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Hossein Arshad

Human Evacuation Planning for Passenger Ships- Uncertainty Modeling

Doctoral thesis

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Abstract

The burgeoning cruise industry has emphasized the importance of maritime safety and efficient evacuation protocols. The tangible risks and past incidents involving passenger ships spotlight the critical necessity for enhanced protection and effective evacuation strategies. This pressing demand has propelled initiatives by organizations such as the International Maritime Organization (IMO) and the Maritime Safety Committee (MSC) to fortify safety protocols and evacuation plans to safeguard various stakeholders, including passengers, crew members, and emergency response teams.

This research pivots on the critical analysis and development of human evacuation models, in the context of passenger ships. While traditional models have been divided into simplified and advanced analyses, this study endeavors to address the complexities and uncertainties inherent in human evacuation models rendering it more advanced than simple.

A systematic literature review was conducted to assess the existing state of human evacuation modeling for passenger ships and subsequently identify gaps. Based on the identified gaps and critical parameters and objectives in this research area, three distinct human evacuation optimization models (HEM 1, HEM 2, and HEM 3) for passenger ships under varying uncertainties were developed. The first model optimizes total evacuation time considering the uncertainty in passenger walking speed by utilizing robust optimization (*RO*) by introducing uncertainty sets. The second model, addressing the hybrid uncertainty of passenger walking speed and travel distance, employs a risk-neutral, two-stage, scenario-based stochastic optimization technique (*RSSP*). The third model optimizes the total evacuation time under mixed uncertainty involving walking speed and door capacity disruptions by applying *HRSSRP* (hybrid risk-neutral, two-stage, scenario-based stochastic ρ-robust programming). Further, the generated scenarios for passenger walking speed are updated throughout evacuation to follow the real-time circumstances. Moreover, the modeling process incorporated considerations for various starting locations, situational awareness (i.e., alert or non-alert), and the passenger ship's general arrangement (e.g., number of exit doors and corridor's width).

Another contribution of this research is the inclusion of families as separate entities in the models to capture the unique dynamics of group evacuations. Also, the models maintain proximity between crew and passengers by allocating optimal crew-to-passenger ratios during the evacuation process. The models were validated using a single deck of a real-life passenger ship.

The developed models serve dually on macroscopic and microscopic levels to facilitate decision-making in overall evacuation organization and devising individualized evacuation plans under uncertainties. This research carves out a pathway for practical applications in various domains, such as ship design, simulation software development, digital twins, and machine learning algorithms, all within the human evacuation process from passenger ships. The developed models were built using real-world data from the IMO and then underwent partial validation via a case study focused on a single deck of a passenger ship. Nonetheless, it is crucial to acknowledge that this validation is not yet complete. Further investigation and real-time testing are necessary to fully confirm their effectiveness and accuracy for broader applications, including multi-deck environments, in future studies.

While this study provides a robust foundation, limitations such as its focus on single-deck evacuation scenarios and reliance on fixed parameters for initial passenger location and awareness levels open avenues for future research; future improvements could integrate multi-deck scenarios with real-time data through sensor technology. Additionally, exploring other uncertainty modeling techniques, such as Bayesian network-based approaches, could offer additional insights by leveraging the expertise of maritime specialists and mitigating data scarcity in this research area.

Acknowledgments

Heartfelt gratitude envelops my journey, most notably towards my supervision team, Professor Guoyuan Li and Associate Professor Runar Ostnes and, specifically my immediate supervisor, Professor Jan Emblemsvåg, whose sagacity and perennial support have been monumental pillars throughout my graduate voyage.

A cascade of thanks flows towards my colleagues at the Department of Ocean Operations and Civil Engineering at the Norwegian University of Science and Technology. Their navigational guidance and bolstering support throughout this doctoral expedition have been priceless, offering invaluable perspectives and advice that shaped my journey.

To my peers in the group for Shipping and Nautical, I extend my appreciation for the fellowship and sustenance provided. The insightful dialogues and collaborative ethos within our group have been a lighthouse amidst the scholarly seas.

A special acknowledgment is bestowed upon Assistant Professor Xilei Zhao. Her supervision during my stay as a courtesy scholar at the Department of Civil and Coastal Engineering, University of Florida, USA has been pivotal, guiding my research with expertise and insight.

In the gentlest of reflections, my family, the silent stronghold behind my academic endeavors, deserves a world of thanks. Their dedicated support and encouragement have been my anchor perennially. A tender and special note to my late father, whose memory and spirit have silently accompanied me, particularly in the nascent weeks of my Ph.D., providing an unseen, yet profoundly felt, strength.

Contents

List of publications

This dissertation comprises a central section (Chapters 1 - 9) and several papers. The content of the main body has been previously explored and detailed in four journal papers. These papers are enumerated below and can be found in the Appendix of this document. Both here and in the Appendix, the papers are organized chronologically. It is important to note that Paper 1 and Paper 3 have been published, Paper 2 is currently undergoing the second revision, and Paper 4 is under review.

Paper 1:

- Arshad, H., Emblemsvåg, J., Li, G., Ostnes, R., 2022. Determinants, methods, and solutions of evacuation models for passenger ships: A systematic literature review. Ocean Eng. 263, 112371. https://doi.org/10.1016/j.oceaneng.2022.112371

Paper 2:

- Arshad, H., Emblemsvåg, J., Li, G., 2023. Multi-period human evacuation model for passenger ships under walking speed uncertainty. Ocean Eng. Under review (2nd revision).

Paper 3:

- Arshad, H., Emblemsvåg, J., Zhao, X., 2024. A data-driven, scenario-based human evacuation model for passenger ships addressing hybrid uncertainty. Int. J. Disaster Risk Reduct. 100, 104213. https://doi.org/10.1016/j.ijdrr.2023.104213.

Paper 4:

- Arshad, H., Emblemsvåg, J., Zhao, X., Li, G., 2023. Stochastic-robust human evacuation planning for individual and family travelers: A Ro-Ro passenger ship. Ocean Eng. Under review.

List of Abbreviations

IMO	International Maritime Organization
MSC	Maritime Safety Committee
HEM	Human Evacuation Model
RO	Robust Optimization
RSSP	Risk-neutral, Two-stage, Scenario-based Stochastic Programming
HRSSRP	Hybrid Risk-neutral, Two-stage, Scenario-based Stochastic ρ-robust Programming
MCS	Monte Carlo Simulation
BN	Bayesian Networks
FO	Fuzzy Optimization
DDRO	Data-Driven Robust Optimization
SBO	Scenario-Based Optimization
SO	Stochastic Optimization
GA	Genetic Algorithm
LPCE	Legendre Polynomial Chaos Expansion
CAIE	Cellular Automata with Interaction Effect
MVZ	Main Vertical Zone
R	Response Period
T	Travel Period
ET	Evacuation Time
ST	Start Time
CT	Complete Time
NLP	Non-Linear Programming
IR	Influence Rate
MIP	Mixed Integer Programming
GAMS	General Algebraic Modeling System
STD	Standard
TET	Total Evacuation Time
Ath	Athwartship
For	Fore-aft
Fas	Fast
Nor	Normal
Deg.	Degradation

List of Notations

Sets and indices		
		Application
P	Set of passengers, indexed by $p \in P$	HEM 1 to 3
F	Set of family groups, indexed by $f \in F$	HEM 1 to 3
E	Set of exit doors, indexed by $e \in E$	HEM 1 to 3
I	Set of starting locales, indexed by $i \in I$	HEM 1 to 3
T	Set of periods, indexed by $t \in T$	HEM 1 to 3
S	Set of walking speed scenarios, indexed by $s \in S$	HEM 2 to 3
U	Set of travel distance scenarios, indexed by $u \in U$	HEM 2
W	Set of disruption scenarios, indexed by $w \in W$	HEM 3
J	Set of potential locations for crew teams, indexed by $j \in J$	HEM 1 to 3
Parameters		
v_{pt}	Walking speed of passenger $p \in P$ in period $t \in T$ (meters/second)	HEM 1 to 3
$\acute{v}_{ft}$	Walking speed of family $f \in F$ in period $t \in T$ (meters/second)	HEM 1 to 3
v^{s}_{pt}	Walking speed of passenger $p \in P$ in period $t \in T$ in scenario $s \in S$ (meters/second)	HEM 2 to 3
$\acute{v}^{s}_{ft}$	Walking speed of family $f \in F$ in period $t \in T$ in scenario $s \in S$ (meters/second)	HEM 2 to 3
$v^{\tilde{s}}_{pt}$	Walking speed of passenger $p \in P$ in period $t \in T$ in scenario $s \in S$ adjusted by diminution function (meters/second)	HEM 2 to 3
$\acute{v}^{\tilde{s}}_{ft}$	Walking speed of family $f \in F$ in period $t \in T$ in scenario $s \in S$ adjusted by diminution function (meters/second)	HEM 2 to 3
d^{i}_{pe}	Travel distance by passenger $p \in P$ located in starting locale $i \in I$ to exit door $e \in E$ (meter)	HEM 1 to 3
$\acute{d}^{i}_{fe}$	Traveled distance by family $f \in F$ located in starting locale $i \in I$ to exit door $e \in E$ (meter)	HEM 1 to 3
d^{iu}_{pe}	Traveled distance by passenger $p \in P$ located in starting locale $i \in I$ to exit door $e \in E$ in scenario $u \in U$ (meter)	HEM 2
$\acute{d}^{iu}_{fe}$	Traveled distance by family $f \in F$ located in starting locale $i \in I$ to exit door $e \in E$ in scenario $u \in U$ (meter)	HEM 2
cap_{et}	Capacity of exit door $e \in E$ in period $t \in T$ (per passenger)	HEM 1 to 3
r_{pet}	Equal to 1 if passenger $p \in P$ is in a radius of potential exit door $e \in E$ in period $t \in T$; 0, otherwise	HEM 1 to 3
r_{fet}	Equal to 1 if family $f \in F$ is in a radius of potential exit door $e \in E$ in period $t \in T$; 0, otherwise	HEM 1 to 3
θ_p	Equal to 1 if passenger $p \in P$ is fully alert; 0, otherwise	HEM 1 to 3
$\acute{\theta}_f$	Equal to 1 if family $f \in F$ is fully alert; 0, otherwise	HEM 1 to 3
ϑ^{i}_{p}	Equal to 1 if passenger $p \in P$ is located in starting locale $i \in I$; 0, otherwise	HEM 1 to 3
$\acute{\vartheta}^{i}_{f}$	Equal to 1 if family $f \in F$ is located in starting locale $i \in I$; 0, otherwise	HEM 1 to 3
ε_f	The size of family $f \in F$	HEM 1 to 3
η_j	The size of crew team located in $j \in J$	HEM 1 to 3
π_s	Probability occurrence of scenario $s \in S$	HEM 2 to 3
π_u	Probability occurrence of scenario $u \in U$	HEM 2
π_w	Probability occurrence of scenario $w \in W$	HEM 3
ϱ_s	Deviation rate from nominal value for producing scenario $s \in S$	HEM 2 to 3
ς_u	Deviation rate from nominal value for producing scenario $u \in U$	HEM 2
o_w	Deviation rate from nominal value for producing scenario $w \in W$	HEM 3
σ_i	Availability area of locale $i \in I$ (meter^2)	HEM 1 to 3
λ_t	Traffic flow of passengers in period $t \in T$ (passengers)	HEM 1 to 3
ϕ_i	Initial density of passengers in locale $i \in I$ (passengers)	HEM 1 to 3
Δ^{solo}	Conservatism level of solo travelers	HEM 1
Δ^{family}	Conservatism level of families	HEM 1
ℓ	The crew's assistance capacity	HEM 1 to 3
ω	Corridor width (meter)	HEM 1 to 3

τ	Average shoulder width of passengers (meter)	HEM 1 to 3
ι	Non-alert distance factor for passenger $p \in P$	HEM 1 to 3
κ	Non-alert distance factor for family $f \in F$	HEM 1 to 3
ρ	Confidence level	HEM 3
α	Safety factor	HEM 1 to 3
β	Correction factor	HEM 1 to 3
γ	Counterflow correction factor	HEM 1 to 3
∂	Degradation constant for passenger walking speed $p \in P$	HEM 1 to 3
μ	Degradation constant for family walking speed $f \in F$	HEM 1 to 3
N	The total number of solo travelers	
M	A big number	HEM 1 to 3
$\mathcal{E}$	A very small number	HEM 1 to 3
Decision variables		
Positive variables, ≥ 0		
ψ_{ws}	The total evacuation time in scenario $w \in W$ and $s \in S$	HEM 3
Z_3	The total evacuation time	HEM 3
ψ_{us}	The total evacuation time in scenario $u \in U$ and $s \in S$	HEM 2
Z_4	The total evacuation time	HEM 2
Z_1	The total evacuation time of the slowest passengers among solo travelers	HEM 1
Z_2	The total evacuation time of the slowest passengers among families	HEM 1
Binary variables, $\in \{0,1\}$		
Y_{et}	Equal to 1 if the potential exit door $e \in E$ in period $t \in T$ is established; 0, otherwise	HEM 1 to 3
G_{jt}	Equal to 1 if the potential crew team $j \in J$ in period $t \in T$ is established; 0, otherwise	HEM 1 to 3
X_{pet}	Equal to 1 if passenger $p \in P$ is traveling to the exit door $e \in E$ in period $t \in T$; 0, otherwise	HEM 1 to 3
H_{fet}	Equal to 1 if family $f \in F$ is traveling to the exit door $e \in E$ in period $t \in T$; 0, otherwise	HEM 1 to 3
X_{pet}^{sw}	Equal to 1 if family $f \in F$ is traveling to the exit door $e \in E$ in period $t \in T$ in scenario $w \in W$ and $s \in S$; 0, otherwise	HEM 3
X_{pet}^{su}	Equal to 1 if passenger $p \in P$ is traveling to the exit door $e \in E$ in period $t \in T$ in scenario $u \in U$ and $s \in S$; 0, otherwise	HEM 2
H_{fet}^{sw}	Equal to 1 if family $f \in F$ is traveling to the exit door $e \in E$ in period $t \in T$ in scenario $w \in W$ and $s \in S$; 0, otherwise	HEM 3
H_{fet}^{su}	Equal to 1 if family $f \in F$ is traveling to the exit door $e \in E$ in period $t \in T$ in scenario $u \in U$ and $s \in S$; 0, otherwise	HEM 2
Γ_w	Equal to 1 if disruption happens to the exit door $e \in E$ in period $t \in T$; 0, otherwise	HEM 3

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Research stay at the Herbert Wertheim College of Engineering, University of Florida

During my doctoral studies, a significant milestone was my research stay as a Short-term Scholar at the Herbert Wertheim College of Engineering, University of Florida, within the Engineering School of Sustainable Infrastructure & Environment, United States. This period, spanning from January 9, 2023, to June 8, 2023, was instrumental in broadening the scope of my research and refining its robustness.

Integration of global perspectives and advanced methodologies:

The opportunity to engage with a diverse academic community at the University of Florida provided me with invaluable insights, allowing me to incorporate a broader range of perspectives into my research. Working alongside esteemed professionals in the field of Civil and Coastal Engineering, I gained exposure to advanced methodologies and cutting-edge technologies. This experience was not only enriching on a professional level but also pivotal in enhancing the quality and depth of my doctoral research.

Collaborative research outputs:

During my tenure at the Herbert Wertheim College of Engineering, I collaborated on two papers, namely Paper 3 and Paper 4. These papers, which form an integral part of my dissertation, are the result of research and collaborative effort. They reflect the interdisciplinary approach and international collaboration that were the hallmarks of my research stay.

Personal and academic growth:

This period was also a time of substantial personal and academic growth. Immersing myself in a different academic environment, I encountered new challenges and perspectives that pushed me to think more critically and creatively. The insights gained during this time were instrumental in improving the robustness of my PhD research, supplying a more comprehensive understanding of the subject matter.

In conclusion, my time at the Herbert Wertheim College of Engineering was an experience that contributed to the progression and success of my doctoral research. The knowledge and skills acquired during this period have been indispensable in shaping my dissertation.

1. Introduction

The expansion of the global tourism industry, mainly through passenger ship voyages, highlights an urgent and undeniable imperative: the need to assure maritime safety and establish planned and efficiently executed evacuation protocols. With an industry generating billions in revenues and mobilizing millions of passengers annually, the tangible risks and tragic histories of passenger ship accidents necessitate rigorous and innovative approaches to enhance protection and develop effective evacuation plans for passenger ships. In 2019, cruise ships carried 29.7 million passengers, generating over $154 billion globally (Cruise Lines International Association, 2021).

However, the cruise industry experienced fluctuations due to global events in the following years. The impact of the coronavirus pandemic was distinctly evident in 2020 and 2021, with passenger numbers plummeting to 5.8 million and 4.8 million, respectively. Despite these challenges, in 2023, cruise tourism is predicted to bounce back, reaching 106% of the 2019 levels with 31.5 million passengers. The sector, one of the fastest-growing in tourism, hosted 20.4 million ocean-going cruise passengers in 2022 and is forecasted to rise substantially to 39.5 million by 2027 (Cruise Lines International Association, 2023). Plus, Allianz (2023) reported 70 passenger ship losses from 2013 to 2022. In addition, see Table 1, at least 2,630 people lost their lives due to incidents from 2011 to 2019.

Table 1. Passenger ship incidents

Year	Ship name	Type	Fatalities	Reference
2011	• MV Spice Islander	• Passenger ferry	1,529[1]	(Fundi, 2018)
2012	• Costa Concordia	• Cruise ship	32	(Vanem and Skjong, 2006)
2013	• MV ST Thomas Aquinas	• Passenger ferry	120	(Fahcruddin et al., 2019)
2014	• MV Sewol	• Passenger ferry	304	(Kim et al., 2016)
2015	• Dongfang Zhi Xing	• Cruise ship	442	(Baird, 2018)
2016	• Aung Soe Moe Kyaw 2	• Passenger ferry	99	
2017	• Zahro Express	• Passenger ferry	> 23	(Christine and Bonnemains, 2018)
2018	• MV Butiraoi	• Passenger ferry	81	
2019	• MV Viking Sky	• Cruise ship	0	(Ibrion et al., 2021)
Total			> 2,630	

Prompted by the above facts and safety concerns, the IMO and MSC have enforced regulations and highlighted evacuation models as crucial for minimizing casualties at sea (IMO, 2016, 2007, 2000, 1999; Q. Xie et al., 2020a). These regulations by the IMO and MSC focus on evacuation analysis for passenger ships, evolving over time. Starting in 1999, they provided initial guidelines for Ro-Ro passenger ships (MSC/Circ.909), extending in 2001 and 2002 to high-speed passenger crafts and all passenger ships (MSC/Circ.1001, MSC.1/Circ.1033). By 2007, comprehensive guidelines for simple and advanced evacuation analyses were established (MSC.1/Circ.1238). Recent updates in 2015 and 2016 (MSC/Circ.1166, MSC.1/Circ. 1533) revised these guidelines, which highlighted enhanced safety and minimizing casualties at sea.

Moreover, understanding various evacuation factors is crucial to enhancing the precision and efficacy of human evacuation models (HEM). These factors, pivotal during the evacuation process, encompass environmental, configurational, behavioral, and human aspects, each contributing distinct challenges and variables to the evacuation dynamics. As categorized and defined by Arshad et al. (2022) and Lee et al. (2003) in Table 2, environmental factors delineate the external influences affecting passengers' walking speeds, while configurational aspects encompass the structural layout of the ship

[1] 203 passengers tragically lost their lives, while 1,326 passengers remain unaccounted for but presumably dead.

that can facilitate or hinder evacuation. On the other hand, behavioral factors encapsulate passengers' responses and interactions during an emergency, and human factors involve the physical and demographic properties of the evacuees.

Table 2. Aspects of evacuation process for passenger (Arshad et al., 2022; Lee et al., 2003).

Aspect	Definition	Features
• Environment	• It outlines the external factors influencing the walking speed of passengers.	• Ship conditions (motions, stability) • Hazards (e.g., fire, heat, smoke)
• Configuration	• It encompasses the structural design of a passenger ship.	• Evacuation routes design • Functional areas
• Behavior	• It pertains to how passengers respond to a given situation.	• Walking speed, • Group behavior • Counter flows
• Human	• It consists of passenger characteristics.	• Age, • Gender • Physical state

Evacuation models are developed and applied based on the evacuation factors. Two primary categories emerge in evacuation analysis: simplified and advanced analysis (IMO, 2016). The former, the simplified analysis adheres to a deterministic method, visualizing passengers as nonautonomous agents and thus fails to account for the variability in human behavior during emergencies. Conversely, advanced analysis steps into uncertainty by recognizing passengers as autonomous agents whose actions are influenced by uncertain and fluctuating input parameters, such as ship motion (Nasso et al., 2019).

In response to the gaps identified in the literature review, the research focuses on targeted inquiries that will inform further investigations and model development. These efforts aim to bridge the identified knowledge gaps and improve the real-world efficacy of HEMs. This pursuit is grounded in the main research question (RQ) and is driven by specific research objectives (RO) that guide the systematic approach to enhancing HEM reliability and applicability:

1.1. ROs and main RQ

The principal research question is as follows:

- How can human evacuation models be developed to improve the evacuation process on a single deck of a passenger ship while taking uncertainty into account and by using mathematical optimization techniques?

To address this central research question, the following four sub-research questions, each tackled by Papers 1 through 4 respectively, are implied. Due to its prescriptive, structured approach (defining objective functions, constraints, and variables), mathematical optimization is used in this thesis to develop strategic, scalable evacuation plans. More explanation is offered in section 2.3. Following the main research question, the first research objective (RO 1) is as follows:

1.2. RO 1: Propose human evacuation models for passenger ships by employing uncertainty modeling techniques—robust, stochastic, and hybrid optimization—focused on walking speed, travel distance, and exit door capacities.

This objective focuses on the creation of optimization models for dynamic ship-based evacuation on a single deck of a passenger ship. This objective is addressed through the development of three distinct human evacuation optimization models in Papers 2 to 4, each tackling a specific aspect of the evacuation process under different uncertainties. These models aim not only at time minimization but also at determining strategic decisions, such as exit door quantities within passenger ship evacuations.

1.3. Sub RQs

Addressing sub-RQ 1 will contribute to the achievement of RO 1.

- Sub RQ 1: how can a systematic literature review reveal the current state, gaps, and future directions in human evacuation modeling, specifically addressing uncertainties in parameters like passenger walking speed and travel distance?

In addressing Sub RQ 1, Paper 1 (Arshad et al., 2022), a systematic review of more than 115 studies, guided by IMO guidelines (IMO, 2016), was undertaken to uncover gaps and propose new avenues for research in human evacuation analysis. This review analyzed key factors affecting evacuation processes, including walking speed, travel distance, and exit door capacity. It highlighted a gap in the current understanding of how combined uncertainties, such as the interplay between walking speed and travel distance or the relationship between walking speed and exit door capacity, impact the development of personalized human evacuation plans. And how uncertainty modeling techniques, such as robust optimization, stochastic optimization, and hybrid robust-stochastic optimization, can manage these uncertainties when developing human evacuation plans. To bridge this gap, models were designed to manage these (hybrid) uncertainties.

- Sub RQ 2: how can robust optimization be employed to formulate a human evacuation model that manages uncertainties related to walking speeds during the evacuation process on a single deck of a passenger ship?

To tackle this, Paper 2 develops a human evacuation model that optimizes a critical uncertain factor, passenger walking speed. This model, employing robust optimization techniques, contributes to achieving RO 1 and RO 2 by addressing practical uncertainties.

- Sub RQ 3: how can a scenario-based approach be utilized to develop an evacuation optimization model that simultaneously navigates hybrid uncertainties in passenger walking speed and travel distance during the evacuation process on a single deck of a passenger ship?

Paper 3 builds on the previous model by addressing additional uncertainties in human evacuation optimization in the context of passenger ships. Paper 3 addresses Sub RQ 3 by integrating additional uncertainties. This paper furthers RO 1 and RO 2 by optimizing evacuation plans through a comprehensive scenario-based approach, which enhances the model's practicality and adaptability.

- Sub RQ 4: how can a hybrid robust-stochastic approach be applied to design an evacuation optimization model that simultaneously navigates hybrid uncertainties in passenger walking speed and disruption in exit door capacities during the evacuation process on a single deck of a passenger ship?

In addressing Sub RQ 4, Paper 4 introduces a mathematical model optimizing evacuation plans concentrating on macroscopic and microscopic factors. The model employs a hybrid stochastic-robust approach, contributing to RO 1 and RO 2 by offering robust and adaptable evacuation strategies for diverse emergency scenarios (Two of the papers referenced in this thesis, Paper 2 and Paper 4, have been submitted for publication but have not yet been published. It is essential to highlight that the versions of these papers included here may differ from their final published versions. Paper 2 is currently undergoing its second revision, while Paper 4 is under review.).

1.4. RO 2: Testing and validating the proposed models

RO 2 involves the practical application and validation of the developed models. This objective is met by applying these models to a real-life case study using a single deck of an actual passenger ship. The validation process can ensure the models' effectiveness and provides insights for ship designers and emergency response planners.

Decoding these aspects is imperative, not merely for comprehending the complexities of the evacuation process but also for improving the HEMs. Therefore, in this dissertation, the decoding was achieved through a systematic literature review to afford a holistic understanding and reveal existing knowledge and gaps in this field. Following this, three human evacuation optimization models for passenger ships were formulated, each building on insights derived from the literature review and adapted to meet the challenges and scenarios unveiled.

The developed models center on a location-allocation optimization model, (Azarmand and Neishabouri, 2009), that assigns passengers to evacuation exits based on parameters like walking speed, current location, and travel distance and combined uncertainty such as passenger walking speed and travel distance.

Each sub-research question addresses a specific aspect of the broader challenge. The discussion begins with Paper 1, which lays the groundwork by establishing an understanding and pinpointing gap in the existing literature. While efforts to tackle these research questions have been documented in the literature, challenges remain. The necessity of crafting personalized evacuation plans for solo travelers and families, considering hybrid uncertainties such as the interplay between passenger walking speed and travel distances, as well as walking speed and exit door capacity, remains an area not fully explored. Identifying these uncertainties necessitates the use of appropriate modeling techniques for effective handling. This study proposes two specific uncertainty modeling approaches—robust and stochastic optimization— and introduces a combination of robust-stochastic optimization (*HRSSRP*) to address these challenges. Implementing these techniques sheds light on potential gaps in current methodologies for modeling uncertainties in developing human evacuation plans for passenger ships and highlights the nature of this work.

This work, while taking steps to address these complexities, acknowledges its limitations and presents opportunities for refinement and further exploration in future research. These uncertainties are examined in Papers 2 to 4 through uncertainty modeling techniques, including robust optimization, stochastic optimization, and hybrid robust-stochastic optimization. The focus here is on formulating HEMs in the context of these diverse uncertainties. A more detailed introduction to the relevant literature, its shortcomings, and the distinctiveness of the approach adopted will be provided in Chapter 2. This approach facilitates a detailed progression towards addressing the main research question.

Through these studies (Papers 1 to 4), this dissertation transcends traditional models, navigating through the complexities and uncertainties inherent in HEMs, and introducing optimized, robust, and resilient models that not only address the varied uncertainties in passenger evacuation scenarios but also accommodate the dynamic and unique challenges presented by group evacuations and real-time adjustments in evacuation scenarios. While concentrating on single-deck evacuation scenarios, the models introduced in this research offer insights that could inform practical applications and future studies. They suggest a basis for exploring broader applications, including ship design enhancements, simulation software development, and the incorporation of digital twins and machine learning algorithms. This work proposes potential pathways for extending investigations to multi-deck scenarios and incorporating real-time data through sensor technology. Such improvements could improve the safety and efficiency of passenger ship evacuations, highlighting the importance of further research in these areas.

1.5. Organization of the dissertation

The dissertation is organized in a traditional way, starting with the introductory matters, followed by a literature review. The actual research is organized as shown in Figure 1. Figure 1 illustrates the systematic progression from Paper 1 through 4 by depicting how each subsequent study builds upon its predecessor to address the sub-research questions methodically and converge toward answering the overarching main research question about developing HEMs amidst the uncertainties of evacuating a single deck on passenger ships.

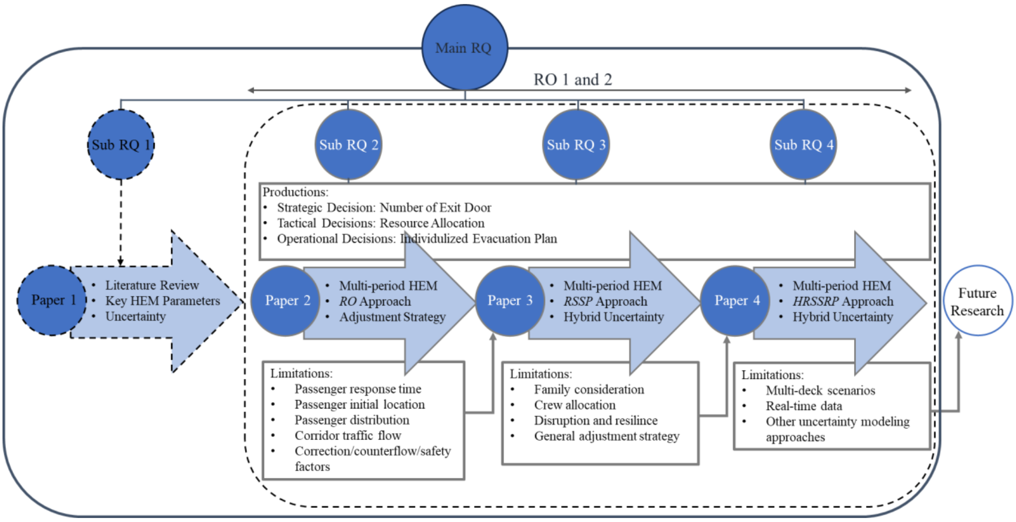


Figure 1. Influence of main RQ to subsequent research (Papers 1-4). It highlights the pivotal contribution of Paper 1 in devising this dissertation RO.

Beginning at the lefthand side of Figure 1, the literature review is essentially the sum of Paper 1 with further refinements gained from the research performed after its publication. In Paper 1, a systematic literature review of over 115 studies from January 1999 to August 2022 was conducted, comprising scientific journals, peer-reviewed conference papers, and doctoral and master dissertations. Each publication was analyzed through the lens of IMO guidelines to identify prevailing gaps and offer future research directions. Paramount parameters in developing HEMs, such as passenger/family walking speed (influenced by age, gender, and physical condition), traveled distance, response time, starting location, the number of exit doors, crew allocation, ship's general arrangement, passenger distribution, traffic flow across corridors, initial density, exit door capacity, and correction/counterflow/safety factors, were determined. Notably, real-world parameters like walking speed, travel distance, and door capacity introduce sources of uncertainty that impact the evacuation process. A HEM should inherently be robust to such uncertainties to mitigate the impact of parameter variations during the evacuation period.

While several studies have incorporated parameter uncertainty in analyzing HEMs for passenger ships (e.g., Grandison et al. (2017) and Xie et al. (2020)), a gap exists in the academic literature concerning the incorporation of individual uncertainty in walking speed, travel distance, and door capacity in the computational optimization of evacuation time for each passenger on board passenger ships. Addressing these uncertainties is crucial in crafting evacuation optimization models to ensure they are not only realistic and reliable but also robust and versatile by navigating various emergency scenarios. This ensures evacuation plans are safe, efficient, and inclusive, minimizing bottlenecks and facilitating orderly passenger movement while adhering to international safety regulations and standards. Embracing uncertainties promotes effective crisis management, reducing potential panic and enabling coordinated responses during emergencies whilst also facilitating continuous improvement and iterative enhancements in evacuation planning to underpin a framework safeguarding all onboard. Consequently, the models were developed, duly considering the aforementioned parameters and sources of uncertainties.

Paper 2 tackles evacuation modeling by focusing on pivotal factors such as walking speed (a key determinant of human behavior), the capacity of transitional areas like exit stairs (moving forward, the objective is to reach the initial transition point located on the same deck. This transition point could be stairs, exit doors, or similar egress pathways.), and passenger proximity to these exits, ensuring swift and secure evacuations. The paper introduces a multi-period human evacuation model designed to optimize each passenger's evacuation plan, with a particular emphasis on minimizing the evacuation time of the slowest individual. Additionally, the model, developed within the context of Paper 2, identifies the optimal number of exit stairs and formulates evacuation routes, even amidst uncertainties in walking speeds influenced by a passenger ship's heeling angle. In addressing uncertainty, a Robust Optimization (*RO*) approach is utilized to manage the spectrum of possible walking speeds to ensure the resilience of the optimal solution amidst various uncertainties within a defined boundary (Ben-Tal and Nemirovski, 2008). A lower and upper limit demarcates this boundary under the presumption that uncertain parameters reside within this set (Ben-Tal et al., 2009). *RO* offers two principal benefits: firstly, it maintains computational tractability regardless of the number of uncertain parameters, and secondly, it utilizes historical data and expert input to define the boundaries of uncertainty sets, negating the need for exact probability distribution estimates (Keyvanshokooh et al., 2016).

Furthermore, *RO* allows decision-makers to modulate the conservatism level of results relative to parameter uncertainty, where conservatism represents a deliberate trade-off for model robustness (Bertsimas et al., 2011; Bertsimas and Sim, 2004). Specifically, it gauges the impact of potential alterations in objective value against a standard solution (Roos and den Hertog, 2020). Consequently, *RO*'s merits align seamlessly with the requisites of a human evacuation plan. Furthermore, considering the fluctuation of walking speed over time, an adjustment strategy is introduced for each angle. Walking speed data, contingent on age, gender, and mobility level on flat terrains under standard conditions, is derived from IMO (2016) and utilized to build the uncertainty sets. Kim et al. (2019) discovered a sharper decline in walking speed as one approached the end of the horizon. Consequently, an adjustment strategy is introduced to update walking speeds to adapt to real-time situations. Sun et al. (2018) calculated the walking speeds for different individuals, revealing the varied impact of heeling angles on speed. Accordingly, the influence rate (*IR*) for each angle on walking speed is introduced to adjust speed dynamically in response to unfolding scenarios during the evacuation horizon.

While Paper 2 presents a robust human evacuation optimization model, it also highlights certain limitations, such as accounting for variables like response time (considering passenger awareness levels - alert or non-alert), initial passenger location, distribution, corridor traffic flow, initial density, and correction/counterflow/safety factors. Efforts to mitigate these limitations are discussed in Paper 3. Moreover, with passenger travel distance adding another dimension of uncertainty, the development of a human evacuation optimization model that simultaneously addresses the hybrid uncertainties of passenger walking speed and travel distance was pursued. In this endeavor, a hybrid uncertain optimization modeling approach was adopted for human evacuation planning for passenger ships.

Paper 3 introduces an evacuation optimization model that simultaneously models uncertain parameters, compromising passenger walking speed and travel distance, with deterministic elements, including deck layout, door capacity, initial density, and corridor traffic flow. The model also regards diverse starting locations and incorporates two awareness levels — alert and non-alert. The optimization model determines the optimal number of stairs and allocates passengers to exit doors by navigating through a landscape of hybrid uncertainty. This versatile model can accommodate fixed and potential transitional points in terms of their numbers and locations. The model employs a data-driven method, specifically the *k*-means algorithm, to cluster historical data regarding passenger walking speeds and subsequently generate scenarios. An adjustment mechanism is incorporated to consider the ship's rolling motion, which influences passenger speeds throughout the duration of the evacuation planning. Scenarios for travel distance are developed to encapsulate the effects of various route choices for each passenger. A risk-neutral, two-stage, scenario-based stochastic programming (*RSSP*) model is devised to manage uncertainties. The two-stage stochastic programming approach enables decision-makers to strategically plan exit door locations that are robust across various scenarios and to adaptively manage passenger allocation to these exits during an actual emergency to guarantee that the evacuation is as efficient and safe as possible given the real-time conditions and uncertainties. This technique leverages both deterministic and stochastic elements to provide a balanced, risk-mitigated, and optimized decision-making framework suitable for human evacuation planning under uncertainty. Utilizing *RSSP*, the human evacuation optimization issue is formulated as a two-stage, scenario-based model under a risk-neutral stance (Birge and Louveaux, 2011).

Birge's approach uses stochastic optimization in a two-stage model to handle uncertain parameters, dividing decision variables into 'here-and-now' and 'wait-and-see' categories. The first-stage objective function embeds the expected value of second-stage decisions to facilitate a robust and foresighted optimization strategy. This ensures initial decisions, like exit door locations, and subsequent ones, such as passenger-door allocation, are proactive and adaptive to balance risk and opportunity management throughout the evacuation planning.

