A Dynamic Bayesian Network Model for Predicting Congestion During a Ship Fire Evacuation

Parvaneh Sarshar, Jaziar Radianti, Ole-Christoffer Granmo, Jose J. Gonzalez

***Abstract*— In this paper, a new simulation model to analyze congestions in ship evacuation is introduced. To guarantee a safe evacuation, the model considers the most important real-life factors including, but not limited to, the passengers' panic, the age or sex of the passengers, the structure of the ship. The qualitative factors have been quantized in order to compute the probability of congestion during the entire evacuation. We then utilize the dynamic Bayesian network (DBN) to predict congestion and to handle the non-stationarity of the scenario with respect to the time. Considering the worst-case scenarios and running the simulation for two groups of passengers (different in sex, age, and physical ability), we demonstrate the distinct effects of these groups on the congestion. The role of decision supports (DS), such as evacuation applications and rescue team presence is also studied. In addition, the impact of congested escape routes on the evacuation time is investigated. The results of this paper are of great importance for maritime organizations, emergency management sectors, and rescuers onboard the ships, which try to alleviate the human or property losses.**

***Index Terms*—Congestion, dynamic Bayesian network, evacuation time, ship fire.**

I. Introduction

Each year, we witness different types of disasters all around the world. If we look for very recent disasters in 2013, we can find many natural or man-made disasters including Typhoon Soulik in China, Asiana Boeing 777 crashed and burned in San Francisco, or Boston marathon bombings. One of these hazardous situations is fire onboard a ship which requires an emergency evacuation either from some part of the ship or from the entire ship. Unfortunately, ship fire is not a rare accident. In 2013 several cruise fires have been reported from all over the world. For instance, fire on royal Caribbean cruise in Bahamas or the Carnival Triumph ship in Alabama. All these crisis situations dealt with a large number of people and needed a proper and safe evacuation in time.

Ship emergency evacuations especially during fire have always been very critical and vital. Many studies have been done on how to have the best evacuation during crisis situations and how different factors influence the evacuation and evacuation time. These factors can be passengers' characteristics (age, health, gender, interrelationship, and the degree of panic), onboard crew (skill and training level), and the ship structure (the number of decks, size and location of emergency exits, seats arrangement, etc.). The aforementioned factors can cause to a bigger problem during evacuation, i.e., congestion in the escape routes.

The international maritime organization (IMO) has defined congestion as [1] : 1) initial density equal to, or greater than, 3.5 persons/m2; or 2) accumulation of more than 1.5 persons per second between ingress and egress from a point. During an emergency evacuation, congestion can become critical and lead the evacuation time to exceed from the designated standards. This can be a surplus threat along with the actual hazard (fire) for passengers' lives during evacuation. Based on [2], a passenger may waste up to 89% of their personal evacuation time held up in congestion.

Most of the investigations on the evacuation procedure have also looked at the concept of congestion, clogging or jamming (see, e.g., [3]–[12]).This is an evidence to show the critical importance of these concepts. To prevent or solve congestion during emergencies, a variety of algorithms, applications or software developments, and/or corresponding regulations have been proposed in the literature. For instance, in [4]–[6], a social force model has been employed to scrutinize congestion caused by crowds. Several cellular automaton models have been proposed in e.g. [7]–[10] that focus on the occurrence of a congestion. Furthermore, Ferscha and Zia [10] developed a wearable device, called LifeBelt to handle the evacuation procedure and the inevitable congestion. Fujihara and Miwa [11] used opportunistic communications for handling congested routes. They showed a correct guidance can effectively reduce the congestion and evacuation time. Ad-hoc networks were used in a proposed disaster evacuation system in [12] to avoid congestion. IMO has also organized some regulations [1] that should be applied by marine organizations to avoid congestions during ship evacuation.

Going deep in the literature reveals the fact that the literature on congestion still lacks appropriate models to dynamically describe complex and uncertain situations in time. In this paper, we propose a new congestion model based on DBN, which is a potent tool to model highly uncertain conditions and to predict complex phenomena in time. In this regard, our proposed model analyzes the factors affecting congestion and predicts how the probability of congestion changes during an evacuation process in different time steps. In addition, we investigate the impact of the escape routes congestion on the evacuation time. We also study how the existence of DS can influence the

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congestion and evacuation time. The model and the results support the decision making process for the rescue team members and passengers onboard.

