IoT Performance for Maritime Passenger Evacuation

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***Abstract*—The safe and swift evacuation of passengers from Maritime Vessels, requires effective Internet of Things (IoT) and information and communication technology (ICT) infrastructures. However, during emergencies, delays in IoT and ICT systems that provide guidance to evacuees can impair the effectiveness in the evacuation process. This paper presents simulations that explore the impact of this key aspect. The methodology builds upon the deadline-aware adaptive navigation strategy (ANS), offering at each decision step the path segment which minimizes the evacuation time for each evacuee. The simulations on a real cruise ship configuration, show that delays in the delivery of correct instructions to evacuees can significantly hinder the effectiveness of the evacuation service. These findings stress the need to design robust and computationally fast IoT and ICT systems to support evacuation systems for ships, underscoring the key role played by IoT for the success of passenger evacuation.**

In case of emergencies, evacuation methods are critical to managing people and vehicles in a manner that guarantees their safety [1–3]. These methods rely on the sensing, communication, and signaling technologies that are required to (a) know where people and vehicles are located, (b) how one can communicate with them or inform them about ongoing conditions, so as to (c) direct them along effective pathways towards safety.

Research in this area includes the use of sensing and communication technologies [4], crowd monitoring [5], hazard modeling and prediction [6], evacuation simulation [7], and evacuation path planning [8]. In particular, offline simulation of evacuation schemes 30 aids the design and comparison of the sensing and communication technologies, and of the algorithms [9] that improve or optimize the performance and robustness of evacuation strategies.

Thus, emergency management simulation research addresses simulations that represent the movement of people who congregate in sports arenas, touristic sites, and other leisure venues [10,11], as well as in large ships [12], in the presence of unusual and extreme conditions such as the breakdown of some facilities or adversarial situations such as fire or panic.

With the increased popularity of the cruise ship industry worldwide, more attention has been paid to passenger safety in maritime transportation [13]. Although advanced accident prevention systems are deployed in modern passenger ships, maritime transport accidents unfortunately do occur, such as the Sewol Ferry accident in South Korea that caused 304 casualties on April 16, 2014 [14], the Chinese Eastern Star accident that caused 42 casualties on June 1, 2015 [15], and the collision of two passenger ships in the Padma River in Bangladesh, resulting in 26 deaths on May 3, 2021 [16]. Therefore effective evacuation methods for passengers on cruise or passenger ships are of great importance [17], and significant research is recently being conducted in this area [18].

Since such accidents or emergencies cannot be artificially created or reproduced, or easily observed for data analysis when they do occur, the simulation of human evacuation on ships has become a key tool in the design of both civilian and military naval vessels [19–21]. In particular, the International Maritime Organization (IMO) has issued several Circulars about evacuation simulation and analysis for passenger and roll-on-roll-off ships, and the IMO approved the guidelines for evacuation simulation for new and existing passenger ships in 2016 [22]

However, this research and guidelines do not consider many realistic features that impact the speed and safety of human beings during emergencies [9,23], such as variations in traversal times across passages and staircases due to the age and conditions of passengers as well as vessel motion, human behavior uncertainty caused by the misunderstanding instructions, as well as panic, noise, and overcrowding. To these a priori unpredictable aspects, one must add the impact of technology, such as network congestion resulting in delay and loss of messages which impairs the correct and up-to-date instructions that are received by the evacuees [24,25]. Hence, this paper investigates the influence of such random 62 effects on the performance of state-of-the-art simulation methods for vessel evacuation.

emergency management simulation, of imperfections that result from communication technology, e.g. lost or delayed messages, as well as from the misunderstanding of instructions or panic by the passengers. The tool with which we illustrate and evaluate these effects is built on the AnLogic simulator [26] as described in Section 2.

AnLogic is used as part of the current offline simulation study, but we do not claim or suggest that this tool should be used for real-time decision-making during an emergency. We expect that the system used to manage the emergency could include a fast discrete-event purpose-built simulator that updates - in real-time – the dynamic spread of hazards which are reported via physical sensors installed in the cruise ship, or other built structures, which are being considered.

The rest of the paper is organized as follows. The related work about evacuation in passenger ships and built structures

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is reviewed in Section 1.1. A detailed description of the ship emergency evacuation simulation we use is described in Section 2, while the simulation results regarding the impact of delay and lost messages, which result from communication system congestion, are given in Section 3. Then, Section 4 discusses simulations of the effect of uncertainties in human behavior. Finally, Section 5 provides conclusions and suggestions for future research.

There has been extensive work in using the IoT to support emergency management[27], and advanced systems such as Unmanned Aerial Vehicles have also been suggested as a means to provide further observation and sensing. While the current study does not assume that individual evacuees are localized and tracked during the evacuation, there has been work on the issue of localization of specific groups of people, such as elderly people who may have greater difficulty in reaching exits safely.

Emergency management systems that direct evacuees typically use Path-planning algorithms (e.g., Dijkstra, A*, RRT, Ant Colony Optimization, Genetic algorithms, Cognitive Packet Networks, etc.,) to minimize evacuation delay or to maximize the distance from the hazard nodes to the exit node, using 2D/3D maps of a built environment [30,31]. However, the decisions regarding the choice of paths do not always include the effects of unexpected hazards that may be encountered, such as the spread of a fire, flooding of parts of the ship, or failures in the emergency management systems themselves.

Some work has attempted to address the dynamics of danger through the Expected Number of Oscillations (ENO) concept [32], which quantifies the dynamics of the emergency and explores navigation paths that have the smallest probability of changing repeatedly. Furthermore, such global path planning methods require that the system be completely specified regarding the parameters needed to choose optimal paths, in contradiction with many realistic situations. Therefore, follow-up studies have relaxed the 101 requirement that all the information about the hazards and exits is precisely known prior to path computation, which enhances their applicability [9,33].