Paper 3 developed a robust HEM amidst hybrid uncertainty yet faced limitations like family consideration and crew allocation, which are addressed in Paper 4. Paper 4 formulates an evacuation model, considering uncertainties in passenger walking speed and potential exit door disruptions. Introducing this new uncertainty source, a robust toolkit for managing evacuations across varied scenarios was offered, thereby boosting the safety and resilience of evacuation plans.

Paper 4 proposes an HEM for passenger ships by navigating macroscopic and microscopic viewpoints amid uncertainty. At a macroscopic scale, it determines the number of exit doors, factoring in their functional variability, to oversee the broader evacuation orchestration. Microscopically, it addresses individual behaviors, accounting for fluctuations in passenger walking speed for both individuals and families, and strategically allocates passengers to ideal exit doors. The model endeavors to minimize evacuation time and the number of exit doors while ensuring proximity between crew and passengers. Crew members are not initially modeled as evacuating entities. However, the model's design accommodates flexibility, considering evacuation plans for crew members, including allocating specific exits for their use. A hybrid scenario-based stochastic *p*-robust programming technique is utilized to manage uncertainties by incorporating an adaptable, risk-neutral, two-stage, scenario-based stochastic method for walking speed variability and a feasibility-driven *p*-robust approach for potential exit door capacity disruptions. This hybrid approach not only provides robust and optimized evacuation plans under varying walking speeds but also allows passengers to navigate to a safe location (an exit door), especially in disrupted scenarios. This is vital for handling real-world emergencies, in the intricate and dynamic context of a passenger ship. The pedestrians' walking speeds may diminish as danger levels or ship motion amplifies and as the evacuation progresses by incorporating this assumption into the proposed human evacuation model. The model assumes a temporal decrease in passengers' walking speeds by accommodating this with two degradation constants for families and individuals. These assumptions help to adjust to new developing circumstances. Adjustment formulas, assuming exponential and linear degradations in walking speed, are applied to account for this adjustment.

2. Summary of relevant literature

Steering through the intricate realms of maritime safety involves a strategic intertwining of regulatory adherence, human evacuation modeling, and management of uncertainties. The MSC Circulars provide a regulatory backbone for establishing rigorous safety and emergency protocols for passenger ships, which fundamentally shape the development of HEMs. While aiming to distill the chaotic and dynamic realities of evacuation scenarios into computationally replicable formats, these models should concurrently encounter sources of uncertainties that characterize actual emergencies.

Thus, this review sails through the confluence of these three interconnected realms (understanding MSC Circulars, HEMs, and uncertainty management), which seek to craft evacuation models that are not only anchored in regulatory compliance but also demonstrate resilience and adaptability amidst uncertain real-world evacuation scenarios.

2.1. MSC circulars

MSC circulars (Circ.) concerning evacuation analysis for passenger ships establish a comprehensive framework through structured guidelines and methodologies to secure the enactment of safe and efficient evacuation procedures. The circulars delineate two primary methods for evacuation analysis: simplified and advanced. Simplified evacuation analysis is depicted as a deterministic method where passengers are assumed to be nonautonomous agents, adhering to a predefined, unvarying set of behaviors.

In contrast, advanced evacuation analysis employs a stochastic process to treat passengers as autonomous agents, thereby accounting for the variability and uncertainty in individual behaviors and responses during evacuation scenarios. The analysis guarantees that maritime entities have a range of analytical tools at their disposal for conducting swift assessments or undertaking detailed evacuation planning as necessary. This approach is consistent with international standards and enhances the safety of passengers in diverse maritime contexts. In the following, some issued circulars are briefly described in Table 3.

Table 3. MSC Circs.

Date	Document Number	Title	Reference
May 1999	MSC/Circ.909	Interim guidelines for a simplified evacuation analysis on ro-ro passenger ships	(IMO, 1999)
June 2001	MSC/Circ.1001	Interim guidelines for a simplified evacuation analysis of high-speed passenger crafts	(IMO, 2001)
June 2002	MSC.1/Circ.1033	Interim guidelines for a simplified evacuation analysis for new and existing passenger ships	(IMO, 2002)
October 2007	MSC.1/Circ.1238	Guidelines for both simplified and advanced evacuation analysis for new and existing passenger ships	(IMO, 2007)
June 2015	MSC/Circ.1166	Guidelines for a simplified evacuation analysis for high-speed passenger crafts	(IMO, 2015)
June 2016	MSC.1/Circ. 1533	Revised guidelines on the evacuation analysis for new and existing passenger ships	(IMO, 2016)

The MSC Circs have evolved over the years to address various facets of evacuation planning and analysis for passenger ships. Starting with MSC/Circ.909 in May 1999, preliminary guidelines were introduced, focusing on simplified methods for modeling evacuations on ro-ro passenger ships. Subsequent circulars, such as MSC/Circ.1001 and MSC.1/Circ.1033, expanded the scope by presenting provisional guidelines for high-speed crafts and standardizing methodologies across various ship types. MSC.1/Circ.1238 in October 2007 marked a shift towards integrating advanced evacuation analysis, which signaled a recognition of the need for both complex and simplified approaches in planning. The progression continued with MSC/Circ.1166 in June 2015, which refined guidelines for high-speed crafts to provide methodologies that stayed abreast of emerging insights.

The trajectory of these circulars not only enhances the depth and breadth of evacuation analyses but also increasingly prioritizes considering a wide array of human factors to guarantee guidelines are both relevant and effective in varied maritime evacuation scenarios. Continuing with MSC.1/Circ. 1533, issued on June 6, 2016, the guidelines delved deeper into simplified and advanced evacuation analyses, encompassing updates and refinements to align with the latest understanding of human behavior during evacuations and developments in evacuation.

2.1.1. Simplified evacuation analysis:

- Basic and Accessible:

The method, while foundational and potentially suitable for initial ship design phases due to its straightforwardness, is underpinned by several assumptions (e.g., deterministic behavior of passengers) that may not cater to all realistic, variable, and dynamic evacuation contexts found in actual emergency scenarios (IMO, 2016; Nasso et al., 2019).

2.1.2. Advanced evacuation analysis

- Detailed and individualized:

This method tries to accommodate the variabilities and specificities of individual passenger behaviors and response times, which aims to produce more accurate and reliable evacuation duration predictions than the simplified approach (IMO, 2016; Nasso et al., 2019).

2.1.3. Reflecting on MSC.1/Circ. 1533

- Integrating enhancements:

This circular acknowledges and incorporates improvements in understanding and modeling human behavior during evacuations. It encompasses modifications that cater to a more detailed exploration of evacuation dynamics. Thus, it provides a more thorough framework that recognizes the complexities and variabilities inherent in real-world evacuation scenarios (Bucci et al., 2016; IMO, 2016; Nasso et al., 2019).

- Balancing simplicity and detail:

While simplified analysis provides a quick and accessible means of predicting evacuation durations, advanced analysis brings forth a detailed, albeit more complex, method of planning, which becomes pivotal in scenarios where diverse and dynamic human factors play a significant role (Bucci et al., 2016; IMO, 2016; Nasso et al., 2019).

In this vein, MSC.1/Circ. 1533 culminates in a guideline that seeks to harmonize regulatory, practical, and human-centric perspectives in evacuation modeling, which desires to safeguard passengers through both the design and operational phases of passenger ships.

2.1.4. Limitations and discussion

To the best of current understanding, IMO guidelines reveal gaps, especially in addressing dynamic and uncertain human behavior, including factors like passenger walking speed, awareness, and capacity uncertainties at critical points like exit doors for developing human evacuation plans. Although the existing models in the literature primarily cover single-deck scenarios, they aim to mitigate these gaps and lay the groundwork for future enhancements, including applications in multi-deck settings (Arshad et al., 2022; IMO, 2016; Ni et al., 2017b; Sarvari et al., 2018). Acknowledging this, there is room for improvement and further refinement.

A pertinent example for future exploration can be the complex dynamics of passenger behavior (e.g., passenger walking speed moving between decks) in multi-deck passenger ship evacuations. Though not comprehensive, the approach is adaptable and aims to enhance evacuation planning in both current studies and practical implementations.

- Family consideration:

Ignoring familial units could result in evacuation models that fail to mirror real-life situations, where family members are likely to navigate together, potentially at the pace of the slowest member, which impacts overall evacuation times and dynamics.

- Uncertainty management:

The apparent dismissal of the impact of uncertainties from various evacuation factors may result in models that are overly optimistic and potentially misaligned with actual evacuation trajectories, especially considering the diverse passenger characteristics and behaviors during emergencies.

- Uniform starting point:

Assuming a uniform starting point for all passengers simplifies the complexities related to individualized starting points, which is more reflective of actual scenarios, particularly on larger ships or those with intricate layouts.

- Static speed assumption:

Holding the speed constant for each passenger neglects the natural variations and reductions in speed due to environmental factors during the evacuation.

- Exit and crew allocation:

Overlooking exit allocation and having ambiguous crew allocation criteria may result in suboptimal resource deployment, potentially increasing evacuation times and reducing the efficacy of the evacuation process, particularly in scenarios where specific exits become congested or impassable.

- Real-world preparedness:

Without strategies to dynamically manage disruptions, such as blocked or malfunctioning exit doors, the guidelines may lack robustness in safeguarding against plausible real-world evacuation hindrances. The dilemma surrounding the assumption of simultaneous evacuation without hindrance highlights two pivotal shortcomings:

- Door capacity limitations:

A static model may inadvertently direct evacuees towards congested exits, which exacerbates bottlenecks. Conversely, by recalibrating and rerouting passengers upon reaching door capacity, multi-period models may enhance flow, safety, and efficiency by effectively mitigating such congestion.

- Missed intervention points:

A lack of multi-period evacuation planning may overlook crucial intervention junctures, potentially missing opportunities to strategically allocate crew members to manage flows and prevent bottlenecks, particularly at vital stages or locations during the evacuation.

In essence, while the MSC guidelines provide a foundational framework for evacuation modeling, their limitations highlight an imperative for further refinement and enhancement to navigate the challenges of real-world passenger ship evacuations more accurately, reliably, and safely. These insights underscore the necessity of continued research and development in this domain to safeguard lives at sea further.

2.2. Human evacuation models

Navigating the multifaceted domain of HEM, within the maritime context, necessitates thoroughly exploring and discerning the diverse modeling paradigms prevalent in the extant literature, predominantly rooted in land-based environments. Primarily, HEMs articulate a strategic framework for evacuation by entailing the orchestration of evacuee movement through a defined network from their respective locations to specified safe destinations, aware of the temporal, spatial, and behavioral dynamics inherent to evacuation scenarios. The present discourse delineates a time-variant, unstructured, and disaggregated evacuation model, which inherently conforms to the convoluted nature of the maritime evacuation context under uncertainty (Karabuk and Manzour, 2019).

Literature categorizes evacuation models under various attributes, temporal variance, structural framework, granularity of evacuation planning, and traffic assignment methodologies. Time-variant models, such as those proposed by Bish et al. (2014), dynamically calculate the evolving state of evacuation against time-invariant counterparts that adhere to static temporal parameters (Yamada, 1996). Structurally, models may be delineated as either structured, mandating predefined evacuee entry into the system (Bish and Sherali, 2013; Liu et al., 2006), or unstructured, perceiving it as a variable integral to solution derivation (Bish et al., 2014; Chiu and Zheng, 2007; Sbayti and Mahmassani, 2006). Additionally, models traverse the spectrum from aggregate, strategizing for cohesive evacuee groups, to disaggregate, necessitating granular planning at, for instance, individual levels (Chiu and Mahmassani, 2002; Zheng et al., 2010).

Further bifurcation is witnessed in the paradigm of traffic assignment problems, oscillated between system-optimal formulations, which may potentially discriminate to elevate overall system performance (Ma et al., 2014), and user equilibrium formulations, grounded in the assumption of self-interest among individual evacuees (Pel et al., 2012; Yi et al., 2017). The macroscopic and microscopic modeling dichotomy further enriches the human evacuation modeling landscape, with the former focusing on optimizing egress routes from a global standpoint by treating crowds as a continuum and the latter zooming into individual behaviors by accounting for external and internal influencers of pedestrian movement (Hamacher and Tjandra, 2001).

Upon examining the models through the lens of macroscopic and microscopic perspectives, they can be categorized based on their similarities within these two approaches. Macroscopic-type models can encompass time-invariant, structured, and aggregate models. Conversely, microscopic-type models can include time-variant, unstructured, and disaggregate models.

2.3. Methodologies in HEM

Mathematical human evacuation models bring advantages owing to their prescriptive nature and structured methodology for formulating and solving complex problems (Bayram, 2016). These models, recognized for their optimization capabilities, can play a pivotal role in devising scalable evacuation strategies (Liu et al., 2016; Saadatseresht et al., 2009). They are inherently prescriptive, which provides specific guidelines or recommendations on the optimal courses of action based on quantitative data and established algorithms. This aspect is crucial in evacuation scenarios, where strategic decision-making should be swift and sound. However, the prescriptive nature of mathematical models means they often require data and can sometimes oversimplify scenarios, not fully capturing human behavior during emergencies (Hamacher and Tjandra, 2001; Vermuyten et al., 2016).

Conversely, simulation models, such as cellular automata, social force models, and agent-based simulations, are instrumental in solving crowd evacuation challenges by offering a detailed depiction of evacuation scenarios. These models can replicate real-world conditions, enabling planners to visualize and comprehend the dynamics of critical factors like congestion. Pereira et al. (2017)

developed a cellular automata model considering group characteristics for optimizing evacuation routes. J. Li et al. (2021) proposed a social force model for the temporal-spatial dynamics on stairs, while Sun and Liu (2021) merged a density evacuation algorithm with a social force model for efficient path planning. Despite their ability to describe complex evacuation behaviors and interactions, simulation models require significant computational resources, especially for large populations or complex environments (Haghani, 2020). Tools such as VELOS, AENEAS, EVI, and maritime-EXODU simulate evacuation scenarios but often lack direct optimization capabilities, such as optimization under uncertainty (Galea et al., 2004; Ginnis et al., 2010; Meyer-König et al., 2007; Valanto, 2006; Vassalos et al., 2003). These models can provide essential insights into potential challenges and decision-making processes during evacuation, yet translating these insights into strategic actions demands further analytical effort.

Current research on emergency evacuation also incorporates surveys and statistical models to enhance understanding and efficiency (Finiti, 2021). Studies have examined evacuee performance, focusing on reaction times, walking speeds, and behaviors during crowd evacuation (Na et al., 2019; W. Xie et al., 2020; D. Zhang et al., 2017). Research has delved into the determinants of evacuation decisions, employing the random parameter binary logit model for assessment (Sarwar et al., 2018). Dulebenets et al. (2019) designed a statistical model to explore factors influencing evacuation and to bolster regional evacuation strategies in disaster scenarios. These approaches can offer practical insights into evacuation decision-making processes, identify key evacuation influencers, explore characteristic evacuation behaviors, and support the refinement of evacuation planning (K. Liu et al., 2022; Vanem and Skjong, 2006).

While they can provide a description of events, they do not inherently suggest the best course of action. While their descriptive nature is practical for understanding a situation, they often require additional interpretative effort to translate insights into strategic actions. Also, their reliance on specific, sometimes narrow scenarios can limit the scope of their application without substantial adjustments. Furthermore, they can be computationally heavy, especially when dealing with large populations or extensive facilities, and they require calibration and validation against real-world scenarios, which are often practically and ethically challenging. Again, the outcomes from simulations can sometimes be challenging to generalize for broader applications, as they are usually tailored for specific scenarios (Bachelet and Yon, 2007; Carson, 2005; Iassinovski et al., 2003; Noorhazlinda, 2019).

In human evacuation planning, both prescriptive mathematical models and descriptive simulation models hold benefits. Mathematical models shine by providing optimized evacuation plans experienced at handling diverse constraints and uncertainties, delivering actionable and practical guidance suitable for emergencies. Their strategic optimization capabilities can manage uncertainties. This thesis applies mathematical optimization to tackle these uncertainties.

2.4. Uncertainty management

Uncertainty, pervasive in research and planning, critically influences predictive analytics and decision-making, especially in domains where decisions are paramount, such as maritime safety. Effective management of uncertainty is crucial to ensure the resilience and viability of resulting models under diverse conditions (Dellino and Meloni, 2015).

The primary strategic aspects addressed through the generic human evacuation modeling for passenger ships involve the following: Which evacuation routes should be prioritized? What should be the estimated time frame for complete evacuation in various emergency scenarios? How many safe zones should be established? Where should these safe zones be placed within the ship? Which collaboration partners (e.g., crew members) should be selected? What evacuation, communication, and safety technologies should be adopted, and what should be their capacity? Which areas of the ship should be accessible/avoided during specific emergencies? The activities under consideration naturally include evacuation and emergency response, and recovery activities following the event may also be relevant (Balakhontceva et al., 2015; Galea et al., 2013; IMO, 2016; Kruke and Auestad, 2021; K. Liu et al., 2022; Ma et al., 2024; Ng et al., 2021; Wang et al., 2022a; Yue et al., 2022). These questions are often examined in isolation, mainly when prompted by events such as the introduction of new ship models, regulatory changes, or major incidents. Beyond these questions, various factors contribute to the complexity of human evacuation modeling. The first is the ship's layout and potential obstacles during evacuation—for instance, challenges involving complex evacuation processes in ships with intricate designs (Arshad et al., 2022; Ni et al., 2017b).

A second aspect involves the incorporation of passenger autonomy and diverse characteristics into the modeling (Arshad et al., 2022; K. Liu et al., 2022). It necessitates a strategic approach that not only prioritizes safety but also considers the individual and collective behaviors, preferences, and needs of passengers as autonomous agents, which adds a layer of complexity to the decision-making processes within the model. A third crucial aspect is the long-term impact of the evacuation model decisions (Arshad et al., 2022; K. Liu et al., 2022). Using a static, short-term model may be reasonable when the decisions are limited to small-scale evacuations or drills; however, when dealing with the evacuation of large ships, particularly where different scenarios, such as capsizing, are considered, more than static models are needed. This introduces a fourth complexity aspect: uncertainty.

Most models proposed in the literature are not only static but deterministic (Arshad et al., 2022; Q. Xie et al., 2020c, 2020b). When considering multiple potential emergency scenarios, the problem becomes dynamic and non-deterministic (e.g., stochastic). Moreover, more is needed to consider typical variables such as passenger walking speed, passenger travel distance, and ship layout (Arshad et al., 2024; Wang et al., 2022a); one could also include extreme events such as severe weather incidents that may affect the evacuation process (Balakhontceva et al., 2016; Stefanou et al., 2024). Significant investments are often required to implement strategic evacuation modeling decisions. Generally, stakeholders and safety regulators may require an assessment of safety and effectiveness before approving these decisions. Safety comes from the net lives saved and injuries prevented by utilizing an evacuation model during an emergency: safe evacuations and minimized injuries less any risks or injuries associated with the evacuation process. These safety metrics and risks should be anticipated in the evacuation model.

2.4.1. Deterministic HEMs

A deterministic human evacuation model for passenger ships determines the movement of individuals from a point of danger to a point of safety, which assumes a predefined and fixed set of parameters and conditions without variability (IMO, 2016). In this context, every passenger abides by a set route and timeline dictated by the model's input parameters, such as fixed walking speed and unvarying decision-making patterns, ignoring the natural human tendencies towards uncertainty. Despite its deterministic nature, this model seeks to optimize evacuation times and assess the efficiency of existing safety protocols within a ship. It provides a baseline scenario where all variables function optimally and without stochastic interruption (Nasso et al., 2019). While it may lack the uncertainty of real-world evacuations, it offers a simplified and controlled environment to analyze fundamental aspects of evacuation strategies and identify primary areas of improvement in a ship's safety design and emergency procedures.

Despite providing valuable insights into optimal scenarios, deterministic human evacuation models bear several disadvantages owing to their inherent inability to account for the multifaceted and uncertain nature of human behavior and how situations unfold, particularly in emergencies. First, they often fail to accurately represent the variability and randomness, such as walking speed, in movement during evacuations (Sun et al., 2018b). Second, deterministic models overlook the potential impact of unforeseen variables, such as obstructions and variations in individual physical abilities, which can influence evacuation processes (Kim et al., 2019). Lastly, they may underestimate the actual evacuation time and potential bottlenecks, as they do not consider the possible random elements introduced by uncertain decision pathways during an emergency (Nasso et al., 2019).

Given these limitations, there is an argument for integrating uncertainty modeling into human evacuation scenarios. Uncertainty models allow researchers and safety planners to explore a broader range of possible outcomes by acknowledging human actions' inherent uncertainty and variability (Arshad et al., 2024; Lovreglio et al., 2016; Wang et al., 2015; Q. Xie et al., 2020b). In this research, uncertainty involves including stochastic (random) elements that simulate the uncertainty often seen in real-life situations. Specifically, in evacuation dynamics, this means accounting for factors such as the varying speeds at which passengers move and passenger travel distances. These speeds and distances can change due to various reasons like panic, physical limitations, obstacles, or different environmental conditions (e.g., ship motions) encountered during an evacuation (Ni et al., 2017b). Uncertainty modeling can offer a more realistic representation of evacuation dynamics by incorporating stochastic elements, such as fluctuating movement speeds and travel distances (Arshad et al., 2022; Bayram, 2016). Additionally, uncertainty may stem from the onboard facilities, including the capacity of transitional points like exit doors, which can experience bottlenecks. Furthermore, mixed uncertainties can emerge, including variability in passenger walking speeds and travel distances.

This shift towards embracing complexity and uncertainty ultimately enables the development of more robust, adaptable, and resilient evacuation strategies, which can provide enhanced safety and preparedness in real-world emergency scenarios on passenger ships.

2.4.2. HEMs under uncertainty

While deterministic models offer a fundamental basis for HEMs, their inability to account for uncertainties and potential variations in future scenarios limits their predictive and adaptive capacities. Since these models do not incorporate unforeseen variables and information inaccuracies about conceivable future circumstances, transitioning towards uncertainty modeling emerges as a vital step toward enhancing the realism and applicability of HEM designs.

Uncertainty, risk, and certainty have been pivotal in shaping decision-making models and further specifications from (Mousavi and Gigerenzer, 2014). Certainty implies a straightforward decision-outcome link; risk involves probabilistic outcomes, while uncertainty conveys situations where outcome probabilities cannot be assigned. The widely accepted distinction between risk and uncertainty is not universal, with traditional risk management defining risk as a function of the probability and impact of adverse events (Aven and Zio, 2011; Grossi, 2005). Various models, including fuzzy sets and belief functions, have been used to quantify the likelihood of future events. This discourse proposes classifying decision scenarios based on information quality: decisions under certainty are made with perfect information, while those under uncertainty involve imperfect information, leading to risks, which denote the potential for undesired outcomes and grow with the probability and severity of these outcomes.

Given that uncertainty is interpreted and applied diversely across various disciplines, this section will briefly discuss data uncertainty and the different methodologies employed to model it.

2.4.2.1. Data uncertainty

Navigating the complex landscape of data uncertainty necessitates understanding its origins and the data types. The onset of complexity in data analysis is rooted in diverse aspects of data uncertainty, which includes challenges such as measurement inaccuracies, the presence of missing values, and inconsistency in the data. It substantially impacts the reliability and credibility of subsequent data analysis and decision-making processes. This complexity is further entwined with the intrinsic characteristics of the data itself. Numerical, categorical, and linguistic data each present unique challenges and opportunities in uncertainty management. Numerical data, embodying quantifiable metrics such as age, offers a tangible measure yet is susceptible to variability and measurement errors

(Aggarwal and Yu, 2009). In contrast, categorical data, exemplified by non-quantitative classifications like gender and linguistic terms, which encapsulate qualitative descriptors such as high or low, are often considered subjective and interpretative uncertainties (Singh et al., 2007).

Under the umbrella of uncertainty, the presence of either perfect or imperfect/partial information steers the decision-making process toward scenarios of certainty or uncertainty. Within uncertainty, three primary forms emerge randomness, hazard, and deep uncertainty (Lempert et al., 2006). Randomness, arising from the stochastic nature of events, pertains to routine business operations with minimal impact and assumes the existence of ample, reliable historical data to estimate probability distributions. Hazard embodies low-probability, high-impact unusual events, whereas deep uncertainty emanates from an inability to estimate the probability of potential future extremes due to insufficient information (Klibi et al., 2010). Additionally, Mula et al. (2007) bifurcates uncertainty into fuzziness, associated with flexibility in constraints and objectives, and epistemic uncertainty, which pertains to knowledge deficiencies regarding input data, often expressed through linguistic attributes or judgmental data (Bairamzadeh et al., 2018).

However, it's essential to recognize the inherent limitations in fully addressing epistemic uncertainty, especially in the context of unknown unknowns. While methods exist to manage known variables/parameters and even those uncertainties that can be anticipated, there remain challenges in dealing with aspects that are wholly unforeseen or beyond current understanding. Furthermore, model and parameter uncertainties emerging from modeling simplifications and parameter estimation variabilities, respectively, necessitates a tailored approach towards uncertainty management (Y. Wang et al., 2013).

Thus, a comprehensive strategy pivots on identifying and understanding these uncertainties to ensure that the subsequent selection and application of uncertainty management methods are precisely tuned to the distinctive challenges posed by the specific data and uncertainty types in question. This interweaving of understanding the data and its associated uncertainties lays a robust foundation for informed, resilient, and effective decision-making and analysis in the omnipresent haze of uncertainty.

2.4.2.2. Uncertainty modeling approaches

Table 4 delineates a variety of techniques employed for managing uncertainties in different decision-making contexts. Techniques such as Monte Carlo Simulation (MCS) and Robust Optimization (RO) deal with numerical data and uncertainties through randomness and bounded uncertainty, respectively, while others, like Bayesian Networks (BN) and Fuzzy Optimization (FO), navigate through categorical data and linguistic uncertainties. The approaches such as Data-Driven Robust Optimization (DDRO) and Scenario-Based Optimization (SBO) utilize historical and observational data to enhance decision-making resilience across various potential scenarios. Stochastic Optimization (SO) manages numerical data and inherent randomness, which aligns decisions with diverse realizations of random parameters in multi-stage decision scenarios. Each technique is tailored to specific application contexts, considering the nature of data and uncertainties encountered, with references provided for deeper insights and explorations into each methodology.

Table 4. Comparative analysis of uncertainty handling techniques in decision-making models.

Technique	Applicable datatype	Associated uncertainties	Application context and characteristics	Reference
MCS	• Numerical data with known • Estimable probability distributions	• Randomness • Parameter uncertainty	• Problems involving random variables. • Suitable for complex systems • Assessing impact due to variable inputs.	(Harrison et al., 2010; Dirk P. Kroese et al., 2014)
RO	• Numerical data with bounded uncertainty	• Epistemic • Model uncertainty	• Solutions are viable under all considered scenarios. • Solutions are least sensitive to parameter changes.	(Gabrel et al., 2014; Yanıkoğlu et al., 2019)
BN	• Categorical • numerical data with causal relationships	• Epistemic • Parameter uncertainty	• For modeling probabilistic relationships • Dependencies among variables.	(Chen and Pollino, 2012; Marcot and Penman, 2019)
SO	• Numerical data with inherent randomness	• Randomness • Parameter uncertainty	• Applicable in multi-stage decision problems with randomness, • Aligning decisions to various realizations of random parameters.	(Powell, 2019; Zheng et al., 2015)
FO	• Data expressed with linguistic terms	• Linguistic • Epistemic uncertainty	• Handles vagueness and imprecision. • Useful for human-like reasoning and decision-making	(Kahraman et al., 2015; Mittal et al., 2020)
DDRO	• Historical data • Observational data	• Epistemic • Model uncertainty	• Utilizing historical data to guide optimization. • Offering resilience to solutions.	(Bertsimas et al., 2018; Shang et al., 2017; Shang and You, 2018)
SBO	• Numerical data	• Epistemic • Model uncertainty	• Engaging multiple scenarios to derive decisions that are feasible or near optimal. • Managing trade-offs across scenarios.	(Knueven et al., 2023; Mars and Hundt, 2009)

Table 5 presents a comparative analysis of various uncertainty modeling techniques, which highlight their respective strengths and challenges. While these techniques showcase specific overlapping attributes, the optimal application of each largely hinges upon particular data characteristics and application contexts.

Table 5. Comparative overview of uncertainty modeling techniques: strengths and challenges.

Technique	Strength	Challenge
MCS	• Handling complex systems • Assessing variable impact • Simulates various scenarios	• Computational expense • Slow convergence rates • Dependence on random number generators • Requirement for known probability distributions
RO	• Computational tractability • Utilization of historical data • Parameter stability • Scenario viability	• Conservative solutions • Boundaries definition • Ignorance of probability distribution
BN	• Representation of dependencies • Prior knowledge incorporation • Ability to update beliefs	• Computational complexity and cost • Parameter learning • Difficulty in translating dependencies
SO	• Risk management • Multistage decision-making • Inclusive stakeholder perspective	• Computational complexity and cost • Big data requirement to estimate probabilistic distributions • Scenario generation and reduction
FO	• Handling imprecision • User-centric approach • Flexible solution mechanism	• Accuracy compromises • Objective standardization • Computational demands
DDRO	• Incorporating big data in decisions • Enhancing reliability and robustness • Balancing optimality and feasibility	• Big data quality and availability • Computational complexity • Overfitting risk
SBO	• Adaptive decision making • Utilization of static and dynamic optimization	• Computational complexity • Data and scenario management • Robustness against diverse scenarios

MCS leverages repeated random sampling to navigate through complex systems despite its computational demands and reliance on high-quality random number generators. On the other hand, *RO* utilizes historical data to provide stable solutions across varied scenarios, even without precise probability estimates, though this might sometimes constrain its predictive accuracy. While BN can depict relationships among variables and parameters, use existing knowledge, and adapt to new data, they also pose challenges related to computational demands, learning from data, and accurately representing dependencies in mathematical terms. SO analyzes risks and supports adaptable, multi-stage decision-making, inclusively accounting for diverse stakeholder perspectives. However, it confronts limitations like computational complexity and cost, a necessity for substantial data, and the task of crafting and condensing plausible scenarios for model development. FO provides a valuable toolkit for navigating through uncertainties and imprecisions using a user-friendly and flexible approach.

However, it brings challenges, such as computational demands, concerns regarding precision, objectivity, and issues related to standardization, which require careful consideration in its application. DDRO operates data to make informed decisions but has burdens like needing good data and lots of computer power. It can also get too tailored to existing data (overfitting). SBO adapts decisions using a mix of planned and on-the-spot optimization, which steers through various situations flexibly. However, its sophisticated decision-making demands weighty computational power, extensive data and scenario management, and a sturdy approach to perform well across diverse, possibly unforeseen situations.

Finally, hybrid uncertainty modeling methodologies are emerging as potent tools in managing complex, uncertain systems by integrating the strengths of various individual modeling techniques (Aien et al., 2016; Wu et al., 2017). These methodologies aim to mitigate the limitations inherent in using a single modeling approach, especially in complex environments with multiple uncertain factors.

One such approach is *HRSSRP* (Hybrid Risk-Neutral, Two-Stage, Scenario-Based Stochastic ρ-Robust Programming). *HRSSRP* addresses real-life challenges by offering an approach to risk assessment and decision-making. Its comprehensive risk analysis goes beyond traditional methods, accommodating diverse future scenarios and mitigating overt optimism and undue caution. The model's strength lies in its adaptability, navigating uncertainties through a two-stage decision process that adjusts strategies based on evolving data, much like in real-world situations.

Furthermore, *HRSSRP*'s flexibility can make it useful for handling the multifaceted nature of live data sources. This approach is crucial because it aligns the modeling technique closely with the data's behavior. However, it's essential to acknowledge that while *HRSSRP*'s advanced capabilities make it a tool for dynamic, uncertain conditions, it demands computational resources and expertise in data management.

2.4.2.3. Risk perspective in uncertainty modeling

In uncertainty modeling and optimization, three distinctive risk perspectives influence decision-making: risk-neutral, risk-averse, and risk-seeking. A risk-neutral perspective guides through uncertainties by considering all scenarios without leaning excessively towards security or gain, aiming for a balanced, unbiased decision-making approach (Shapiro, 2021). In contrast, a risk-averse perspective prioritizes safety, preferring decisions that minimize potential risks and avoid undesirable outcomes, even at the expense of higher rewards (Li and Grossmann, 2021; Shapiro et al., 2013).

On the opposite spectrum, a risk-seeking perspective embraces risks for the potential of higher rewards, which opts for bolder strategies that, while riskier, could lead to more advantageous outcomes if the risks pay off (Yu et al., 2021). Each perspective represents a different stance towards managing risk versus reward in the face of uncertainty, which directs decision-makers based on their propensity to either embrace or mitigate risks.

2.5. Literature gap

Evacuation strategies, critical in emergencies within various settings, have evolved significantly over the past decade. Researchers have delved into optimizing evacuation procedures, which focus on personalized routes, uncertainty management, infrastructure adaptation, and behavioral considerations. This literature review briefly synthesizes identifying thematic intersections and divergences that shape contemporary understanding and application.

- The interplay of macroscopic and microscopic considerations

The body of literature unveils a shift from generic, macroscopic strategies towards more granular, microscopic analyses. Saeed Osman and Ram (2013) and Ni et al. (2017) modeled a structured system-optimal formulation, which balances time-variant considerations with aggregate and disaggregate planning. Their foundational work paved the way for Gao et al. (2020) and others, which began integrating macroscopic structures and microscopic human behaviors, acknowledging that efficient evacuation is not merely systemic but inherently human-centric. Yang et al. (2022) further this discourse, introducing a stochastic user equilibrium model that factors in human uncertainty. Their approach highlighted the need for dynamic planning that accounts for human behavior, an aspect often sidelined in earlier deterministic models.

- Optimization amidst uncertainty

Uncertainty management remains a pivotal challenge, with early models often paying attention to real-time variabilities. Pourrahmani et al. (2015) marked a transition with their fuzzy-set theory, accommodating uncertainties in evacuee numbers. Successive studies, particularly by Ghasemi et al. (2020) and Shin and Moon (2022), embraced stochastic considerations, embedding uncertain elements like resource availability and structural integrity into their frameworks.

Xie et al. (2020b) developed further, recognizing the uncertainty of passenger travel time, yet their focus on initial passenger density hinted at the need for more comprehensive analyses. This gap, indicating a need to broaden uncertainty parameters, was partially bridged by Lozowicka (2021) and Guo and Zhang (2022), who factored in individual selection and passenger behavior stochasticity, setting the foundation for improved uncertainty management in evacuation scenarios.

- Solution methodologies: From theoretical to practical

The solution methodologies evolved, which reflects a greater emphasis on practical, real-world applications. Early methods relied on mathematical programming, with Saeed Osman and Ram (2013) and Gao et al. (2020) utilizing integer programming and constraint-based design. However, with Yuan et al. (2014) and Ni et al. (2017)'s simulation models, there was a noticeable shift towards more dynamic scenario planning. This trend was exemplified by Xie et al. (2020c) and Lozowicka (2021), who integrated genetic algorithms with surrogate-based modeling, which realized the unpredictability of real-world situations like fire impact and individual behaviors. Cotfas et al. (2023) took this a step further, which simulates the practical application of guidance apps, thereby merging technological advancements with traditional evacuation methodologies.

- Settings: land-based versus ship-based applications

The reviewed literature diverges in application settings, with distinct methodologies emerging for land-based and ship-based evacuations. Studies like those by Ghasemi et al. (2020) and Shin and Moon (2022) often focused on land-based evacuations, which incorporate urban complexities and building infrastructures. In contrast, Yuan et al. (2014) and Fang et al. (2023) ventured into maritime contexts, which consider ship-specific dynamics and constraints, diversifying the applicability of evacuation research. This distinction highlighted challenges within different environments, such as the influence of ship motion, confined spaces, and passenger density in maritime evacuations.

The literature reveals consistent limitations across various studies in the context of evacuation models, which highlight a critical need for more comprehensive, real-world applicable solutions. Notable shortcomings include Osman and Ram's (2013) oversight of flow capacities, Pourrahmani et al.'s (2015) struggles with real-time uncertainties and Gao et al.'s (2020) neglect of environmental and behavioral complexities within evacuation spaces. These issues, alongside Ghasemi et al.'s (2020) disregard for diverse transportation modes and uncertainties, Guo and Zhang's (2022) difficulties with real-time data, and Shin and Moon's (2022) narrow focus on structural uncertainties, highlight the models' disconnect with on-ground realities.

In maritime contexts, gaps persist, with Yuan et al. (2014) and Ni et al. (2017) simplifying passenger behaviors and interactions, and Xie et al. (2020b, 2020c) limiting their focus to specific variables like initial passenger density and fire scenarios while neglecting broader influencing factors. Even with methods, as employed by Fang et al. (2023), Cotfas et al. (2023), and Chen et al. (2023), practical complexities of ship evacuations — such as specific disaster scenarios, complex crowd dynamics, and the influence of physical variables — are often underexplored. These collective insights indicate a pressing need for evolved models that are intricately aligned with the multifaceted realities of maritime evacuation contexts.