The novelty of the paper arises from the utilization of the DBN for congestion modeling and analysis in ship evacuation, which has not been addressed in the literature before. The proposed model considers the most important factors causing congestion on escape routes. The corresponding input of the model has been derived from the literature which makes the model more realistic and trustworthy.

The remainder of this paper is structured as follows. Section II describes the idea of DBN in details. In Section III, we illustrate our proposed DBN model. The results gained in this research are presented in Section IV and eventually, Section V concludes the paper.

II. Dynamic Bayesian Network

The DBN, firstly introduced by Dean and Kanazawa [13] in 1988, is an extension of the Bayesian network (BN) [14] to model dynamic systems, which vary over the time. In this regard, a DBN allows a probabilistic graphical model to describe the level of uncertainty with variety of applications targeting the computational complexity reduction and reasoning under uncertain situations. Analysis of highly complex phenomena and decision making in complex situations where, e.g., variables are highly interlinked [15] and/or data is ambiguous, are also parallel achievements of utilizing DBNs.

In DBNs, the system state at time t is shown by a set of random variables $X^t = X_1^t \dots X_n^t$. If the system state depends only on the immediate preceding state (i.e., $k = 1$), the system is called first-order Markov (Markov Chains) with the transition distribution $P(X^t|X^{t-1})$ given by [16]:

$$P(X^t|X^{t-1}) = \prod_{i=1}^{n} P(X_i^t|P_a(X_i^t)). \qquad (1)$$

Given GeNIe [17] as a domain to implement a DBN, the procedure of the design is quite similar to the one planned for a BN, which is reported in [15]. Accordingly, we start from a static BN containing variables (nodes) and dependencies (arcs). Defining the conditional probability table (CPT) of the nodes, we then quantify the considered qualitative factors, which have the most important impact on occurring congestion. In each column of CPTs, the probability values are normalized to fall into the range of [0,1]. As a result, the sum of the probabilities in each column must meet the unity.

To obtain the aforementioned probability distributions, there exist several methods in the literature. For instance, if the exact knowledge of data is not at hand, they can be determined based on suggestions from associated experts. Another classical method is to use maritime incident databases provided, e.g., in [18].

The next step is to convert the network to the DBN by equipping the BN with the temporal plates and temporal arcs. In this connection, Fig. 1 displays an example of the DBN developed in GeNIe. The illustrated network has one normal node, A, two temporal nodes, B and C, and a temporal plate consisting of 3 time steps. The straight darker

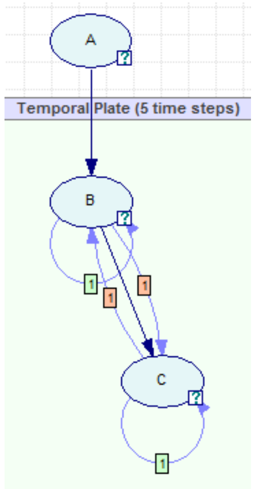


Fig. 1. An example of a DBN developed in GeNIe.

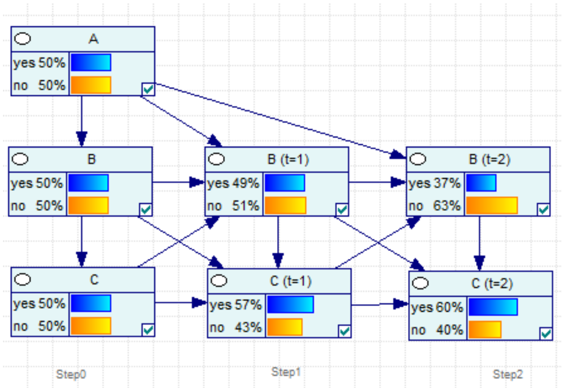


Fig. 2. The model unrolled for 3 time steps.

arcs are devoted to normal (static) arcs, whereas curvy lighter arcs with tags on them show temporal arcs. The temporal arc with the tag “1” exhibits the dependency of the child node at time t on the status of the parent node at time $t-1$. The node B with the shown temporal arc to itself demonstrates the fact that the status of node B in the former time step affects its current status. The choice of the tags and their orders change from scenario to scenario.