Methods such as Artificial Potential Fields [34], and local neighborhood techniques [35,36] with possible partial reversal, can help evacuees avoid entering hazardous areas. However, most studies do not consider the need to provide directions that assure that the "time needed to reach the exit" for each evacuee, remains under a specified upper bound (e.g., the ship survival or capsizing time) in worst-case circumstances. Thus this paper uses the ANS evacuation algorithm [37], which explicitly incorporates a guaranteed exit deadline bound, for each evacuee in each location. This deadline bound can be obtained, as described below, from the known recommendations of the International Maritime Organization (IMO) when dealing with ships, and there are corresponding safety recommendations for office buildings, dwellings, etc.

We now describe the simulation framework that we use to evaluate the effects of both the computer and communication technology delay in providing routing instructions to evacuees, and the uncertainties related to their behavior, within an event-driven simulation framework. This framework contains two parts:

The first part is the simulation software AnyLogic [26], in which the layout of the physical where the evacuation occurs, is incorporated. The "pedestrian" software library of AnyLogic adopts a social force model, similar to social potential fields, for the movement of evacuees. Secondly, we add a path-planning module written in Python, that computes the evacuation direction for evacuees based on ANS, which is described below. This module transfers the computed instructions to the AnyLogic simulation software at each simulation step when the movement instructions need to be updated.

ANS is implemented in our simulator to move evacuees along the path with minimum delay, avoiding the harmful effects caused by dynamic hazards. ANS assumes knowledge about the propagation of hazards (velocity and direction), and the typical and worst-case delay across each edge in the paths.

As hazards progress in the simulation, ANS calculates for each evacuee the direction it should take to avoid hazards. In a real evacuation, this direction should be computed and then communicated to each evacuee via a wired or wireless network. In previous 135 work, the possible delays of this communication were not taken into account. However, wireless or wired networks, and computational servers that are used for decision-making, are likely to experience congestion, especially in emergency situations when decisions and communications are frequently updated and many messages are sent to evacuees, and to the staff in the ship. This congestion can cause delays in updates regarding the navigation direction, and transmitting network packets and hence messages can be lost, and decisions may contain errors due to the use of delayed or obsolete data in the decision algorithms [39–41]. While most prior work neglects these effects, the present paper specifically evaluates their impact on the resulting time 144 needed for evacuation.

In addition, the passengers being evacuated may themselves be unable to follow the instructions they receive due to noise, panic, or misunderstanding. 147Thus these delays and possible errors due to Information and Communication Technology (ICT), including network packet losses, as well as the possible effects of panic 149 or misunderstandings by the evacuees, will be simulated and evaluated in this paper.

The IoT could – in principle – use the personal identification of each passenger via "smart badges", "RFID" (radio-frequency identity), or communicating "wristwatches". However such devices requiring radio-frequency communications can be unreliable within naval vessels. Indeed, ships can have high steel content with possible Faraday cage effects, as well as the refraction and reflection of high-frequency radio waves. In addition, the numerous electric motors (e.g. for ventilation and lifts) and ongoing automatic switching of equipment (e.g., on-off of air-conditioning equipment, multiple refrigerators, fans), as well as multi-path reflections, can lead to substantial radio-frequency interference. Thus in this paper, we assume that individual identification of the location of each passenger is not used.

However, we do assume that Infrared Sensors, connected to the ICT infrastructure, are placed throughout the vessel (in cabins, corridors, etc.) to detect human presence without identifying the individual. Of course, such sensors can also detect hazards such as high temperatures caused by fire, and electrical short circuits. There will also be a variety of temperature and smoke sensors. Passage locations and Common Areas (e.g. restaurants, decks, bars and lounges) are equipped with video cameras to estimate the number of people present, and also for the purpose of security.

In addition, throughout the ship and connected to the ICT infrastructure, there will be various Emergency Direction Providers (EDPs). These will activate if an emergency, and will have red/white signs throughout the locations of the ship, which flash and provide directions to the passengers, with instructions such as "Exit Here", "Turn Right", "Turn Left", "Go Straight", "Wait Here", etc. to provide directions to help evacuate the passengers. The ICT infrastructure is connected to a reliable Data Center (DC) which must contain the passenger and staff list, which can be updated when passengers or staff leave or join the ship (for instance at intermediate stops during a cruise or journey). Note that both the LAN and DC infrastructure should – to the extent possible – include redundancies in network communication paths and equipment in order to deal with system failures, or damage to some equipment during an emergency. In case of an emergency, the DC runs the ANS evacuation algorithm to determine for the passengers, the Evacuation Movement Recommendations (EMRs). Thus the simulations in the present paper evaluate the effectiveness of the EMRs in the presence of: Delays in the reception of the EMRs at the locations of the EDPs throughout the vessel. These delays can be caused by LAN delays and congestion, and DC delay and congestion during an emergency. Errors made by evacuees in following instructions from the EDPs during an emergency evacuation, due to confusion and panic. System Parameters for the Simulation. The indoor environment we simulate is the second, third, and fourth floors of the Yangtze Gold.

The indoor environment we simulate is the second, third, and fourth floors of the Yangtze Gold 7 Cruise Ship, as shown in Figure 2, with 346 nodes from which evacuees originate or pass through, including connection points between corridors or rooms through which evacuees may pass, and a single exit node for the evacuation. There are also 6 passageway segments and 5 staircase segments in the graph that connect these nodes.