Table 6 categorizes critical research in human evacuation, which outlines themes like macroscopic and microscopic model scope, optimization of evacuation strategies, management of uncertainties, various applied solution methodologies, and the diverse settings of model application.

Table 6. Summary of relevant literature.

Paper	Macroscopic	Microscopic	Optimization	Uncertainty management	Solution methodology	Setting
Saeed Osman and Ram (2013)	• Structured • System-optimal formulation	• Time-variant	Deterministic		• Two-phase evacuation routing (2PER) • Integer programming • Multi-commodity network flows	Land-based
Yuan et al. (2014)		• Time-variant • Disaggregate • User-equilibrium	Stochastic: • Behavior of passengers	PSO	• Simulation	Ship-based
Pourrahmani et al. (2015)		• Disaggregate • User-equilibrium	Fuzzy: • Specific number of evacuees (demand)	FO	• Mathematical programming	Land-based
Ni et al. (2017)	• Structured • System-optimal formulation	• Time-variant • Disaggregate	Deterministic		Simulation: • Agent-based modeling	Ship-based
Gao et al. (2020)	• Time-invariant • Structured • Aggregate • System-optimal formulation		Deterministic		Mathematical programming: • Constraint-based design • Branch and bound algorithm	Land-based
Xie et al. (2020b)		• Disaggregate	Stochastic: • Passenger travel time	• Polynomial chaos expansion • Nested sampling technique	Simulation: • Surrogate- based modeling	Ship-based
Xie et al. (2020c)	• Structured	• Time-variant • Disaggregate	Stochastic: • Passenger response time	• LPCE • GA	Simulation: • Surrogate- based modeling	Ship-based
Ghasemi et al. (2020)	• Structured • System-optimal formulation	• Time-variant	Stochastic: • Demand for resources and services	• Stochastic multi-objective optimization • Simulation for probabilistic demand estimation • Chance constraint	• Mathematical programming	Land-based
Lozowicka (2021)	• Aggregate • Structured • System-optimal formulation	• Time-variant	Stochastic: • Selection of individuals for GA process	• GA	• Simulation-mathematical approach	Ship-based
Wang et al. (2021a)		• Time-variant • Disaggregate • User-equilibrium		• Quantifying the variability in walking speeds	• Experimental analysis	Ship-based
Guo and Zhang (2022)	• Structured • System-optimal formulation	• Time-variant • Disaggregate	Deterministic: • Physical characteristics Stochastic: • Passenger behavior	• Light Gradient Boosting Machine • Non-dominated sorting GA III	Simulation-mathematical approach	Land-based
Shin and Moon (2022)		• Time-variant • Disaggregate	Stochastic: • Structural integrity of the building • Potential collapse scenarios	RO	Mathematical programming	Land-based

Yang et al. (2022)		• Time-variant • Disaggregate • User-equilibrium	Stochastic: • Pedestrian behavior • Crowd movement	Stochastic user equilibrium model	Mathematical programming: • Social force model • Adaptive average method	Land-based
Fang et al. (2023)	• Structured	• Time-variant • Disaggregate • User-equilibrium	Deterministic		Simulation	Ship-based
Cotfas et al. (2023)	• Structured	• Time-variant • Disaggregate • User-equilibrium	Deterministic		Simulation: • Agent-based modeling	Ship-based
Chen et al. (2023)	• Structured	• Time-variant • Disaggregate	Deterministic		Simulation: • CAIE	Ship-based
This research	• Structured	• Time-variant • Disaggregate • User-equilibrium	Stochastic: • Passenger walking speed • Passenger travel distance • Disruption in exit doors	• *RO* • *RSSP* • *HRSSRP*	Mathematical programming	Ship-based

Table 7 outlines a variety of simulation tools designed for human evacuation analysis. Some models are discrete, allowing agents to occupy specific points, while others are continuous, providing an uninterrupted sequence within a defined space (Arshad et al., 2022).

Table 7. Evacuation simulation tools (Arshad et al., 2022).

Name	Field	Space representation	Purpose	Reference
MaritimeEXODUS	• Maritime	• Discrete	• Simulation of evacuation behaviors and • Pedestrian dynamics	Gwynne et al. (2003)
IMEX	• Maritime, • Aerospace, and • Civil Engineering	• Discrete	• Pedestrian dynamics and • Human behavior simulation	Park et al. (2004)
AENEAS/PedGo	• Maritime	• Discrete	• Distribution of passengers and • Route definition/evacuation simulation	Meyer-König et al. (2007)
UNITY engine	• A broad range, including maritime	• Hybrid	• Simulation	Unity (2008)
VELOS	• Maritime	• Continuous	• Assessment of passenger and crew activities	Ginnis et al. (2010)
EVI	• Maritime	• Hybrid	• Pedestrian movement simulation	Guarin et al. (2014)
SIMPEV	• Maritime	• Discrete	• Evacuation analysis based on human behavior	Roh and Ha (2013)

While these tools have proven to be robust and widely utilized in the field, this thesis pivots towards leveraging optimization techniques to tackle (hybrid) uncertainties in optimizing personalized human evacuation plans. This shift is motivated by the latest discussions in academic circles and the approach of uncertainty modeling, which seeks to address through uncertainties employing various methods detailed in the contributions of Arshad et al. (2022), and as further elaborated in Table 6.

Building on this, the current research delves into mathematical optimization models to refine human evacuation plans under (hybrid) uncertainties, concentrating on key parameters such as passenger walking speed, travel distance, and exit door capacity. By deploying mathematical formulations, HEMs are constructed. These models can be valued in evacuation planning due to their capacity to generate optimal and scalable solutions that are aligned with specific objectives. They can be considered for their adaptability in incorporating constraints, facilitating sensitivity and scenario analyses, and handling stochastic characteristics to mitigate uncertainties. This adaptability can render them robust tools for formulating evacuation models (Hamacher and Tjandra, 2001; Vermuyten et al., 2016).

The distinction between simulation and optimization techniques is fundamental to the applied approach in this thesis. Simulation tools, such as VELOS, can mirror complex realities, enabling the exploration of diverse scenarios based on varying inputs (Ginnis et al., 2010; Konstantinos V Kostas et al., 2014a). These tools can offer a visual grasp of evacuation processes but do not always ensure the attainment of the optimal solution. Optimization techniques, conversely, can identify the most suitable solution that aligns with established objectives and constraints, focusing on delivering the evacuation plans by evaluating different factors and uncertainties (Bachelet and Yon, 2007). This thesis applies optimization techniques over simulation for developing evacuation plans, advocating for their use in addressing the complexities and uncertainties inherent in human evacuation planning.

This dissertation has delved into the complexities of human evacuation research to navigate its uncertainties and the uncertain nature of human behavior in emergencies. An evaluation of existing literature, including an examination of MSC guidelines and insights from systematic reviews such as those by Lee et al. (2003), Sarvari et al. (2018), and Arshad et al. (2022), revealed gaps in current evacuation models. These gaps are particularly in managing uncertain parameters like passenger walking speeds, travel distances, and exit door capacities, as well as in addressing the combined uncertainties of these factors during emergencies.

Addressing these deficiencies, the research introduces three mathematical optimization models, each designed to manage time-sensitive and individual-specific evacuation scenarios focusing on user equilibrium and structured methodologies. These models prioritize an individualized approach, accommodating each evacuee's speed, distance, potential exit blockages, and initial location to create a personalized evacuation plan. The contribution of this dissertation lies in its application of uncertainty modeling techniques—robust optimization, stochastic optimization, and a hybrid robust-stochastic method for developing personalized evacuation plans. These methods, while offering a new perspective and contributing insights to the field, are acknowledged as not being flawless. The exploration of these optimization techniques uncovers their potential for contributions to evacuation research despite being relatively unexplored within the existing body of literature.

Moreover, the dissertation extends the application of these models to determine the optimal number of exit doors required, considering various factors such as walking speeds, travel distances, door capacities, and passenger numbers. The practical validity of these models is further demonstrated through the application to a real-life case study, utilizing the Evi simulation tool for a passenger ship's single deck.

This research employed *RO*, *RSSP*, and *HRSSRP* to model and manage hybrid uncertainties, including passenger walking speed, travel distance, and potential disruptions in exit doors. Doing so emphasized creating a robust framework capable of withstanding real-world variabilities and emergencies.

This dissertation marks progress by moving beyond traditional evacuation methods, especially in addressing hybrid uncertainties and employing uncertainty modeling techniques. It suggests a future where evacuation protocols, in maritime settings, are tailored, adaptable, and conscious of individual human factors. The insights offered here can pave the way for further development of these models and their potential integration into standard practices, which can play a vital role in enhancing safety. This work highlights the importance of continued research and refinement in this crucial area, highlighting that while strides have been made, there remains ample scope for improvement.

3. Human evacuation problem description

This section outlines the structure of the human evacuation optimization problem during maritime emergencies, which is central to this study. When a threat emerges, the ship initiates evacuation protocols. In high-risk situations, the crew and emergency teams enforce a compulsory evacuation. This research considers various real-world uncertainties within the evacuation process, such as potential exit blockages, the need for resilience, and uncertain factors such as passenger walking speeds and travel distances. These factors can be influenced by ship motions, passenger interactions, and any hazard which affects their walking speed capability (Chen et al., 2023; Fang et al., 2023). A dynamic method for adjusting walking speeds over time is also introduced, acknowledging that factors like developing hazards, ship motions, and passenger congestion can slow progress. This model navigates these real-world challenges and seeks to formulate an optimized, resilient evacuation plan.

For enhanced clarity and decision-making efficiency, the ship's deck plan is converted into a network graph (J. Wang et al., 2013). This graph features nodes (representing cabins, facilities, exit points, and crew areas) and edges (depicting evacuation routes from current locations to designated exits). The evacuation dynamics is addressed, acknowledging passengers' diversity, categorized into individuals ($P = \{p_1, p_2, \ldots, p_n\}$ and family groups ($F = \{f_1, f_2, \ldots, f_m\}$) of varying compositions. These groups are defined by specific attributes (age, gender, physical condition), which influence mobility factors like walking speed and travel distance. A collective speed is considered dictated by the slowest member, particularly for families, acknowledging that families prefer to stay together during evacuation scenarios (Ditlev Jorgensen and May, 2002).

Another essential aspect is the passengers' state of alertness, referring to their ability to quickly notice, understand, and react to emergency cues, including alarms. This alertness level can shape the response time, which covers the interval from the alarm's onset to the evacuation decision, where more alert individuals tend to respond faster. Passengers engaged in activities such as sleeping, using their phones, drinking, or eating may have diminished alertness, which leads to longer response times (Brown, 2016). Passengers are berthed in various cabins situated within the corridors of several main vertical zones (MVZ). Each MVZ encompasses multiple corridors, and within these corridors, cabins are distributed ($L = \{l_1, l_2, \ldots, l_h\}$). The types of cabins range from standard and magic to owner suites, having different capacities, with some featuring terraces.

However, these cabins do not have direct evacuation routes, which require occupants to proceed through specific corridor pathways to reach evacuation doors during an emergency. Evacuation doors ($E = \{e_1, e_2, \ldots, e_o\}$) are integral components in the corridors, which serve as critical junctions that connect passengers from their current positions to exit points, ultimately leading to muster stations. These connections form what is known as evacuation routes, strategically planned pathways that expedite the safe relocation of passengers in emergencies. Nonetheless, the effectiveness of these doors is subject to capacity constraints, which are influenced by the size of the corridor, the capacity at assembly points, or decisions made by the emergency team. These factors highlight the necessity for a versatile model capable of adapting to these variables to manage passenger movement dynamically in emergencies.

Multi-period evacuation planning can enhance the adaptability and efficiency of emergency protocols, cater dynamically to real-time developments, and deliver a higher safety level for everyone involved. It positions the versatile model not just as a static response mechanism but as a proactive, strategic tool in emergency management (Hamacher and Tjandra, 2001; Minas et al., 2020). Let's denote ($T = \{t_1, t_2, \ldots, t_q\}$) as the distinctive intervals that make up the entire evacuation planning timeframe. Each interval ends when the exit doors have been used to their full potential, which indicates maximum occupancy.

Within this structure, the model succeeds in a dynamic, multi-stage setting. Passengers are guided to designated exit doors along an evacuation path, which depends on the doors' residual capacity. The practical limit of any evacuation route is determined by the maximum throughput of the exit doors, which guarantees a practical and streamlined evacuation rate throughout the process. This strategy harmonizes the thorough use of available evacuation paths with the exit doors' capacity constraints, which paves the way for a well-orchestrated evacuation effort. Moreover, it accentuates the critical importance of managing capacities to preserve the integrity and efficiency of the evacuation proceedings (Dressler et al., 2010).

Passengers onboard a ship are dispersed across various facilities such as dining venues, cabins, and entertainment areas. Each location is at a distinctive distance from emergency exits, which affects evacuation times. Given the ship's architecture and diverse passenger needs, it's critical to provide explicit evacuation instructions from all these unique starting points. Proper allocation of emergency resources is essential, as is a strategic approach to crowd control and communication based on passengers' precise locations. This detailed understanding of passenger distribution is fundamental for practical emergency drill planning.

In this context, multiple starting points are accounted for during emergencies, which assign different initial locations ($I = \{i_1, i_2, \ldots, i_b\}$) for passengers based on their accurate location at the time of the emergency. Additionally, various strategic positions ($J = \{j_1, j_2, \ldots, j_c\}$) are allocated for crew members to assist passengers (while the direct modeling of the evacuation crew is not initially included, the research designates locations—either potential or fixed—for crew members to facilitate support and assistance to passengers in need.). Here, p_n^i signifies passenger n at location i, and f_m^i indicates family group m at the same point. The terms $\left(p_n^i, e_o\right)$ and $\left(f_m^i, e_o\right)$ define the specific routes for individuals and family groups, respectively, which moving from their initial location i to the designated evacuation exit e_o.

This research also considers two key features: the initial density of passengers at I and the traffic flow along the corridors. The initial density describes the spatial distribution of passengers in each i at the beginning of an evacuation. The initial density refers to the number of people present in a specific area at the start of the evacuation process. It is a crucial metric in emergency planning and response, as it influences the approach and resources required for a safe and efficient evacuation. Considering the initial density of passengers in each area of a ship is crucial for enhancing evacuation procedures. By maintaining a standard number of individuals in different sections, the management team can enforce safety protocols more effectively, mitigating risks associated with overcrowding, such as trampling and panic during emergencies. This strategic control of passenger distribution not only provides a safer and more manageable environment but also allows for the development of personalized evacuation strategies. Recognizing the specific density and layout of each area, from the width of corridors to the number of available exits, enables the creation of tailored plans. Continuous monitoring of initial density is essential for ensuring no specific location exceeds its allowable capacity before any emergency arises. This precaution helps maintain manageable evacuation conditions and upholds safety protocols.

In contrast, traffic flow characterizes the movement of passengers through the evacuation routes in the event of an emergency at each period. Monitoring people's flow helps prevent bottlenecks in tight spaces by distributing crowds more evenly. Several factors can influence traffic flow, including the width and design of corridors, the number of exit doors, the average shoulder width of passengers, and factors related to passenger behavior, such as physical ability and walking speed.

In this research, three pivotal factors identified by the IMO are integrated for calculating evacuation time on passenger ships: safety (α), correction (β), and counterflow correction (γ). α is used as a form of risk management (IMO, 2016). It is an additional layer of protection applied in human evacuation process to account for uncertainties in the design process that are not covered by β and γ. β acknowledges the intricate realities of passenger dynamics, including varied behaviors and physical states. γ compensates for time lags due to intersecting movements of passengers. β and γ adjust for known or anticipated deviations from ideal models due to simplifications.

These elements collectively contribute to the precision and dependability of the predictions (IMO, 2016). As a result, a mathematical optimization model is presented tailored for human evacuation on passenger ships. The approach focuses on minimizing evacuation time, optimizing door usage, and guaranteeing optimal proximity between crew and passengers during emergencies. The model respects constraints such as the ship's layout, individual walking speeds, the distances that passengers must travel to reach exits, door capacities, and the initial distribution and movement of passengers accounting for uncertainties during the evacuation process.

These considerations lead to a more organized and efficient evacuation process, which assures that all passengers, such as those in high-density areas, have clear, accessible routes to safety during critical situations. Figure 2 showcases the network configuration central to this study's analysis, which visually represents passenger distribution — encompassing solo travelers and family groups — throughout the ship's deck.

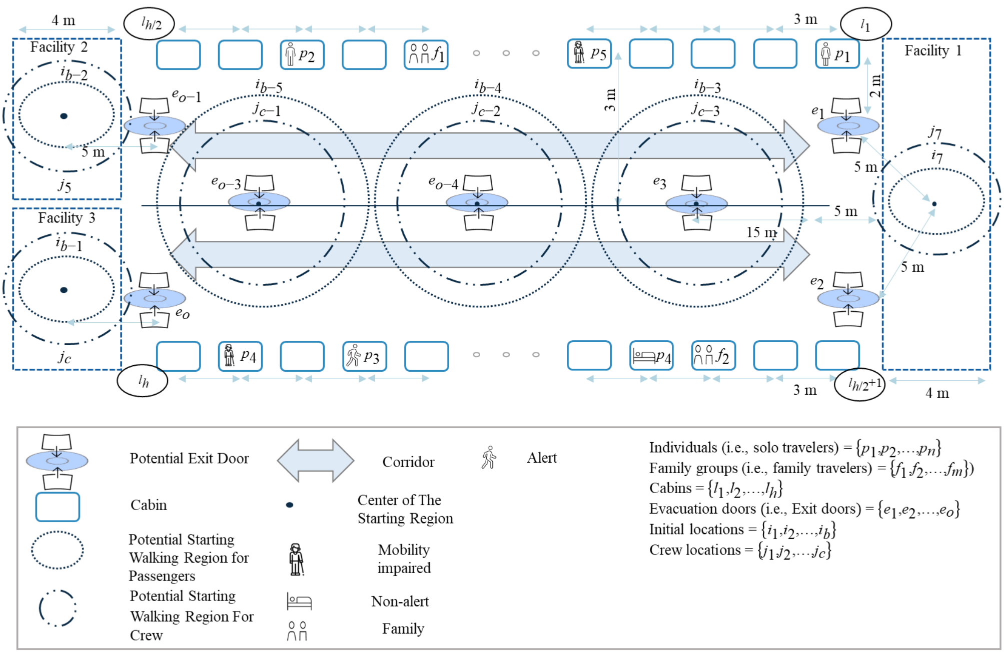


Figure 2. Spatial distribution of passengers on a single ship deck.

In the study at hand, the evacuation procedure is dissected into two consecutive, unique phases: (1) the response period (R) and (2) the travel period (T). Central to this study is the concept of evacuation time (ET), formulated in equation (1) as follows:

$$ET = R + T \tag{1}$$

The process begins with the response period, initiated upon receiving initial cues (such as ship's motions), and continues up to the moment of deciding to evacuate. Subsequently, the travel period encompasses the journey from the commencement of movement until an exit is reached. It's important to note that the computation of evacuation time is individualized, accounting for each passenger, with considerations extending from solo travelers to families. Refer to Figure 3, which delineates these sequential periods.

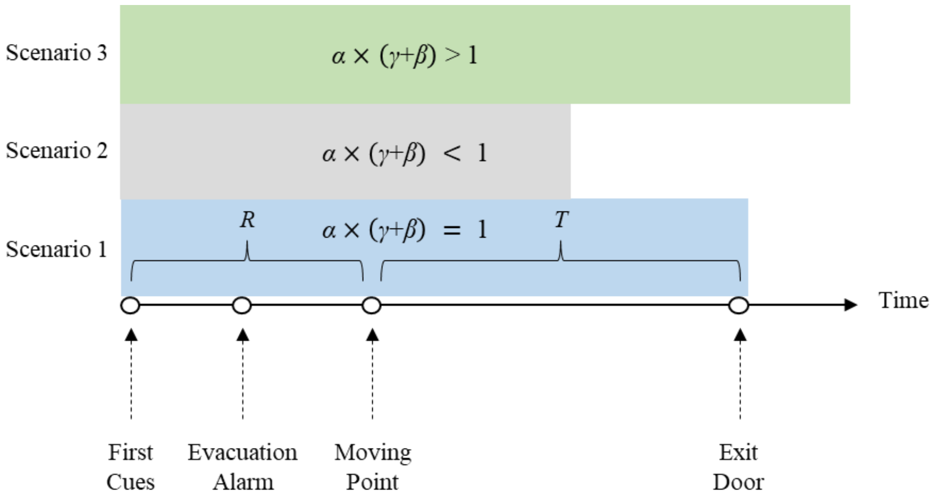


Figure 3. Periods of the evacuation process (IMO, 2016)

Scenario 1 ($\alpha\times(\gamma+\beta) = 1$) outlines an evacuation approach, aligning safety, efficiency, and counterflow considerations harmoniously, indicating the possibility of achieving the optimal evacuation time under specified conditions. This scenario aligns with IMO standards for evacuation procedures. In contrast, Scenario 2 ($\alpha\times(\gamma+\beta) < 1$) reflects an optimistic evacuation strategy, suggesting that there might be room for enhancing evacuation efficiency, possibly through strategic reallocation of resources or modifying safety measures without undermining overall safety. Scenario 3 ($\alpha\times(\gamma+\beta) > 1$) signals a situation requiring additional time beyond IMO standards, indicating that the initial estimates for evacuation might be overly optimistic (IMO, 2016).

Every passenger, solo travelers or families, has a specific time they start and complete the evacuation. Start time (*ST*) is how long a passenger waits before they have to start leaving. Complete time (*CT*) is start time plus *R* and *T* as equation (2).

$$CT = ST + R + T \tag{2}$$

The scope of this study is delineated through the establishment of four key assumptions and simplifications that underpin the models' formulation. These foundational elements are outlined below:

- The model acknowledges uncertainty in passengers' walking speed, as discussed in Papers 2 through 4.

This aspect acknowledges that each passenger's walking speed is subject to fluctuation. Such variability stems from a multitude of factors, possibly encompassing individual physical capabilities, psychological states, and external conditions within the ship or immediate environment. These divergent elements contribute to an uncertain range of walking speeds.

- It similarly recognizes uncertainty surrounding the distance passengers travel, a vision explored in Paper 3.

Passengers, while navigating towards exits, might not adhere to a direct or shortest path for various reasons such as crowd dynamics, individual decision-making, physical obstructions, or the influence of unfolding circumstances during the emergency. This uncertainty in movement patterns introduces additional layers of uncertainty to estimating travel distances for each passenger.

- In Paper 4, the number of available exit doors with the likelihood of potential disruptions is associated.

An element of uncertainty enveloping the capacity of each exit door is considered. This is about the physical limitations or maximum thresholds. Factors contributing to this uncertainty could include sudden door blockages, varying rates of passenger flow, or individual panic—all potentially altering the functional capacity of each door and, consequently, the overall evacuation dynamics.

- A central premise across Papers 2 to 4 is the necessity for the complete evacuation of all passengers.

Furthermore, the model operates on the principle of fixed and predefined parameters in certain aspects:

- The locations of both cabins and potential exit doors are established as constants within the model's framework (referenced in Papers 2 through 4).
- Similarly, the stationed locations of crew teams are set parameters within the model (discussed in Papers 2 through 4).

By stating these elements are fixed and predefined, the potential facilities (exit doors and crew team locations) are predetermined; the model determines which ones to operationalize.

- This research is focused on a single deck of passenger ships to allow for a detailed examination of evacuation plans, safety procedures, and logistical challenges within a simplified environment. This methodical limitation avoids the complex variables introduced by multi-deck configurations, thereby facilitating more precise validation and verification of the developed models. It is important to note that this approach does not imply superiority over multi-deck studies but rather serves as a step toward developing scalable and robust safety strategies. The objective is to ensure that insights garnered from this singular-deck analysis contribute to the groundwork for future, more complex multi-deck modeling. This strategy aligns with the aim to enhance safety protocols, emergency preparedness, and evacuation procedures in a progressively systematic manner, acknowledging both the potential and limitations of the current methodology. This focused analysis is a preliminary yet critical step in advancing toward comprehensive models that can navigate the intricacies of multi-level environments more effectively.

To establish the framework of this study, assumptions and simplifications are introduced for the model's structure, outlined as follows:

- Passenger walking speeds are considered uncertain in HEM 1 to HEM 3.
- In HEM 2, the passenger's travel distances are treated as uncertain.
- In HEM 3, the operability of exit doors is regarded as a potential variable, reflecting possible disruptions.
- A primary goal is evacuating all passengers to get transitional points (e.g., exit doors or stairs) and evacuate from the deck (in all HEMs).
- Fixed and predefined elements include cabin locations, potential exit doors, potential crew team positions, and corridor layouts (in all HEMs).
- Crew teams are positioned at their assigned locations before the initiation of the evacuation process for passengers.
- The capacity of exit doors is assumed to be known and constant in HEM 1 and HEM 2.

4. Human evacuation problem formulation

This section formulates three optimization models for the described human evacuation problem in passenger ships, evolved across Papers 2 to 4. Each model enhances the previous by adding human evacuation elements and addressing uncertainties from different uncertainty modeling techniques. The models are mathematically articulated, with occasional linearization to introduce a computationally efficient version (Asghari et al., 2022).

For a coherent comparison, the models from Papers 2 and 3 are adjusted to mirror the most updated version presented in Paper 4. This uniformity across models means they share the same mathematical framework, including variables, parameters, equations, and objectives. However, due to differing underlying uncertainties, distinctive uncertainty management techniques are implemented for each, including *RO*, *RSSP*, and *HRSSRP*. This approach allows us to observe the models' responsiveness and the nature of the solutions they generate under various uncertain scenarios. The models decide on the allocation of each passenger and family to appropriate exit doors at the appropriate period, response time for each passenger, travel and evacuation time for each passenger, the total evacuation time, the number of exit doors, the number of crew teams, and identify additional byproducts of the models such as the slowest passengers.

4.1. HEM 1 formulation

The initial model, introduced in Paper 2, aims to minimize the evacuation time for the slowest passengers, encompassing families and solo travelers, by assigning them to the appropriate exit doors amidst uncertainties in walking speed. This uncertainty is tackled through *RO*. The discussion starts with addressing the uncertainty in passenger walking speed on a passenger ship, then explores the suitability of robust optimization for the problem at hand, and ultimately, formulates the premier optimization model (HEM 1).

4.1.1. Uncertainty in passenger walking speed

Walking speed, measured in meters per second, is a cornerstone in the mechanics of human evacuation in the maritime context of passenger ships. This critical metric serves as one of the foundations for calculating the time required for individuals to traverse from their initial standings to designated exits, a vital component directly influencing total evacuation time, managing crowd density, and orchestrating the systematic flow toward safety (Na et al., 2019; Wang et al., 2021a). The consideration of walking speed is instrumental not only in crafting practical evacuation models but also in fortifying passenger safety (Bles et al., 2001; Weng et al., 2006). Acknowledging the spectrum of individual mobility, including those with special needs, provides an inclusive safety strategy. This attention to detail in evacuation dynamics also facilitates the actual deployment and allocation of emergency response resources, which enhances the efficacy of coordinated rescue efforts.

Moreover, adherence to these calculated parameters is paramount in complying with maritime safety norms, thereby reinforcing the commitment to preserving lives and maintaining regulatory standards in emergency preparedness (Katuhara et al., 2003; Walter et al., 2017). This element, therefore, intertwines practical planning, individual safety, operational synchronization, and regulatory adherence, all governed by the pivotal role of walking speed in human evacuation logistics.

In emergencies aboard passenger ships, walking speed becomes subject to a confluence of elements like crowd density, the ship's physical configuration, individual mobility constraints, ship motions, observable hazards, and psychological factors such as stress (Ditlev Jorgensen and May, 2002; Kwee-Meier et al., 2017; Sun et al., 2018a; Wang et al., 2021a). These aspects can alter walking dynamics, which highlights the reliance of passengers on their fundamental ability to walk to reach safety exits. Obstructions or inconsistencies in walking speed may trigger substantial evacuation delays, which escalate into risky conditions during urgent evacuations (Ni et al., 2018). An insight into these determinants allows for the formulation of proficient evacuation tactics and structural planning, reducing the dangers linked with slow egress and guaranteeing swift access to safety in alarming situations. Uncertainty in walking speed pertains to the uncertain nature and fluctuations in individuals' speed, particularly evident during evacuations. This uncertainty stems from a multitude of sources encompassing personal attributes (like age or physical health), environmental dynamics (including smoke or minor hindrances), psychological states (panic or stress), ship motions, clear yet hazardous conditions, and situational variables (such as managing belongings or aiding others) (J. Wang et al., 2013; Q. Xie et al., 2020a, 2020c).

Exploring this uncertainty is imperative for myriad reasons (Arshad et al., 2022). It not only recognizes the diversity in human capacities and behaviors, thereby promoting safety protocols that accommodate this diversity, but it also fosters the establishment of robust evacuation simulations. These simulations consider possible anomalies that move beyond the unreliable method of generalizing speeds. Furthermore, it underlines the necessity for flexible evacuation plans that can adapt to diverse needs and circumstances. In emphasizing and examining the uncertain nature of walking speed, entities involved in ship design, regulation, and emergency response can anticipate actual emergency contexts more accurately (Volodina and Challenor, 2021). This proactive approach enhances evacuation methodologies, potentially safeguarding lives by addressing the complications introduced by unexpected hindrances in reaching emergency exits.

4.1.2. *RO* for HEM 1

Employing *RO* in HEMs, when dealing with uncertainties in walking speed can present a strategically advantageous approach for several compelling reasons. The imperative to integrate *RO* into HEM arises primarily from accommodating the uncertain nature of human behavior and varying mobility capacities in evacuation scenarios.

One of the primary motivations for utilizing *RO* in this context is to critically evaluate its performance relative to other techniques used in this research (in HEM 2 and HEM 3). This comparative analysis can help identify reliable, efficient, and adaptable strategies for evacuation modeling. Furthermore, the credibility of *RO* is well-established across various disciplines, which has consistently yielded promising results in supply chain management and logistics, energy systems, finance, and healthcare (Gabrel et al., 2014; Moret et al., 2020; Pishvaee et al., 2011). Its proven track record of versatility enhances the appeal of its application in HEM (Jenkins et al., 2020; Ji and Qi, 2020; Sun et al., 2021).

Delving deeper into the specifics of *RO*, its theoretical framework excels in addressing uncertainties intrinsic to optimization problems. *RO* does not merely seek solutions within an ideal scenario; instead, it fortifies the model against diverse realizations of uncertainty within a predefined bounded set (Ben-Tal and Nemirovski, 2008). This bounded uncertainty set, demarcated by specific upper and lower limits, presupposes that all uncertain parameters are contained within this range, thereby safeguarding the optimal solution against potential variations.

Two salient advantages catapult the efficacy of *RO* in this domain. Firstly, the robust counterpart maintains computational tractability regardless of the number of uncertain parameters. This aspect ensures that the model remains practical and executable even when confronted with multiple variables. Secondly, the model is incredibly accommodating in terms of data requirements. It permits the integration of historical data and subjective expert opinions in establishing the boundaries of uncertainty sets, which bypass the necessity for precise probabilistic distributions (Keyvanshokooh et al., 2016).

Additionally, *RO* empowers decision-makers with the ability to calibrate the level of conservatism in their models, which influences the robustness of the proposed solutions. Conservatism is a price for model robustness that represents a deliberate trade-off. It allows for tailored defensive measures against variations in outcomes (Bertsimas and Sim, 2004). Specifically, it provides a mechanism to gauge the impact of deviations from the nominal solution, which offers foresight into potential shifts in the objective value (Roos and den Hertog, 2020).

HEM 1 employs robust optimization by defining uncertainty sets to manage the uncertainty associated with passenger walking speeds. This approach is beneficial in scenarios where detailed data may be scarce (Gabrel et al., 2014). It can facilitate the development of evacuation plans using minimal information, such as known minimum and maximum walking speeds, to account for variations in walking speeds. To address the challenge of limited data, this thesis introduces the uncertainty sets for passenger walking speed. These sets are designed to mitigate data scarcity by encompassing potential variations within their bounds.

4.1.3. Mathematical optimization formulation of HEM 1

The process initiates by establishing a deterministic model, which then progresses to the linearization phase. The next step is to construct a robust counterpart of the model addressing uncertainty. After generating the robust counterpart, the passenger walking speed adjustment strategy is explained. The final stage involves converting two objectives into a single objective.

4.1.3.1. Deterministic formulation

In terms of the notation (HEM 1), the described human evacuation problem (section 3) can be formulated as a Non-Linear Programming (NLP) mathematical optimization model as follows.

$$Z_1 = \min\{\max_{p \in P,\, e \in E,\, i \in I,\, t \in T} (d^i_{pe} + (1 - \theta_p) \times \imath / v_{pt}) \times X_{pet} \times \vartheta^i_p)\} \tag{3}$$

$$Z_2 = \min\{\max_{f \in F,\, e \in E,\, i \in I,\, t \in T} (d^i_{fe} + (1 - \theta_f) \times \imath / \acute{v}_{ft}) \times H_{fet} \times \acute{\vartheta}^i_f)\} \tag{4}$$

The objective functions are subjected to the following constraints:

$$X_{pet} \leq r_{pet} \qquad \forall\, p \in P,\ e \in E, \text{ and } t \in T \tag{5}$$

$$H_{fet} \leq r_{fet} \qquad \forall\, f \in F,\ e \in E, \text{ and } t \in T \tag{6}$$

$$X_{pet} \leq Y_{et} \qquad \forall\, p \in P,\ e \in E, \text{ and } t \in T \tag{7}$$

$$H_{fet} \leq Y_{et} \qquad \forall\, f \in F,\ e \in E, \text{ and } t \in T \tag{8}$$

$$\sum_{e \in E} r_{pet} \times Y_{et} \geq 1 \qquad \forall\, p \in P \text{ and } t \in T \tag{9}$$

$$\sum_{e \in E} r_{fet} \times Y_{et} \geq 1 \qquad \forall\, f \in F \text{ and } t \in T \tag{10}$$

$$\sum_{p \in P} X_{pet} + \sum_{f \in F} H_{fet} \times \varepsilon_f \leq cap_{et} \times Y_{et} \qquad \forall\, e \in E \text{ and } t \in T \tag{11}$$

$$Y_{et} \leq \sum_{p \in P} X_{pet} \qquad \forall\, e \in E \text{ and } t \in T \tag{12}$$

$$Y_{et} \leq \sum_{f \in F} H_{fet} \qquad \forall\, e \in E \text{ and } t \in T \tag{13}$$

$$\sum_{e \in E} \sum_{t \in T} X_{pet} = 1 \qquad \forall\, p \in P \tag{14}$$

$$\sum_{e \in E} \sum_{t \in T} H_{fet} = 1 \qquad \forall\, f \in F \tag{15}$$

$$(\sum_{p \in P} X_{pet} + \sum_{f \in F} H_{fet} \times \varepsilon_f) \times \tau \leq \omega \times \lambda_t \qquad \forall\, e \in \text{ and } t \in T \tag{16}$$

$$G_{j(t-1)} \leq G_{jt} \qquad \forall\, j \in J \text{ and } t \in T \tag{17}$$

$$\sum_{j \in J} \eta_j \times G_{jt} \geq (N + \sum_{f \in F} \varepsilon_f) / \ell \qquad \forall\, t \in T \tag{18}$$

$$Y_{e(t-1)} \leq Y_{et} \qquad \forall\, e \in E \text{ and } t \in T \tag{19}$$

The optimization objectives of the proposed model focus on a min-max optimization problem, which minimizes the variables outlined in equation (3-4). This approach targets identifying the slowest passenger and family to ensure optimal distribution of resources. The min-max approach not only optimizes resources but also stabilizes the overall system against fluctuations in individual circumstances. Constraint (5-6) states that passengers within the coverage radius of an exit door can reach the respective stair. Constraint (7-8) guarantees that, in each respective time interval, passengers are required to proceed toward the established operational exit door. Constraint (9-10) assures that in each period, at least one exit door is opened to serve evacuees. Constraint (11) stipulates that evacuees traveling toward an exit door at each period must be less than the capacity of the corresponding facility. Constraint (12-13) ascertains that at least one evacuee must travel to the established exit stair at each period. Constraint (14-15) imposes that each passenger is evacuated only one time over the horizon period. Constraint (16) assures that the number of evacuees past the corridor per unit of clear width of the corridor involved must be less than or equal the traffic flow of passengers in each period. Constraint (17) assures that a location, once evaluated for a crew team, must stay available for the entire planning phase. Constraint (18) ensures crew members are positioned to assist passengers during evacuation. It aims to strategically place crew in locations where they can be helpful in enhancing evacuation efficiency without obstructing passenger movement. Constraint (19) stipulates that, once they are installed, exit door must retain their existence without interruption throughout the entire span of the planning timeline.