The joint probability density function of a sequence of t time steps can be attained by “unrolling” the network until t slices are at hand (see Fig. 2). In this way, the trend of the probability fluctuations for each node in all time steps can be analyzed in details. In the area of DBNs, the actual observation of an event is called *evidence*. By providing such evidences and updating the network, the whole network and belief of the nodes will be changed[1].

In this paper, the proposed DBN models the factors affecting congestion occurrence, assisting rescue teams to obtain a sound understanding of the evacuation procedure, passengers’ role and their impact on the evacuation time. This enables them to make the best decisions in case of emergency.

III. Our Proposed DBN Model For Congestion

In this section, we first overview the main factors affecting passengers to cause congestions during evacuation

[1] To study more details on the concept of DBN refer to [18] and [19].

of a ship burning in fire. These factors are employed in the DNB model designed in GeNIe. The congestion impact on the evacuation time is also studied.

To reduce the mathematical complexity of the proposed model, we consider some realistic assumptions, targeting a simple model. The simplification results in a very high-speed simulation model and very well suits for the optimization of the evacuation process, more especially in complex situations.

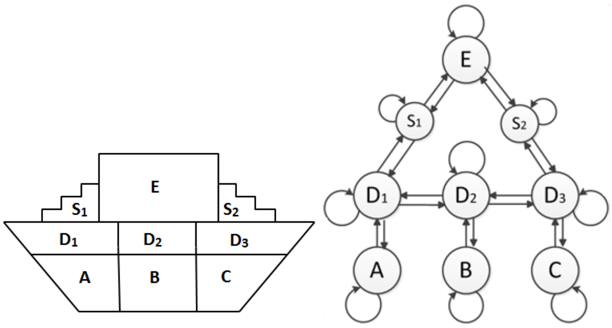
In this regard, we assume a simplified layout of the ship, which is shown in Fig. 3 (a). According to this structure, the ship consists of 3 compartments, A, B, and C, as well as a corridor divided into 3 sections, D1, D2, and D3. Referring to Fig. 3 (a), S1 and S2 display the staircases (or ramps for emergency exits) to link the three former sections to the compartment E which stands for the embarkation area (assembly station). Notice that compartment D2 has an access to the compartment E via the compartments D1 and D2, but not a direct access.

The associated bidirectional graph illustrating the connections between the aforementioned compartments is shown in Fig. 3 (b). Exemplarily, people are able to move from A to D1 or from B to D2 and vice versa, whereas for arriving at E, passing from S1 or S2 is indispensable. The loops connected to each compartment, present the fact that passengers might stay in their current locations as well (due to panic, congestion, or etc.). To make the model more realistic, we also suppose that the ship engine is located in compartment A (back of the ship), so the chance of the fire happening in this compartment is much higher than the others. Another assumption is that the compartment E is safe from getting fired. Therefore, as the safest compartment, this compartment is the final destination of the passengers and the rescue team. We also consider the day case scenario [1], where all the passengers are equally spread all over the ship (not in a specific compartment) except compartment E, which only consists of 25% of the crew (rescue team) members in normal conditions.

The network designed in GeNIe allows users to choose between two different views, namely icon view (as shown in Fig. 4) or bar chart view with more details (as shown in Fig. 2). Fig. 4 represents the proposed DBN model using icon view followed by Table I, which lists detailed information on cause and effect relationship of the nodes presented in Fig. 4. Herein, the oval shapes show the nodes and the arcs determine causal relationships between the nodes. The oval shapes with double lines are called deterministic nodes. The states of the nodes are provided in Table I. The rectangular shapes are called sub-models that have some nodes inside.

The initial probabilities and the CPTs are defined for the entire network. The CPTs are obtained according to the data in the literature, related databases, authors' reasoning. In future the input data to this DBN model can also be collected from the sensors installed on the ship and on the passengers' smartphones.

Based on IMO [1], the maximum total evacuation time for passenger ships is 60 minutes. In our model, we have divided this time into 15 time steps. We have also studied both the flow of passengers (macro model) and each individual (macro models). The simulation results are presented and discussed in the following section.



(a) (b)

Fig. 3. The simplified ship layout (a) and the corresponding bidirectional graph (b).

