times \Delta H$, where ε is the coefficient factor of fire burning, which stands for the degree of fuel that has been burned; $\dot{m}$ is the mass burning rate for the fuel (kg/s); and ΔH represents the heat of combustion of the fuel (kJ/kg). Traditionally, the coefficient factor (ε) is a predefined value between 0.3 and 0.9, and it is defined as 0.6 in this paper. Moreover, based on the previous study (Themelis et al., 2010), $\dot{m}$ and ΔH are 0.016 and 17.3 for the wooden materials, respectively, and $\dot{m}$ and ΔH are 0.026 and 22.5 for the polyester foam, respectively. Based on these parameters, the HRR ($\dot{Q}$) in this paper can be calculated as 1.952 MW (2) The fire growth rate (α). As the fuels are wooden materials and polyester foam, the fire growth rate can be defined as 0.04689 kW/m^2 from Table 1. The above parameters are summarized in Table 6.

3.2.2. Simulation result of critical time for temperature

Since ASET is determined by the critical temperature and critical smoke, detectors are used in this model to obtain the temperature and smoke. In this paper, four heat detectors are used with one in the ship cabin and three in the corridor. Eight smoke detectors for CO and CO_2 detection are also used. The detectors are installed at a height of 1.65 m, which is close to the height of humans (defined as 1.8 m in this paper). From the investigation report, the fire spread quickly, therefore, the simulation time is set as 600 s in this paper. After defining these parameters, the simulation result of temperature change over time is shown in Fig. 7.

From Fig. 7, three phenomena can be observed. First, obvious stratification of temperature field exists in the fire accident development process, and the upper and lower layers of temperature differ substantially. Second, the temperatures at the same height are approximately the same in different locations, this can be discovered that the colours in the height are approximately the same except for the fire sources in Fig. 7(c) and except for the places close to the door in Fig. 7 (d), this finding is useful and can be used to predict the critical temperature by defining a predefined height for human beings. Third, the temperature increases suddenly in the initial accident development process, and the highest temperature (i.e. 287 °C, from the output of the simulation results) is at 300 s. Note that there are no flammable materials in the corridor, the results of temperature changes used in this paper are all in the cabin because the temperature in the corridor is always lower than in the cabin. Since temperatures (T_{temp}) greater than 100 °C may cause serious injury to humans, the time when the temperature reached 100–120 °C is assumed to be the critical time (t_{temp}). Therefore, the regression analysis of the critical time for temperature is carried out, and is shown in Fig. 8. Based on this regression analysis, the critical time for temperature can be defined as $t_{temp} = uniform(152{,}167)$ s.

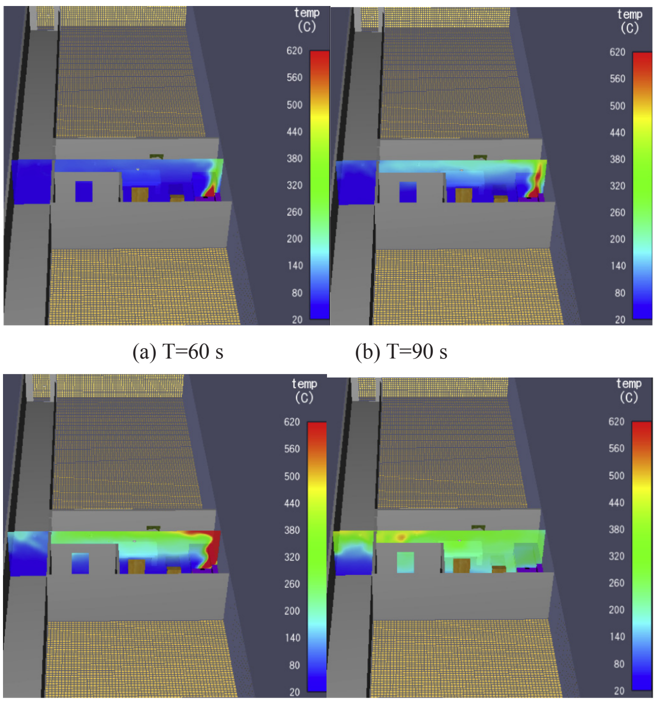
3.2.3. Simulation result of critical time for fire smoke toxicity

Traditionally, combustion products are water vapour and carbon dioxide (CO_2). However, incomplete combustion will produce toxic products, such as carbon monoxide (CO). According to the fire experiment conducted by the National Institute of Standards and Technology (NIST) in the United States (Yeoh and Yuen, 2009), the production rate in the cabin is as follows.