4.1.3.2. Linearization

A linearization technique is applied to decrease the computational complexity of the original non-linear optimization model and, ultimately, facilitate decision-making (Asghari et al., 2022). In this regard, $\Theta_1 = \min \{\max_{p \in P,\, e \in E,\, i \in I,\, t \in T} (d^i_{pe} + (1 - \theta_p) \times \iota / v_{pt}) \times X_{pet} \times \vartheta^i_p)\}$ is considered. As the left-hand side represents the maximum value of the right-hand side, Θ_1 is, therefore, greater, or equal to all terms generated by the right-hand side. The structure of the mathematical model is reformulated by adding equations (20-25) to equations (5-19).

$$Z_1 = \Theta_1 \tag{20}$$
$$\Theta_1 \geq d^i_{pe} + (1 - \theta_p) \times \iota / v_{pt}) \times X_{pet} \times \vartheta^i_p \qquad \forall\, p \in P,\, e \in E,\, t \in T,\, i \in I \tag{21}$$
$$\Theta_1 \geq 0 \tag{22}$$

The process applies to the second objective.

$$Z_2 = \Theta_2 \tag{23}$$
$$\Theta_2 \geq d^i_{fe} + (1 - \theta_f) \times \iota / \acute{v}_{ft}) \times H_{fet} \times \acute{\vartheta}^i_f \qquad \forall\, p \in P,\, e \in E,\, t \in T,\, i \in I \tag{24}$$
$$\Theta_2 \geq 0 \tag{25}$$

4.1.3.3. Robust counterpart of HEM 1 under uncertainty

Consider the following deterministic linear optimization model.

$$\min_x f(x) \text{ s.t. } A_{mn} \times x_n \leq b_i,\ \forall i = 1, \ldots, m \text{ and } x \in R_+ \tag{26}$$

It is assumed that only the elements of matrix A, i.e., a_{ij}, are subjected to uncertainty. Generally, an uncertain parameter, $\tilde{a}_{ij}$, can be defined as $\tilde{a}_{ij} = \bar{a}_{ij} + \xi_{ij} \times \hat{a}_{ij}$. Where $\bar{a}_{ij}$ stands for a nominal value, $\hat{a}_{ij}$ corresponds a perturbation value, and ξ_{ij} represents a parametrized mapping of the uncertain parameter (Bertsimas and Sim, 2004; Namakshenas et al., 2022). In doing so, a model with the uncertain parameter can be redeveloped as:

$$\underset{x}{\text{Min}} f(x) \ \ s.t. \ \sum_{j=1}^{n} \bar{a}_{ij} \times x_j + \sum_{j=1}^{n} \hat{a}_{ij} \times x_j \leq b_i, \ \forall i = 1, \ldots, m \text{ and } \xi_{ij} \in U, x \in R_+ \tag{27}$$

Where U is the uncertainty set imposed on the model representing the oscillation of the uncertain parameter state within the set, the uncertainty set is derived from properties of vector norms describing the size and extent of the uncertain parameter. One of the techniques to build a robust model can be the determination of the worst-case value over all possible values which uncertain input parameters may take within the described uncertainty set. According to (Bertsimas and Sim, 2004, 2003), (27) is reformulated as:

$$\underset{x}{\text{Min}} f(x) \ \ \text{s.t.} \ \sum_{j=1}^{n} \bar{a}_{ij} \times x_j + \max_{\xi_{ij} \in U} \left(\sum_{j=1}^{n} \hat{a}_{ij} \times \xi_{ij} \times x_j \right) \leq b_i, \ \forall i = 1, \ldots, m \text{ and } x \in R_+ \tag{28}$$

The inner maximization part of inequality (28) is affected by uncertainty. The dual norm properties are employed to derive a deterministic explicit counterpart from it. Accordingly, the robust counterpart is written as follows; interested readers referred to Ben-Tal and Nemirovski (2008, 1998), Ben et al. (2004), and Namakshenas et al. (2022).

$$\text{Dual}\left\{ \max_{\xi_{ij} \in U_h} \left\{ \hat{a}_{ij} \times \xi_{ij} \times x_j \right\} \right\} = \Delta^{solo} \times \left\| \hat{a}_{ij} \times x_j \right\|_q, \ \forall i = 1, \ldots, m, \ \forall j = 1, \ldots, n \ \text{ and } x \in R_+ \tag{29}$$

Where h and Δ^{solo} are some values associated with the h-norm of vector x and a positive number representing the conservatism level, respectively. Regarding q, it is satisfied based on $\frac{1}{h} + \frac{1}{q} = 1$.

As an example, a robust counterpart for the inner maximization part in inequality (28) based on the box uncertainty set, $U_\infty = \left\{ \left\{ \xi_{ij} \middle| \left\| \xi_{ij} \right\|_\infty \leq \Delta^{solo} \right\} \right\}$, is equivalent to:

$$\text{Dual}\left\{ \max_{\xi_{ij} \in U_\infty} \left\{ \hat{a}_{ij} \times \xi_{ij} \times x_j \right\} \right\} = \Delta^{solo} \times \left\| \hat{a}_{ij} \times x_j \right\|_1 = \Delta^{solo} \times \sum_{j=1}^{n} \left| \hat{a}_{ij} \times x_j \right| \ , \forall i = 1, \ldots, m \text{ and } x \in R_+ \tag{30}$$

According to the proposed model in this study, the uncertainty from passenger walking speed is expressed as $\tilde{v}'_{pt}$. It becomes any value in the box uncertainty set oscillated in $\tilde{v}'_{pt} = \left[\hat{v}'_{pt} - v'_{pt}, \ \hat{v}'_{pt} + v'_{pt} \right]$. The same process applies to families walking speed. According to inequalities (21 and 24) and (29-30), the tractable form of the constraint subjected to the uncertainty in this study can be stated as follows:

$$\bar{v}'_{pt} \times \Theta_1 + \Delta^{solo} \times \hat{v}'_{pt} \times |\Theta_1| \geq d^i_{pe} + (1 - \theta_p) \times \imath / v_{pt}) \times X_{pet} \times \vartheta^i_p \qquad \forall \, p \in P, e \in E, t \in T, i \in I \tag{31}$$

$$\bar{v}'_{ft} \times \Theta_2 + \Delta^{family} \times \hat{v}'_{ft} \times |\Theta_2| \geq d^i_{fe} + (1 - \theta_f) \times \imath / \acute{v}_{ft}) \times H_{fet} \times \acute{\vartheta}^i_f \qquad \forall \, p \in P, e \in E, t \in T, i \in I \tag{32}$$

Accordingly, the robust counterpart of the proposed human evacuation model with uncertain passengers' walking speed by box uncertainty sets is equivalent to the following MIP model:

$\text{Min } (Z_1) = \Theta_1$
$\text{Min } (Z_2) = \Theta_2$
Subjected to:
(5-19)

$$\bar{v}'_{pt} \times \Theta_1 + \Delta^{solo} \times \hat{v}'_{pt} \times \Theta_1 \geq d^i_{pe} + (1 - \theta_p) \times \imath / v_{pt}) \times X_{pet} \times \vartheta^i_p \qquad \forall \, p \in P, e \in E, t \in T, i \in I \tag{33}$$

$$\bar{v}'_{pt} \times \Theta_1 - \Delta^{solo} \times \hat{v}'_{pt} \times \Theta_1 \geq d^i_{pe} + (1 - \theta_p) \times \imath / v_{pt}) \times X_{pet} \times \vartheta^i_p \qquad \forall \, p \in P, e \in E, t \in T, i \in I \tag{34}$$

$$\bar{v}'_{ft} \times \Theta_2 + \Delta^{family} \times \hat{v}'_{ft} \times \Theta_2 \geq d^i_{fe} + (1 - \theta_f) \times \imath / \acute{v}_{ft}) \times H_{fet} \times \acute{\vartheta}^i_f \qquad \forall \, p \in P, e \in E, t \in T, i \in I \tag{35}$$

$$\overline{v'}_{ft} \times \Theta_2 - \Delta^{family} \times \widehat{v'}_{ft} \times \Theta_2 \geq d^i_{fe} + (1 - \theta_f) \times \iota / \acute{v}_{ft}) \times H_{fet} \times \acute{\vartheta}^i_f \quad \forall\, p \in P, e \in E, t \in T, i \in I \tag{36}$$

4.1.3.4. Passenger walking speed adjustment

Evacuation models traditionally rely on static average walking speeds, which fall short of accurately predicting human behavior during emergencies. Kim et al. (2019) observed that individuals do not maintain a constant speed throughout evacuations; instead, factors like increasing hazards (e.g., ship motion influence), psychological stress, and physical fatigue reduce speed, particularly near the end of evacuation paths. In real-world emergencies, people's responses vary dramatically, which leads to uncertain speed changes. This variability is intensified by environmental challenges, like navigating a tilting ship or avoiding obstacles, which traditional models don't account for. It is crucial to integrate dynamic walking speed adjustments to enhance the realism and reliability of these models. These adjustments allow models to mirror actual human responses to changing threat levels and environmental conditions, which can result in more accurate evacuation timelines.

In Paper 2, the focus was on understanding the impact of the heeling angle on the walking speed during evacuations, drawing from empirical data (Sun et al., 2018a). They conducted an in-depth analysis, quantifying how various heeling angles—specifically 0º, ±5º, ±10º, ±15º, and ±20º—alter individuals' walking speeds. Their study revealed the diverse effects of heeling angles on passenger movement, findings that are applied to walking speed adjustment in Table 8. The table illustrates the specific influence rate (*IR*) that each respective angle has on walking speed during the evacuation process, which provides pivotal insights that inform the subsequent methodologies. Armed with this knowledge, a system is implemented within the evacuation model to adjust walking speeds dynamically, which accounted for these angle-induced variations. This adjustment mechanism is governed by the algorithm outlined in Equation (37), which provides that each individual's walking speed is realistically represented and updated according to the changing circumstances during the evacuation process.

$$\acute{v}_{pt} = v_{pt} \times (IR^t) \tag{37}$$

Table 8. The adjusted walking speed after applying IR. The o is an integer value representing the number of evacuation periods.

	IR	t_1	t_2	… t_o
Heel -15º	0.9831	$\acute{v}_{pt^1} = v_{pt^1} \times (0.9831^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.9831^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.9831^o)$
Heel -10º	0.9834	$\acute{v}_{pt^1} = v_{pt^1} \times (0.9834^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.9834^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.9834^o)$
Heel -5º	0.9118	$\acute{v}_{pt^1} = v_{pt^1} \times (0.9118^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.9118^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.9118^o)$
Heel 0º	1	$\acute{v}_{pt^1} = v_{pt^1}$	$\acute{v}_{pt^2} = v_{pt^2}$	… $\acute{v}_{pt^o} = v_{pt^o}$
Heel 5º	0.9583	$\acute{v}_{pt^1} = v_{pt^1} \times (0.9583^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.9583^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.9583^o)$
Heel 10º	0.9490	$\acute{v}_{pt^1} = v_{pt^1} \times (0.9490^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.9490^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.9490^o)$
Heel 15º	0.9462	$\acute{v}_{pt^1} = v_{pt^1} \times (0.9462^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.9462^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.9462^o)$
Heel 20º	0.9462	$\acute{v}_{pt^1} = v_{pt^1} \times (0.939^1)$	$\acute{v}_{pt^2} = v_{pt^2} \times (0.939^2)$	… $\acute{v}_{pt^o} = v_{pt^o} \times (0.939^o)$

In Paper 3, the relationship between the ship's rolling angle and passenger walking speed is explored, guided by the empirical findings of (Wang et al., 2021b). They illuminated how the rhythmic swaying of a ship, rolling motions, progressively hampers evacuees' walking speeds. Recognizing this, an adjustment scheme is introduced to mimic these real-world uncertainties, specifically those triggered by ship movements. The methodology revolved around recalibrating walking speeds for each passenger throughout the designated evacuation period ($t \in T$), which accounted for the ship's ongoing instability. This dynamic approach ensures the model isn't static; instead, it evolves, reflecting emerging realities and unforeseen developments within the evacuation scenario (Schwartz, 2012). Wang et al. (2021b) observed that even subtle shifts in the ship's rolling angle (ranging from 0 to 4º) could have a substantial impact on walking speeds size, which vary between athwartship and fore-aft directions. Within the context of these insights, Table 9 details the *IR* (Equation 38) each rolling angle has on walking speeds during an evacuation, which emphasizes the non-linear nature of human movement in these scenarios.

$$v_{pt}^{s'} = v_{pt}^{s} \times (IR^{t}) \tag{38}$$

Table 9. The walking speed after adjusting to a new situation.

	IR	t_1	t_2	...	t_o
Rolling 0 - 4º (athwartship)	0.9295	$v_{pt^1}^{s'} = v_{pt^1}^{s} \times (0.9295^1)$	$v_{pt^2}^{s'} = v_{pt^2}^{s} \times (0.9295^2)$	...	$v_{pt^o}^{s'} = v_{pt^o}^{s} \times (0.9295^o)$
Rolling 0 - 4º (fore-aft)	0.9114	$v_{pt^1}^{s'} = v_{pt^1}^{s} \times (0.9114^1)$	$v_{pt^2}^{s'} = v_{pt^2}^{s} \times (0.9114^2)$	...	$v_{pt^o}^{s'} = v_{pt^o}^{s} \times (0.9114^o)$

In Paper 4, the model adopts the premise that walking speeds can decrease in both linear and exponential manners, which is contingent on various factors emergent in an evacuation. Specifically, how the escalation of perceived danger might realistically affect a passenger's speed. This consideration led to the incorporation of degradation constants in the model: $\mathcal{M}$ for family units and Ȝ for solo travelers. The model employs adjustment formulas, which assume an exponential decay in walking speed, as detailed below (Equations 39-40):

$$v_{pt}^{\tilde{s}} \approx v_{pt}^{s} \times e^{(\text{Ȝ} \times (t-1))} \quad \forall\, p \in P,\ t \in T, \text{ and } s \in S \tag{39}$$
$$\acute{v}_{ft}^{\tilde{s}} \approx \acute{v}_{ft}^{s} \times e^{(\mathcal{M} \times (t-1))} \quad \forall\, f \in F,\ t \in T, \text{ and } s \in S \tag{40}$$

Moreover, understanding the necessity to accommodate a spectrum of influences on walking speed, a linear adjustment mechanism is introduced to bolster the model's resilience and realism. This procedure is as follows (Equations 41-42):

For $\forall\, p \in P,\ t \in T,$ and $s \in S$:
If $v_{pt}^{s} > \text{Ȝ} \times (t - 1)$, update the speed as: $v_{pt}^{s} = v_{pt}^{s} - \text{Ȝ} \times (t - 1)$
If $v_{pt}^{s} <= \text{Ȝ} \times (t - 1)$, update the speed as: $v_{pt}^{s} = \mathcal{E}$ (41)

And for $\forall\, f \in F,\ t \in T,$ and $s \in S$:
If $\acute{v}_{ft}^{s} > \mathcal{M} \times (t - 1)$, update the speed as: $\acute{v}_{ft}^{s} = \acute{v}_{ft}^{s} - \mathcal{M} \times (t - 1)$
If $\acute{v}_{ft}^{s} <= \mathcal{M} \times (t - 1)$, update the speed as: $\acute{v}_{ft}^{s} = \mathcal{E}$ (42)

This model acknowledges the deceleration of evacuees based on their initial speeds, represented through exponential and linear functions, which embody the environmental tolls of the evolving emergency. As hazards intensify, the model intuitively reflects the human tendency for reduced urgency, which captures the authentic dynamics of an evacuation scenario. The three models, HEM 1, 2, and 3, are subsequently subjected to testing using the adjustment technique finalized in Paper 4.

4.1.3.5. Multi-objective formulation

The proposed model has two objectives, each aiming for minimization. Achieving an optimum in one doesn't guarantee an optimum in others (Marler and Arora, 2004). The LP-metric method is applied to manage competing priorities, known for multi-objective decision-making (MODM) (Branke et al., 2008). Despite sensitivity to the norm order and potential computational demands, its flexibility, robustness to outliers, and adaptability make it a powerful tool (Deza and Deza, 2013). Optimal values are determined for each objective, and the bi-objective model is transformed into a single-objective model using the formula (43).

$$\text{Min } Z^{\text{LP}} = \left(\left(w_1 \times \left(\frac{Z_1 - Z_1^*}{Z_1^*} \right)^h \right) + \left(w_2 \times \left(\frac{Z_2 - Z_2^*}{Z_2^*} \right)^h \right) \right)^{\frac{1}{h}} \tag{43}$$

Z_1^* and Z_2^* are optimal values of the three objective functions. w_1 and w_2 represent the weights assigned to each of these objective functions ($w_1 + w_2 = 1$ and $w_1, w_2 \geq 0$). Setting $h = 1$ (Manhattan distance) provides robustness to outliers where extreme values can distort outcomes (Tahraoui et al., 2022). The model runs independently for each objective, minimizing one function without considering the others. Equation (43) updates to (44), resulting in a single objective function (44) with constraints (5-19) and (33-36).

$$\text{Min } Z^{\text{LP}} = \left(w_1 \times \left(\frac{Z_1 - Z_1^*}{Z_1^*} \right) \right) + \left(w_2 \times \left(\frac{Z_2 - Z_2^*}{Z_2^*} \right) \right) \tag{44}$$

4.2. HEM 2 formulation

In Paper 3, a subsequent model has been developed, focusing on minimizing the total evacuation time for all passengers on board, encompassing families and solo travelers. This effort requires the clear allocation of passengers to the appropriate exit points due to the uncertain nature of walking speeds and travel distances, which are integral to computing evacuation time. The approach adopts *RSSP* to counter these uncertainties. The narrative starts by exploring the variable factors of walking speed and travel distance in the context of a passenger ship. It proceeds to justify the relevance of *RSSP* in managing these uncertain aspects. The discussion then leads to the establishment of an optimization model, identified as HEM 2.

4.2.1. Uncertainty in passenger walking speed and travel distance

In the previous discussion, the uncertainty of passenger walking speed was explored. Now, attention turns to the uncertainties associated with passenger travel distance. In the intricate dynamics of an evacuation, especially on passenger ships, calculating the time needed for each passenger's safe exit is crucial. A critical factor in this calculation is the passenger travel distance, which influences evacuation timelines.

- Understanding passenger travel distance and its role in evacuation time calculation:

The concept of travel distance in evacuation refers to the actual length of the path that a passenger must traverse to reach a safe point, typically from their current location to the nearest appropriate exit on a ship. This distance is not a constant but varies based on several factors, including the passenger's location, the ship's layout, and potential obstructions or diversions that might occur during an emergency.

The importance of travel distance becomes evident when it refers to the basic physics of motion. Considering the equation of motion where time (t) is calculated by dividing distance (d) with speed (s) ($t = d/s$), it is clear that the total distance a passenger needs to cover directly impacts the time they require to evacuate. Even if two individuals have the same walking speed, the one with a longer travel distance will inherently take more time to reach safety. Hence, understanding and optimizing these travel distances is paramount to minimizing overall evacuation time.

- Addressing uncertainty in passenger travel distance:

Uncertainty in travel distance arises from the uncertain nature of emergencies. In emergency scenarios, especially on a passenger ship, several unforeseen factors could alter travel paths—debris, a surge in passenger crowds, temporary obstructions, or changes in the ship's motions due to the emergency. This uncertainty produces a range of possible travel distances for each passenger.

Studying these uncertainties is vital because preparing for a spectrum of scenarios than a deterministic situation enhances the robustness of the evacuation plan. It can provide the strategy is adaptable and resilient in various contingencies, potentially saving more lives by accounting for situations beyond optimistic travel distance estimates.

- Importance of considering hybrid uncertainty in both walking speed and travel distance:

While it's critical to study the uncertainties in travel distance independently, considering them in conjunction with uncertainties in walking speed takes the evacuation model's accuracy a step further. This hybrid uncertainty acknowledges the interplay between how fast one can move (walking speed) and how far one needs to go (travel distance), each with its range of variability.

By studying both uncertain components simultaneously, planners can prepare for a broader array of scenarios and construct a more robust, fail-safe evacuation strategy. It accounts for the weakest links (e.g., slower individuals with longer travel distances) and ensures inclusive safety measures. This holistic view is essential because, during an actual evacuation, both factors' variability might compound, and the model should accommodate such complexities to be effective in real-world scenarios.

4.2.2. *RSSP* for HEM 2

In human evacuation modeling, those designated as HEM 2, addressing the inherent uncertainties is crucial for developing evacuation plans. In this context, the application of risk-neutral, two-stage, scenario-based stochastic programming (*RSSP*) proves especially pertinent due to its unique handling of uncertainties and robust decision-making framework. Below, the suitability of *RSSP* for modeling hybrid uncertainties in passenger walking speed and travel distance within human evacuation models under hybrid uncertainties is explored.

The two-stage, scenario-based structure of *RSSP* is inherently compatible with the dynamics of human evacuation planning. This approach divides decision-making into two intuitive phases: *here-and-now* decisions, made in the absence of complete information, and *wait-and-see* decisions, adjusted once uncertainties are realized (Birge and Louveaux, 2011). This mirrors real-life evacuation scenarios where initial decisions should be made quickly, even with incomplete information, and later adjusted as the situation unfolds (Knueven et al., 2023). The model integrates uncertainty directly into the optimization process by incorporating scenarios representing possible outcomes of uncertain parameters (like walking speed and travel distance). This scenario-based framework is vital in human evacuation contexts as it allows for adaptability and informed decision-making in response to evolving circumstances on the ground. For example, different scenarios can account for varying conditions on a passenger ship, such as obstructions or passenger density, each affecting travel distance and walking speed.

Optimizing the total evacuation time for all passengers under uncertain conditions is a challenging task that seeks to minimize the average time required for the entire evacuation process. A risk-neutral perspective is beneficial as it aims for an optimization strategy that neither specifically avoids nor seeks risk. Instead, it considers the general expectation of the entire set of passengers' evacuation time, which treats gains and losses equally in terms of impact (Shapiro, 2021; Shapiro et al., 2013). This approach contrasts with a risk-averse strategy that might focus on worst-case scenarios, which potentially leads to overly conservative planning and inefficient use of resources. By adopting a risk-neutral stance, the *RSSP* method handles the randomness presented by uncertain parameters across the entire scenario set than being overly cautious and planning solely for the extreme cases (Bayram and Yaman, 2018; Liang et al., 2019).

This balance can be important in evacuation scenarios, where overly conservative strategies may result in unnecessary delays or resource allocation inefficiencies. Instead, focusing on the average expected outcome ensures a more balanced, practical approach, optimizing resource utilization while maintaining an acceptable level of preparedness for less likely but more impactful adverse scenarios.

4.2.3. Mathematical optimization formulation of HEM 2

The process initiates by establishing a deterministic model, which then progresses to the scenario generation phase. After that, a step is constructing a scenario-based counterpart of the model addressing hybrid uncertainty.

4.2.3.1. Deterministic formulation

The described human evacuation problem (section 3) can be formulated a MIP mathematical optimization model as follows as well.

$$Z_4 = \alpha \times (\gamma + \beta) \times \Big(\sum_{p \in P} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} (d^i_{pe} + (1 - \theta_p) \times \iota / v_{pt}) \times X_{pet} \times \vartheta^i_p + \sum_{f \in F} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} d^i_{fe} + (1 - \theta_f) \times \iota / \acute{v}_{ft}) \times H_{fet} \times \acute{\vartheta}^i_f \Big) \tag{45}$$

The objective function (45) is subjected to the constraints (5-19).

The objective function (45) optimizes the total evacuation time based on travel distances, non-alert travel distances, walking speed, and the current starting locale affected by the counterflow correction and safety factors. Equation (45) is subjected to constraints (5-19), which were previously explained.

4.2.3.2. Passenger's walking speed and travel distance scenarios

The IMO provides real-world data on passengers' walking speeds, categorized by age, gender, and mobility. Table 10 reveals uniformly distributed speeds ranging from a set minimum to a maximum.

Table 10. Walking speed on flat terrain (e.g., corridors).

Passenger's characteristics	Min. $(\frac{meters}{second})$	Max. $(\frac{meters}{second})$
Females younger than 30 years	0.93	1.50
Females 30–50 years old	0.71	1.19
Females older than 50 years	0.56	0.94
Females older than 50, mobility impaired (1)	0.43	0.71
Females older than 50, mobility impaired (2)	0.37	0.61
Males younger than 30 years	1.11	1.85
Males 30–50 years old	0.97	1.62
Males older than 50 years	0.84	1.40
Males older than 50, mobility impaired (1)	0.64	1.06
Males older than 50, mobility impaired (2)	0.55	0.91
Mobility impaired (1) and (2): limited mobility without and with the need for assistance, respectively.		

Using the speed range limits, Equation (46) guides the random generation of walking speeds, with the Python library NumPy (*np*) facilitating sample creation for individual passengers.

Walking speed samples=
(Max. value of speed - Min. value of speed) × *np*.random.random_sample(*number of samples*) (46)
+ Min. value of speed $\forall p \in P$

The method is similarly used to generate walking speed samples for family groups. Following this, the *k*-means clustering method simplifies scenario creation by promoting data condensation and trend identification, which is crucial in informed decision-making under uncertainty. Clustering algorithms, particularly *k*-means, streamline scenario generation by facilitating data reduction and pattern recognition, which enhances decision-making amid uncertainties (Xu and WunschII, 2005). Their computational efficiency, scalability, and rapid convergence make them ideal for processing large datasets and forming distinct clusters, revealing patterns and trends. Employing Python's NumPy and scikit-learn libraries, the k-means approach not only generates speed scenarios for each passenger but also employs the inertia metric for cluster quality evaluation (Jain, 2010).

Figure 4 demonstrates the strategic placement of cluster centroids to minimize intra-cluster variances, which reduce as more clusters form due to finer data segmentation.

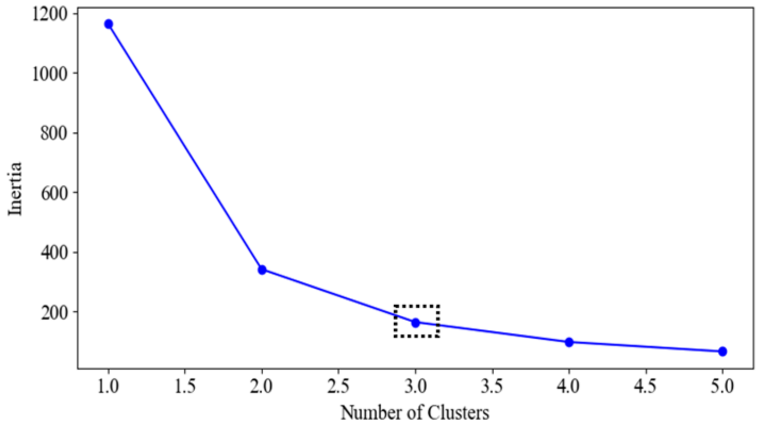


Figure 4. Cluster analysis: centroid positions for passenger walking speeds.

Up to three distinct scenarios emerge from these clusters, with an additional one reflecting the passenger's standard walking speed. Each cluster's core (centroid) dictates the walking speed for its respective scenario, authenticated by historical data from Table 10. These scenarios are then depicted as $S = [S_1, S_2, S_3, S_4]$, where S_s represents the centroid for clusters 1 through 3, and S_4 denotes the typical passenger walking speed.

Passenger travel distance is gauged based on a passenger's proximity, presumed to be in I possible spots, to various potential exit doors. Scenarios can constructed by applying a deviation rate (dr_{u_k}) from nominal distance values. This approach acknowledges that such distances can fluctuate according to the specific layout of a passenger ship. Additionally, the the deviation rates used may be modified in accordance with the insights and opinions of decision-makers. The dr_{u_k} is measured in meters and extends the base travel distance. Travel distance scenarios stem from Equation (47), with Equation (48) elaborating on these scenarios. In particular, Equation (49) outlines three distinct travel distance scenarios for each passenger.

$$dr_{u_k}=U_k \quad \text{for } k=1, 2, 3,\dots, K \tag{47}$$

$$\text{travel distance under scenario } U_k = dr_{u_k} + \text{nominal value of travel distance} \tag{48}$$

$$d_{pe}^{iu} = dr_{u_k} + d_{pe}^{i} \quad \text{and} \quad dr_{u_{k\in[1,2,3]}} = \left[dr_{u_1}=10,\ dr_{u_2}=5,\ dr_{u_3}=0\right] \tag{49}$$

The given dr_{u_k} for k in [1,2,3] demonstrates the impact of uncertainties on travel distance. In scenarios U_1 to U_3, the uncertainty of route selection contributes an additional 10, 5, and 0 units (meters), respectively, to the nominal distance.

4.2.3.3. Scenario-based HEM 2 under hybrid uncertainty

The described human evacuation problem is presented as HEM 2, with the objective function expressed as a minimization optimization within the proposed HEM 2.

$$\text{Min } (Z_4) = \textstyle\sum_{s \in S} \sum_{u \in U} \pi_s \times \pi_u \times \psi_{us} \tag{50}$$

Subjected to:

$$\psi_{us} = \alpha \times (\gamma+\beta) \times (\sum_{p \in P} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} (d^{iu}_{pe} + (1 - \theta_p) \times \imath / v^{s'}_{pt}) \times X^{su}_{pet} \times \vartheta^{i}_{p} + \sum_{f \in F} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} (d^{iu}_{fe} + (1 - \theta_f) \times \imath / \acute{v}_{ft}) \times H^{su}_{fet} \times \times \acute{\vartheta}^{i}_{f}) \quad \forall\, u \in U \text{ and } s \in S \tag{51}$$

$$X^{su}_{pet} \leq Y_{et} \qquad \forall\, p \in P,\ e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{52}$$

$$H^{su}_{fet} \leq Y_{et} \qquad \forall\, f \in F,\ e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{53}$$

$$\sum_{p \in P} X^{su}_{pet} + \sum_{f \in F} H^{su}_{fet} \times \varepsilon_f \leq cap_{et} \times Y_{et} \qquad \forall\, e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{54}$$

$$\sum_{e \in E} \sum_{t \in T} X^{su}_{pet} = 1 \qquad \forall\, p \in P,\ u \in U \text{ and } s \in S \tag{55}$$

$$\sum_{e \in E} \sum_{t \in T} H^{su}_{fet} = 1 \qquad \forall\, f \in F,\ u \in U \text{ and } s \in S \tag{56}$$

$$Y_{et} \leq \sum_{p \in P} X^{su}_{pet} \qquad \forall\, e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{57}$$

$$Y_{et} \leq \sum_{f \in F} H^{su}_{fet} \qquad \forall\, e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{58}$$

$$\sum_{p \in P} (X^{su}_{pet} + \sum_{f \in F} H^{su}_{fet} \times \varepsilon_f) \times \tau \leq \omega \times \lambda_t \qquad \forall\, e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{59}$$

(17-19)

The objective function (50) aims to minimize the overall evacuation time's present value, which takes into account various scenarios ($u \in U$ and $s \in S$) influenced by their respective probabilities. This represents the duration required for passengers to evacuate from their initial location to an exit. Constraint (51) generates the total evacuation time based on travel distances, non-alert travel distances, adjusted walking speed, and the current starting locale affected by the counterflow correction and safety factors with consideration of s and u. To be more specific, the total travel distances are divided by the walking speed depending on where the passengers, solo travelers, and families are located. Constraints (52-53) state that an exit door must be available to be passed by a passenger in each period under s and u. Constraint (54) stipulates that evacuees traveling toward an exit door at each period must be less than the capacity of the corresponding facility under s and u. Constraints (55-56) imposes that each passenger is evacuated only one time over the horizon period under s and u. Constraints (57-58) ascertain that at least one evacuee must travel to the established exit door at each period under s and u. Constraint (59) assures that the number of evacuees past the corridor per unit of clear width of the corridor involved must be less than or equal the traffic flow of passengers in each period under s and u. Constraints (17-19) are established independent of scenarios s and u.

4.3. HEM 3 formulation

In Paper 4, a follow-up model was introduced with an emphasis on minimizing the overall evacuation time for all passengers, including families and solo travelers. Achieving this goal demands an assignment of passengers to specific exit points, taking into account potential disruptions and the variable walking speeds essential to determining evacuation times. The methodology leverages *HRSSRP* to address these uncertainties. The discussion begins by examining the fluctuating factors of walking speeds and the capacities of exit doors in the context of a human evacuation from a single deck of a passenger ship. It then shows the role of *HRSSRP* in addressing these uncertain elements. The discussion culminates in the introduction of an optimization model termed HEM 3.

4.3.1. Uncertainty in passenger walking speed and disruption in exit doors' capacities

In prior sections, the uncertainty of passenger walking speeds was examined. Now, the uncertainties related to the capacities of exit doors is addressed. Exit door capacity on passenger ships, defined by the number of individuals that can safely pass through within a specific period, is influenced by the door's size, design, and functional attributes. However, various disruptions can directly compromise this capacity and hinder the efficient and safe evacuation of passengers (Łozowicka, 2011):

- Physical obstacles: debris, fallen objects, or even luggage can block exit pathways, which restricts the flow of evacuees.
- Door failures: malfunctions, whether mechanical or electronic, could prevent doors from opening or cause them to only partially open.
- Hazardous conditions: for example, water ingress near an exit from flooding could render exit doors inaccessible or unsafe.
- Design limitations: some exit doors might have inherent design flaws or might not be adequately sized to handle high capacities.

Uncertainty in exit door capacity refers to the uncertainty or inconsistency in the actual number of people that can pass through an exit door due to disruptions or other unforeseen factors, such as structural damage to the exit door mechanism (pull, push, and slide). In human evacuation modeling, the real-world dynamics of emergencies dictate that exit door capacities can be variable. Factors such as debris, door malfunctions, and other unforeseen obstacles can diminish the actual throughput of people through these exits. Furthermore, the efficiency of any evacuation route can be tied to the capacity of its exit doors; a disruption at any exit point can compromise an optimized route. Thus, factoring in the uncertainty in exit door capacity can be critical. It not only fosters more realistic and resilient evacuation models but also enables planners to establish a safety margin, which can provide timely evacuations even when faced with disruptions.

Hybrid uncertainty refers to the combined uncertainty in both the walking speeds of passengers and the capacity of exit doors. Hybrid uncertainty encapsulates the simultaneous uncertainty associated with individual walking speeds and exit door capacities. In the web of real-world evacuation scenarios, uncertainties rarely manifest in isolation. An example is the Scandinavian Star disaster in 1990, where thick smoke and panic affected passengers' walking speeds while locked or inaccessible exit doors constrained evacuation routes, which led to the tragic death of 159 people (Shin et al., 2019; Thoresen et al., 2017). Such factors influencing walking speeds can interplay with those affecting door capacities, which can impact overall evacuation times. Integrating this multifaceted uncertainty enhances the realism and reliability of evacuation models, which can align them more closely with emergencies like the Scandinavian Star tragedy.

Given these potential disruptions to exit door capacity, resilience becomes vital. This resilience, defined as the system's ability to adapt and return to safe operations after a disruption (Hosseini et al., 2016), is essential for a robust HEM on passenger ships. Ensuring the safe and timely evacuation of all passengers is paramount, which makes the understanding of exit door capacities essential for predicting feasible evacuation durations and confirming they align with safety standards. In human evacuation modeling and irrespective of the evacuation route chosen, passengers must ultimately traverse an exit door, which positions the door's capacity as the concluding factor in the evacuation trajectory.

4.3.2. *HRSSRP* for HEM 3

This modeling technique merges two approaches: a risk-neutral, two-stage, scenario-based stochastic technique for managing walking speed uncertainties and a feasibility-based ρ-robust approach to tackle potential disruptions in exit door capacities.

The two-stage, scenario-oriented structure of the *HRSSRP* aligns with the dynamic nature of human evacuations. It divides decision-making into preliminary *here-and-now* decisions, made amidst information deficits, and subsequent *wait-and-see* decisions, refined as uncertainties unfold—a reflection of real-world evacuation scenarios (Birge and Louveaux, 2011). This duality is where decisions are rapidly initialized, even with partial data, and later modified based on emerging realities. By embedding diverse scenarios, which manifest potential outcomes of uncertain variables like walking speed and disruptions, the model becomes adaptable. Various disruption scenarios can be outlined in a way that could impact exit door capacities. A stochastic ρ-robust approach based on feasibility is applied to address potential exit door capacity challenges. A feasibility-based stochastic ρ-robust approach is a method that aims to find feasible solutions across various uncertain scenarios (Snyder and Daskin, 2006). It provides that solutions meet specific constraints and operates the ρ parameter to determine how well these solutions can handle uncertainty. Integrating ρ-robust technique in HEM 3 can provide the following benefits:

- Adaptive scenario planning: given the uncertainty of events like severe weather conditions affecting passenger ships, the ρ-robust method can model various types of door disruptions, from slight barriers to total obstructions, shaping flexible evacuation plans in response.
- Optimizing safety and efficiency: rapid evacuation of a vast number of passengers necessitates a balance between swift movement and safety. Using the ρ-robust technique ensures a robust evacuation, even when faced with diverse exit door challenges.