In our simulation setting, the worst-case traversal time across each segment is calculated according to the worst-case traversal speed of the evacuees, which is set to 0.067 meters/second. On the other hand, the typical traversal time experienced in traversing each segment is calculated based on the average moving speed on a passenger ship where the walking condition remains "horizontal", i.e. when the ship is in normal safe conditions, which is 0.67 meters/second. In addition, the total time available to an evacuee for evacuation, for an evacuee who receives the "evacuate" message, is denoted by TD and can be estimated as follows:

where TS is the ship's survival duration (e.g. until it capsizes), TA is the delay between the start of the emergency until the "evacuate" message is received by the evacuees, and TEL is the embarkation time plus the launching time for life-boats, i.e., the time required to abandon the ship, for all the evacuees who have reached the exit point.

The schematic diagram of the simulation layout for the three passenger floors of the Yangtze Gold 7 Cruise ship is shown in Figure 2. The dotted diagram on the right-hand side shows the "dots" (i.e. nodes) which are locations where passengers may be staying or meeting (e.g. cabins, lobby, and restaurant), while the edges show the passageways, stairs, or corridors. The simulation also allows the inclusion of the effect of the inclination angle of the damaged ship, which can change at regular intervals. This can affect the average traversal time encountered across each individual corridor or staircase which changes (shorter or longer time) with the inclination.

Schematic description of the layout for the Yangtze Gold 7 Cruise ship over three passenger floors (second, third, and fourth). This layout is used for simulating all the effects studied in this paper, including the delays in communicating the guidance information to the evacuees, and the possible uncertainty in the behavior of the evacuees. of both the delay in navigation service and the behavior uncertainty. Here (a) is the layout of the physical space of the second, third, and fourth floors, and (b) is the evacuation graph model of the physical space.

The ANS provides each evacuee, at each of the nodes of all the evacuation paths in the ship, an estimate of the next-step hazard-free node that the evacuee should enter to head toward the exit, based on the estimated total minimum delay from its current location to the exit. However, conditions during emergencies are highly dynamic and can rapidly change with time. Furthermore, the computer and communication system that computes these directions and forwards the decisions to the nodes on each path may be congested during an evacuation. Thus the resulting messages to evacuees may be delayed or lost. Therefore, in this Section, we analyze the impact of these possible delays, which are caused by performance imperfections and congestion of the underlying Information Technology System (ITS). To this effect, we define the "information lag" (IL) which refers to any generic node in the ship evacuation topology. IL = 0 means that each node in the evacuation topology of nodes and paths has received, from the ITS system, the exact direction recommendation which is based on the current true location of the evacuees at each node. On the other hand, IL = 1 means that each node provides information to the evacuees, regarding the next move they should make, based on the status of all nodes based on the location of the evacuees just prior to the current arrival of evacuees to their current node. Thus IL = 1 means that the computation and transmission of the information is delayed by one step. We also define the "probability of delay" (PoD), which indicates whether the information lag is IL = 1 with probability PoD or IL = 1 with probability 1 - PoD. PoD is a value that is probabilistically attributed to each node, since the delay may differ from node to node, due to the communication system delays. In the rest of this section, we evaluate the effect of PoD on the evacuation system's performance. All simulation results that are shown, are obtained by drawing the probability PoD separately for each of the nodes, and for 100 independent simulations, under the same initial conditions. The figures that are shown for each simulation, also show the 95% confidence intervals.

The first evaluation is conducted to determine the average evacuation time from all of the 346 nodes, relative to the ideal case with IL = 0. Thus Figure 2 (a) depicts the average evacuation time from all possible 346 starting nodes until the exit, as a function of PoD. Figure 2 (b) shows the performance ratio of average evacuation time for different values of PoD, to the average for the ideal case of PoD = 0. Averages are taken over all nodes and based on 100 distinct independent simulations. We also show the standard deviation (black bars) for the value of the evacuation time from all of the 346 nodes. These curves show clearly that as PoD increases to 0.5, the increase in average evacuation delay is quasi-linear, but that for higher values the increase continues but more slowly. When for all nodes PoD = 1, the average evacuation time over all nodes is 50% higher than PoD = 0 (where the ITS provides up-to-date information to all nodes). In addition, we also implement a group of simulations to evaluate the average evacuation time for passengers located in cabins. 3 (above) illustrates the average evacuation time taken by the passengers originating from cabins, influenced by different probabilities PoD. The performance ratio in average evacuation time for passengers in cabins, relative to the case PoD = 0, is given in Figure 3 (b). It can be observed that the evacuation of passengers from cabins deteriorates with the increase in PoD. Next, we measure the average evacuation time for passengers located in the restaurant. Figure 4 (a) presents the average evacuation time of passengers who stay in the restaurant. It is obvious that IL has a slighter influence on the evacuation time of passengers in the restaurant compared to that of passengers in cabins when PoD is low, such as PoD = 0.1 and PoD = 0.2.

The average evacuation time from all 346 nodes to the exit (above), as a function of PoD (x-axis), and (below) the performance ratio in average evacuation time as compared to the ideal case of PoD = 0. Averages are over all nodes for 100 distinct independent simulations, with the standard deviation (the black bars) for the evacuation time.

The average evacuation time taken by passengers in cabins to the exit (left), as a function of PoD (x-axis), and (right) the performance ratio in average evacuation time as compared to the ideal case of PoD = 0. Averages are taken over all passengers starting from cabins for 100 distinct independent simulations, with the standard deviation (the black bars) for the evacuation time.

Finally, we perform a group of simulations to evaluate the average evacuation time for different numbers of passengers, influenced by different PoD values. In this group of simulations, half of the passengers are randomly located in the cabins, while the other half stay in the restaurant. Note that there are at most two passengers in a cabin due to the capacity limit of the cabin. As shown in Figure 5 (a), the average evacuation time exhibits an increase with the growing of passengers. This is mainly attributed to the increased waiting time resulting from the more serious congestion due to a large scale of passengers being evacuated. Besides, we can also see That the average evacuation time increases with PoD, regardless of the number of passengers. Figure 5 (b) shows the performance ratio in average evacuation time for different numbers of passengers under the impact of different probabilities PoD. The performance ratio is always larger than 1, which indicates that as PoD is larger, then the evacuation duration grows, and the impact is more significant for higher PoD.