1) When the fuel is a wooden material, the production rate of CO is 0.3 g per gram of fuel (0.3 g/g), the production rate of CO_2 is 1.1 g/g, and the consumption rate of oxygen is 0.9 g/g.

Table 6
Parameters used for FDS simulation.

Factor/variable	Value	Description
Number of meshing grids	47,250	Number of meshing grids is $2^{300} \times 3^{75} \times 5^{21}$, where 300, 75 and 21 are the meshing grid in the x, y and z direction.
Cabin height	2.1 m	The height of the ship cabin is approximately 2.1 m.
Cabin length	5 m	The cabin length is approximately 5 m.
HRR	1.952 MW	HRR can be calculated as described.
Fire growth rate	0.04689 kW/m^2	The majority of the cabin is furnished with wood fuels.



(a) T=60 s (b) T=90 s
(c) T=140 s (d) T=300 s

Fig. 7. Simulation result of temperature change over time.

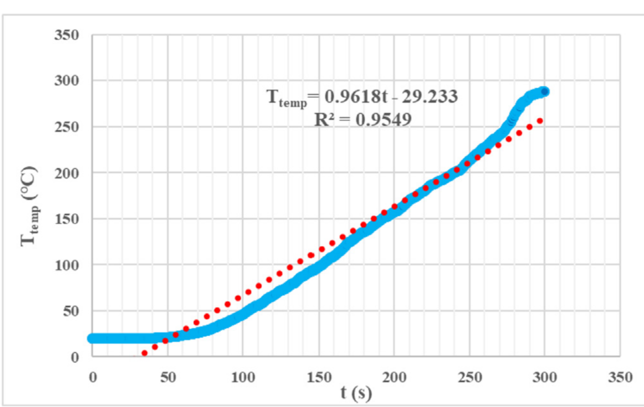


Fig. 8. Regression analysis of temperature change over time.

2) When the fuel is furniture, the production rate of CO is 0.2 g/g, the production rate of CO_2 is 1.5 g/g, and the consumption rate of oxygen is 1.8 g/g.

Since the majority of the fuels in the ship cabin are wooden and furniture, the production rate of CO is assumed to be 0.25 g/g, and the production rate of CO_2 is assumed to be 1.5 g/g. After installing the eight smoke detectors, the development of toxic gases can be derived as shown in Fig. 9.

As shown in Fig. 9(b), the ship cabin is filled with smoke after 40 s.

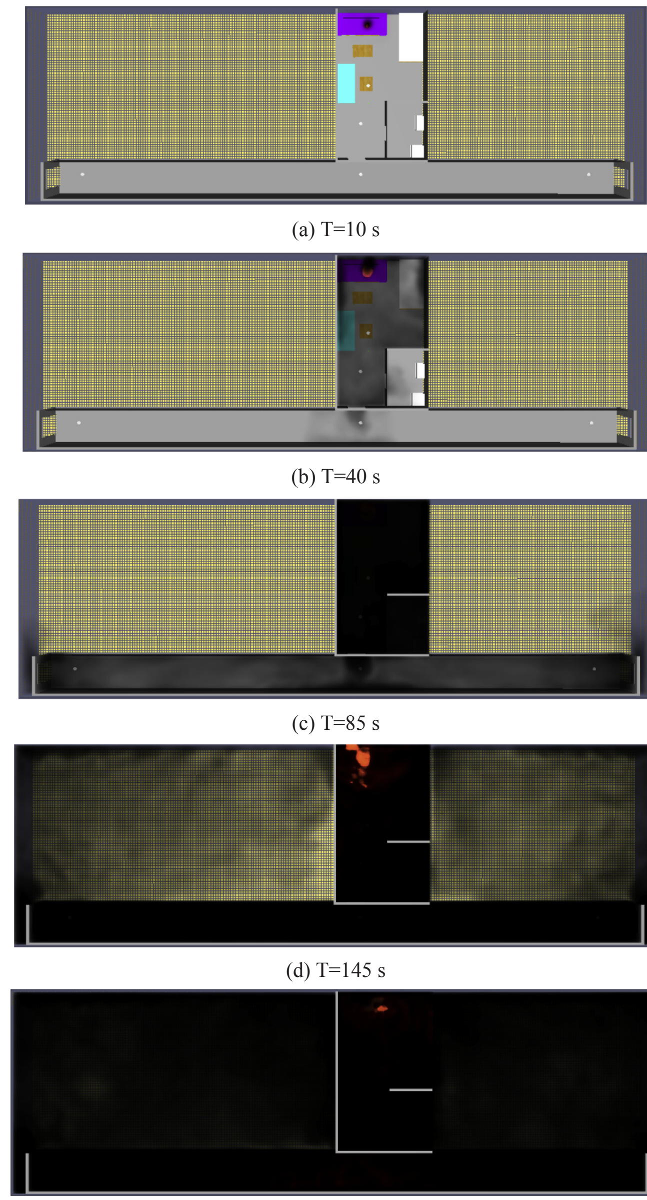

(a) T=10 s
(b) T=40 s
(c) T=85 s
(d) T=145 s
(e) T=200 s

Fig. 9. Development of toxic gases for ship fire.