Such a framework is essential in human evacuation scenarios, which enables flexibility and informed decision-making to cater to evolving ground realities, from varying obstructions to fluctuating passenger speeds. The model combines the best of both SO and RO to manage uncertainties in evacuation planning. While aiming to reduce evacuation times like SO, it also ensures reliable performance in various evacuation situations, which highlights the benefits of RO. By adjusting certain parameters, the approach can be tailored to find a balance between average and worst-case evacuation times. Unlike some traditional methods that overly focus on worst-case scenarios, the method can offer a more balanced and realistic approach. This ensures consistent performance in different scenarios and can be applied to various ship designs. Moreover, the challenge of optimizing the cumulative evacuation time under such uncertainties is met with a risk-neutral outlook in *HRSSRP*. Unlike a risk-averse stance, which might emphasize worst-case scenarios leading to excessive caution and resource inefficiencies, the risk-neutral perspective aims for a balanced strategy. It neither actively sidesteps nor pursues risk but gauges the overall expected evacuation time for all passengers. This perspective navigates the randomness of uncertain parameters across the entire scenario spectrum than adhering strictly to extreme cases. This equilibrium can guarantee a practical approach, which optimizes resources while still being sufficiently prepared for less frequent but impactful scenarios.

4.3.3. Mathematical optimization formulation of HEM 3

The procedure begins by formulating a deterministic model. This is subsequently advanced to the phase of generating scenarios. Following this, a scenario-based version of the model is developed to tackle the hybrid uncertainty.

4.3.3.1. Deterministic formulation

The described human evacuation problem (section 3) can be deterministically formulated as a MIP mathematical optimization model as follows as well.

$$Z_3 = \alpha \times (\gamma + \beta) \times \Big(\sum_{p \in P} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} (d^i_{pe} + (1 - \theta_p) \times \iota / v_{pt}) \times X_{pet} \times \vartheta^i_p + \sum_{f \in F} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} d^i_{fe} + (1 - \theta_f) \times \iota / \acute{v}_{ft}) \times H_{fet} \times \hat{\vartheta}^i_f \Big) \tag{60}$$

The objective function (60) is subjected to the constraints (5-19).

The objective function (60) optimizes the total evacuation time based on travel distances, non-alert travel distances, walking speed, and the current starting locale affected by the counterflow correction and safety factors. Equation (60) is subjected to constraints (5-19), which were previously explained.

4.3.3.2. Passenger's walking speed and exit door's capacity disruption scenarios

This part focuses on generating scenarios for passenger walking speeds and potential disruptions to exit door capacities during evacuations.

- Passenger walking speed scenarios:

Scenarios for passenger walking speeds are derived using IMO data (Table 10), which provides insights into pedestrian walking speeds on level surfaces, specifically in the context of passenger ships. The justification for utilizing IMO data to derive scenarios for passenger walking speeds lies in the IMO's comprehensive and authoritative nature concerning maritime safety standards. This data is selected for its relevance, reliability, and representation of various people groups (IMO, 2016). It provides a robust basis for representing the walking speed effect in developing human evacuation plans. While in the earlier model, HEM 2, the *k*-means clustering technique was employed to discern general patterns and clusters in walking speeds, the current study, HEM 3, adopts a different approach. In HEM 3, walking speed scenarios are shaped by a deviation rate from the nominal value. This shift in methodology arises from the distinct objectives of the two studies. While HEM 2 focused on understanding patterns, HEM 3 delves into the deviations in walking speeds under different conditions. The deviation rate, denoted as ϱ_s, gauges the extent to which the speed diverges from the nominal walking speed in each scenario. As depicted in Figure 5, empirical studies have shown that walking speed can amplify and diminish in response to ship motions. The modeling process entails multiplying the benchmark walking speeds by the deviation factor, as detailed in Equations (61-62).

$$v^s_{pt} = \varrho_s \times v_{pt} \qquad \forall\, p \in P,\, t \in T, \text{ and } s \in S \tag{61}$$

$$\acute{v}^s_{ft} = \varrho_s \times \acute{v}_{ft} \qquad \forall\, f \in F,\, t \in T, \text{ and } s \in S \tag{62}$$

Thus, a scenario with ($\varrho_s = 0.6$) signifies a condition where the walking speed is just 60% of the nominal value. Each of these scenarios is also complemented by a probability, (π_s), which signifies the anticipated likelihood of each scenario's occurrence (Kaut and Stein, 2003). This methodology captures the variability within walking speed groups, which can provide an understanding not confined to a singular technique and providing robust and consistent conclusions across varied modeling techniques.

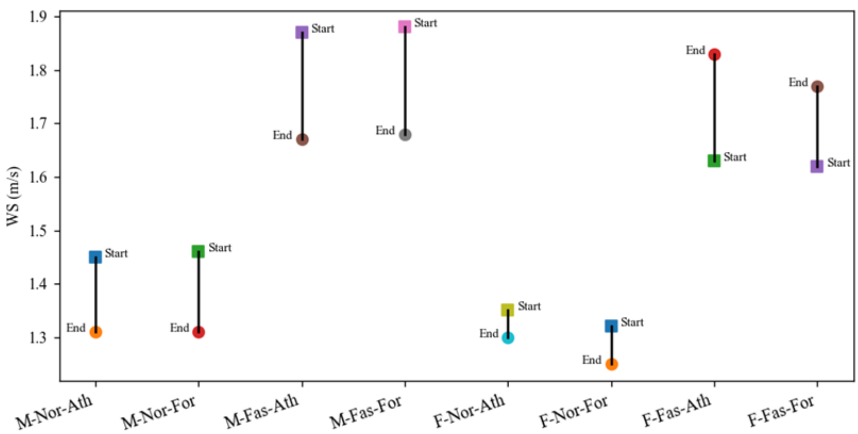


Figure 5. The influence of rolling conditions of a passenger ship on evacuees' walking speeds in athwartship (Ath) and fore-aft (For) directions in fast (Fas) and normal (Nor) modes (Sun et al., 2018a; Wang et al., 2021a).

- Disruption scenarios to exit door capacities:

In emergency evacuations, exit doors represent pivotal egress points, and their consistent functionality is paramount. However, in this study, scenarios have been crafted to reflect reduced exit door capacities during such evacuations. The varying door capacity denoted as cap_{et}, is depicted across multiple scenarios. Specifically, a quantifier, ς_w, is introduced to measure the rate at which the exit door capacity dwindles. To illustrate, a value of ς_w=1 implies a decrement by a single unit in the exit door's capacity. This modeling approach seeks to simulate the model's efficacy under scenarios where the exit door's capacity is compromised. Real-world emergency evacuations are rife with uncertainties, and factors such as obstructions, door malfunctions, or even human-induced blockages can curtail the effective capacity of these exit points.

4.3.3.3. Scenario-based HEM 3 under hybrid uncertainty

The described human evacuation problem is presented as HEM 3, with the objective function expressed as a minimization optimization within the proposed HEM 3.

$$\text{Min } (Z_4) = \sum_{s \in S} \sum_{w \in W} \pi_s \times \pi_w \times \psi_{ws} \tag{63}$$

Subjected to:

$$\psi_{ws} = \alpha \times (\gamma + \beta) \times \Big(\sum_{p \in P} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} (d_{pe}^{iw} + (1 - \theta_p) \times \iota / v_{pt}^{s'}) \times X_{pet}^{sw} \times \vartheta_p^i + \sum_{f \in F} \sum_{e \in E} \sum_{t \in T} \sum_{i \in I} (d_{fe}^{iw} + (1 - \theta_f) \times \iota / \acute{v}_{ft}) \times H_{fet}^{sw} \times \acute{\vartheta}_f^i \Big) \quad \forall\, w \in W \text{ and } s \in S \tag{64}$$

$$X_{pet}^{sw} \le Y_{et} \quad \forall\, p \in P,\ e \in E,\ t \in T,\ w \in U \text{ and } s \in S \tag{65}$$

$$H_{fet}^{su} \le Y_{et} \quad \forall\, f \in F,\ e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{66}$$

$$\sum_{p \in P} X_{pet}^{sw} + \sum_{f \in F} H_{fet}^{sw} \times \varepsilon_f \le (cap_{et} - \varsigma_u) \times Y_{et} + M \times \Gamma_w \quad \forall\, e \in E,\ t \in T,\ w \in W \text{ and } s \in S \tag{67}$$

$$\sum_{e \in E} \sum_{t \in T} X_{pet}^{sw} = 1 \quad \forall\, p \in P,\ w \in W \text{ and } s \in S \tag{68}$$

$$\sum_{e \in E} \sum_{t \in T} H_{fet}^{sw} = 1 \quad \forall\, f \in F,\ w \in W \text{ and } s \in S \tag{69}$$

$$Y_{et} \le \sum_{p \in P} X_{pet}^{sw} \quad \forall\, e \in E,\ t \in T,\ w \in W \text{ and } s \in S \tag{70}$$

$$Y_{et} \le \sum_{f \in F} H_{fet}^{sw} \quad \forall\, e \in E,\ t \in T,\ w \in W \text{ and } s \in S \tag{71}$$

$$\sum_{p \in P} \Big(X_{pet}^{sw} + \sum_{f \in F} H_{fet}^{sw} \times \varepsilon_f\Big) \times \tau \le \omega \times \lambda_t \quad \forall\, e \in E,\ t \in T,\ w \in W \text{ and } s \in S \tag{72}$$

$$\sum_{w \in W} \pi_w \times \Gamma_w \le 1 - \rho \tag{73}$$

(17-19)

The objective function (63) aims to minimize the overall evacuation time's present value, which considers various scenarios ($w \in W$ and $s \in S$) influenced by their respective probabilities. This represents the duration required for passengers to evacuate from their initial location to an exit. Constraint (64) generates the total evacuation time based on travel distances, non-alert travel distances, adjusted walking speed, and the current starting locale affected by the counterflow correction and safety factors with consideration of s and w. To be more specific, the total travel distances are divided by the walking speed depending on where the passengers, solo travelers, and families are located. Constraints (65-66) state that an exit door must be available to be passed by a passenger in each period under s and w. Constraint (67) ensures that the number of evacuees moving towards an exit door in each period does not exceed the uncertain capacity of that exit, as can be determined under different scenarios ($w \in W$).

This uncertainty accounts for the dynamic nature of exit capacities, acknowledging that they can be reduced to accommodate varying emergencies under s and w. Constraints (68-69) imposes that each passenger is evacuated only one time over the horizon period under s and w. Constraints (70-71) ascertain that at least one evacuee must travel to the established exit door at each period under s and w. Constraint (72) assures that the number of evacuees past the corridor per unit of clear width of the corridor involved must be less than or equal the traffic flow of passengers in each period under s and w. Constraint (73) enforces the ρ-robustness condition. To keep feasible the constraint (67), Γ_u takes value and costs by change in the confidence and reliability of the model in the constraint (73). Constraints (17-19) are established independent of scenarios s and u.

The scale of the problem is driven from HEM 3 described in the following. This process involves computing all varieties of variables and constraints.

Binary variables = $(|T|\times|S|\times|W|)\times((|P|\times|E|+|F|\times|E|)+|T|\times(|J|+|E|))$

Free variables = $(|I|+|T|+|S|\times|W|+1)$

Constraint = $(|S|\times|W|)\times(|P|\times|E|\times|T|+|F|\times|E|\times|T|+|P|+|F|+(3\times|E|\times|T|)+1+(|E|\times|T|))+1$.

The developed model is a linear program. The multiplication of the number of variables and constraints influences the order and complexity of the model. For instance, an increase in the number of solo travelers (P) can heighten the complexity due to the additional variables and constraints introduced, affecting the computational resources required for solving the model. While adding variables and constraints increases the problem size linearly, the time it takes for solvers to find a solution can increase exponentially depending on the solver's efficiency and memory usage (Boyd and Vandenberghe, 2004).

5. Solution methodology

Initially, various optimization packages suitable for solving the developed HEMs are discussed, followed by a detailed account of the optimization process employed in this research.

5.1. Optimization packages

Having formulated the human evacuation problem in section 3 through the development of three MIP-based formulations (HEM 1 to HEM 3), the subsequent step involves resolving these models. Solving a mathematical optimization model is ascertaining the best solution for the described human evacuation problem within the given set of constraints and parameters. The best solution is synonymous with minimizing the total evacuation time, an operational metric indicative of the efficiency that the models seek to enhance. An optimization package, such as GAMS (General Algebraic Modeling System), can help solve the models. It works like a translator and a problem-solver.

- Translator: The formulated models can be translated into a language that the optimization package understands. This includes the objective function (minimizing the total evacuation time), variables, and constraints.
- Library of solvers: The package is not just one tool, but a collection of tools called solvers, such as CPLEX. Each solver is good at solving certain types of problems. Some are great for linear problems, others for non-linear, and some are specialized for MIP problems.
- Problem-solving process: When the optimization package is run, it first converts the problem into a form that solvers can understand. Then, it can pick the most suitable solver for the problem. The solver uses mathematical techniques, such as branch-and-cut, to explore possible solutions and hone in on the best one.
- Results: After the solver has done its job, the optimization package translates the solution back into a form that one can understand, which shows the values for the variables that give the best outcome according to the model's objective and constraints.

Optimization packages like GAMS, Gurobi, and CPLEX are powerful tools used to code and solve mathematical optimization models. Here's a brief overview of each, including their advantages and challenges:

- GAMS (GAMS, 2023):

GAMS is known for its high-level, user-friendly modeling language, which makes it easier to formulate complex models. It is especially good for large-scale problems and has a broad range of solvers integrated into its system, which makes it versatile for different problem types.

It can be costly, and while it's user-friendly, the performance can sometimes be outpaced by more specialized solvers for certain types of problems. Also, the flexibility in solver choice means users must know which solver is best for their problem type, which can be a learning curve.

- Gurobi (Gurobi, 2020):

Gurobi is renowned for its speed and robustness, often providing faster solutions to optimization problems, especially linear and MIP.

The major downside of Gurobi is that it can be expensive, particularly for commercial use. It is also more of a solver than a modeling platform, which means it might require additional software or programming expertise to formulate the model.

- CPLEX (Cplex, 2008):

CPLEX is another optimization tool known for its performance and wide range of algorithms for different problem types.

Similar to Gurobi, CPLEX can be quite costly, and while it's powerful, it can have a steeper learning curve for those not familiar with its programming model.

When it comes to choosing the right package for the formulated mathematical optimization models, GAMS can be a good option due to several factors (GAMS, 2023):

- Algebraic modeling language: GAMS is designed with a high-level, algebraic modeling language that is intuitive for representing complex mathematical relationships and constraints, which are common in MIP problems. This makes it easier to translate real-world problems into mathematical models.
- Solver integration: GAMS is not tied to a single solver. It provides the flexibility to choose from a wide range of solvers that are specialized for different types of optimization problems, including MIP. Users can switch between solvers like CPLEX, Gurobi, and others that are particularly efficient at solving MIP problems to find the most effective one for their specific case.
- Preprocessing and automatic reformulation: Before solving, GAMS can preprocess and reformulate MIP problems to make them more tractable. This includes tightening bounds, removing redundancies, and identifying special structures that can be exploited by solvers, which improves computational efficiency.
- Scalability: GAMS is designed to handle very large and complex models. This scalability is crucial for MIP problems, which can grow exponentially in size due to the binary or integer variables involved.
- Branch-and-cut algorithm: The CPLEX uses an advanced method known as the branch-and-cut algorithm. This approach, which is an extension of the branch-and-bound technique, is instrumental in navigating a tree structure populated with a multitude of potential solutions (Abeledo and Ni, 2003). This algorithm divides the problem into subproblems, determines bounds for feasible solutions, and filters non-integer solutions. It navigates a solution tree, discarding non-viable nodes, and ultimately identifies the optimal solution meeting all constraints by exploring the tree structure and refining the search based on established bounds (Gadegaard et al., 2019).
- Advanced features for MIP: It includes advanced features like user cuts and others. These advanced techniques are essential for improving the solution process of MIP problems by guiding the solver, reducing solution space, and accelerating convergence to an optimal solution.

Consequently, despite the merits that other packages may present, GAMS is selected as the modeling platform and CPLEX as the solver to address the HEMs (HEM 1 to 3) outlined in this study.

5.2. Optimization process

Figure 6 presents a systematic depiction of the optimization process used to address the described human evacuation problem detailed in Section 3. It begins with the verbal formulation of the problem, followed by the development of three deterministic optimization models. The models are then expanded to include uncertainty, utilizing uncertainty sets in HEM 1 and scenario generation in HEM 2 and 3. Different modeling approaches are applied to manage uncertainty: *RO* for HEM 1, *RSSP* for HEM 2, and *HRSSRP* for HEM 3. The model also accounts for variations in walking speed over the evacuation process between solo travelers and families. This culminates in a stochastic optimization model, which is then solved using the CPLEX solver. Ultimately, the results are showcased, with decisions delineated across multiple tiers: not just strategic and tactical—like the quantity and placement of exit doors and crew allocation—but also operational, which delivers a detailed evacuation plan for each passenger, be they solo travelers or family groups.

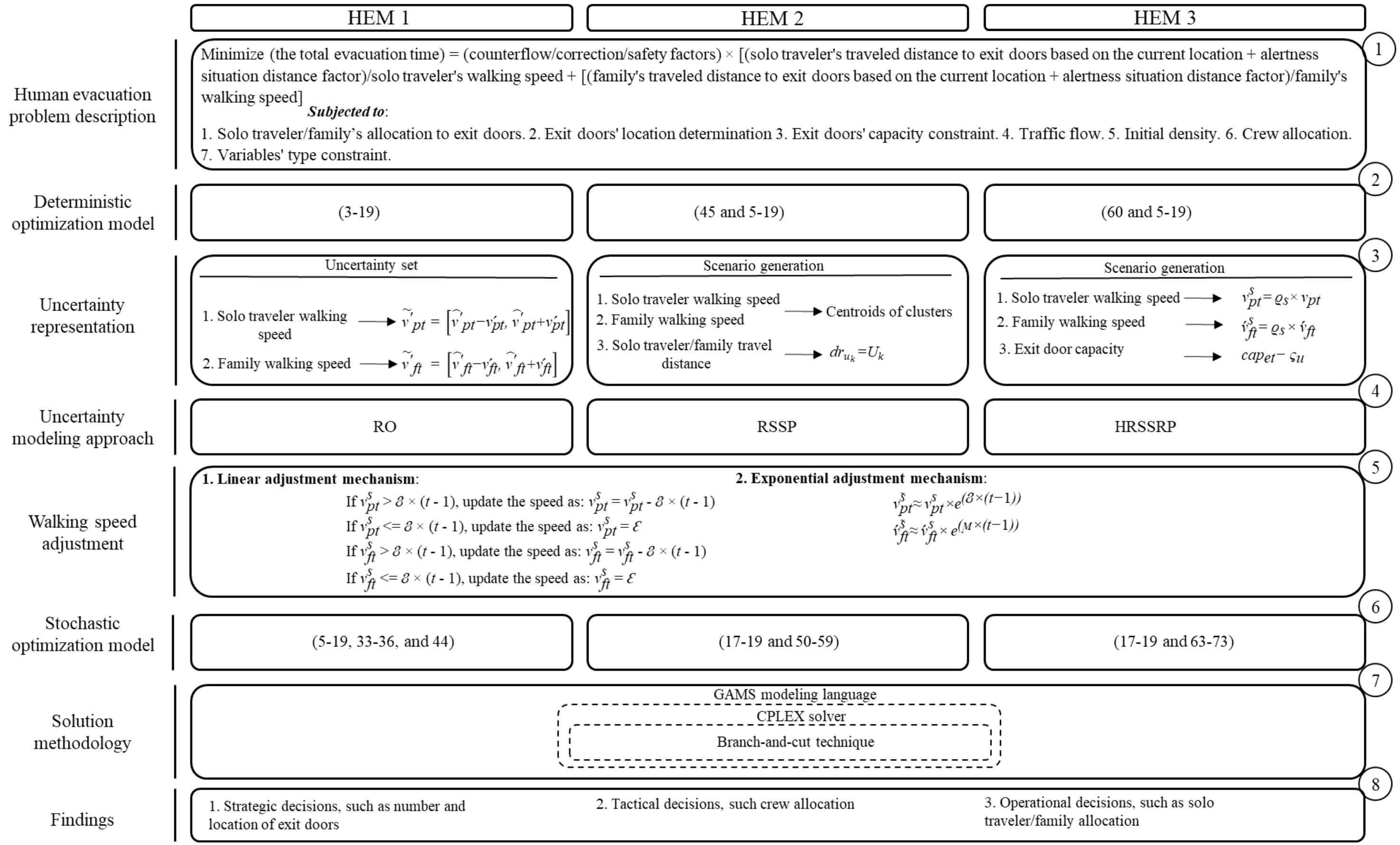


Figure 6. Methodological flowchart for human evacuation modeling under uncertainty (HEM 1 to HEM 3).

In the subsequent section, the results will be detailed, and further discussion will be provided on various managerial decision-making aspects.

6. Solution results

This section describes the case study, details the data used, outlines the design of the experiments, and presents the computational results.

6.1. Case study description

This case study centers on Deck 10 of a Ro-Pax vessel. The selection of Deck 10 as the focal point for this study is strategic, due to its high density of passenger cabins. This characteristic renders it an environment for the validation and testing of the HEMs. Focusing on a deck that houses a number of cabins, and therefore has a higher potential passenger capacity, allows for a robust assessment of the models' performance in scenarios that are complex and indicative of peak occupancy conditions. This approach can enhance the relevance and applicability of the HEMs in real-world situations where efficient space utilization and passenger management are critical. The following attributes of the vessel are delineated, which provides a framework for the validation of the HEM 1 to HEM 3 models developed within the scope of this dissertation:

- Breadth: The interior breadth of the vessel, defined as the distance from one side of the hull's inner plating to the other, is 30.50 meters. This dimension is crucial for the models that assess structural design and space optimization.
- Length: The ship extends 223.72 meters from bow to stern.
- Main Vertical Zones (MVZ 1 to MVZ 5): Deck 10 is segmented into five principal vertical zones, which serve as a basis for the models' analysis of compartmentalization and evacuation dynamics.
- Cabins: The deck houses 286 passenger cabins, varying from standard (STD) accommodations to more exclusive Magic and owner-specific cabins. These variations are considered in the models, particularly in evaluating passenger comfort and space allocation.
- Exit doors: On Deck 10, ten designated exit doors have been incorporated into the models to implement evacuation scenarios. While these doors are initially modeled as exit stairs for analysis purposes and to maintain consistency throughout the documentation, they are referred to as exit doors. The study explores the impact of additional potential exit doors on key performance metrics, such as total evacuation time, to understand their influence on evacuation efficiency.
- Crew service locations: Four designated crew service areas are factored into the models, which are pivotal for analyzing operational efficiency and serviceability. While these areas are accounted for in the current modeling, the effects of introducing additional crew service areas on specific objectives, such as enhancing service to the slowest-moving passengers, will also be investigated.
- Corridors: The 19 corridors across the deck are key parameters in the models that examine passenger flow and safety in emergencies.

Figure 7 illustrates the detailed layout of Deck 10.

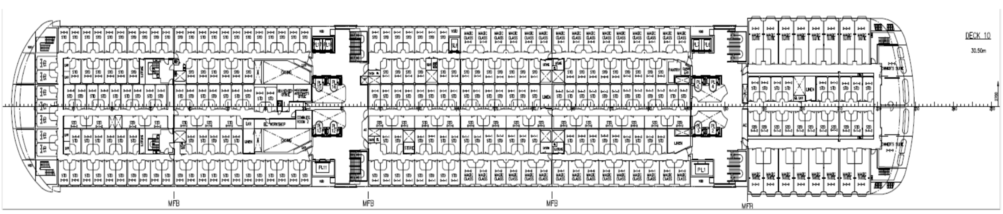


Figure 7. General arrangement of Deck 10.

These elements of Deck 10 will be examined through the HEM 1 to HEM 3 models to validate their accuracy and reliability in enhancing the passenger ship's interior design for strategic decision-making, optimizing human evacuation plans for operational effectiveness, and refining crew allocation for tactical decisions.

6.2. Data description

In the case study, passengers into ten distinct groups are categorized: five for females (F1 through F5) and five for males (M1 through M5), based on their respective age brackets. The categorization of passengers into ten distinct groups is based on the data presented in the case study, which delineates walking speeds into five categories, each for females and males. Groups F4, F5, M4, and M5 comprise individuals with mobility limitations. The range of walking speeds (v_{pt} and $\acute{v}_{ft}$) for each group is as follows:

- Females in group F1 had speeds between 0.25 to 1.24 m/s, with ages uniformly distributed between 10 and 20 years.
- Group F2 females had speeds between 0.25 to 0.95 m/s, aged 20 to 40 years.
- Group F3 females walked at speeds ranging from 0.25 to 0.75 m/s, aged between 40 and 60 years.
- For groups F4 and F5, the walking speeds were slower, ranging from 0.25 to 0.57 m/s and 0.25 to 0.49 m/s, respectively, with ages spanning from 10 to 60 years due to their mobility impairment.
- Males in group M1 had walking speeds from 0.25 to 1.48 m/s within the 10 to 20 age group.
- Group M2 males had speeds ranging from 0.25 to 1.30 m/s, aged 20 to 40 years.
- Group M3 males walked at speeds between 0.25 to 1.12 m/s, aged 40 to 60 years.
- Groups M4 and M5, which included mobility-impaired individuals, had walking speeds ranging from 0.25 to 0.85 m/s and 0.25 to 0.73 m/s, respectively, with ages uniformly distributed between 10 and 60 years.

The overall percentage distribution of various solo traveler categories in the experiments is, with groups F3 and M3 each constituting 15.98%, followed by groups M5, F4, F5, and M4 at 10.06%, and groups F1, M2, M1, and F2 each comprising 6.95% of the total demographic of solo travelers.

However, the case study did not include family units. Upon further consideration, family groups are included with the following characteristics:

- The size of a family is determined by a uniform integer distribution between 2 and 4 members.
- A family may consist of adult females and males aged between 10 and 60 years, as well as children and infants under one year old.
- Some family members may be mobility impaired.
- While individual walking speeds vary, the family's overall walking speed is considered to be the slowest member's speed.

Distance measurements (d^{i}_{pe} and $\acute{d}^{i}_{fe}$) and layout description, for different facilities, such as corridors, can be obtained from Figure 8. Figure 8 serves as the blueprint for Figure 7. For each passenger (solo travelers and families), 20 possible initial positions considered are on deck 10. The designation i_1 indicates that the passenger is stationed in their private cabin, whereas designations i_2 through i_{20} signify that the passenger is located in one of the 19 corridors throughout the deck.

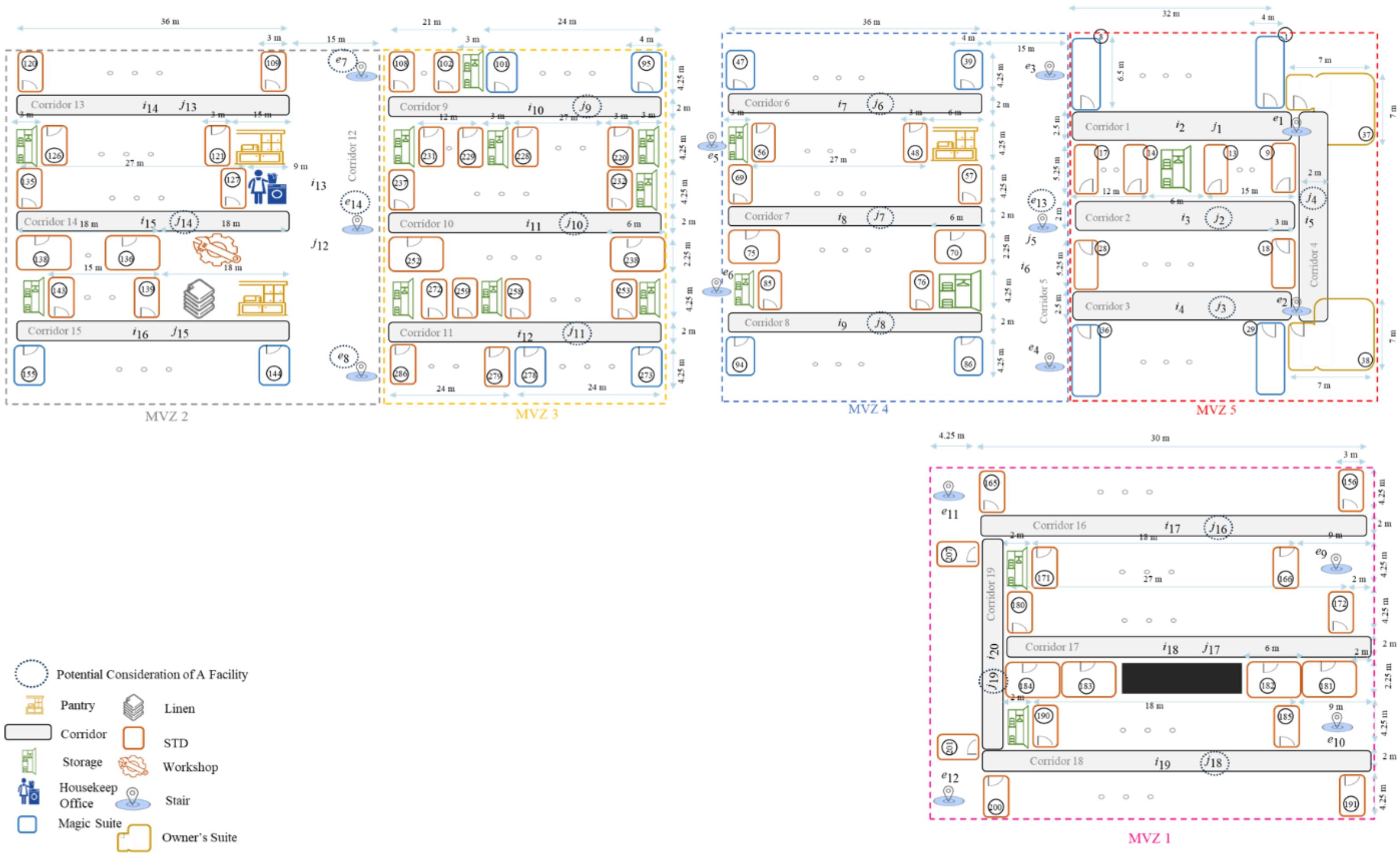


Figure 8. Blueprint of Deck 10 general arrangement.

The response time for solo travelers is presumed to follow a uniform distribution ranging from 1 to 3 meters (ι). Similarly, the response time for family groups is estimated to have a uniform distribution between 3 to 5 meters (κ). Each crew team is composed of 5 members (η_j). Every team is tasked with overseeing a designated corridor, supplying service and assistance to passengers within that area. For instance, the crew assigned to j_1 is responsible for attending to passengers in corridor 1. Each exit door is estimated to have a base capacity of accommodating four passengers per period (cap_{et}). The safety factor is set at 1.25 (α), while the counterflow and correction factors are established at 0.5 (β and γ).

6.3. Experiment design

Five distinct experiments (E) are designed, which incorporate variables such as diurnal/nocturnal settings, the initial distribution of passengers denoted by ϑ_p^i and $\hat{\vartheta}_f^i$, along with the alertness levels of passengers, θ_p and $\hat{\theta}_f$. Table 11 presents the experimental design configurations influenced by the time of day (day vs. night), current location, and the alertness levels of passengers (alert vs. non-alert). For Es conducted under nocturnal conditions, the emphasis was on placing passengers predominantly within their respective cabins and in a non-alert state. Conversely, for diurnal conditions, the focus was on allocating passengers primarily to different locales and ensuring they were alert.

Table 11. Experimental design configurations for passenger distribution and alertness levels.

E ID	Time of day	% in i_1	% in other locales	% alert (θ_p and $\hat{\theta}_f = 1$)	% non-alert (θ_p and $\hat{\theta}_f = 0$)
$E_{1\text{-}1}$	Night	100	0	0	100
$E_{1\text{-}2}$	Night	100	0	25	75
$E_{2\text{-}1}$	Day	0	100	100	0
$E_{2\text{-}2}$	Day	0	100	75	25
$E_{2\text{-}3}$	Day	5	95	50	50

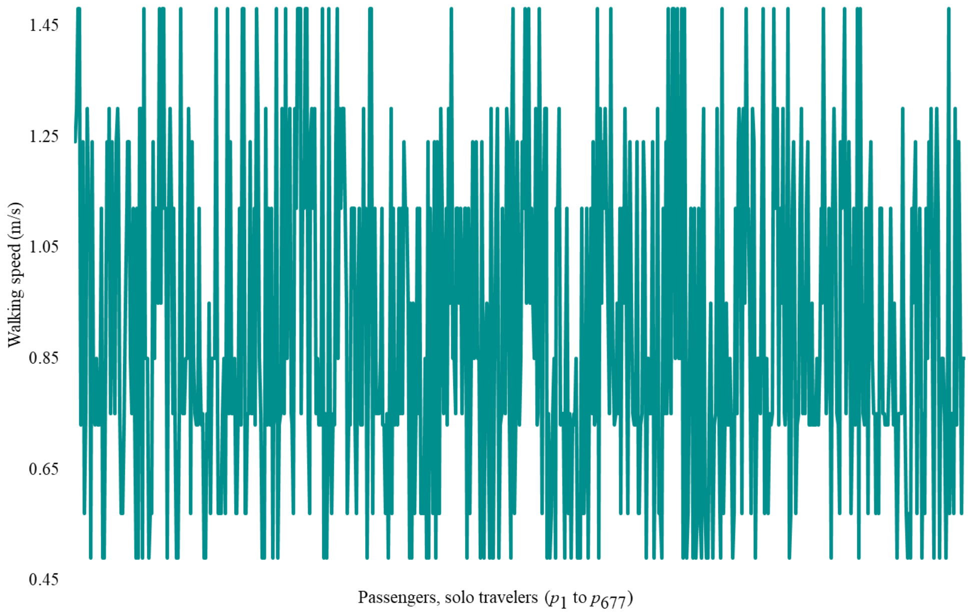
6.4. Computational results and validation

In this section, the computational results are presented, which are pivotal in demonstrating the robustness and practical applicability of the developed models, HEM 1 to HEM 3. This analysis serves not only as a testament to the theoretical foundations of these models in terms of uncertainty modeling but also as an exploration of their real-world effectiveness. The validation process for each model begins with comparing their outputs against empirical data to establish accuracy and reliability across various scenarios. This is followed by a sensitivity analysis, systematically examining the influence of different parameters on the outcomes of each model. Such analysis is crucial for understanding the dynamics and dependencies within the models.

6.4.1. The developed models versus the case study

The first developed model, HEM 1, applies the *RO* approach to address uncertainty in passenger walking speed. The configuration of the *RO* parameters for this run is $\Delta^{solo} = 0.2$ as well as $\widehat{v'}_{pt} = 0.1$. This model considers the variability of passenger walking speeds by constructing uncertainty sets based on the case study data. This approach is particular because it does not require complex statistical methods to predict walking speeds (following a specific probability distribution function). Instead, it looks directly at the minimum and maximum speeds individual/family passengers might have during an emergency on a ship.

For instance, let's consider an evacuation scenario on a passenger ship. Each passenger has a different walking speed, which can vary under ship motion. Some might move very fast due to urgency, while others might be slower due to factors like age or physical ability. HEM 1 observes these variations and forms a range for each passenger, which covers their slowest and fastest possible walking speeds during an evacuation. HEM 1 simplifies the complexity into a single representative set (i.e., uncertainty set) for each passenger's speed, leading to a single output upon each model run. Figure 9 illustrates the variation in passenger walking speeds, ranging from minimum to maximum values.