When an emergency occurs, the motion of evacuees may be influenced by panic or difficulties in reading or hearing the instructions, resulting in their choice of a random direction instead of the direction provided by the evacuation system. Therefore, in this Section, we investigate the impact of the non-compliance with the evacuation suggestion. To this effect, we define the "probability of error" denoted as PoE, which indicates whether a passenger does not obey the provided evacuation direction with probability PoE or moves.

PoE is a value that is a probability that is chosen itself at random and attributed to each passenger, since the behavior may differ from passenger to passenger.

First, we conduct simulations to measure the average evacuation time from all of the 346 nodes to the exit under various values of PoE. Figure 6 presents the results of the performance ratio in the average evacuation time, relative to the ideal case with PoE = 0 where passengers fully comply with the ITS recommendation. Clearly, all the values of the performance ratio exceed 1, which shows that the behavior uncertainty of passengers prolongs the average evacuation time. Besides, we can observe that with the increase in the probability with which passengers ignore the evacuation guidance, the performance ratio in average evacuation time also increases. However, compared to PoD, the uncertain behavior of passengers has a less pronounced effect on the evacuation time. We also carry out a set of simulations to evaluate the impact of behavior uncertainty on the evacuation time of passengers in cabins. Passengers are initially located at random, at nodes representing passenger cabins. Figure 7 plots the average evacuation time and the performance ratio in average evacuation time compared to the ideal case with PoE = 0. The standard deviation is also shown for the evacuation time taken by passengers in cabins. It can be observed that the average evacuation time increases with the increase in the probability of behavior uncertainty.

The average evacuation time with a 95% confidence interval, taken by different numbers of passengers where half of them originate in the cabins, while the other half start from the restaurant (above), and (below) the performance ratio in average evacuation time as compared to the ideal case with PoD = 0. The performance ratio in average evacuation time from all of the 346 nodes to the exit compared to that in the ideal case with PoE = 0.

The average evacuation time taken by passengers in cabins and the performance ratio in average evacuation time compared to the ideal case with PoE = 0.

The average evacuation time for passengers in the restaurant is also measured as shown in Figure 8. We can see that failing to escape according to the provided navigation direction impairs the capability of the evacuation scheme and prolongs the average evacuation duration for passengers originating from the restaurant. Again, it is evident the uncertain behavior results in a relatively milder increase in the average evacuation time for passengers in the restaurant compared to passengers in cabins. Furthermore, we measure the average evacuation time for different numbers of passengers with different probabilities of neglecting the supplied navigation direction. In this group of simulations, half of the passengers are placed in the restaurant, while the other half stay in their cabins. Figure 9 plots the average evacuation time with the 95% confidence interval for different numbers of passengers with different probabilities of uncertain behavior. We can see that the average evacuation time increases with the increase in the probability of behavior uncertainty. However, behavior uncertainty has a minor effect on average evacuation time, especially when the number of passengers is smaller than 300. Generally, the impact of behavior uncertainty is less than the effect of PoD, which means that the ANS method is more resilient to behavior uncertainty to ITS system error.

The average evacuation time for passengers in the restaurant and the performance ratio in average evacuation time compared to the ideal case with PoE = 0.

The relative difference in evacuation time between escaping without behavior uncertainty and with different uncertainty probabilities for each evacuee located at different nodes.

In passenger ships and other large vehicles and aircraft, reliable emergency evacuation is required for ensuring passenger trust in the means of travel, and for their safety and wellbeing. Thus over the last decade, substantial research has been conducted in designing 336 technology-assisted means to provide passengers with the best advice regarding evacuation procedures during emergencies [42] and many of the proposed approaches use some form of optimization [43]. However during emergencies, especially if the vessel is damaged, it becomes very challenging both for the underlying ICT (Information and Telecommunication Technologies) and for the passengers and staff to implement and follow instructions that are based on prior optimization and established routines. In addition, the ICT infrastructure may also be damaged and disconnected, and the recommended evacuation routes and the communication network may be congested. Thus the need to support evacuee safety and evacuation in such complex and dynamic environments with many rapidly changing variables can also overwhelm the ICT-based emergency management system itself [44]. In addition, path planning based on the updated emergency situation may be accompanied by messages that flood the communication system about environmental dynamics, aggravate congestion, and result in packet losses and longer end-to-end delays in communicating 350 decisions. Thus this work is the first study of the influence of such key side effects of emergency evacuation in a practical ship evacuation scenario. Through extensive simulations, this paper

analyzes the effects on passenger evacuation performance in ship emergencies, of realistic features including the behavior uncertainty represented with different probabilities, the dynamics of traversal time with change frequencies, and the different delays in the arrival of navigation instructions to passengers. Furthermore, these simulations use real-world parameters from the real passenger cruise ship "Yangtze Gold 7" and its passenger evacuation system, and evaluate the effect of delays in the information that reaches the human evacuees during its passenger evacuation. Assuming that ongoing situational information is gathered by wireless sensor networks [45–47], we have considered the effect of delayed decisions which are computed and forwarded by a central decision ICT system, to all end evacuees as they pass through pre-determined "nodes" that guide them towards safe exit points. As these delays increase, we see that the emergency exit times of passengers are often substantially increased. Although the current study is conducted on a detailed representation of a specific cruise ship, we may expect that the main conclusions of the present study, regarding the impact of delays of the ICT and IoT system in conveying the evacuation recommendations to the evacuees, and of the errors that evacuees may make in following these recommendations, would also carry through to similar situations in large buildings, streets, etc. 371 In future research we plan to take into account the delaying factors in advance, so as to design novel decentralized emergency navigation systems for guiding passengers to safety, that prelocate advisory data to passengers in key system intermediate locations, and also combine centralized decisions together with individual evacuee decision aids with hand-held mobile devices [36].