Smoke spreads through the door to the corridor, and the corridor is filled with smoke at 85 s, as shown in Fig. 9(c). Finally, the entire computational domain is filled with smoke at 200 s, as shown in Fig. 9(e). Moreover, the production of CO and CO_2 are obtained from this simulation. The regression analysis of the two toxic products of fire smoke, CO_2 concentration (C_{CO2}) and CO concentration (C_{CO}), is shown in Fig. 10 and Fig. 11, respectively.

Based on previous studies on the critical time of toxic gases (Zukoski and Kubota, 1980; Gupta et al., 2001), humans are in danger when the

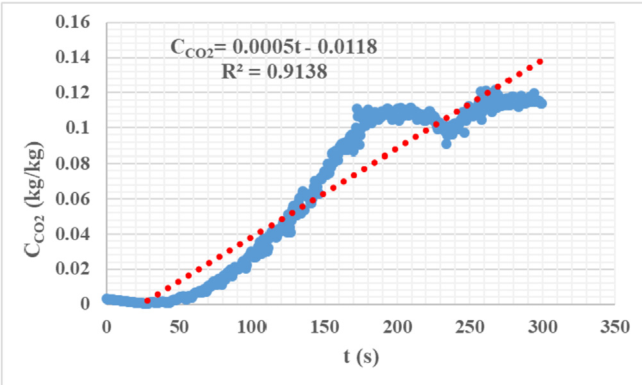


Fig. 10. Regression analysis of CO_2 production.

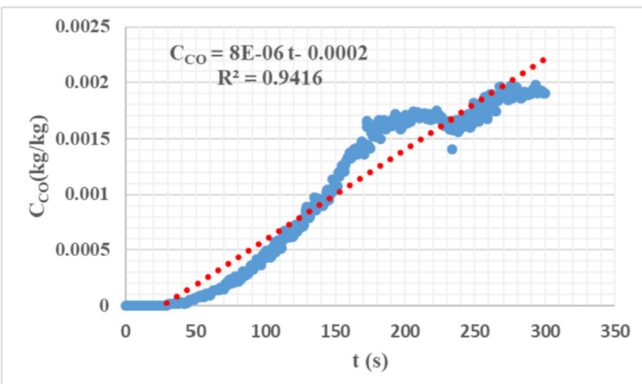


Fig. 11. Regression analysis of CO production.

rate of CO_2 is 0.05 kg/kg (i.e., 5000 ppm). Moreover, from Figs. 10 and 11, as the production rate of CO_2 is greater than that of CO, the critical time of CO is longer than that of CO_2. Therefore, in this paper, only the critical time of CO_2 is considered because the critical time is shorter, and the critical CO_2 rate is defined as 0.05–0.06 kg/kg. From these assumptions, the critical time for CO_2 is $t_{smo} = t_{co_2} = Uniform\ (123,143)$ s.

3.3. Result of fatality prediction for fire accidents

3.3.1. Quantifying input variables of probabilistic model

To obtain the estimated fatalities of fire accidents, the input variables should be quantified using distribution functions. From the investigation report, the width and length of the corridor are approximately 0.9 m and 24 m, respectively, so they are defined as following a normal distribution with expected width and length. Similarly, the width and length of the stairs also follow a normal distribution. Since there are only three decks in this fire accident, the evacuation location is defined as a discrete distribution with a probability of 0.2 in the main deck, and a probability of 0.4 in the wheelhouse and engine room. The time of day follows a Bernoulli distribution by defining daytime as 1 and night-time as 0. The detection and alarm time vary in different scenarios and are assumed to follow a normal distribution by defining 75 s as the average. This is consistent with the investigation report, which determined the alarm time to be 80 s. Moreover, the number of people is 17, because there are 17 crewmembers. All these crewmembers are assumed to be well-trained as they are authorized to be certified and are required to carry out fire drills each month. The critical temperature and critical smoke are derived from the simulation result using FDS, which is described in an earlier subsection. These variables and the corresponding description are summarized in Table 7.