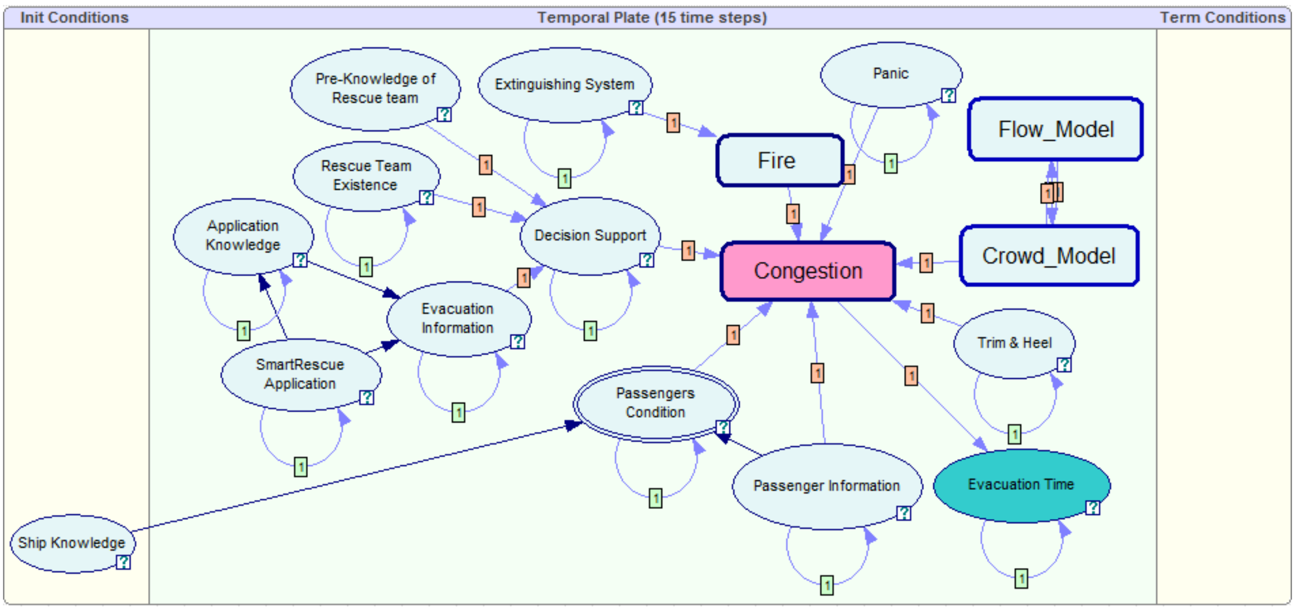


Fig. 4. Our proposed DBN model for congestion.

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TABLE I. THE DESCRIPTION OF THE DBN NODES AND THEIR STATES

Sub-models	# Nodes	Nodes	# states	States of each node	Description
Fire	8	A/B/C/D1/D2/D3/S1/S2	4	No Starting Developed Burnout	This sub-model consists of 8 nodes, and each node has 4 states. This sub-model can show how the probability of fire is dynamically changing through time steps.
Congestion	8	A/B/C/D1/D2/D3/S1/S2	2	Free/Congested	This sub-model shows the probability of congestions in each of the compartment.
Crowd	8	A/B/C/D1/D2/D3/S1/S2	3	Empty/Some/Many	This sub-model shows the crowdedness of passengers in each compartment.
Flow	24	In_A/Out_A/Decrease_A In_B/Out_B/Decrease_B In_C/Out_C/Decrease_C In_D1/Out_D1/Decrease_D1 In_D2/Out_D2/Decrease_D2 In_D3/Out_D3/Decrease_D3 In_S1/Out_S1/Decrease_S1 In_S2/Out_S2/Decrease_S2	2	True/False	This sub-model computes how the flow of passengers moves among different compartments.
		Extinguishing System	2	Reliable/UnReliable	This node shows the status of the extinguishing system of the vessel, if they are working properly or not.
		Trim & Heel	2	Yes/No	This node shows if the ship is vertically or horizontally imbalanced.
		Rescue Team Existence	2	Yes/No	This node represents if the passengers have the guidance of the rescue team members rather than being alone on their own during a disaster.
		Pre-Knowledge of Rescue Team	2	Yes/No	This nodes depicts if the rescue team members have been trained properly.
		Application Knowledge	2	Yes/No	“Application” is an emergency mobile app that is developed in the SmartRescue project. The node represents if the passenger is familiar with the app or not.
		SmartRescue Application	2	Working/Not-working	This node indicates if the application is working on mobile phones or not.
		Evacuation Information	2	Yes/No	This node explains if the passengers are receiving any information about the evacuation procedure using their smartphones which are equipped with SmartRescue application.
		Decision Support	2	Yes/No	In this paper, decision support (DS) means if the rescue team members are doing their assigned tasks during emergencies properly, if they have been trained efficiently, if the SmartRescue app is working and the passengers have the sufficient knowledge about it.
		Panic	2	Yes/No	This node represents the passengers' psychological condition if they are panicking or not.
		Passenger Condition	2	Safe/Injured	In this model, even though passengers can also have the state “dead”, it is not considered due to the fact that a dead passenger cannot trap in congestion, so does not influence the evacuation time.
		Passenger Information	10	Female_under_30 Female_between_30and50 Female_above_50 F_Disabled_under_50 F_Disabled_above_50 Male_under_30 Male_between_30and50 Male_above_50 M_Disabled_under_50 M_Disabled_above_50	Based on IMO [1], the passengers in ships are divided into 10 different groups based on the gender, age and disability.
		Ship Knowledge	2	Yes/No	This node indicates if the passengers have any pre-knowledge about the structure of the ship.
		Evacuation Time	2	Exceeded/Standard	This node denotes the duration of evacuation process, if it is on time or exceeding the expected duration.