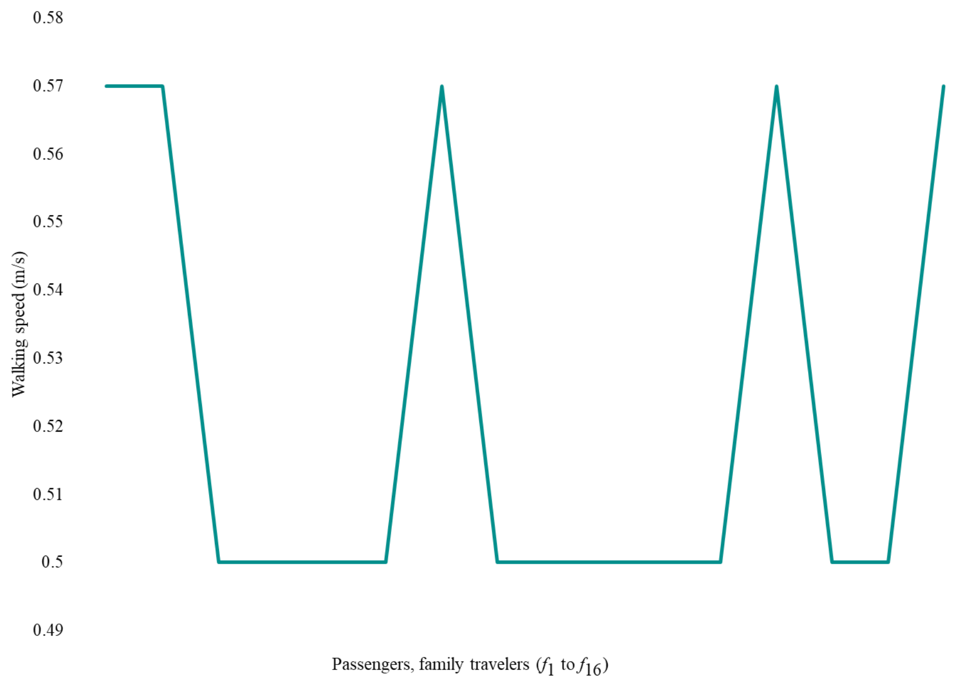
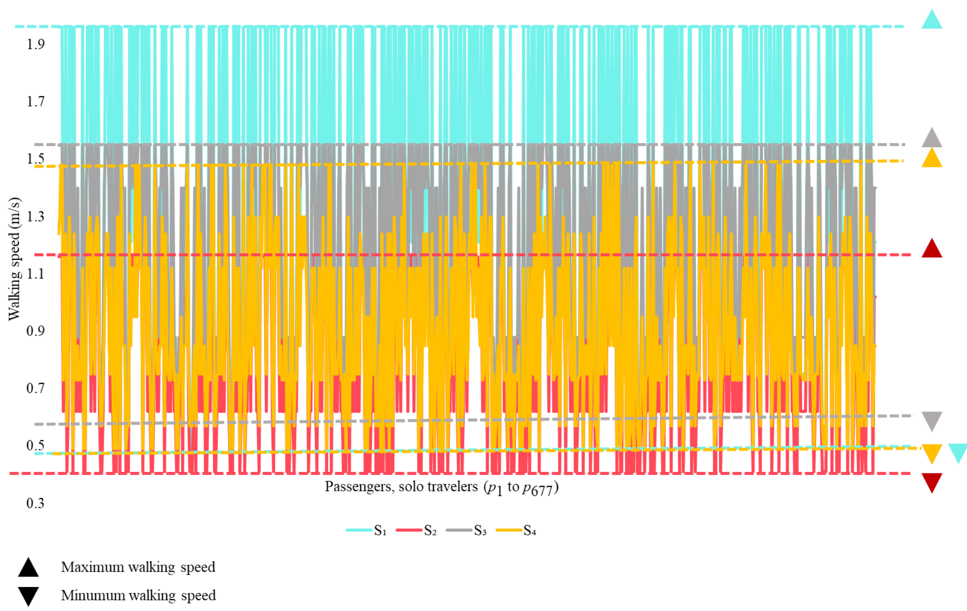


Figure 9. Variation in passenger walking speeds: for constructing uncertainty sets in *RO* approach

Moving to the second model, HEM 2, an improvement in the treatment of uncertainty using the *RSSP* technique is seen. This model departs from the single-set output of HEM 1 by employing the *k*-means algorithm to cluster passenger walking speed data into four distinct scenarios for each passenger (s_1, s_2, s_3, s_4) based on Equation (46). Figure 10 presents the distribution of passenger walking speeds across different scenarios.



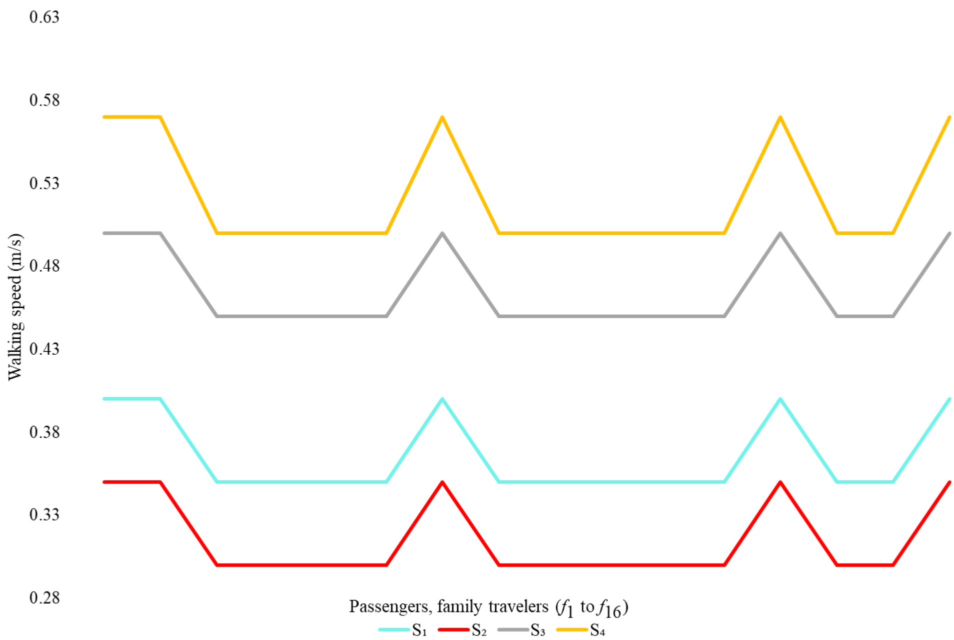


Figure 10. Passenger walking speeds across four different scenarios in *RSSP* approach.

To further refine the model, travel distances for passengers are categorized into three scenarios (u_1, u_2, u_3) utilizing the principles set forth in Equations (47-49), with associated deviation rates $[dr_{u_1}=10, dr_{u_2}=5, dr_{u_3}=0]$. As a result, HEM 2 offers 12 scenarios in total, enabling a multifaceted output of 12 different results upon completion of a single run. It encompasses combinations like (s_1, u_1), (s_1, u_2), (s_1, u_3) through to (s_4, u_3). Each pair represents a broader exploration of the potential outcomes, which provides a spectrum of possibilities that better captures the essence of uncertainty in evacuation scenarios. For example, when $RSSP_{s_1u_1}$ is discussed, this analyzes the combined (hybrid) effect of the first walking speed scenario (s_1) and the first travel distance scenario (u_1) within the *RSSP* framework.

The scenario s_1 represents the first cluster of walking speeds, which includes a range of speeds that a passenger might exhibit. This cluster captures the variability in a single passenger's walking speed under different conditions. It averages various walking speeds into a representative cluster, which reflects the speed a passenger might have when their speed falls into this first cluster. This category is crucial for understanding how individual/family differences in walking speed can influence evacuation dynamics. u_1 is the path from a passenger/family's location to an exit, which might be around 50 meters. Under the u_1 scenario, this distance is extended by ten units, which results in a travel distance of 60 meters. Such an increase could be due to temporary obstructions, a detour in the evacuation route, or the closure of a nearer exit, which directs passengers to a more distant one.

When the (s_1, u_1) scenario applies in the model, this scenario essentially optimizes the evacuation time for situations where passengers exhibit walking speeds from the first cluster (s_1), but concurrently face an increased travel distance (u_1). This combination reflects a realistic evacuation scenario, such as an exit blockage or an unforeseen obstacle, requiring passengers to use an alternative, longer route. This gives us an insight into the specific case where both variables are at their first scenario level, thus tailoring the evacuation time prediction to a particular set of conditions.

HEM 3, the third model, introduces the *HRSSRP* technique to handle uncertainty further. It considers three scenarios for passenger walking speed (s_1, s_2, s_3), referenced in Equations (61-62), with associated deviation rates ϱ_s= [0.7,1,1.2], to account for varying passenger walking speeds.

Additionally, HEM 3 assesses the impact of exit door disruptions, considering three different scenarios (w_1, w_2, w_3) with corresponding deviations ς_w= [0,1,2]. Consequently, HEM 3 concludes with 9 distinct scenarios. For example, when $HRSSRP_{s_1w_2}$is discussed, this scenario analyzes the combined (hybrid) effect of the first walking speed scenario (s_1) and the second exit door capacity disruption scenario (w_2) within the *HRSSRP* framework.

The scenario s_1 reflects a condition where every passenger's average walking speed is reduced to 70% of their normal speed. This could be due to various factors, such as slippery deck conditions or passengers being in a state of mild panic. For example, if the usual walking speed is 1.4 meters per second, under s_1 it drops to 0.98 meters per second. Simultaneously, w_2 represents a scenario where the capacity of exit doors decreases by one unit. This could happen if one of the main exit doors is partially obstructed or malfunctioning, reducing the number of passengers that can pass through it per unit of time. For instance, if an exit door typically allows ten passengers to pass through per minute, under w_2 it might only accommodate nine passengers per minute.

When these two conditions – (s_1, w_2) – co-occur, they create a compounded effect on the evacuation process. The slower walking speeds (s_1) mean passengers take longer to reach the exits, and the reduced exit capacity (w_2) leads to potential bottlenecks or delays at the exits. In the example, this might manifest during an evacuation where passengers (solo and family travelers), moving slower due to challenging conditions, face additional delays due to the reduced throughput at the exits. This scenario is critical for emergency planning as it provides insights into how combined factors can impact evacuation times. Figure 11 depicts walking speed and disruption scenarios.

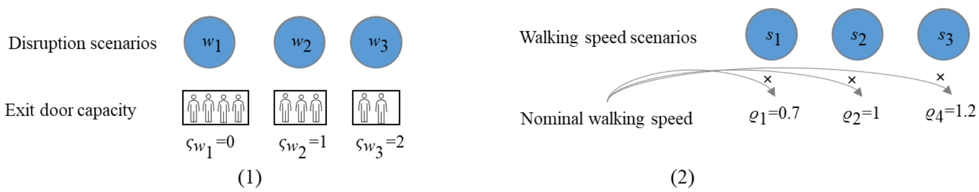


Figure 11. Walking speed and disruption scenarios for *HRSSRP* approach in HEM 3.

The range of models, HEM 1 through HEM 3, are implemented for 646 passengers, all are solo travelers. This selection was chosen to align with the solo traveler focus of the case study, allowing for a direct comparison of the results with those specific to deck 10 in the case study (the same as $E_{1\text{-}1}$). The passenger composition was divided into male and female categories, with the following percentage distributions: males were segmented into groups M1 through M5, with respective proportions of 6.95%, 6.95%, 15.98%, 10.06%, and 10.06%. The female groups, F1 through F5, had the same percentage distribution as the male groups.

Each model, HEM 1 to HEM 3, underwent a single run under a nighttime scenario, which mirrors the case study conditions where all passengers are in their cabins and not alert. When each model is run independently, HEM 1 results in a single total evacuation time (*TET*). In contrast, HEM 2 and HEM 3 produced multiple distinct *TET*s, 12 and 9, respectively. These results have been recorded in Table 12. This table compares the HEMs, showcasing *TET*s before and after adjustments (applying an α =1.53) and detailing congestion times. The case study applied Evi for the evaluation analysis. Evi, Evacuation Index, is multi-agent certified software for evacuation analysis on passenger ships. It focuses on "evacuability" – a measure of a person's ability to evacuate the ship (Nasso et al., 2019; Vassalos et al., 2003). In the case study, the time required to evacuate deck 10 is calculated independently across 18 simulations.

Table 12. Comparative analysis of *TET*s (s) for HEM 1 to HEM 3 and the case study.

Model	Approach		*TET* before affecting α	*TET* after affecting α	Congestion time
HEM 1		*RO*	754.12	1,153.80	0
HEM 2	*RSSP*	$RSSP_{s_1u_1}$	1,051.59	1,608.94	0
		$RSSP_{s_1u_2}$	868.03	1,328.09	
		$RSSP_{s_1u_3}$	746.02	1,141.41	
		$RSSP_{s_2u_1}$	1,259.10	1,926.42	
		$RSSP_{s_2u_2}$	1,089.66	1,667.18	
		$RSSP_{s_2u_3}$	916.42	1,402.12	
		$RSSP_{s_3u_1}$	886.86	1,356.90	
		$RSSP_{s_3u_2}$	785.44	1,201.72	
		$RSSP_{s_3u_3}$	661.74	1,012.46	
		$RSSP_{s_4u_1}$	1,037.51	1,587.39	
		$RSSP_{s_4u_2}$	869.33	1,330.08	
		$RSSP_{s_4u_3}$	715.01	1,093.97	
HEM 3	*HRSSRP*	$HRSSRP_{s_1w_1}$	1,282.81	1,962.69	0
		$HRSSRP_{s_1w_2}$	1,295.55	1,982.19	
		$HRSSRP_{s_1w_3}$	1,307.18	1,999.99	
		$HRSSRP_{s_2w_1}$	903.30	1,382.05	
		$HRSSRP_{s_2w_2}$	918.99	1,406.05	
		$HRSSRP_{s_2w_3}$	902.72	1,381.16	
		$HRSSRP_{s_3w_1}$	733.63	1,122.46	
		$HRSSRP_{s_3w_2}$	768.58	1,175.93	
		$HRSSRP_{s_3w_3}$	744.36	1,138.87	
Case study		Evi	Avg.$_{18\ \text{runs}}$= 923.64	Avg.$_{18\ \text{runs}}$= 1,413.17	580

To focus the comparison on *TET*, the scenarios are clustered based on whether their evacuation times are lower or higher than Evi's average *TET* before α, which is 923.64 seconds (refer to Table 12).

- Cluster 1: Scenarios with lower *TET* than Evi (before affecting α):
  - RO approach: the only output of HEM 1 under RO approach outperforms the Evi' result.
  - *RSSP* approach: It includes scenarios $RSSP_{s_1u_2}$, $RSSP_{s_1u_3}$, $RSSP_{s_2u_3}$, $RSSP_{s_3u_1}$, $RSSP_{s_3u_2}$, $RSSP_{s_3u_3}$, $RSSP_{s_4u_2}$, and $RSSP_{s_4u_3}$where each scenario represents a different combination of walking speed and travel distance uncertainties. These scenarios have a *TET* of less than 923.64 seconds.
  - *HRSSRP* approach: It contains scenarios $HRSSRP_{s_2w_1}$, $HRSSRP_{s_2w_2}$, $HRSSRP_{s_2w_3}$, $HRSSRP_{s_3w_1}$, $HRSSRP_{s_3w_2}$, $HRSSRP_{s_3w_3}$.
- Cluster 2: Scenarios with higher *TET* than Evi (before affecting α):
  - *RSSP* approach: It includes scenarios $RSSP_{s_1u_1}$, $RSSP_{s_2u_1}$, $RSSP_{s_2u_2}$, $RSSP_{s_4u_1}$, where each scenario represents a *TET* of more than 923.64 seconds.
  - *HRSSRP* approach: It contains scenarios $HRSSRP_{s_1w_1}$, $HRSSRP_{s_1w_2}$, $HRSSRP_{s_1w_3}$.

Based on Table 12, the analysis of the different approaches is as follows.

- Management of uncertainty:

- *RO* Approach: Integrates walking speed uncertainty using historical data, which offers a more realistic estimation of evacuation times compared to Evi.
- *RSSP* approach: Incorporates uncertainties in walking speed and travel distance, generating 12 possible outcomes per run, in contrast to Evi's single outcome.
- *HRSSRP* approach: Addresses uncertainties in walking speed and exit door capacities, producing nine potential outcomes per run, which provides a broader evacuation scenario spectrum than Evi.

- Congestion management:
  - All approaches report no congestion, which is attributed to strategic passenger allocation to exit doors and effective evacuation flow management.
- Scenarios performance:
  - In Cluster 1, all approaches surpass the Evi results. This performance is attributed to the strategic allocation of passengers to the most suitable exit doors, which is determined based on their walking speed and proximity to these exits, with a focus on minimizing the total evacuation time. This optimization is further enhanced by effectively managing uncertainties related to walking speed, travel distance, and potential exit door disruptions. The utilization of various scenario combinations contributes to more efficient evacuation times. Additionally, the optimal distribution of passengers across exit doors, taking into account their walking speeds and the capacities of these doors, ensures that exit facilities are used in the most balanced manner.
  - In Cluster 2, scenarios such as $RSSP_{s_1u_1}$, $RSSP_{s_2u_1}$, and $RSSP_{s_4u_1}$, exhibit higher Total Evacuation Times due to increased travel distances, which in some cases extend by up to +10 meters. Scenarios like $RSSP_{s_2u_2}$ present a situation where passengers experience the slowest walking speeds (in comparison to s_1, s_3, and s_4 scenarios) along with a moderate increase in travel distance (+5 meters), resulting in prolonged evacuation times. Similarly, scenarios $HRSSRP_{s_1w_1}$, $HRSSRP_{s_1w_2}$, and $HRSSRP_{s_1w_3}$ show higher *TET*s than Evi, primarily due to a reduction (30%) in walking speed. This indicates a more cautious modeling approach, emphasizing safety and realism, potentially at the expense of evacuation speed.

6.4.2. Family allocation optimization in in evacuation planning

In the models (HEM 1 to 3), a crucial element that the case study overlooks—the consideration of families in the evacuation process—is introduced. This addition forms the basis of a new subsection, delving into the results derived from this aspect. Although data from the case study is utilized, the analysis is expanded upon by integrating family dynamics into the existing framework for uncertain parameters. This approach allows us to explore how family units, with their unique characteristics and speed, impact evacuation modeling and outcomes (for the configuration of the *RO* parameters, $\Delta^{familiy}$= 0.2 and $\widehat{v}_{ft}$ = 0.1 are also needed). The suite of models, HEM 1 to HEM 3, was executed for a total of 715 passengers, encompassing 677 solo travelers and 38 members belonging to 16 families. Regarding family members, the breakdown is as follows:

- Adult females constitute 42.11%.
- Adult males make up 26.32%.
- Children represent 7.89%.
- Infants account for 23.68%.

Furthermore, the population of families is differentiated by mobility, with 61.54% being non-impaired and 38.46% being mobility-impaired. Each model, from HEM 1 to HEM 3, was run once for a daytime scenario, with the possibility of passengers commencing from any of 20 different locations (the same as $E_{2\text{-}3}$). The outcomes are systematically documented in Table 13. It compares HEMs' performance by showing pre- and post-adjustment *TET*s (applying an α =1.25 as applied by IMO and $\beta+\gamma=1$), optimization iterations, and model complexity.

Table 13. Comparative analysis of *TET*s for HEM 1 to HEM 3 considering families.

Model		Approach	*TET* before affecting α, β, and γ	*TET* after affecting α, β, and γ	Iterations	Nodes	Block of variables	Block of equations
HEM 1		*RO*	848.21	1,060.17	505,987	467	9	19
HEM 2	*RSSP*	$RSSP_{s_1u_1}$	1,243.13	1,553.92	37,243	0	6	12
		$RSSP_{s_1u_2}$	1,074.41	1,343.02				
		$RSSP_{s_1u_3}$	916.70	1,145.87				
		$RSSP_{s_2u_1}$	1,487.93	1,859.92				
		$RSSP_{s_2u_2}$	1,251.44	1,564.30				
		$RSSP_{s_2u_3}$	1,064.96	1,331.19				
		$RSSP_{s_3u_1}$	1,044.31	1,305.39				
		$RSSP_{s_3u_2}$	895.32	1,119.15				
		$RSSP_{s_3u_3}$	761.49	951.86				
		$RSSP_{s_4u_1}$	1,101.52	1,376.90				
		$RSSP_{s_4u_2}$	942.66	1,178.32				
		$RSSP_{s_4u_3}$	809.15	1,011.44				
HEM 3	*HRSSRP*	$HRSSRP_{s_1w_1}$	1,463.42	1,829.27	21,376	0	7	13
		$HRSSRP_{s_1w_2}$	1,476.34	1,845.42				
		$HRSSRP_{s_1w_3}$	1,424.46	1,780.57				
		$HRSSRP_{s_2w_1}$	991.35	1,239.18				
		$HRSSRP_{s_2w_2}$	1,001.32	1,251.65				
		$HRSSRP_{s_2w_3}$	979.62	1,224.53				
		$HRSSRP_{s_3w_1}$	847.05	1,058.81				
		$HRSSRP_{s_3w_2}$	864.53	1,080.66				
		$HRSSRP_{s_3w_3}$	847.90	1,059.88				

Based on the data provided in Table 13, here is a description of the performance of the applied approaches in managing uncertainty in HEMs in terms of their *TET* before affecting α, β, and γ:

- *RO* approach in HEM 1: It exhibits the most efficient evacuation time among the three approaches, with a TET of 848.21 seconds. This approach to handling uncertainty suggests a good efficiency level in the *RO* model due to its robust handling of uncertainties and optimized allocation of families/passengers to exit doors. The *RO* model's strength lies in its ability to minimize evacuation time while effectively managing potential variations in walking speeds and distances to exit doors.
- *RSSP* approach in HEM 2: It shows a range of evacuation times across different scenarios, which indicates variability in its effectiveness. The *TET*s vary from 1,487.93 seconds in the $RSSP_{s_2u_1}$ scenario to as low as 761.49 seconds in the $RSSP_{s_3u_3}$ scenario. The varying *TET*s across scenarios suggest the *RSSP* approach's adaptability in handling different combinations of walking speed and travel distance uncertainties. It demonstrates the ability to model a broad spectrum of evacuation conditions.
- *HRSSRP* approach in HEM 3: Like *RSSP*, *HRSSRP* also shows variability in evacuation times across its scenarios. The *TET*s range from 1,476.34 seconds in the $HRSSRP_{s_1w_2}$scenario to 847.05 seconds in the $HRSSRP_{s_3w_1}$scenario. This approach's strength lies in its hybrid modeling of uncertainties, including walking speed and exit door capacities. The range of *TET*s indicates

an approach to modeling various evacuation scenarios, potentially providing a more resilient perspective of evacuation dynamics.

- The HEM 1 to HEM 3 models optimize evacuation scenarios by incorporating a mix of families and solo travelers, which reflects the complexity of human behavior in emergencies. Families, which move slower due to group dynamics, and solo travelers, who are generally faster and more adaptable, are included to enhance realism. This diverse approach offers a more accurate prediction of evacuation dynamics and potential congestion. In contrast, studies focusing solely on solo travelers, such as the referenced case study, may underestimate evacuation times and congestion risks, lacking the broader perspective provided by including family groups.

As a result, the *RO* approach stands out for its efficiency in evacuation time, suggesting a focused and effective optimization strategy. In terms of scenario flexibility, both the *RSSP* and *HRSSRP* approaches offer flexibility through multiple scenarios, which allows for a more detailed and varied analysis of potential evacuation conditions. In light of resilience and robustness, the *HRSSRP* approach, with its hybrid modeling of uncertainty in walking speed and disruption in exit doors, potentially provides a more robust and realistic assessment of evacuation scenarios compared to *RSSP*, factoring in additional complexities like exit door capacities along with walking speed and travel distance.

Table 12 also provides computational outputs for HEM 1 to HEM 3, each employing a different approach to modeling uncertainty: *RO*, *RSSP*, and *HRSSRP*. These outputs, which are the result of using the CPLEX solver within the GAMS for solving MIP models, offer a quantitative basis to compare the complexity and computational effort required by each approach.

- The number of iterations and nodes needed for each model to converge to a solution provides insight into the computational intensity of the optimization process. HEM 1 requires the most iterations and nodes, which indicates that the *RO* approach should explore more solution space to find the optimal solution. In contrast, HEM 3 requires the fewest iterations, which can suggest a more efficient search through the solution space, due to the hybrid nature of the *HRSSRP* approach that provide better initial estimates and bounds.
  Additionally, the *HRSSRP* approach does not incorporate the same number of uncertain parameters as the *RSSP* approach. Specifically, in the *RSSP* model, both the walking speed and travel distance of passengers and families are treated as uncertainties, with distinct scenarios assigned to each passenger. In contrast, the *HRSSRP* model primarily focuses on scenarios related to passenger walking speed and includes scenarios for exit door disruptions. However, these scenarios are fewer in comparison to the walking speed scenarios for each passenger in the *RSSP* model.
- The formulation complexity of the HEM models varies, with HEM 1 exhibiting the most complexity. This is evidenced by its higher counts of variable and equation blocks. HEM 1's complexity primarily stems from modeling uncertainties related to passenger and family walking speeds within an uncertainty set. This approach necessitates additional constraints to represent these uncertainties.
  In contrast, HEM 2 and HEM 3 manage uncertainties through scenario-based approaches. These models integrate scenarios to address uncertainty without adding extra constraints to their deterministic counterparts. Therefore, while HEM 1 focuses on a more constraint-intensive method for uncertainty modeling, HEM 2 and HEM 3 opt for a scenario-based approach, which results in a relatively simpler formulation in terms of constraints.
- The number of clique table members can indicate the complexity and the strategy employed in the optimization process. In the context of HEM 3, the notably high number of clique table members, totaling 501,597 compared to 77,612 for HEM 1 and 29,916 for HEM 2, suggests a more intricate and aggressive strategy in handling the model's complexities. This substantial figure in HEM 3 is reflective of a sophisticated approach to managing a broader range of uncertainties, which is essential for the model's efficiency. The larger number of clique table

members in HEM 3 contributes to the model's ability to navigate and simplify the complex solution space, which can lead to fewer iterations in finding the optimal solution.

The data suggests a trade-off between model complexity and computational efficiency. HEM 1, while being the most complex, requires the most iterations to solve, which could be due to its thoroughness in encompassing uncertainty through *RO*. On the other hand, the *RSSP* and *HRSSRP* models demonstrate a reduction in structural complexity and the number of iterations needed. This reduction may be attributed to a more focused representation of uncertainty that balances model fidelity with computational speed.

HRSSRP approach stands out for its use of cuts to refine the solution space, which aligns with its fewer iterations, suggesting an effective utilization of solver strategies to enhance computational performance. This efficiency might be especially beneficial when scaling the model for larger, more complex scenarios or when rapid solutions are necessary, as in real-time evacuation planning. Furthermore, the *RO* technique demands the most computational resources. The *HRSSRP* model strikes an effective balance, which potentially offers a more practical approach for large-scale applications where computational resources and time are constrained. The choice of model would thus depend on the specific requirements of the evacuation scenario and the availability of computational resources.

6.4.3. Multi-period evacuation process in HEM 1 to HEM 3

This section concentrates on the multi-period nature of the evacuation process, analyzing in detail each period, including the number of evacuees, the duration, and the reasons for these metrics. Additionally, since the scenario-based models (HEM 2 employing *RSSP* and HEM 3 applying *HRSSRP*) generate multiple scenarios, a single scenario from their outputs is selected for a concise comparison with HEM 1, which applies the *RO* approach. This process allows us to contrast these models with the *RO*-based model. The chosen scenarios for this analysis are $RSSP_{s_1u_3}$ and $HRSSRP_{s_2w_1}$. The insights gained from this analysis also apply to other scenarios. Figure 12 illustrates the duration of each period and the number of evacuees, solo travelers (upper box), and families (lower box) evacuated under the three models per period.

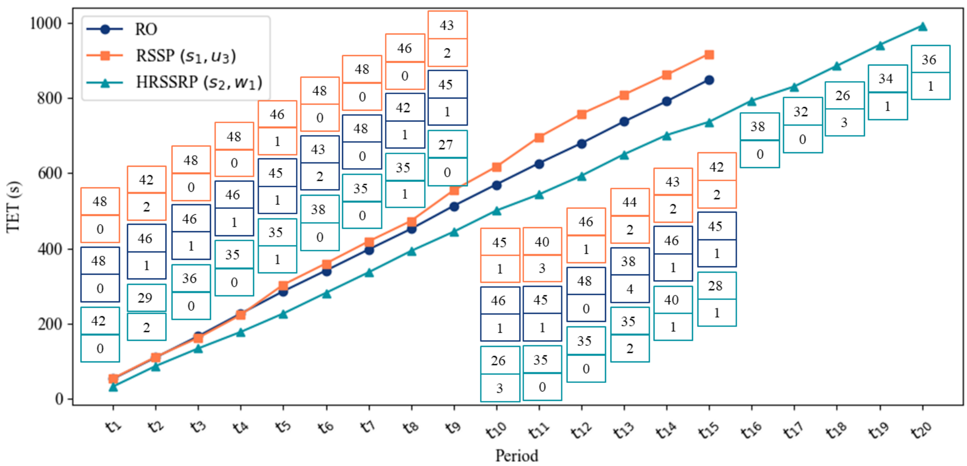


Figure 12. Comparative analysis of evacuation periods and evacuee numbers.

HEM 1 manages uncertainties related to each passenger's walking speed, and HEM 2 addresses uncertainties related to each passenger's walking speed and travel distance. These uncertainties are integrated directly into the optimization objective function to minimize total evacuation time. In these models, the focus is on optimizing the allocation of passengers, solo travelers, and families, minimizing the total evacuation time within a set of constraints, allowing for a more straightforward and time-efficient evacuation process, which results in the 15-period duration. HEM 3 addresses uncertainties in passenger walking speed alongside disruptions in exit door capacities.

Unlike HEM 1 and 2, which integrate uncertainties directly into their optimization objective, HEM 3 treats exit door disruptions as constraints. This methodological shift impacts the model's optimization strategy. By treating exit door capacity disruptions as constraints, HEM 3 prioritizes the robustness of the evacuation plan against these potential disruptions. Constraints related to critical evacuation resources, like exit door capacities, inherently restrict the model's flexibility in routing and scheduling evacuations. In scenarios where exit door capacities are diminished, HEM 3, handled with *p*-robust feasibility stochastic optimization, is designed to explore and adopt alternative evacuation plans. These plans, while potentially less direct and therefore less efficient than those in HEM 1 and 2, are chosen to ensure the evacuation plan remains viable under a wider array of uncertain conditions. This emphasis on robustness and adaptability in the face of exit door disruptions naturally extends the evacuation process, accounting for why HEM 3 requires 20 periods for complete evacuation, as opposed to the 15 periods in the other models. The extended period in HEM 3 reflects a strategic trade-off: prioritizing the resilience and reliability of the evacuation process over mere efficiency, which is crucial in ensuring safety in highly uncertain and dynamic environments such as passenger ship evacuations. Considering Equation (73), the reliability metric for HEM 3 is calculated at 66% (computed as (0.33 × 1 + 0.33 × 1 + 0.33 × 0) × 100), under the condition where the variable Γ_{W_3}=1, Γ_{W_2}, and Γ_{W_1}=0. This calculation is based on the example where each exit door can accommodate four passengers per period.

Based on Figure 9, The statistical analysis offers insights into the outputs of the HEM 1, HEM 2, and HEM 3 models across their respective evacuation periods. By examining these statistics, it can be understood why evacuation times vary across models per period.

- Average evacuation time:
  - HEM 1: 56.54 seconds
  - HEM 2: 61.11 seconds
  - HEM 3: 49.57 seconds

HEM 3 shows the shortest average evacuation time, which might seem counterintuitive given its longer overall evacuation period. However, this indicates that while HEM 3 takes more periods to evacuate everyone, the average time per period is efficiently minimized due to its robust handling of uncertainties in both walking speed and exit door capacities.

- Variance of period time:
  - HEM 1: 5.05
  - HEM 2: 100.42
  - HEM 3: 52.00

The variance in HEM 2 is higher than in the other models, suggesting more significant inconsistency in evacuation times per period. This is attributed to the dual uncertainties in walking speed and travel distance that HEM 2 manages.

- Skewness:
  - HEM 1: 0.45
  - HEM 2: 1.11
  - HEM 3: -0.99

The skewness values indicate the asymmetry in the distribution of evacuation times per period. HEM 3's negative skew suggests a concentration of shorter evacuation times.

- Kurtosis:

It reflects the tailed property of the distribution. The closer to zero, the more normal-like the distribution is. HEM 3's value is closest to zero, telling a more normal distribution of evacuation times.

- Median:

It provides a measure of central tendency. HEM 3's median is closer to its mean, indicating a more symmetric data distribution.

- Standard deviation:
  - HEM 1: 2.25
  - HEM 2: 10.02
  - HEM 3: 7.21

The statistical analysis of the number of evacuees (both solo travelers and families) across the evacuation periods for HEM 1, HEM 2, and HEM 3 models also provides insights into how each model handles the evacuation process:

HEM 1 and HEM 2 have the same average number of solo travelers and families evacuated per period (45.13 solo travelers and 1.07 families). This similarity suggests that despite different uncertainty factors (walking speed in HEM 1 and both walking speed and travel distance in HEM 2), the models achieve a similar rate of evacuation. HEM 3 shows a lower average (33.85 solo travelers and 0.80 families), which aligns with its approach of managing both walking speed uncertainty and exit door capacity disruptions. The lower average indicates a more cautious and constrained evacuation process, likely due to the additional complexity of managing exit door capacity.

- Variance:
  - HEM 1: 6.25 (solo travelers), 0.86 (families)
  - HEM 2: 6.65 (solo travelers), 1.00 (families)
  - HEM 3: 19.43 (solo travelers), 0.96 (families)

The variance is higher in HEM 3 compared to HEM 1 and HEM 2, which suggests more fluctuation in the number of evacuees per period. This is expected, given HEM 3's additional constraints on exit door capacities.

- Skewness:
  - HEM 1: -1.41 (solo travelers), 1.87 (families)
  - HEM 2: -0.38 (solo travelers), 0.27 (families)
  - HEM 3: -0.39 (solo travelers), 1.05 (families)

The skewness values indicate the asymmetry in the distribution of the number of evacuees. HEM 1 shows a more negative skew for solo travelers, which means a concentration toward higher numbers of evacuees in most periods.

- Kurtosis:
  - HEM 1: 3.37 (solo travelers), 6.36 (families)
  - HEM 2: -1.02 (solo travelers), -1.30 (families)
  - HEM 3: -0.43 (solo travelers), 0.36 (families)

HEM 1 shows a high kurtosis, especially for families, which implies a more peaked distribution with pronounced tails. This means periods of high and low family evacuations.

- Median:
  - HEM 1 and HEM 2: 46.00 (solo travelers), 1.00 (families)
  - HEM 3: 35.00 (solo travelers), 0.50 (families)

The median values are consistent with the averages in HEM 1 and HEM 2, while HEM 3's median for solo travelers is slightly higher than its average, which signifies a skewed distribution.

- Standard deviation:
  - HEM 1: 2.50 (solo travelers), 0.93 (families)
  - HEM 2: 2.58 (solo travelers), 1.00 (families)
  - HEM 3: 4.41 (solo travelers), 0.98 (families)

The standard deviation is higher in HEM 3, consistent with its higher variance. This suggests a greater variability in the number of evacuees per period in HEM 3 because of the added complexity of managing door capacity disruptions.

The statistical analysis of evacuation times and the number of evacuees for HEM 1, HEM 2, and HEM 3 models reveals distinct patterns:

- HEM 1 and HEM 2:
  - Consistency in evacuees: Both models maintain a similar average number of evacuees per period, suggesting efficiency in managing passenger throughput.
  - Time variability in HEM 2: Despite this consistency, HEM 2 shows fluctuation in evacuation times due to its dual focus on passenger walking speed and travel distance.
- HEM 3:
  - Efficient yet restrained: HEM 3 has the shortest average evacuation time per period but evacuates fewer individuals each time. This indicates a more cautious approach, which balances time efficiency with the added complexity of managing exit door capacities.
  - Greater variability: Higher variance and standard deviation in evacuation time and number of evacuees point to a more uncertain evacuation pattern in HEM 3.

Overall, HEM 1 and HEM 2 demonstrate consistency in the number of evacuees despite differing approaches to uncertainty, whereas HEM 3's strategy of managing additional constraints results in quicker but less populated evacuation periods. This reflects the trade-offs between time efficiency and evacuation volume inherent in each model's design.

6.4.3.1. Analysis of the maximum period durations

Z-score analysis is employed to examine the longest evacuation periods in the HEM 1, HEM 2, and HEM 3 models. Z-scores are for identifying outliers, which focus on periods that deviate from the average, thus impacting evacuation efficiency. The standardization feature in the Z-score metric enables direct comparisons across models, regardless of their different evacuation time scales.

Additionally, Z-scores provide insights into the variability of each period, which sheds light on the consistency/inconsistency of each model's performance. Figure 13 offers a visualization of Z-scores for each evacuation period in the HEM 1, HEM 2, and HEM 3 models. It illustrates how each period's evacuation time deviates from the respective model's average, with negative Z-scores indicating shorter times and positive ones indicating longer durations.