3.3.2. Result analysis of estimated fatalities

By introducing the distribution of input variables and the functional nodes in Section 2, the final result of the fatality rate of this ship fire accident is shown in Fig. 12. The simulation result is obtained in three steps. First, the distribution of each variable (input variable) shown in Table 7 is used for simulation. Note that this paper intends to derive the fatality rate from a comparative perspective. The simulation is carried out using a Monte Carlo simulation, and each variable is transformed to a distribution. Therefore, after simulation, the values of each variable have a slight deviation from the crisp values. For example, the number of people is assumed to follow a normal distribution, and the value used for simulation is approximately 17 (with a variance of 0.2). Specifically, it is 16.993, which is shown in Fig. 12. Similarly, the values of other input variables can be derived. Second, the intermediate variables, such as the waiting time at the door, are connected with the input variables using the equations described in Subsections 2.3 and 2.4. Finally, the fatality rate is derived by comparing the ASET and RSET, if RSET is shorter than ASET, the fatality is defined as 1, and if RSET is longer than ASET, the fatality is defined as 0. After a Monte Carlo simulation using 10,000 runs by introducing GeNIe software, the fatality rate is 0.0589 and is shown in Fig. 12, which means there are 589 samples that the RSET is shorter than ASET. The reason why using 10,000 runs is that the result changes a little when increasing the runs, but will be 0.05 when the runs decrease to 1000.

From Fig. 12, the predicted fatality rate is 0.0589, which is close to the real death in this fire accident (i.e. 1/17 = 0.058). Moreover, the RSET is approximately 2 min (i.e., 116 s), which is also approximate to the real scenario because the majority of the crewmembers escaped from the fire accident at that time. Note that there are only 17 crewmembers in this fire accident, so the waiting time is very short and the longest waiting time in the fire accident is waiting at the door, which is 15 s. This is also reasonable since this ship is a bulk carrier and there are no passengers onboard. However, for fire accidents occurring on passenger ships, this waiting time will be long and will cause the RSET to be longer.

4. Discussion

According to Kwiecińska (2015), 9% of fire accidents are caused by unknown factors, which indicates special attention is required investigating such accidents (Baalisampang et al., 2018a). Moreover, fire accident development is complex and uncertainties exist when estimating the fatality rate, which may influence the accuracy of the result. One uncertainty is human response. In this paper, the human response is considered in two components. The first is detection time, which is derived from the accident investigation report, and the second is the individual behaviour in escaping the fire. In this paper, the human behaviours are considered from the statistical data given by IMO (IMO, 2016) according to four reasons. First, the statistical data has considered the human response, which is recommended by IMO guidelines that are also widely used for RSET estimation. Second, the individual responses are widely used for escape time estimation from a micro and absolute perspective. As this paper intends to estimate the fatality rate from a comparative and macro perspective, uncertainty exists but is acceptable from the comparative perspective. Third, the IMO also recommends equations considering the personal responses. However, this is very complex and is difficult to obtain the data in the emergency situation. Fourth, the crews and passengers are requested to participate in fire drills, and individual behaviours seem not as important, but uncertainty will exist if the personal responses are ignored.

Moreover, in this paper, only death caused by critical temperature and critical smoke is considered, while death caused by overpressure and when abandoning ships, which are also significant factors in fatalities in maritime accidents (Jasionowski, 2011; Hu et al., 2013), are not considered. Overpressure is ignored because the main hazards to occupants in fires are smoke, including toxic gases and heat (ISO,

Table 7
Quantified distribution of input variables.

Factor/variable	Description	Distribution
Corridor width [m]	The corridor is approximately 0.9 m wide	Normal (0.9,0.01)
Corridor length [m]	The corridor is approximately 24 m long	Normal (24,0.01)
Stair width [m]	The stairs are approximately 0.9 m wide	Normal (0.9,0.01)
Stair length [m]	The stairs are approximately 3 m long	Normal (3,0.01)
Evacuation location	The majority of crewmembers are in the wheelhouse and engine room	Custom PDF (0, −1,1, 0.2, 0.4,0.4)
Time of day	It is daytime or night-time, 1 = daytime, 0 = night-time	Custom PDF (1,0, 1, 0)
Detect and alarm time [s]	The interval of time from ignition until the fire is detected, and the crewmembers are alerted.	Normal (75,1)
Number of people	The number of people on board when the fire occurred.	Normal (17,0.2)
Fire drills	Well-trained or not, 1 = well trained, 2 = not well trained	Custom PDF (1,2, 1, 0)
Critical temperature [s]	Time when the temperature reaches 100–120 °C, which is derived from FDS simulation.	Uniform (152,167)
Critical smoke [s]	Time when the toxic gases reaches 1.65 m height, which is derived from FDS simulation.	Uniform (123,143)