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IV. Results

We were able to run the simulation for variety of scenarios in our model, but we have carefully selected the more interesting and critical scenarios. The aim of these simulations which have been targeted in different scenarios is a three-fold:

- To observe the role of different factors on congestion, and to study the dynamicity of congestion in different time steps of the evacuation (scenario 1).
- To learn how the congestion can impact the total evacuation time (scenario 2).
- To find out how differently the two genders in the same age can react toward congested escape routes (scenario 3).

To gain these objectives, some assumptions have been made. First, the fire starts in compartment A, since the engine room is there. Second, we have studied worst-case scenarios, where all the evidences achieved from sensors, rescue team members, or smartphones present the worst situations. For instance, the status of “Panic” is “Yes”, which means passengers are panicking, the ship is not stable, so the evidence entered for the node “Trim & Heel” is “Yes”, and there are “Many” passengers in compartment A (node “A” in the sub-model “Crowd” has the status “Many”).

In the first two scenarios we simulated the flow of passengers, which is a macro model, but in the last scenario, we studied the impact of each individual on congestion which indicates the micro model. In the first scenario, we ran the simulation for the mentioned assumptions twice, once without the existence of the DS and the second time, with the existence of the DS for two compartments A and S1. We are able to follow the simulation results for all the compartments and see how congestions are happening in all of them. Nonetheless, we chose only the most important compartments, i.e., room A, since the fire is happening in A and S1, since it is a critical escape path and as a stair, is considered a bottleneck.

Fig. 5 illustrates how the probability of congestion occurrence changes in 15 time steps in compartment A and S1. As can be seen, when there is no DS for the crew and the passengers in compartment A, the probability of congestion grows up to 100% in time step 6. That means, in that time step almost all the passengers in compartment A have started evacuating the place and the probability of congestion reaches to the highest amount. But later in the evacuation, some passengers exited from the compartment, therefore the probability of congestion drops to almost 85%, but remains constant that means not all the passengers in A, are able to leave this hazardous compartment in the standard evacuation time. Almost the same trend applies for S1, when there is no DS. The congestion arises fast after 3 time steps, that means some evacuees get to the stairs after knowing about the fire. After 10 time steps, the probability of congestion in S1 reaches 100% and can be observed that congestion is not solved during the standard evacuation time.

On the other hand, when the passengers and the rescuers have the benefit of DS, even though the probability gets to more than 30%, the congestion in compartment A can be handle after 11 time steps. The situation seems tougher in S1, where the probability of congestions peaks at more than 50%, but it can still be managed after 13 time steps. Where the probability of congestion gets to 0%, this can indicate the fact that either the evacuation has been over or it is being handled smoothly, without any congestion.