Index Terms—**ship evacuation, IoT, emergencies, passenger safety, IoT and ICT performance**

I. Introduction

In the context of emergencies, the effectiveness of evacuation methods is crucial for ensuring the safety of people and vehicles [1]–[3]. These methods rely on technologies encompassing sensing, communication, and signaling, which play pivotal roles in (a) locating individuals and vehicles, (b) communicating with them to relay information about ongoing conditions, and (c) guiding them along efficient pathways to safety.

Research in this field involves the utilization of sensing and communication technologies [4], crowd monitoring [5], hazard modeling and prediction [6], evacuation simulation [7], and evacuation path planning [8]. Specifically, offline simulation of evacuation strategies facilitates the design and comparison of sensing and communication technologies, as well as algorithms [9] aiming to enhance or optimize the performance and robustness of evacuation strategies.

Emergency management simulation research addresses the movement of people in diverse scenarios, including sports arenas, tourist sites, leisure venues [10], [11], and large ships [12], under unusual conditions or adversarial situations like facility breakdowns, fires, or panic. With the global growth of the cruise ship industry, passenger safety in maritime transportation has gained increased attention [13]. Despite advanced accident prevention systems, maritime accidents still occur, underscoring the importance of effective evacuation methods for passenger ships [14]. Recent research in this area has seen considerable developments [15].

Due to the difficulty of artificially creating or reproducing maritime emergencies, simulation of human evacuation on ships has become essential for designing both civilian and military naval vessels [16]–[18]. Notably, the International Maritime Organization (IMO) has issued Circulars and guidelines for evacuation simulation in passenger ships [19]. However, existing research and guidelines often overlook realistic features impacting human behavior during emergencies [9], [20], such as variations in traversal times and the impact of technology-induced delays and message loss [21], [22]. This paper investigates the influence of these unpredictable factors on the performance of contemporary simulation methods for vessel evacuation.

The paper employs a simulation framework to assess the impact of imperfections resulting from communication technologies, such as lost or delayed messages, and from passenger misunderstandings or panic during emergency management simulations. The tool utilized for this investigation is built on the AnLogic simulator [23], as detailed in Section II.

The subsequent sections are organized as follows: Section I-A reviews related work on evacuation in passenger ships and built structures, Section II provides a detailed description of the ship emergency evacuation simulation, and Section III presents simulation results regarding the impact of communication system congestion. Finally, Section IV offers conclusions and suggestions for future research.

A. Related work

Emergency management systems guiding evacuees typically employ **path-planning** algorithms, such as Dijkstra, A*, RRT, ANT Colony Optimization, Genetic algorithms, and others, to minimize evacuation delay or maximize the distance from hazard nodes to the exit node, utilizing 2D/3D maps of built environments [24], [25]. However, the resulting paths may become impractical as they include unexpected hazards like fire spread, flooding, or failures in emergency management systems. Efforts have been made to address dynamic dangers using the Expected Number of Oscillations (ENO) concept [26], quantifying emergency dynamics and exploring paths with the smallest probability of frequent changes. Global path planning methods often require complete system specifications, contradicting realistic scenarios. Subsequent studies relax this requirement, allowing for path computation without precise prior knowledge of all hazard and exit information [9], [27].

Methods such as Artificial Potential Fields and local neighborhood techniques [28], [29], possibly with partial reversal, help evacuees avoid hazardous areas. However, most studies overlook the necessity of providing directions ensuring that the "time needed to reach the exit" for each evacuee remains under a specified upper bound (e.g., ship survival or capsizing time) in worst-case scenarios. Thus, this paper adopts the ANS (Adaptive Navigation Strategy) evacuation algorithm [30], explicitly incorporating a guaranteed exit deadline for each evacuee in each location. This deadline bound is derived from the International Maritime Organization (IMO) recommendations for ships.

II. The Simulation framework

We present the simulation framework employed to assess the impact of computer and communication technology delays on providing routing instructions to evacuees within an event-driven simulation framework. This framework comprises two integral parts: (1) AnyLogic Simulation Software [23]: This software incorporates the layout of the physical environment where the evacuation takes place. AnyLogic utilizes a "pedestrian" software library employing a social force model, akin to social potential fields, for evacuee movement. (2) Path-Planning Module in Python: A path-planning module written in Python computes evacuation directions based on the ANS algorithm, an extension of the Rapid Routing with Guaranteed Delay Bounds algorithm [31] that was called ANT in prior work [30]. This module conveys computed instructions to the AnyLogic simulation software at each simulation step when movement instructions are updated.

The ANS algorithm is implemented in our simulator with the following features:

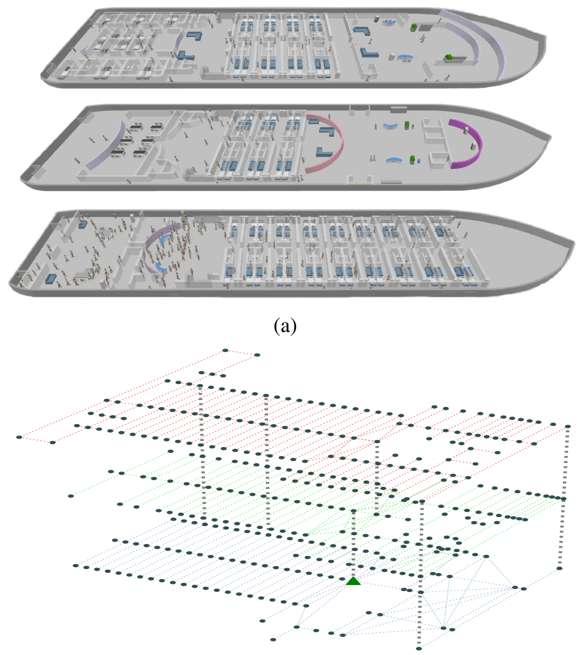
- ANS moves evacuees along paths with minimal delay, mitigating harmful effects from dynamic hazards. The algorithm assumes knowledge of hazard propagation (velocity and direction), as well as typical and worst-case delay across each edge of each path.
- As hazards progress, ANS calculates the direction for each evacuee to avoid hazards. In a real evacuation, this direction should be computed and communicated to evacuees via a wired or wireless network. Notably, prior work has often overlooked the possible delays in this communication.