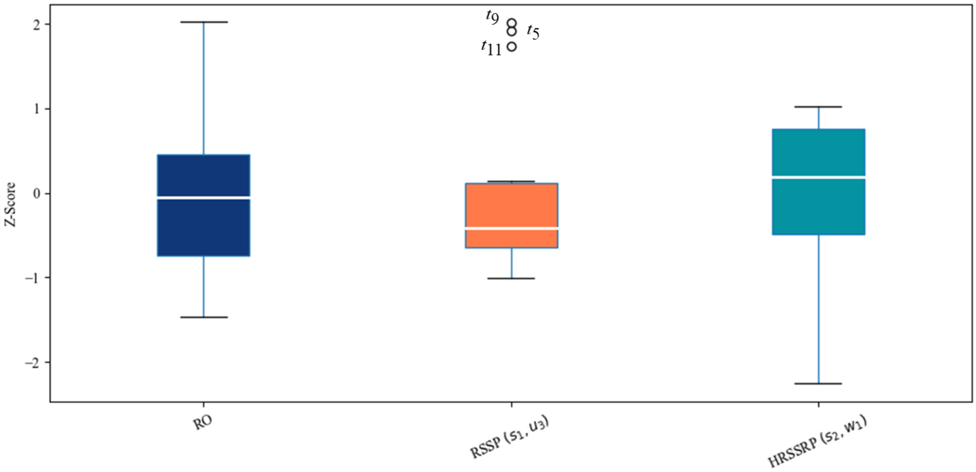


Figure 13. Z-Score analysis of evacuation periods in HEM 1, HEM 2, and HEM 3.

Figure 13 shows that in HEM 2, periods t_{11}, t_5, and t_9 stand out as outliers, with Z-scores of 1.73, 1.91, and 2.01, respectively. These scores indicate that the evacuation times for these periods are longer than the average for HEM 2. In contrast, HEM 1 and HEM 3 do not exhibit any such outliers. This suggests a variability in HEM 2's evacuation process for specific periods because of factors such as the model's handling of uncertainties in both walking speed and travel distance. The absence of outliers in HEM 1 and HEM 3 indicates a more consistent evacuation time across their periods, which reflects the different operational dynamics and uncertainty management strategies in these models.

Figure 14 provides data explaining another reason for the extended evacuation times. It details the evacuation of the slowest-moving families during these specific periods: f_8 in t_5 with an evacuation time of 80.23 seconds, f_{12} in t_9 taking 81.23 seconds, and f_{11} in t_{11} requiring 78.4 seconds. This information from Figure 11 helps us understand that the evacuation of these particular families influences the longer evacuation times for these periods.

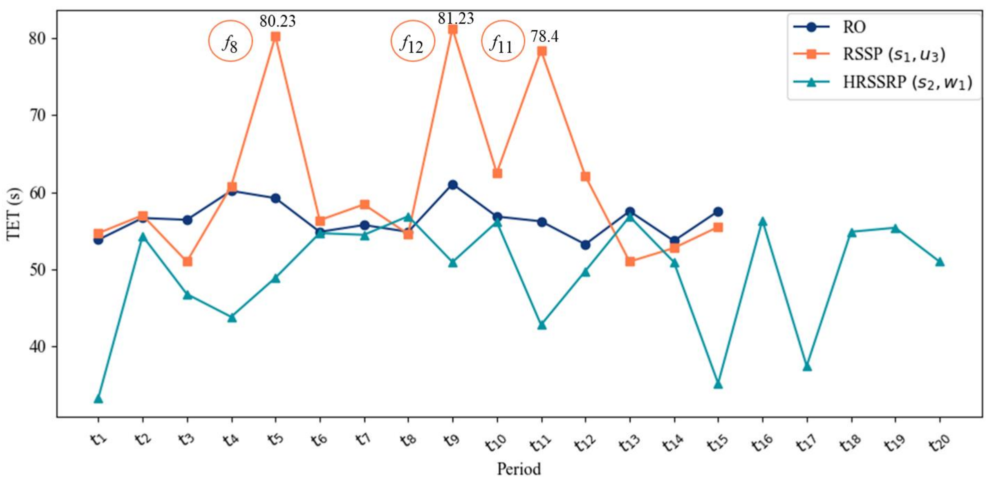


Figure 14. Analysis of extended evacuation times linked to slowest-moving families in HEM 2

Figure 15 offers an analysis of the factors contributing to the extended evacuation times for families f_8, f_{11}, and f_{12} in HEM 2. It details the characteristics of these families, including their size (2, 3, and 2 members for f_8, f_{11}, and f_{12}, respectively), walking speed (all at 0.35 m/s), alertness situation (all non-alert), response times (8.8 seconds for f_8, 9.83 for f_{11}, and 9.8 for f_{12}), their specific locations within the deck 10 (i_7, i_3, i_7), and the exit doors they are offered based on their characteristics, such as speed and closeness to the different exit doors. This granular information from Figure 15 allows for a deeper understanding of why these families contributed to longer evacuation times. Their larger size, particularly for family f_{11}, slower walking speeds, lack of alertness, and longer response times all play a role in delaying their evacuation. Additionally, their locations and the exit doors they used have influenced the overall time taken.

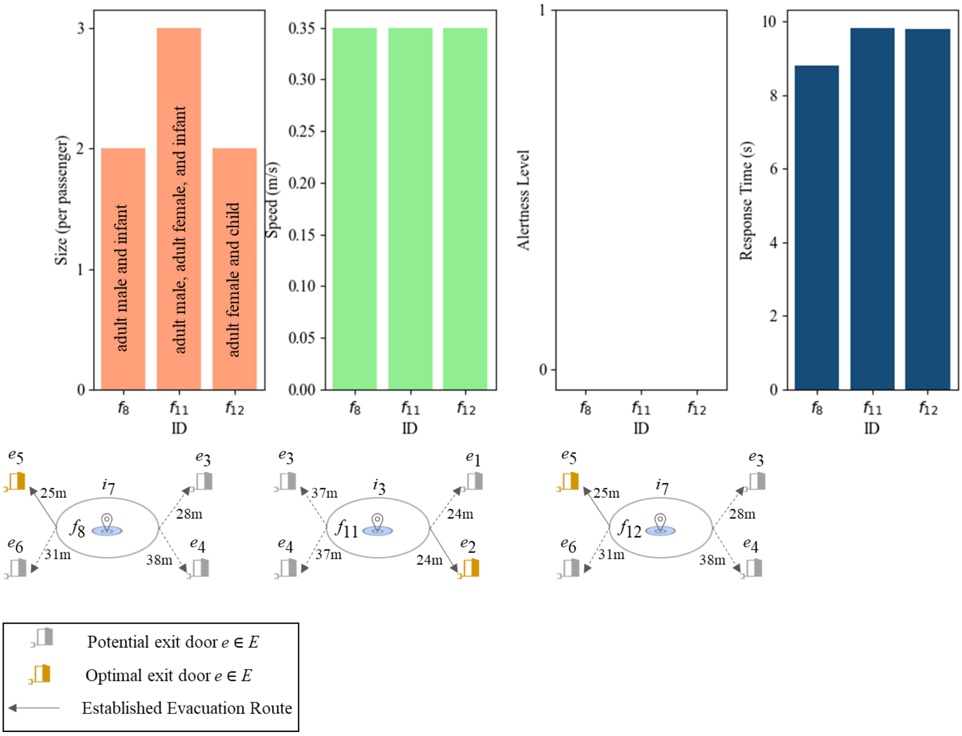


Figure 15. Analysis of factors affecting evacuation times for families f_8, f_{11}, and f_{12} in HEM 2.

Families f_8, f_{11}, and f_{12} are located in specific areas on deck 10, at locale i_7, i_3, and i_7, respectively. Crew teams j_6, j_2, and j_6 are assigned to these locations and are tasked with assisting these families. This arrangement suggests a strategic allocation of crew members to aid families in more challenging evacuation scenarios. The presence of crew members in the same locations as these families, particularly given their slower speeds and non-alert status, is a measure to ensure their safe and efficient evacuation. This assistance mitigates the impact of these families' characteristics on the overall evacuation time, which highlights the importance of effective crew deployment in emergencies.

6.4.3.2. Analysis of passengers' groups distribution across periods

The demographic distribution of solo travelers across all periods in HEM 1 to HEM 3 is depicted in Figures 16-1, 16-2, and 16-3.

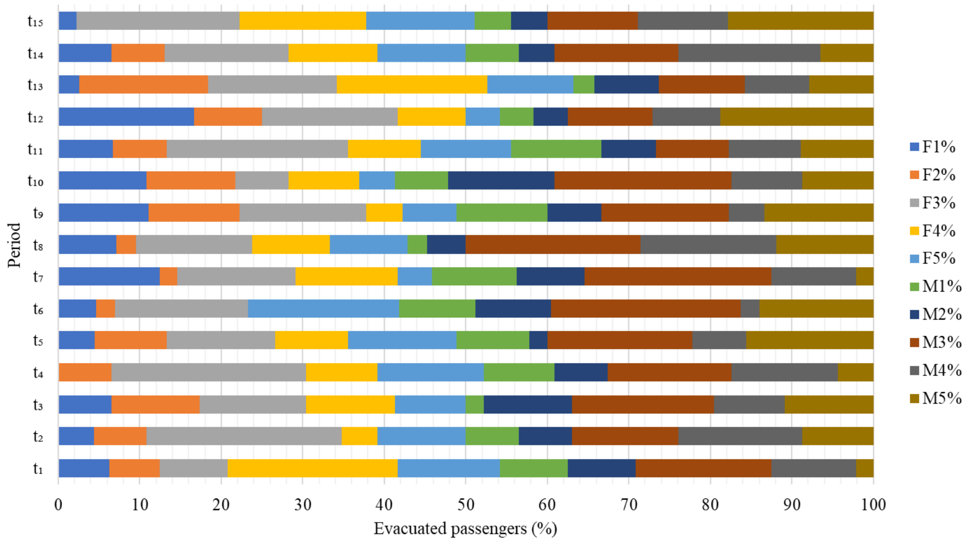


Figure 16-1. The specific demographic group across all periods in HEM 1.

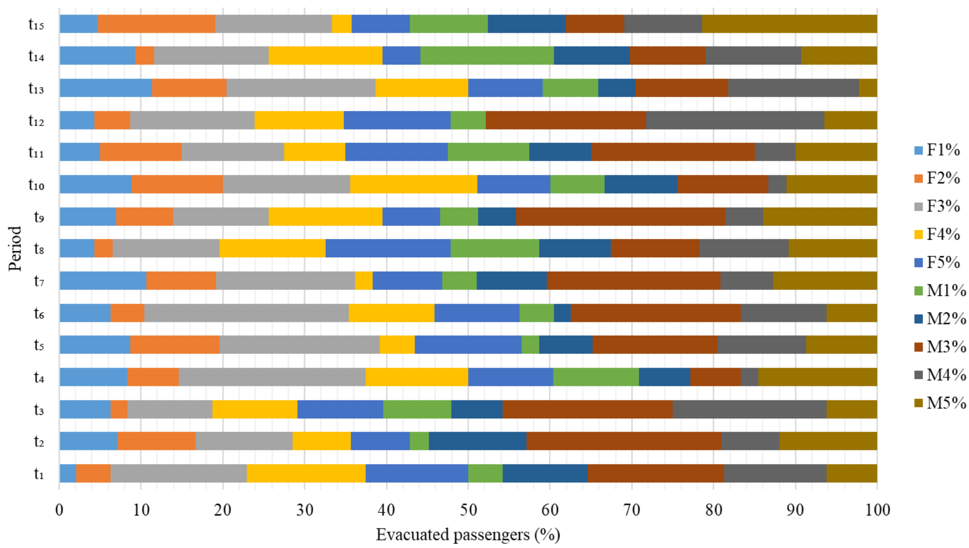


Figure 16-2. The specific demographic group across all periods in HEM 2.

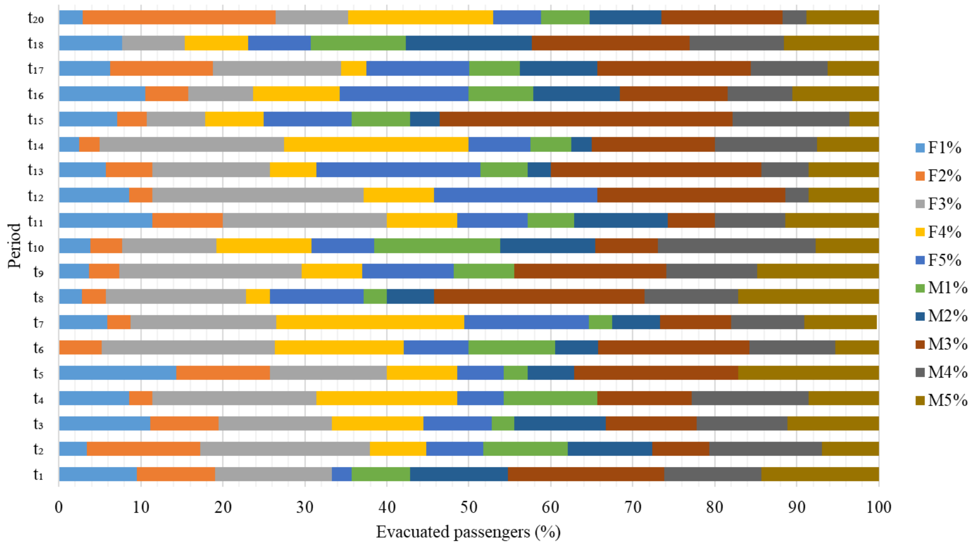


Figure 16-3. The specific demographic group across all periods in HEM 3.

Figure 16. The specific demographic group across all periods through HEM 1 to HEM 3 for solo travelers.

For example, in HEM 1 and HEM 3, during period t_3, the group with the lowest evacuation percentage was the M1 group, consisting of males aged 10-20 years. In contrast, in HEM 2, under the same conditions, the group with the most minor percentage of evacuees was the F2 group, including females aged 20-40. The distinct modeling approaches in each HEM version brought out different aspects of evacuation behavior, revealing how certain demographic groups might be more affected under specific uncertainties and scenario conditions.

The demographic distribution of family travelers across all periods in HEM 1 to HEM 3 is depicted in Figures 17-1, 17-2, and 17-3.

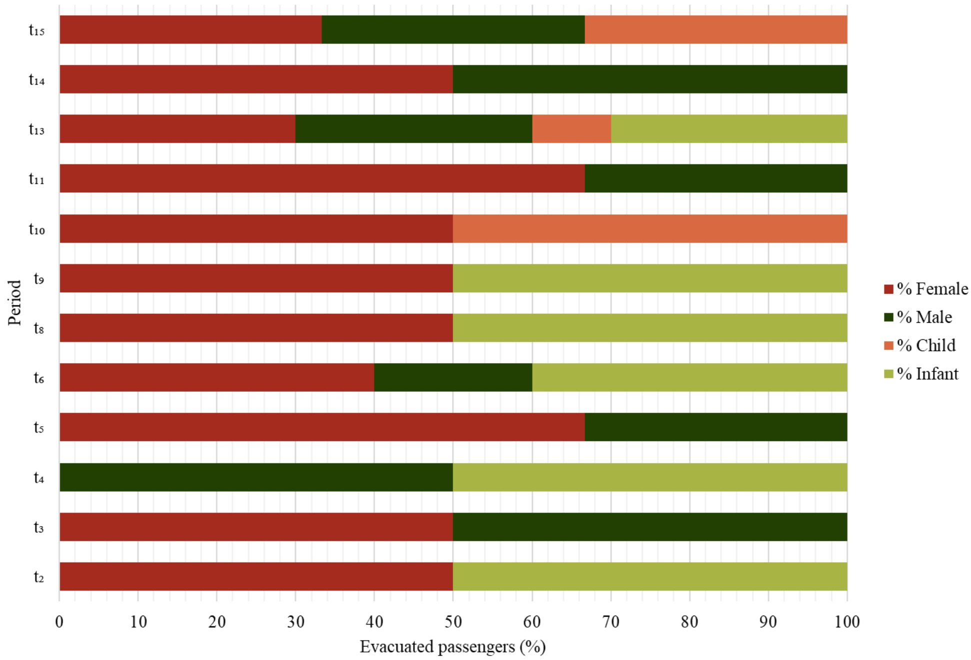


Figure 17-1. The specific demographic group across all periods in HEM 1.

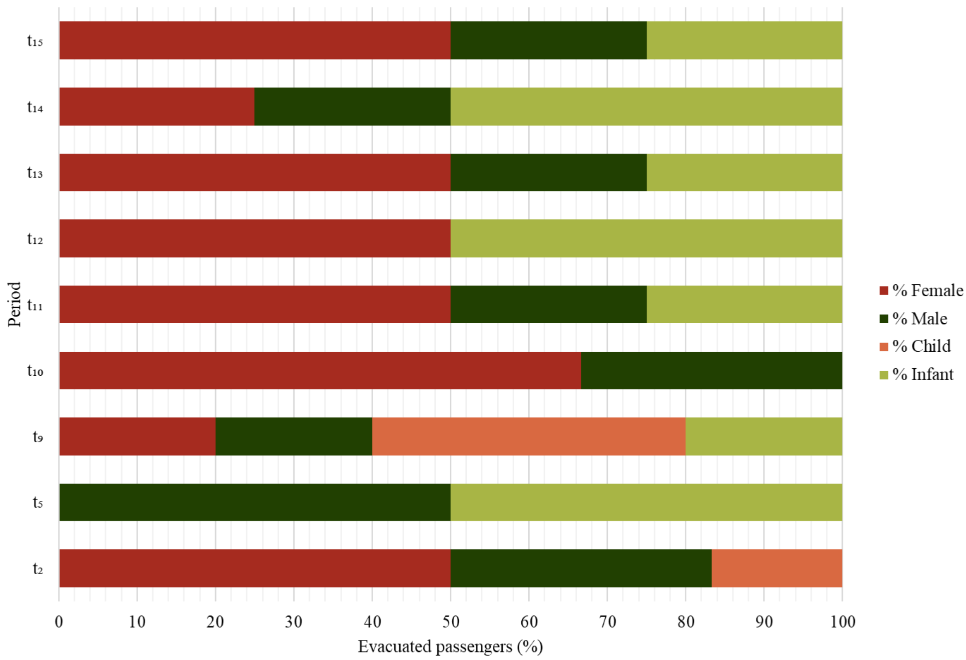


Figure 17-2. The specific demographic group across all periods in HEM 2.

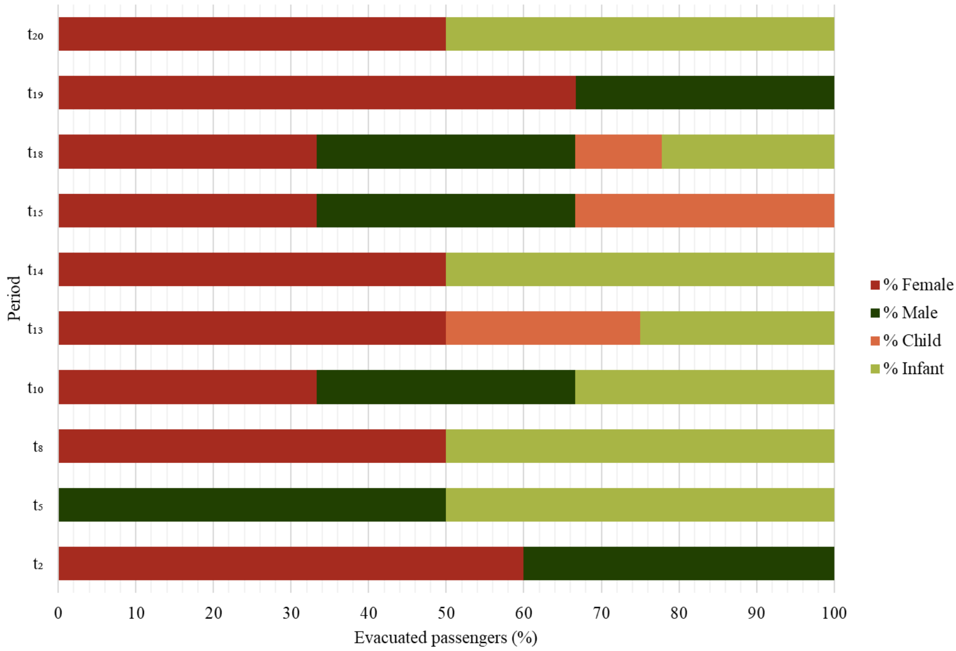


Figure 17-3. The specific demographic group across all periods in HEM 3.

Figure 17. The specific demographic group across all periods through HEM 1 to HEM 3 for family travelers.

In HEM 1, HEM 2, and HEM 3, the percentage of family evacuees varies across different periods, which echoes each model's specific uncertainty considerations. In HEM 1, the highest percentages of family evacuees are noted during periods t_2-t_6, t_8-t_{11}, and t_{13}-t_{15}, suggesting family evacuations during these intervals. HEM 2 shows a different pattern, with peak family evacuations occurring at t_2, t_5, and from t_9-t_{15}, pointing to specific times when families are more evacuating. In HEM 3, family evacuations are most notable at t_2, t_5, t_8, t_{10}, and during extended periods t_{13}-t_{15} and t_{18}-t_{20}, indicating a varied distribution due to the complex interplay of uncertainty factors like walking speed and door capacity.

6.4.4. Evacuation plan analysis

The evacuation models, HEM 1, HEM 2, and HEM 3, are designed to create specific evacuation plans for every passenger, whether they are solo travelers or with families. These plans detail several key factors, such as response time (R), travel time (T), and evacuation time (ET), which is a combination of R and T. Additionally, the plans specify which exit door to go for evacuation, the period of evacuation, the starting time within the system, moving time point within the system, and the complete time point when the evacuation is finished for the corresponding passenger. For instance, p_{78}, a 15-year-old girl from Family Group F5, originally located in Cabin 24 and currently at position i_{10}, receives distinct evacuation plans across different models. Under the HEM 1 model, her evacuation is scheduled for period t_3. She commences her evacuation at a system time of 110.52. Her preparation, or response time, is calculated to be 3.53 seconds. She is assigned to exit through door 5 (e_5), which she can reach in 27.91 seconds.

In addition, she will receive assistance from the crew team j_9 during her evacuation. Consequently, her evacuation is projected to be completed by a system time of 138.43. The final details of the evacuation plan for the same case, along with the results from models HEM 2 and HEM 3, are showcased in Figure 18.

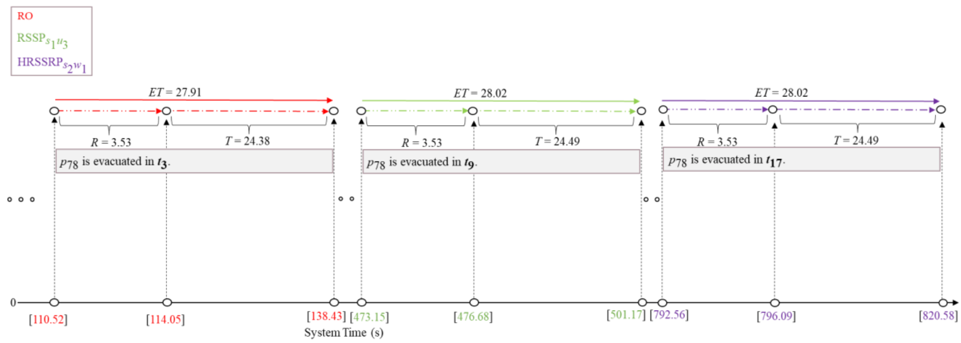


Figure 18. Evacuation plan results for p_{78}: HEM 1, HEM 2, and HEM 3.

6.4.5. Initial location analysis

One key aspect of the models is the consideration of varying starting points for each passenger, accounting for a range of possible locations, $i \in I$, where a passenger might be at the start of an evacuation. The evacuation plan for each individual is then tailored based on their specific starting location. For example, with passenger $p_8$and family group f_2. Their evacuation plans and exit doors vary based on their current locations, which are $i_1$and i_{15}. In the HEM 2 model, under the $RSSP_{s_1u_3}$, if f_2 is at location i_1, they are directed to exit door e_2 during period t_1. However, if they are at location i_{15}, their plan changes to exit through door e_{10}, also in period t_1. Figure 19 displays how solo traveler p_8 and family group f_2 are allocated to different exit doors based on their current locations.

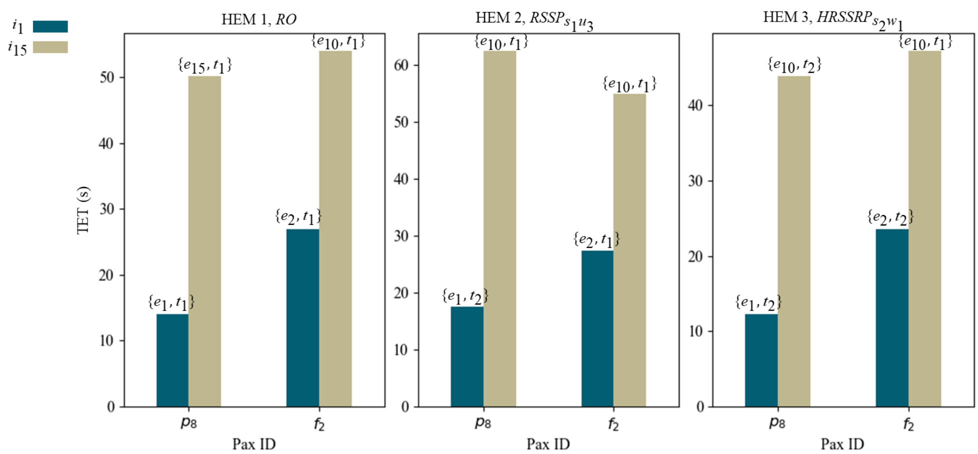


Figure 19. Allocation of exit doors for p_8 and f_2 based on current locations in HEM 1 to HEM 3.

6.4.6. Exit door quantity analysis

Next, how increasing the number of exit doors affects total evacuation time (*TET*) in the models is examined across various scenarios. This section aims to understand better how more exits can improve evacuation efficiency. Figure 20 demonstrates how adding two more exit doors (e_{13} and e_{14}) improved evacuation efficiency. This is evident in the reduction of *TET* across various scenarios.

- HEM 2 results:
  - There's a consistent decrease in TET with the addition of e_{13} and e_{14}.
  - The improvement percentage varies from 15.18% to 19.46%.

- Scenarios like (s_1, u_3) and (s_3, u_3) show the highest improvements (19.46% and 19.03%, respectively).
- The T-test result shows 8.28E-10. It indicates that these improvements are statistically significant, meaning the chances are low that these results are due to random variation. This adds robustness to the conclusion that the additional exit doors improve evacuation efficiency.

- HEM 3 results:
  - Similar to HEM 2, the TET decreased in all scenarios when adding e_{13} and e_{14}.
  - The improvement is slightly lower compared to HEM 2, ranging from 5.02% to 13.58%.
  - The highest improvement was observed in (s_3, w_3) (13.58%).
  - The T-test result of 9.32E-05 again confirms the statistical significance of these improvements, reinforcing the confidence in the positive impact of the additional exits.

Adding exit doors e_{13} and e_{14} enhances evacuation efficiency in both models, with HEM 2 showing slightly higher improvement percentages. The T-test results strongly support the effectiveness of these additional exits in reducing evacuation times.

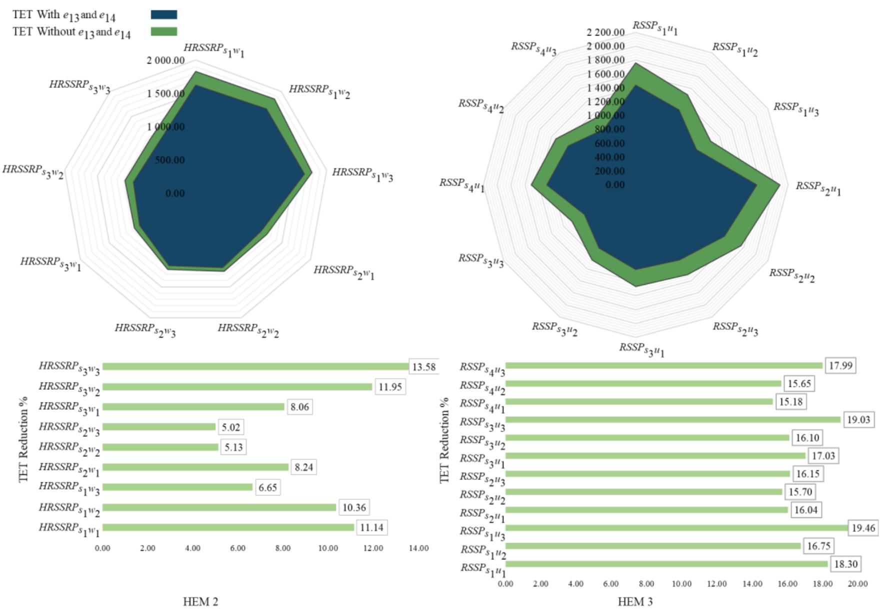


Figure 20. Impact of additional exit doors on *TET* in HEM 2 and HEM 3 models.

6.4.7. Scenario stability analysis

To consider a scenario generation approach as reliable, it should exhibit a quality called stability. Stability is apparent when various scenario trees, generated with the same input data and used for solving a specific problem, consistently produce similar optimal values for the objective function as determined by the scenario pattern (Kaut and Stein, 2003). For instance, f_{11} in HEM 2 under different scenarios have different walking speeds. In scenario s_4, family f_{11} experiences the fastest evacuation speed, leading to its shortest evacuation time. Conversely, in scenario s_2, f_{11} has the slowest speed, resulting in the longest evacuation time. These variations are depicted in Figure 21.

Likewise, given that both solo travelers' and families' nominal walking speeds are influenced by [ϱ_1=0.7, ϱ_2=1, ϱ_3=1.2] in HEM 3 under *HRSSRP* approach it is anticipated that there would be a corresponding reduction in evacuation time since walking speed is increasing. For instance, family f_{11} shows a reduction in *TET* from scenario s_1 to s_3. These variations are depicted in Figure 22. More details about family f_{11}'s evacuation strategies can be found in Figures 21 and 22. For instance, in the HEM 2 under *RSSP* approach, during scenarios (s_1, u_3) and (s_4, u_3), family f_{11} evacuates through exits e_2 and e_1 at times t_{14}, taking 78.4 seconds and 54.88 seconds, respectively.

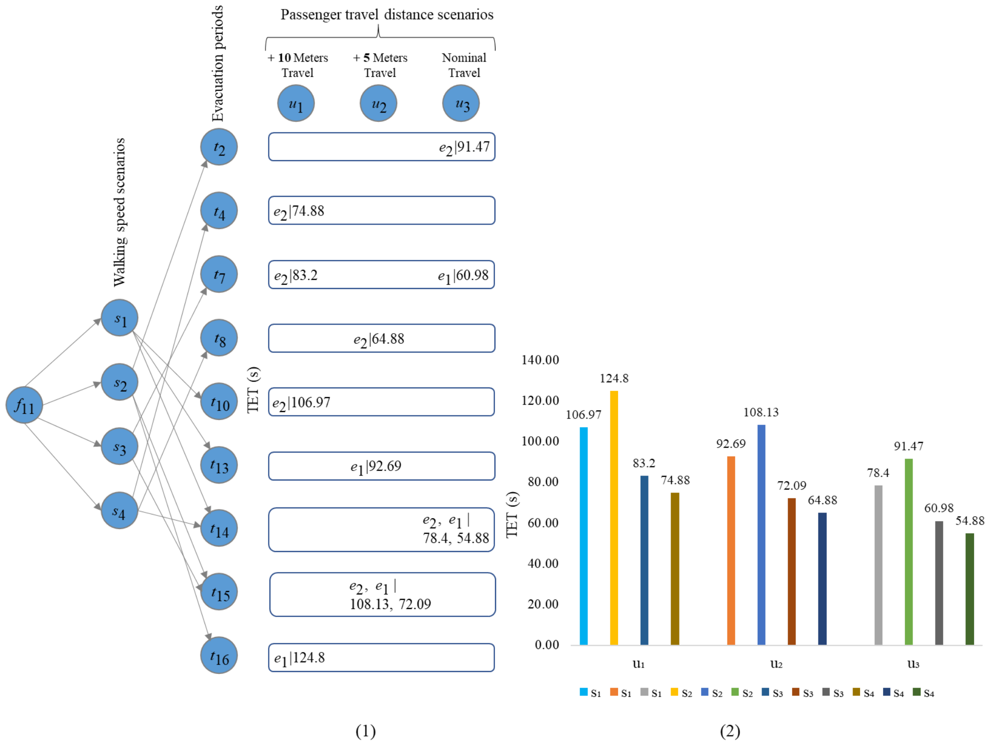


Figure 21. Scenario stability in TET for f_{11} across scenarios s_1 to s_4 in HEM 2 under *RSSP* approach.

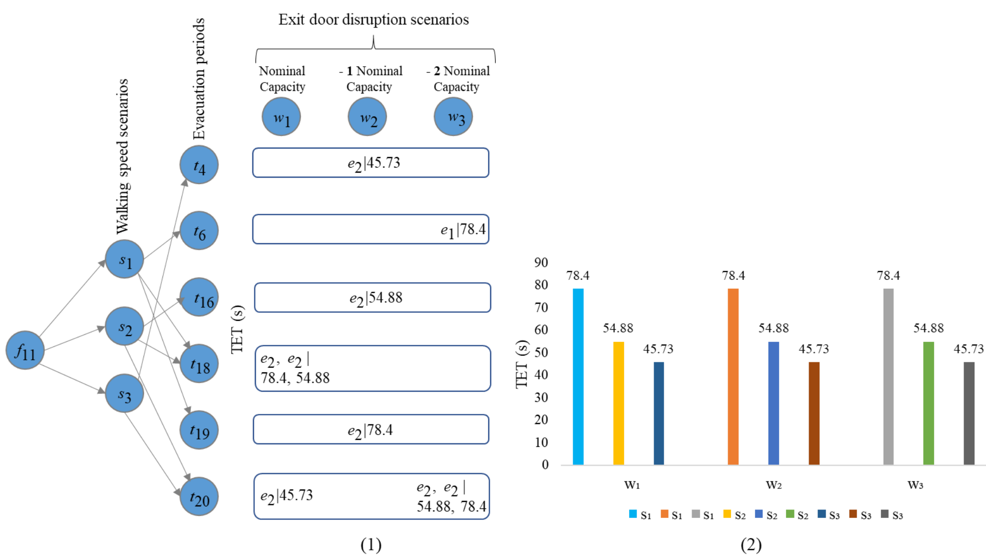


Figure 22. Scenario stability in *TET* for f_{11} across scenarios s_1 to s_3 in HEM 3 under *HRSSRP* approach.

6.4.8. Conservatism level analysis

Applying *RO* to manage uncertainty in passenger walking speed involves a component known as the conservatism level. The conservatism level plays a role in how the model balances the need for efficient evacuation against the uncertainty of passenger walking speeds. The conservatism level in *RO* refers to how conservative or aggressive the model is in considering passenger walking speed uncertainty.

In the context of human evacuation, a high conservatism level means the model prepares for worse-case scenarios regarding passenger walking speeds, such as assuming slower walking speeds for a larger portion of the passenger population. Conversely, a lower conservatism level assumes less variation in walking speeds, leading to a more optimistic evacuation plan. Furthermore, the chosen level of conservatism directly affects the evacuation time. A higher conservatism level results in longer planned evacuation times, as it prepares for slower walking speeds. A lower conservatism level optimizes for shorter evacuation times but could be less effective if actual walking speeds vary from the assumptions. The key to applying *RO* is to find a balance between evacuation efficiency (minimizing *TET*) and safety (accommodating variability in walking speeds). A model that is too conservative might lead to unnecessarily long evacuation times, while one that is not conservative enough might fail to accommodate slower passengers, potentially leading to bottlenecks or unsafe conditions.

In practical terms, setting the right conservatism level involves understanding the demographics and physical abilities of the passenger population and considering factors like age, mobility impairments, or the presence of families. The model can be adjusted to scenarios where there might be a higher concentration of slower-moving passengers (e.g., F4, F5, M4, and M5 groups) or scenarios with more varied walking speeds. Figure 23 visually depicts the impact of varying conservatism levels on the evacuation time of the slowest solo travelers and families, as well as the total evacuation time, in the context of the HEM 1.