In the second scenario shown in Fig. 6, the probabilities of the evacuation time to exceed the standards while the DS is and is not at hand are compared. The probability that the evacuation time exceeds when there is no DS, increases sharply to 100% after 8 time steps and cannot be compensated afterward, whilst the presence of DS helps the evacuation to improve significantly. Although, the probability of the extension of the evacuation time seems to be inevitable and escalates to 45%, the DS can suppress this growth efficiently.

In the last scenario shown in Fig. 7, we focus on the individuals during evacuation procedure that is considered as a micro model. We still follow the assumptions for the worst-case scenario. Since, based on our model, there are 10 distinct groups of passengers onboard, as a case study, we chose a female and a male under 30 years old, both staying in compartment A at the time fire ignites. Fig. 7 represents how these two case studies face the congestion. Both of them start to stick in congestions after 3 time steps. But the female passenger is facing the congestion for a longer time up to 14 time steps and the probability of trapping in congestions arises to 90%, but finally she can evacuate the ship. While, the male passenger can evacuate the ship faster in 10 time steps and the highest probability for him to get stuck in congestion in bottlenecks is around 40%.

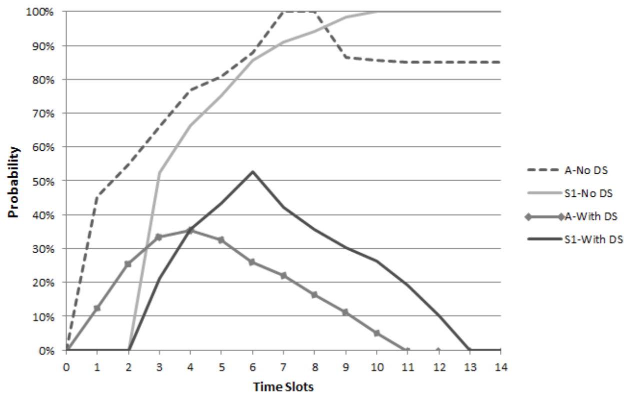

Fig. 5. The probability of congestion occurrence in compartment A and S1, with/without the existence of DS

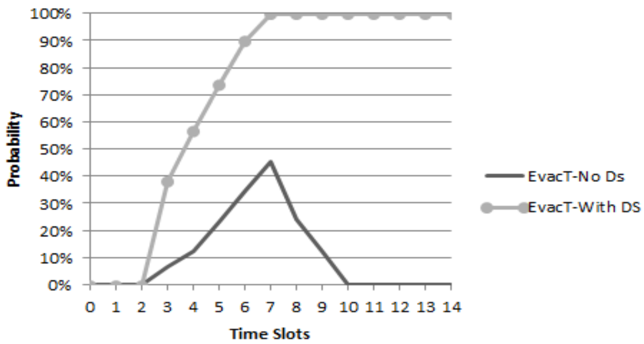

Fig. 6. The probability of the extension of the evacuation time, with/without the existence of DS

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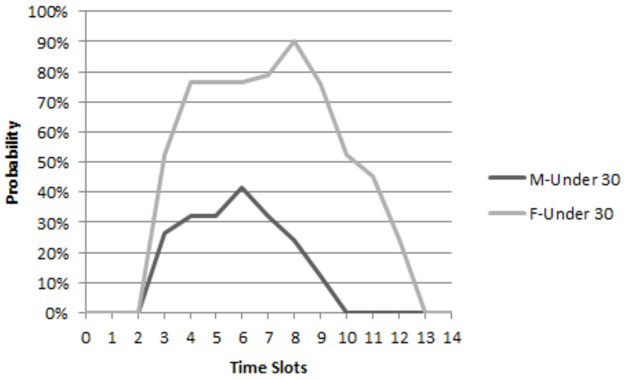

Fig. 7. The probability of trapping in (facing) congestions for a male and a female passenger under 30 years old

V. Conclusion

This paper has presented a DBN model for analyzing congestion during evacuating a ship burning in fire. The proposed model has considered the most significant factors affecting congestion occurrence. We have studied the real-time variations of the congestion and its impact on the evacuation time. The analysis has been performed for the two different genders of the same age. The probability of congestion occurrence for a flow of passengers has also been investigated. It has been shown that the existence of DS can reduce the probability of occurring congestions, considerably. This reduction is up to about 35% for a fully available DS. The results of this paper assist rescuers to make more accurate decisions. Further investigations towards studying the congestion in bottlenecks can be carried out in future works.

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