Networks and servers used for decision-making may experience congestion, especially in emergencies when decisions and communications are frequent. This congestion can lead to delays in navigation direction updates, packet losses, and errors in decisions due to the use of delayed or obsolete data in decision algorithms [32], [33]. While previous studies often neglect these effects, this paper specifically evaluates their impact on evacuation time. Furthermore, potential delays and errors stemming from technology, including network packet losses and server failures.

The simulation framework serves as a comprehensive tool for assessing the intricate dynamics of evacuation scenarios, including the technology-induced delays.

A. System Parameters for the Simulation

We simulate the indoor environment of the second, third, and fourth floors of the Yangtze Gold 7 Cruise Ship, illustrated in Figure 1. The simulation includes 346 nodes



(a)

(b)

Fig. 1. Schematic description of the layout for the Yangtze Gold 7 Cruise ship over its three passenger floors (second, third, and fourth). This layout is used for simulating the effects that are studied in this paper, i.e., the delays in communicating the guidance information to the evacuees. Here (a) is the layout of the physical space of the second, third, and fourth floors, and (b) is the evacuation graph model of the physical space.

representing origin points, passageways, connection points between corridors or rooms, and a single exit node for evacuation. The graph also encompasses 600 passageway segments and 5 staircase segments connecting these nodes.

In our simulation setup, the worst-case traversal time across each segment is computed based on the worst-case traversal speed of evacuees, set at 0.067 meters/second. Conversely, the typical traversal time for each segment reflects the average walking speed on a passenger ship under normal safe conditions, set at 0.67 meters/second. The total time available for evacuation, denoted as T_D, is estimated for evacuees who receive the "evacuate" message:

$$T_D = T_S - T_A - T_{EL}, \tag{1}$$

where: T_S is the ship's survival duration until capsizing (e.g., 60 minutes), T_A is the delay between the start of the emergency until the "evacuate" message is received (e.g., 5 minutes), T_{EL} is the sum of embarkation time and lifeboat launching time for evacuees reaching the exit point. Guidelines from the Maritime Safety Committee (MSC) [19] specify $T_S = 60$ minutes, $T_A = 5$ minutes, and $T_{EL} = 25$ minutes, resulting in $T_D = 30$ minutes, unless otherwise stated. This simulation framework captures essential parameters for evaluating evacuation strategies in maritime emergency scenarios.

B. The IoT and Information and Communication (IC) Environment

The IoT and IC environment that is being considered, is composed of:

1) A centralized Data Center (DC) that stores the list of passengers and staff who are present on the passenger ship. This list is updated when the passengers or staff board the ship, as well as when anyone leaves the ship for various normal reasons, as well as when a passenger is evacuated through a designated exit.
2) The DC also computes the **Evacuation Recommendations (ERs)** and movement directions for all the passengers during an evacuation using the ANS algorithm.
3) A wired communication high-speed Local Area Network (LAN) that runs throughout the ship, with appropriate switching equipment. The LAN is connected to WiFi Hubs and sensors that are placed throughout the ship, including in the cabins, lounges and restaurants, and in the passageways and corridors used for normal movement of passengers and staff, and also used for evacuation.
4) The cabins and passageways contain Infrared Sensors that can detect human presence in different locations. These infrared sensors do not detect the identity of human beings, but simply their presence. Infrared sensors can also be used to detect high temperatures caused by fire and electrical short circuits.
5) Passageways and Common Rooms (Restaurants and Lounges) can also contain Video Camera Sensors, that help to count the number of people in a given area, and also help find people who may have lost their way, and may also be needed for security purposes.
6) Finally, also connected to the LAN, are *Direction Providers which turn ON during an emergency*. These may be red/white flashing signs that say “Go Straight”, “Turn Right”, “Turn Left”, “Wait Here”, etc. to provide directions to evacuees during an emergency. They are activated by the ANS algorithm’s ERs that are computed by the DC described in Item 1 above.

While the individual personal identification of passengers is not considered explicitly for the IoT system in this paper, systems using wireless “RFID” (radio-frequency identity), and “wristwatches” that broadcast the identity of the wearers, can also be used. However, IoT devices with wireless communications may be less reliable inside ships, due to the high metal and steel content of the naval structures, and the resulting absorption, reflection, and refraction of high-frequency radio signals, resulting in high interference and signal attenuation, which may require sophisticated bandwidth management, radio-frequency repeaters, and signal processing.

C. Layout of the Simulation Framework

The schematic diagram of the simulation layout for the three passenger floors of the Yangtze Gold 7 Cruise ship is depicted in Figure 2. On the right-hand side, the dotted diagram illustrates ”dots” representing nodes, which signify locations where passengers may congregate (e.g., cabins, lobbies, deck spaces, and restaurants). The edges in the diagram depict passageways, stairs, or corridors.

The simulation incorporates the effect of the inclination angle of the damaged ship, which can change at regular intervals. This inclination can impact the average traversal time across each corridor or staircase, varying with changes in inclination (resulting in shorter or longer traversal times). Thus the ANS provides the best advice that includes the estimate of traversal time, which may change due to the ship’s inclination. Each simulation is initiated by placing evacuees (passengers) over the nodes. The simulation is then repeated for 100 rounds, with the initial locations of the evacuees being randomized in each round. This approach ensures robustness and comprehensiveness in evaluating evacuation strategies.