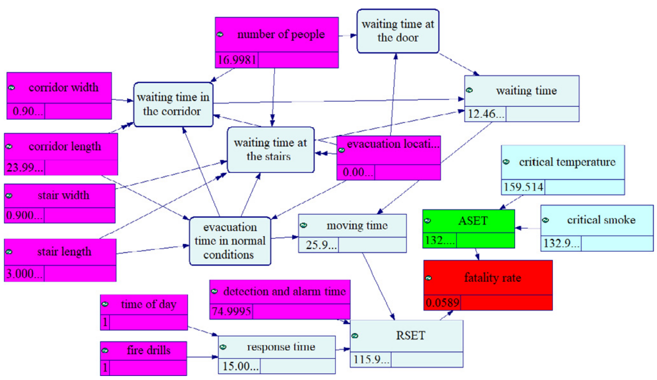


Fig. 12. Estimated fatality rate of fire accident.

1999). In fact, over 80% of fatalities in fires are caused by smoke. Thus, smoke is always the key concern in fire safety engineering (Zhang et al., 2011, 2017). In previous studies, the majority (Hanea and Ale, 2009; Kong et al., 2014; Wang et al., 2013) used critical temperature and smoke to derive ASET; however, overpressure will cause uncertainty and is not be discussed in detail in this paper. The fatalities caused by abandoning ships can be ignored in this specific scenario because the fatalities in this paper are caused by critical smoke. In the future, the time for escaping the fire and the time for abandoning ships should be incorporated to determine RSET from a holistic perspective.

Another significant factor to discuss is the derivation of ASET. In this paper, the ASET is derived using FDS when considering the critical temperature and critical smoke. In practice, when determining the critical time of temperature and smoke using FDS, three significant steps should be carried out. First, the ship cabin should be reconstructed, and the fuels should be defined. Second, the parameters of the fire accident should be set. Specifically, the fire source, HRR and mass loss rates should be specified. Third, the relationship between critical temperature (smoke) and time can be derived. From this analysis, these three steps will cost time because the process is slightly complex. However, in practice, if the estimation of fatality rate costs a substantial amount of time, the result will be meaningless because the response to the fire accident is restricted in time. Therefore, for a quick response to fire accidents and reducing the time for estimating ASET, two methods can be introduced to derive the ASET. First, historical data can be collected, and the distribution of the ASET can be used for estimation. Second, uncertainty analysis can be introduced to obtain the relationship between critical temperature (smoke) and time by using several simulations in different scenarios.

The last factor to discuss is the RSET. In this paper, the accident occurs on a bulk carrier. From the simulation result, the waiting time is very short because there are only 17 crewmembers, which means they did not need to wait since this scenario is not crowded. However, if a passenger ship is considered, the situation will be quite different. When the number of people increases from 17 to 40, the waiting time increases from 6 s to 34 s. Moreover, when the number of people reaches 60, the waiting time is 53 s. This is reasonable because when the number of people increases, there will be crowding in the corridor and especially at the door. Therefore, when estimating the fatality rate, this phenomenon should be noted and carefully considered. However, the stair width, evacuation location and other parameters are also different for passenger ships. When estimating the fatality rate of a fire on a passenger ship, the ASET, which is derived using FDS, should be updated simultaneously using a new simulation.

5. Concluding remarks

The main contribution of this paper is a probabilistic method for estimating the fatality rate of ship fire accidents. Specifically, the fatality rate is estimated by comparing the ASET and RSET. Since the fire accident is complex, this paper focuses on the fatality estimation caused by critical temperature and critical smoke, while the fatalities caused by subsequent incidents are not considered. FDS software, which is widely used for fire development simulations, is introduced to estimate the ASET in ship fires. Moreover, the RSET is estimated using equations derived from historical data in the guideline issued by the IMO. The advantage of the proposed method is that is provides a practical framework for estimating the fatality rate, which is useful for improving ship design and enhancing fire safety.

The proposed method can be extended to fatality estimation due to subsequent incidents, e.g., abandoning ship, flooding and human error. When applying the proposed method in practice, the waiting time in passenger ships should be carefully handled by changing the equations of ASET, which are derived using FDS simulations. Future work can be done to analyse the uncertainty of estimating ASET when considering different types of parameters and ship cabin structures. A generic relationship can be obtained to describe this relationship so the ASET can be quickly derived after the further analysis.

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