III. Impact of Delays in Computing and Communications on Passenger Evacuation

The ANS algorithm provides evacuees a recommendation, at each node along all evacuation paths on the ship, regarding the next-step hazard-free node that the evacuee should move towards the exit. As indicated earlier when we discussed the issue of individual passenger identification, this recommendation is not based on the evacuee’s individual identity, and is generic for all evacuees. It is based on the total minimum delay estimation from the current location to the exit.

However, emergency conditions are dynamic and subject to rapid changes, and the computer and communication system responsible for computing and forwarding these directions may face congestion during an evacuation. As a result, messages to evacuees may be delayed or lost.

In this section, we analyze the impact of these potential delays caused by performance imperfections and congestion in the Information Technology System (ITS). We introduce the concept of ”information lag” (IL) for any generic node in the ship evacuation topology. $IL = 0$ signifies that each node has received the exact direction recommendation from the ITS system based on the current true location of evacuees. Conversely, $IL = 1$ implies that each node provides information to evacuees based on the status of all nodes, derived from the location of evacuees just before their current arrival at the node. Thus, $IL = 1$ denotes a delay of one step in the computation and transmission of information.

We also define the ”probability of delay” (PoD), indicating whether the information lag is $IL = 1$ with a probability of PoD, or $IL = 0$ with a probability of $1 - PoD$. PoD is a probabilistic attribute assigned to each node, considering that the delay may vary from node to node due to communication system delays.

In the following analysis, we evaluate the effect of PoD on the evacuation system's performance. Simulation results are obtained by assigning the probability PoD separately for each node in 100 independent simulations under the same initial conditions. The figures presented for each simulation also include the 95% confidence intervals.

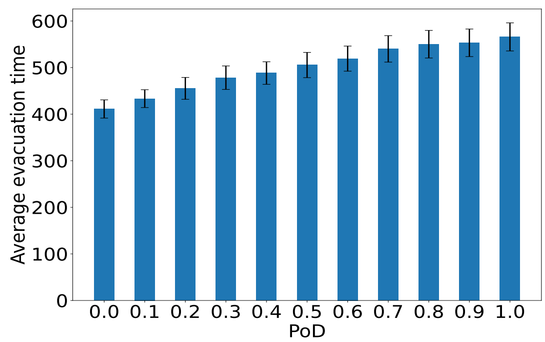
A. Evaluation of the Evacuation Times

We first determine the average evacuation time from all 346 nodes concerning the ideal case with $IL = 0$. Figure 2 (a) illustrates the average evacuation time from all 346 starting nodes to the exit as a function of PoD. Figure 2 (b) presents the performance ratio of average evacuation time for various PoD values relative to the average for the ideal case of $PoD = 0$. The averages are taken over all nodes and based on 100 distinct independent simulations. The standard deviation is also shown as black bars for the evacuation time from all 346 nodes. These curves demonstrate a quasi-linear increase in average evacuation delay as PoD increases to 0.5, and a more gradual increase for higher values. When $PoD = 1$ for all nodes, the average evacuation time over all nodes is 50% higher than $PoD = 0$, where the ITS provides up-to-date information to all nodes.

Additionally, we perform a set of simulations to evaluate the average evacuation time for passengers located in cabins. Figure 3 (above) illustrates the average evacuation time in seconds, taken by passengers originating from cabins, affected by different probabilities PoD. The performance ratio in average evacuation time for passengers in cabins, relative to the case $PoD = 0$, is shown in Figure 3 (b). It is evident that the evacuation of passengers from cabins worsens with the increase in PoD.

Moreover, we investigate the average evacuation time for passengers located in the restaurant. Figure 4 (a) illustrates the average evacuation time of passengers within the restaurant. Notably, we observe that IL has a milder impact on the evacuation time of restaurant patrons compared to passengers in cabins, particularly when PoD is low, such as $PoD = 0.1$ and $PoD = 0.2$

Additionally, other simulations assess the average evacuation time for varying numbers of passengers, influenced by different PoD values. In this simulation set, half of the passengers are randomly distributed in cabins, while the remaining half occupy the restaurant. Notably, the cabin capacity is limited to two passengers at most. As depicted in Figure 5 (a), the average evacuation time demonstrates an increase with a growing number of passengers. This escalation is primarily attributed to heightened waiting times resulting from more pronounced congestion caused by the evacuation of a larger number of passengers. Moreover, we observe that the average evacuation time rises with PoD, irrespective of the number of passengers. Figure 5 (b) presents the performance ratio in average evacuation time



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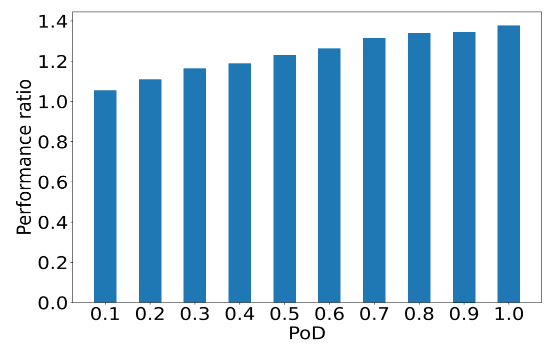


(b)

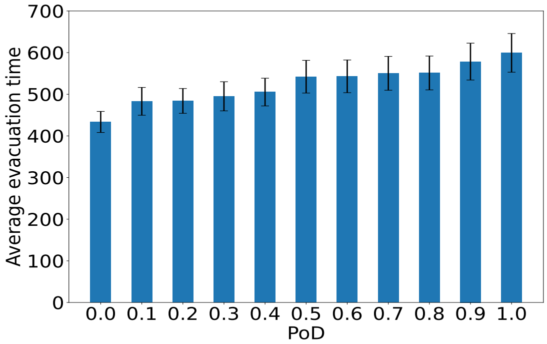
Fig. 2. The average evacuation time, in seconds, from all 346 nodes to the exit (above), as a function of PoD (x-axis), and (below) the performance ratio in average evacuation time as compared to the ideal case of $PoD = 0$. Averages are over all nodes for 100 distinct independent simulations, with the standard deviation (the black bars) for the evacuation time.

for varying passenger numbers under different probabilities of PoD. The performance ratio consistently exceeds 1, indicating that a larger PoD leads to an extended evacuation duration, with a more pronounced impact observed for higher PoD values.

IV. Conclusions and Further Research

Ensuring reliable emergency evacuation is vital, and IoT systems to support evacuation and guide evacuees have been the object of much research [34], [35]. However, challenges arise during emergencies due to congestion, damage to the IoT system supporting an evacuation, and to damages in the built environment.

This paper has considered the use of IoT and ICT for the evacuation of passengers from a cruise ship during an emergency. In particular, we have assessed the impact of IoT and ICT delays in providing timely and accurate directions to passengers using detailed simulations on an existing cruise ship model, namely the "Yangtze Gold 7" and its evacuation system. The simulations have shown the significant increase of the passenger evacuation delays as a function of the increase in the delay with which they receive correct evacuation instructions.



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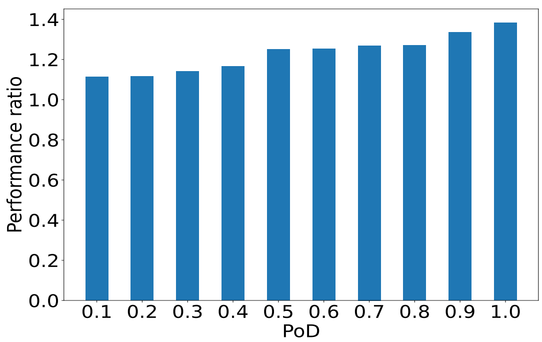
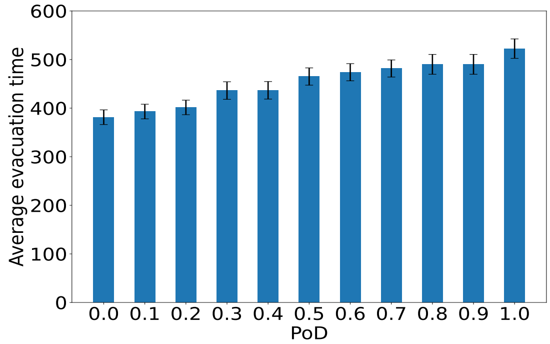


(b)

Fig. 3. The average evacuation time in seconds, taken by passengers in cabins to the exit (left), as a function of PoD (x-axis), and (right) the performance ratio in average evacuation time as compared to the ideal case of $PoD = 0$. Averages are taken over all passengers starting from cabins for 100 distinct independent simulations, with the standard deviation (the black bars) for the evacuation time.



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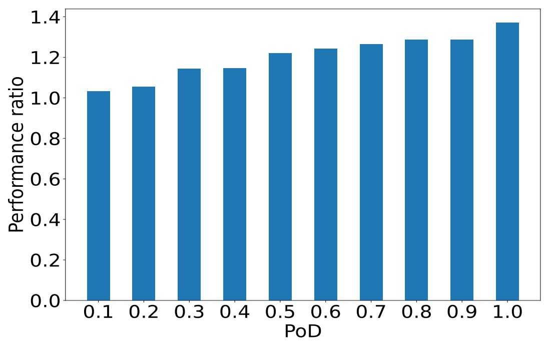

(b)

Fig. 4. The average evacuation time in seconds, taken of passengers in the restaurant to the exit (left), as a function of PoD (x-axis), and (right) the performance ratio in average evacuation time as compared to the ideal case of $PoD = 0$. Averages are taken over all passengers in the restaurant for 100 distinct independent simulations, with the standard deviation (the black bars) for the evacuation time.

In future research, it will be useful to design innovative decentralized emergency navigation systems that do not rely on centralized data processing, and which may proactively compute and store in a distributed manner the needed advisory data at key system intermediate nodes, and also use additional individual evacuee decision aids.

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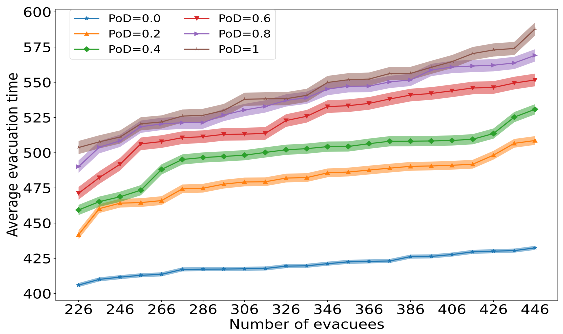

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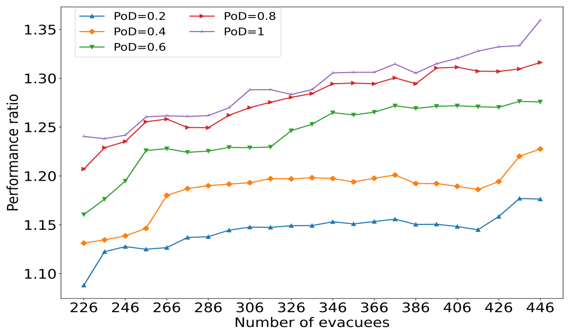

(b)

Fig. 5. The average evacuation time in seconds, with a 95% confidence interval, taken by different numbers of passengers where half of them originate in the cabins, while the other half start from the restaurant (above), and (below) the performance ratio in average evacuation time as compared to the ideal case w$PoD = 0$.

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