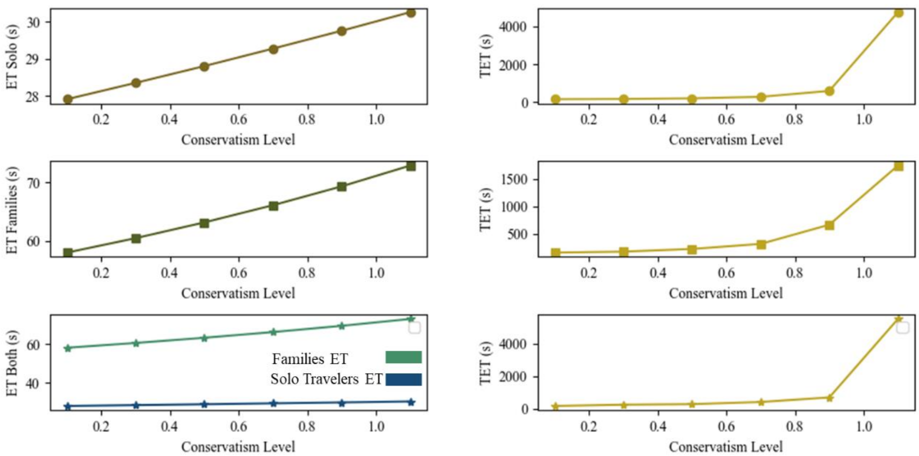


Figure 23. Analysis of conservatism level on *TET* and slowest solo traveler and family in HEM 1.

Regarding solo travelers' conservatism level, as the level increases from 0.1 to 1.1, the evacuation time of the slowest solo traveler slightly increases, which hints that the model progressively accounts for slower walking speeds. *TET* shows a more dramatic increase, especially at higher conservatism levels (e.g., 596.40 seconds at 0.9 and 4,736.36 seconds at 1.1). This suggests that planning for worst-case scenarios in walking speed extends the overall evacuation time. Regarding the family's conservatism level, a similar trend is observed with families. Increasing the conservatism level from 0.1 to 1.1 results in a gradual increase in the evacuation time for the slowest family. The *TET* also rises notably as the conservatism level increases, which reflects the impact of accounting for slower speeds in family groups. When it comes to combined conservatism levels (solo travelers and families), once both solo travelers and families have their conservatism levels grow simultaneously, the evacuation time for the slowest individuals in both groups increases. The combined effect on *TET* is substantial, at higher levels (e.g., 5,537.73 seconds at a conservatism level of 1.1 for both groups). It demonstrates that a high conservatism level across both groups can lead to prolonged evacuation times.

The results show the impact of conservatism level on evacuation efficiency. Higher conservatism levels, while ensuring the model accounts for slower walkers, can lead to much longer evacuation times. In practical terms, this presents that while it's important to plan for slower-moving individuals, overly conservative assumptions can hinder overall evacuation efficiency. The key is to find an optimal conservatism level that strikes a balance between accommodating slower walkers and maintaining a practical total evacuation time. This might involve iterative testing and adjustments based on real-world scenarios and passenger demographics. Finally, the findings also reveal the need to differentiate evacuation plans for solo travelers and families, as their walking speeds and needs might vary.

6.4.9. Exit door capacity analysis

This section explores the role of exit door capacities in evacuation planning, focusing on comparing the capacities of four and five people per period. Such analysis is crucial because minor adjustments in exit capacity can enhance evacuation times, thereby impacting safety and efficiency during emergencies. The goal is to offer clear insights into how changes in capacity can optimize evacuation procedures, thereby enhancing safety in high-occupancy settings. A statistical approach, including *T*-tests, provides robust evidence to inform improved safety practices and emergency preparedness strategies. Table 14 compares *TET* under two different capacities at exit doors: four and five people per period in HEM 2. The focus on HEM 2 and observations from HEM 1 and HEM 3 illustrate how changes in exit door capacities affect evacuation times. The findings from HEM 2, discussed here for streamlined analysis, show that increasing the capacity from four to five people per period reduces the total evacuation time across all scenarios. For example, in scenario $RSSP_{s_1u_1}$, the *TET* reduces from 1553.92 to 516.99, a 66.73% improvement. The improvement percentage is consistently above 65% across all scenarios, which signifies a robust strategy irrespective of the specific walking speed or travel distance conditions. Furthermore, the T-test result of 2.10×10^{-9} confirms that these improvements are statistically significant and not due to random variation.

Table 14. Analysis of *TET* (s) for different exit door capacities in HEM 2.

Scenarios	*TET* with Capacity = four	*TET* with Capacity = five	Improvement %
$RSSP_{s_1u_1}$	1,553.92	516.99	66.73
$RSSP_{s_1u_2}$	1,343.02	439.48	67.28
$RSSP_{s_1u_3}$	1,145.87	373.64	67.39
$RSSP_{s_2u_1}$	1,859.92	614.74	66.95
$RSSP_{s_2u_2}$	1,564.30	534.91	65.80
$RSSP_{s_2u_3}$	1,331.19	447.33	66.40
$RSSP_{s_3u_1}$	1,305.39	421.83	67.69
$RSSP_{s_3u_2}$	1,119.15	369.76	66.96
$RSSP_{s_3u_3}$	9,51.86	314.03	67.01
$RSSP_{s_4u_1}$	1,376.90	451.96	67.18
$RSSP_{s_4u_2}$	1,178.32	384.52	67.37
$RSSP_{s_4u_3}$	1,011.44	320.43	68.32
$RSSP_{s_1u_1}$	1553.92	516.99	66.73

This data implies that a minor increase in the capacity of exit doors can have a profound impact on evacuation efficiency, which is crucial for emergency management and safety planning. The consistency and statistical significance of the data make it a reliable source for future evacuation planning and simulations.

6.4.10. Corridor width analysis

In this section, how the width of corridors (ω) on passenger ships can influence evacuation efficiency is explored, in terms of evacuation time. On passenger ships, where space is at a premium, and the movement of passengers is confined to specific pathways, ω becomes a critical factor in emergency management. The correlation between different corridor widths and their effect on the speed and safety of evacuations is analyzed. This analysis can improve emergency response plans on passenger ships to ensure faster and safer evacuation processes under various emergency scenarios. Figure 24 provides data from HEM 2, which explores the impact of corridor width on *TET* for an experiment for four families and ten solo travelers.

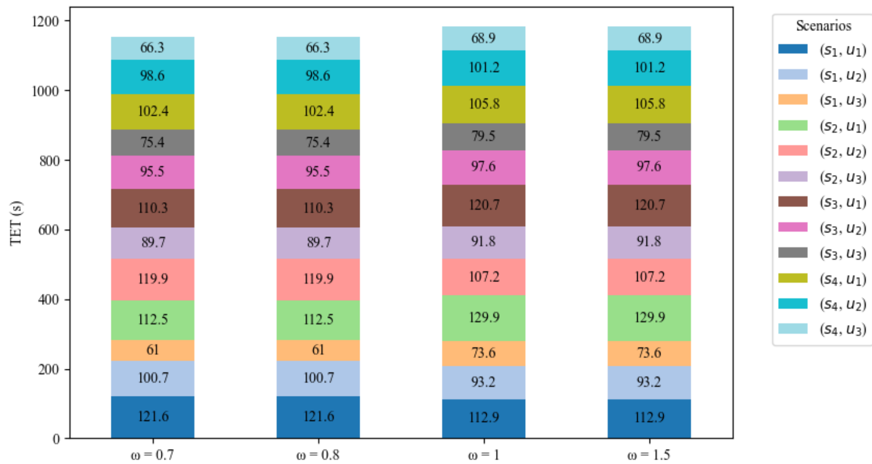


Figure 24. Impact of ω variations on *TET* in different scenarios over HEM 2.

For every scenario, the evacuation times are identical when comparing corridor widths of 0.7 and 0.8 meters. This suggests that within this narrow range, ω does not affect evacuation times. Meanwhile, a change in evacuation times becomes noticeable when ω is increased to 1 meter and then to 1.5 meters. This demonstrates that wider corridors can have an impact on evacuation efficiency. Moreover, the relationship between ω and *TET* is not linear. For example, in scenarios (s_1, u_3) and (s_2, u_1), evacuation times increase when ω is expanded from 1 meter to 1.5 meters, indicating that factors other than just ω influence evacuation times. However, in some scenarios, such as (s_3, u_1) to (s_3, u_3) and (s_4, u_2) to (s_4, u_3), there's a consistent decrease in evacuation times as ω increases, signifying that wider corridors facilitate faster evacuation in these specific cases. It is important to note that corridor widths less than 0.7 meters render the optimization model infeasible, suggesting a minimum functional limit. Additionally, increasing ω beyond 1.5 meters does not yield any noticeable change in evacuation times, which shows a plateau in efficiency gains beyond this point.

6.4.11. Waking speed adjustment strategy analysis

This section delves into the integration of passenger walking speed adjustment over the evacuation process in the models, a critical enhancement over traditional methods that use static average walking speeds. Research, such as that by Kim et al. (2019), highlights the shortcomings of assuming constant speeds in evacuation scenarios. In real emergencies, factors like ship motion, psychological stress, and physical fatigue influence the walking speed, often leading to a reduction, especially towards the end of evacuation periods.

By incorporating these dynamic speed adjustments, the models aim to better reflect actual passenger walking speed under varying conditions and threats, thereby providing more accurate and reliable predictions of evacuation timelines. The focus on HEM 2 and observations from HEM 1 and HEM 3 is due to the consistent trends observed across these models regarding how alterations in the degradation constant influence *TET*s. Figure 25 visually illustrates the effect of varying the linear degradation constant in family ($\mathcal{M}$) travelers on *TET* for scenarios (s_1, u_1), (s_1, u_3), and (s_2, u_3) in HEM 2.

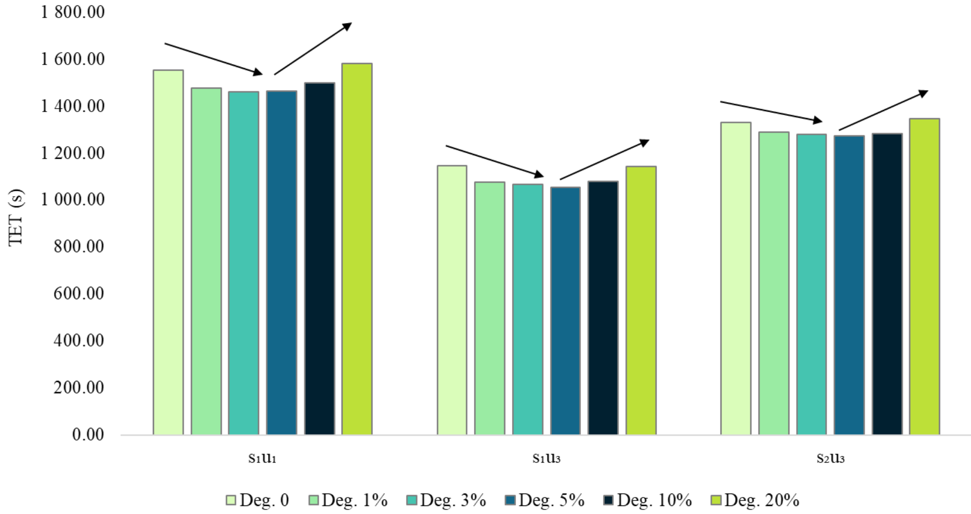


Figure 25. Influence of linear degradation constant (Deg.) on *TET* in HEM 2.

Figure 25 illustrates two distinct trends in *TET* as the linear degradation constant is adjusted from 0% to 20%. Initially, from 0% to 10% degradation, *TET* decreases. This decrease occurs because the model starts evacuating slower passengers earlier, which prioritizes them for evacuation. For instance, in scenario (s_1, u_1), family f_1 with a nominal walking speed of 0.4 m/s is evacuated at period t_{12} when the degradation constant is 0%. However, at a 3% degradation constant, they are evacuated right at the beginning (period t_1) to prevent a further slowdown in their speed due to degradation.

However, the trend reverses from 10% to 20% degradation. *TET* starts to increase. This is because not all passengers can be evacuated immediately in the first period due to exit door capacity limits. As a result, some passengers, like family f_1, are evacuated later, say in period t_2 or t_3, increasing the *TET*. For example, at a 20% degradation constant, the model first evacuates slower passengers like family f_4 (speed = 0.35 m/s). If family f_4 is not prioritized and evacuated later, their speed decreases more due to the 20% degradation, leading to a much longer evacuation time. So, in this case, family f_1 is evacuated in period t_2 with an adjusted speed of 0.2 m/s (referring to Equation (42)), resulting in a much longer evacuation time of 127.85 to allow family f_4 to evacuate earlier.

6.4.12. Day/night and alert/non-alert analysis

This section analyzes how evacuation efficiency on passenger ships is influenced by the time of day (day vs. night) and the alertness levels of passengers (alert vs. non-alert). The criticality of this analysis lies in its ability to reveal how awareness levels intertwine to affect the *TET* during emergencies to refine emergency plans by studying evacuation time variations under different daylight conditions and passenger alertness levels. To gain a deeper insight into the effects of day/night and alert/non-alert conditions on evacuation, five experiments are conducted, under HEM 2 for ten family travelers and 40 solo travelers. The results of these experiments are illustrated in Figure 26.

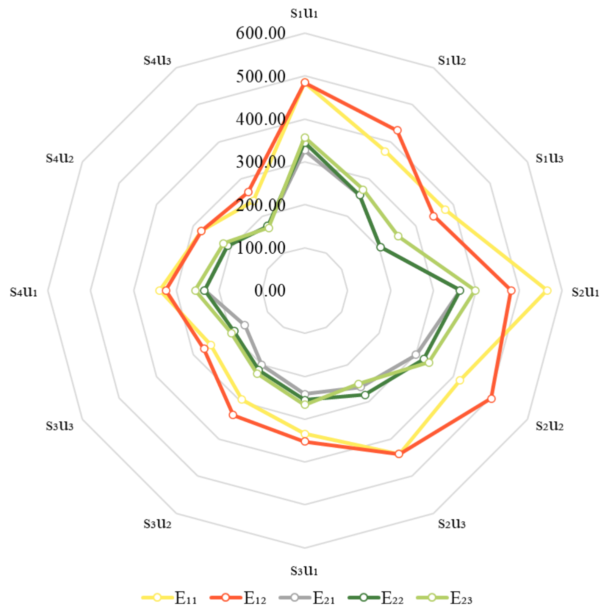


Figure 26. Evacuation experiment outcomes under day/night and alert/non-alert conditions in HEM 2.

- Night Scenarios (E_{11} and E_{12}):

During the night (when passengers are in their own cabins), *TET* tends to be higher. For example, in scenario s_1u_1, *TET* is 484.75 under both E_{11} and E_{12}, which is higher compared to the day scenarios. This suggests that nighttime conditions, potentially due to non-alert situations, negatively impact evacuation efficiency. Day-based experiments (E_{21}, E_{22}, E_{23}): During the day (when passengers are in other locales), *TET* generally decreases. In the same scenario s_1u_1, *TET* ranges from 327.23 to 356.63 under day conditions, which indicates more efficient evacuation. Daytime scenarios benefit from passengers being more alert.

- Non-Alert conditions (100% non-alert in E_{11}) :

High *TET* in scenarios like s_1u_1 and s_2u_1 under E_{11} suggests that when all passengers are non-alert (likely sleeping during the night), evacuation efficiency is reduced.

- Partial alert conditions (mix of alert and non-alert in E_{12}, E_{22}, E_{23}):

Experiments with a mix of alert and non-alert passengers, like E_{22} and E_{23}, show a moderate impact on *TET*. For example, in s_1u_2, *TET* decreases from 431.18 in E_{12} to 271.61 in E_{23} as the percentage of alert passengers increases, which implies that having more alert passengers can improve evacuation efficiency.

- Fully alert conditions (100% alert in E_{21}):

Lowest *TET*s are often observed in scenarios where all passengers are alert, as seen in E_{21}. For instance, in scenario s_2u_2, *TET* drops to 300.00, suggesting that complete alertness enhances evacuation speed.

As a result, night conditions with non-alert passengers lead to longer evacuation times. Daytime experiments, for example, with higher alertness levels, show reduced evacuation times. Data reveals that evacuation times are longer at night when passengers are less alert; emergency procedures could be adapted to include more effective wake-up alerts and guidance systems for nighttime scenarios. Additionally, recognizing that passengers may respond more quickly during the day, daytime emergency plans might focus on efficient crowd handling by allocating crew teams to passengers in demand.

6.4.13. Specific flow of passengers analysis

The specific flow of passengers (λ) on passenger ships is a measure used in emergency planning to determine how quickly people can move through the ship's corridors and exits during an evacuation. It's crucial to ensure everyone can evacuate safely and promptly in an emergency to avoid overcrowding and delays. This concept guides the design of the ship's layout and emergency procedures to keep passengers safe. Table 15 presents the *TET*s under different λ for a range of scenarios.

Table 15. *TET* analysis for various specific flow rates in HEM 2.

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Scenarios	$\lambda = 0.8$	$\lambda = 0.9$	$\lambda = 1$	$\lambda = 1.3$	$\lambda = 1.6$	$\lambda = 2$
s_1u_1	338.23	332.75	338.23	346.11	349.27	346.11
s_1u_2	292.54	281.50	286.89	292.54	281.50	300.25
s_1u_3	227.93	230.68	227.93	246.59	246.59	246.59
s_2u_1	407.58	407.58	407.58	392.00	392.00	403.79
s_2u_2	332.48	348.06	345.35	341.29	341.29	341.29
s_2u_3	280.65	265.92	288.54	288.54	280.65	288.54
s_3u_1	260.61	253.42	274.08	265.50	269.19	265.50
s_3u_2	217.14	225.06	225.22	218.94	231.34	218.94
s_3u_3	175.93	184.94	193.53	185.86	193.99	177.28
s_4u_1	259.68	247.93	244.68	246.30	259.68	257.28
s_4u_2	208.71	209.61	218.80	219.52	223.46	210.34
s_4u_3	180.79	187.24	187.24	181.77	187.24	187.24
Average	265.19	264.56	269.84	268.75	271.35	270.26
Variance	4,832.20	4,619.15	4,512.95	4,339.97	3,946.86	4,761.36

The results across different λ values (0.8 to 2) show variation in evacuation times for different scenarios. Increasing λ does not consistently decrease evacuation times. This proposes that higher flow rates don't always lead to faster evacuations due to factors like exit door capacity. Different scenarios show varying evacuation times, which indicates that factors other than λ (like passenger walking speed, passenger travel distance, and exit door capacity) impact evacuation efficiency. Scenarios s_2u_1 tend to have higher evacuation times compared to others, pointing to less efficient evacuation in these setups. The elevated evacuation times observed in scenario (s_2,u_1) can be primarily attributed to two key factors: an increased travel distance and reduced walking speeds. In this scenario, passengers face an additional travel distance of 10 meters beyond the nominal values.

Additionally, scenario s_2 is characterized by the slowest walking speeds experienced by passengers, further exacerbating the delay. The average evacuation time across all scenarios and λ values is around 267-271 seconds, with minor fluctuations. It tells a relatively stable evacuation duration regardless of the flow rate. This stability means that the specific flow rate, within the tested range, does not drastically alter the overall time it takes to evacuate. The variance (a measure of how much the values are spread out) shows notable differences across λ values. Lower variance at λ=1.6 and higher variance at other λ values suggest more consistency in evacuation times at λ=1.6. In practical terms, this means that at λ=1.6, the evacuation times across various scenarios are more predictable and less subject to extreme variations, making this flow rate potentially more reliable or preferable in planning evacuations. The model becomes infeasible for λ less than 0.8, and for λ values greater than 2, the evacuation time remains the same and does not change.

The single-factor ANOVA test is conducted to analyze the statistical significance of different values of λ on *TET*s. A very low *F*-statistic (0.02) and a high *P*-value (1.00) strongly suggest that there is no significant difference in evacuation times across different λ. This is further supported by the *F*-statistic being much lower than the *F* Critical Value (2.35). The ANOVA test results suggest that the variability in evacuation times is more influenced by individual scenario differences within the same specific flow rate rather than by the differences in the flow rates themselves. The statistical significance of these differences is not supported, which demonstrates that the choice of λ might not be the primary factor affecting evacuation times in these scenarios.

7. Discussion and contribution

In this portion of the dissertation, the discussion turns to the contributions made through this PhD work. These efforts can be seen as steps toward enhancing maritime safety, providing insights that can inform future academic inquiry in the field. The models developed as part of this research were designed using data from the IMO and underwent a partial validation process through a case study focusing on a single deck of a passenger ship.

7.1. Over two-decade literature review in human evacuation models

The systematic literature review presented in Paper 1 contributes to maritime safety, reviewing a wide range of research from January 1999 to August 2022. This analysis of 115 directly reviewed articles reveals a robust knowledge of passenger ship evacuation analysis. Paper 1 highlights the strength of existing literature while suggesting areas for future research, reflecting over two decades of scholarly dedication.

This review emphasizes the solid foundation in the field, highlighting the substantial academic work that precedes and supports this dissertation. It serves not as the first word but as part of an ongoing conversation among scholars and practitioners in maritime safety, offering insights that can further refine and address evacuation plans and methodologies. In acknowledging the depth and breadth of previous research, this paper positions itself as a continuation of the dialogue, aspiring to contribute to the evolving landscape of maritime safety knowledge.

Paper 1 offered insights into managing hybrid uncertainties, by examining the interplay between passenger walking speed, travel distances, and exit door capacities. It provided the application of new uncertainty modeling techniques in this field, such as robust optimization, stochastic optimization, and a hybrid robust-stochastic optimization approach, to address uncertainties. While these methodologies contribute to managing hybrid uncertainties, they also open the door for further refinement and exploration in future research. These initial findings lay a foundation for advancing the developed approaches, suggesting a direction for enhancing evacuation plans through more advanced uncertainty modeling techniques.

Following the insights into hybrid uncertainties, this research developed a mathematical optimization model for a single deck of a passenger ship. This model was designed to examine the impact of the uncertainty modeling techniques—robust optimization, stochastic optimization, and a hybrid robust-stochastic optimization approach—on managing the highlighted sources of uncertainty, which led to the proposal of three human evacuation models in this research (HEM 1, HEM 2, and HEM 3). Although these models represent a step forward in understanding and addressing hybrid uncertainties, it is acknowledged that the model is not without its limitations. The proposed approaches can be refined and expanded upon in future research.

7.2. Model development and validation: a dual-data set approach

This dissertation represents an effort in model development and validation grounded on the utilization of two distinct yet complementary data sets. Initially, the models, designated as HEM 1 to HEM 3, were developed using passenger walking speed data from the IMO data set.

Subsequently, these developed models were further tested by incorporating passenger walking speed data and passenger travel distances based on the layout of Deck 10 of a passenger ship (case study). This phase aimed to assess the stability of the models against real-world data. This case study served as a preliminary test bed, highlighting the potential for future refinements and validations against a more comprehensive array of case studies.

The dual approach of employing the IMO data set for model development and a case study for model validation, in terms of the applied uncertainty modeling techniques (i.e., robust optimization, stochastic optimization, and hybrid robust-stochastic optimization) for handling hybrid uncertainties, underscores a contribution to maritime safety research. It demonstrates the potential of these models to provide new insights into the application of uncertainty modeling techniques, specifically in the context of evacuation or drill procedures on single decks of passenger ships. While the focus of this research is on a single deck, it lays the groundwork for potential expansion into more comprehensive multi-deck human evacuation plans.

7.3. Operational, tactical, and strategical levels

Evacuation plans for human safety at sea can benefit from uncertainty modeling techniques that address inherent uncertainties. Models HEM 1 to HEM 3 introduce methods to manage uncertainties related to passenger walking speed, travel distance, and exit door capacity. These models pursue three objectives:

- Accelerating evacuation
- Minimizing the number of exit doors
- Maintaining crew proximity to passengers

By incorporating critical parameters as sources of uncertainty, these models apply mathematical techniques to navigate these challenges. Although developed specifically for a single deck of a passenger ship, the insights provided by these models suggest a foundation for extending such uncertainty management approaches to multi-deck scenarios. This contribution to the field indicates a direction for future enhancements and broader applications, offering a perspective that may be practical in both academic and industrial contexts. The developed models can give insight and contribution to the academic and industrial settings as follows:

- Operational level: They can generate individualized plans for each solo traveler or family based on how fast they can move (based on their age, gender, and physical mobility), where they are on the ship, how close they are to the exit doors, what is the level of alertness, how many members they have (for families), what is the exit door capacities, what is the ship's layout, what is corridor width, and what is the specific flow in a corridor considering the uncertainty in passenger walking speed (HEM 1), hybrid consideration of passenger walking speed and travel distance (in HEM 2), and hybrid consideration of passenger walking speed and potential disruption in exit doors capacities (in HEM 3). Furthermore, the models offer the flexibility to adapt the evacuation plans dynamically in response to real-time conditions and emerging hazards, such as intensifying ship motions, indicating that walking speeds are not static but can be adjusted as the evacuation progresses. This offer suggests that the evacuation plan for a passenger may change depending on which period of evacuation he/she is in. However, it is recognized that these models are subject to continuous improvement and refinement.
- Tactical level: The tactical level of the evacuation model is about positioning crew members to maximize their ability to assist passengers, especially those who need the most help. The presence of crew members can have a calming effect on passengers. Their ability to provide reassurance and guidance in high-stress situations can be practical, especially for passengers who are vulnerable or at-risk (in the developed models they are recognized as outliers or the slower solo travelers and families). This allocation can maximize crew's ability in assisting them.

At the operational level, the model can form personalized evacuation plans for each passenger, be they solo travelers or families. These plans consider various factors like their specific location on the ship, their walking speed, their proximity to the exit doors, and the ship's layout. By tailoring these plans to individual needs and circumstances, the model can offer a more organized evacuation.

The generated plans vary depending on different scenarios. Therefore, these plans can help different existing passenger ships to find their own plan depending on what scenarios they have experienced during their emergencies. Furthermore, the plans can help the existing passenger ships for appropriate allocation of passengers to cabins depending on their estimated walking speed and mobility.

Individualized plans can inform a more targeted communication strategy during an evacuation. Information can be tailored to the specific needs and locations of passengers, to ensure that they receive relevant and clear instructions. By providing clear and personalized guidance during an evacuation, passengers are likely to experience less stress.

Concurrently, at the tactical level, the model can allocate crew members to assist passengers who need the most help. This can be important for managing areas that are prone to congestion (the prescence of outliers/slowest passengers). The crew can guide passengers, assist with crowd control, and help maintain a steady flow towards the exits. This assistance can be crucial in preventing bottlenecks.

Crew members can be trained on various evacuation scenarios based on these individualized plans. This helps in preparing the crew for a range of potential emergencies, which can enhance their ability to respond effectively.

Detailed plans enable better coordination among crew members. Each crew member can be assigned specific roles and responsibilities tailored to the needs of passengers in their designated area, to ensure that all areas of the ship can receive adequate attention and assistance.

When the model's individualized evacuation plans (operational level) are combined with the placement of crew members (tactical level), congestion can be mitigated. By proactively addressing areas identified as potential congestion points, passengers can receive appropriate guidance and assistance.

Crew members can be assigned to assist elderly passengers, those with disabilities, or families with young children or infants to ensure that these groups move more quickly and do not contribute to congestion.

Regular drills can be conducted based on model predictions and scenarios, to help both crew and passengers to become familiar with evacuation procedures and reducing the likelihood of congestion during an actual emergency.

For existing ships, the develped models can be practical for adhering to safety standards. When the model indicates that the total evacuation duration is too long, the detailed plans and crew allocation strategies can be reviewed and adjusted.

Integrating family-centric strategies into the evacuation models aligns with stringent safety standards for maritime operations. By considering families, such as those with children or elderly members who may require additional assistance, the model can offer that evacuation plans are considerate of several family-needs.

- Strategic level: At this level, the model can play a crucial role in determining the optimal number of exit doors required for an efficient and rapid evacuation. This level involves an analysis of the ship's layout (e.g., corridor width and transition point capacity like exit door) and passenger capacity to ensure that there are enough exits to handle an emergency without causing bottlenecks or delays. The goal is to balance safety with practicality, which can provide that each exit door is strategically placed and sufficient to accommodate the flow of passengers during an evacuation.

The operational and tactical levels of the evacuation model can interplay with the strategic level, such as when considering the design of new ships; for example, in HEM 2, the interrelationship between hybrid consideration of passenger walking speed and passenger travel distance with the number and potential location of exit doors. Therefore, HEM 2, even if it is modeled for a single-deck passenger ship, can give insight into how hybrid consideration of uncertainty in passenger walking speed and passenger travel distance can affect the closeness and quantity of transition points (e.g., exit doors).

The individualized evacuation plans generated at the operational level can provide valuable data on where to go in emergencies. This data can reveal patterns and potential issues, such as areas prone to congestion. When this information is fed back into the strategic level, it can influence the positioning and number of transition points (e.g., exit doors) to manage the flow of passengers during an evacuation.

At the tactical level, the way crew members are allocated helps identify the best methods for guiding passengers. If crew members often assist slow-moving passengers in certain areas, it indicates these spots are likely to get crowded. This information can be practical for making decisions about where to place more exits and how to design evacuation paths on new ships. Furthermore, it can be a sign in order to increase the number of trained crew members in this type of spot.

In the context of new ships, where the total evacuation time is regulated not to exceed predefined limits, insights derived from operational and tactical analyses can guide compliance efforts. Ship designers can refine layouts and evacuation protocols by integrating potential scenarios identified at these levels. This approach can evaluate the impact of mixed uncertainties on evacuation efficiency, such as the combination of passenger walking speeds with travel distances or exit door capacities. Such insights can offer a practical perspective for ensuring ship designs adhere to safety standards across various emergencies. While these insights are from a single-deck, they invite further investigation through additional studies, such as applying these considerations to the complex dynamics of multi-deck settings.

7.4. Uncertainty analysis

The following details how the developed models considering three uncertainty modeling techniques can assist in solving human evacuation problems on passenger ships by handling hybrid uncertainties, including passenger walking speed with passenger travel distance and passenger walking speed with disruption to a transition point (e.g., an exit door).

- HEM 1 uses robust optimization to handle uncertainty in passenger walking speeds, making it suitable for situations where detailed data might not be available. It can assist in creating evacuation plans based on limited information (e.g., a minimum and maximum for a passenger walking speed), ensuring that variations in walking speeds are considered. While robust optimization is utilized in HEM 1 primarily to tackle uncertainty in passenger walking speed, this technique has the potential in managing other uncertainties in the development of evacuation plans for passenger ships, mainly where there is a scarcity of data.
- HEM 2 employs a two-stage scenario-based stochastic approach to manage mixed uncertainties involving passenger walking speed and travel distance. This method enables the examination of different evacuation scenarios, simulating various conditions like changes in walking speeds and distances. It offers a broader perspective on possible evacuation outcomes. This model can be useful for ships with access to more detailed data, such as probability distributions for uncertain parameters or some historical data.
- HEM 3 combines robust and stochastic methods to address walking speed uncertainties and exit door capacity disruptions. Its hybrid approach can be practical for complex and uncertain scenarios. It can simulate disruptions like blocked transition points (e.g., exit doors), providing insights into how these factors impact the evacuation process. This model can produce evacuation plans that are flexible and resilient to potential disruptions to transitional points (e.g., exit doors).
- HEM 2 and HEM 3 have been designed from a risk-neutral perspective. Adopting a risk-neutral perspective means that the model evaluates various evacuation scenarios without prioritizing those with lower risk. Essentially, it treats all scenarios - whether they are high-

risk (like a decreased passenger walking speed and disrupted exit door scenarios, $HRSSRP_{s_1 w_3}$) or low-risk (e.g., increased walking speed and no disrupted exit door, $HRSSRP_{s_3 w_1}$) - with equal importance. The primary focus is on minimizing the average evacuation time rather than giving special consideration to scenarios based on their inherent risks. This perspective can ensure that the plans developed are robust across a wide range of possible scenarios, not just the safest or most controlled ones.

8. Limitations and future research

The following discussion delineates the capability of the models (HEM 1, HEM 2, and HEM 3) to open new avenues for scholarly investigation in human evacuation planning for passenger ships. These models have undergone partial validation by implementing uncertainty modeling techniques (*RO*, *RSSP*, and *HRSSRP*). However, it is crucial to acknowledge that they have yet to attain full validation and necessitate further exploration through real-time testing to solidify their applicability and accuracy in future research endeavors.

- Digital twins for passenger ships: The models can act as a catalyst in advancing the development of digital twins for human evacuation systems for passenger ships. They can provide a framework for simulating and analyzing evacuation scenarios within a virtual environment, which can enable a deeper understanding of evacuation dynamics. By employing these models, researchers can test and refine evacuation plans under a diverse array of scenarios.
- Sensor technology system development for real-time passenger monitoring: The models can serve as a platform for proposing the design and testing of sensor technologies aimed at collecting real-time data on passengers during an evacuation. This research trajectory, enriched by the models, could focus on developing wearable technologies and environmental sensors. These sensors can be envisioned to track critical parameters such as passenger location, movement speed, and even physiological responses during emergencies. By harnessing the insights provided by the models (e.g., adjustment strategy for passenger walking speeds), the development of these sensor systems can offer a more accurate picture of evacuation dynamics, which can enhance the safety measures and emergency responses in maritime travel.
- Sensor technology for hazard detection and response: By incorporating disruption scenarios, in the HEM 3 model that focuses on exit door failures, the models can play a crucial role in enhancing the understanding of the potential impacts of structural failures on human evacuation from large passenger ships. These models simulate various levels of exit door disruptions, which provide practical insights into the severity and consequences of such emergencies in terms of evacuation time and passenger allocations to exit doors. This approach can aid in assessing the uncertainty associated with different disruption scenarios and can equip decision-makers with the necessary data to select and prepare for appropriate evacuation scenarios.
- Data-driven evacuation planning: The developed models can lay a foundational groundwork for constructing machine learning algorithms under hybrid uncertainties focused on optimizing passenger allocation to exit doors. Feeding features into these algorithms - such as passenger walking speeds categorized by age, gender, mobility level, travel distances, alertness levels, and the ship's specific layout - paves the way for predictive models. These machine-learning models can be designed to determine efficient allocations of passengers to various exits. This approach not only can enhance evacuation efficiency but also can revolutionize the way passenger ship evacuation strategies are developed and implemented.
- The models, with the improvements made in HEM 3, can serve as a pivotal foundation for developing enhanced human evacuation models. By introducing the concept of resilience in evacuation plans, HEM 3 has already begun addressing the complexity of disruption scenarios, such as compromised exit door capacities. Building on this, there can be an opportunity to further evolve these models to factor in fire-related disruptions. Such improvements could lead to models that not only anticipate the direct impact of fire on evacuation routes and exit usability but also dynamically adapt evacuation plans in response to the rapidly changing conditions of a fire emergency. This evolution can represent a step forward in ensuring even greater safety and efficiency in maritime emergency responses.

While the study contributes by examining hybrid uncertainties and the application of uncertainty modeling techniques in shaping human evacuation plans, it also recognizes potential areas for enhancement.

- The current binary model for assessing passengers' situational awareness could be enhanced by either integrating intelligent sensor technology or employing fuzzy numbers. This approach can enable the representation of a broader spectrum of awareness situations, which can offer a richer and more accurate depiction of passenger behavior for advanced human evacuation modeling purposes.
- The current iterations of the models, HEM 2 and HEM 3, function as two-stage scenario-based human evacuation models. There is potential for improvement by evolving these into multi-stage models. For example, this enhancement can involve incorporating various stages of hazard development, such as the progression of a fire, to formulate a more dynamic and comprehensive evacuation modeling framework.
- The models have the potential for further enhancement by integrating additional human factors, mainly focusing on the impact of stress levels and panic behavior, to achieve a more holistic and realistic representation of human responses during evacuations.
- The models currently incur substantial computational costs due to their iterative nature. However, the introduction of new algorithmic cuts presents a viable solution to accelerate these computational processes and enhances efficiency.
- The model's present focus on single-deck scenarios opens up the opportunity for expansion into a multi-deck evacuation framework. Such development would add layers of depth and realism to the optimization, more accurately reflecting the complexities of real-world scenarios.
- For future research, exploring other risk perspectives in uncertainty modeling of human evacuation optimization models could yield practical insights. A risk-averse perspective would prioritize scenarios with lower risk, potentially leading to safer, albeit possibly slower, evacuation strategies. This approach could focus on minimizing potential hazards or avoiding worst-case scenarios during evacuations. Conversely, a risk-seeking model might explore more aggressive evacuation plans that could lead to faster overall times but with higher variability in outcomes.
- Another limitation of this thesis lies in its focused exploration of optimization techniques for evacuation planning without delving into the integration of these techniques with simulation methods to form simulation-optimization decision support systems. Although the research applies mathematical optimization models, it does not examine the development and practical application of systems that merge the predictive power of simulations with optimization's precision. This oversight skips the potential for a more real-time evacuation plan that is adaptable to changing conditions and behaviors. Addressing the creation, validation, and deployment of such integrated systems can represent an opportunity for future work to improve evacuation safety and efficiency on passenger ships.
- One limitation of the current modeling approach is the initial exclusion of evacuation crew members. The model determines the placement of crew teams by assessing their proximity to passengers. While the model is capable of incorporating crew members as new agents at both the commencement and conclusion of the evacuation process—for the purposes of determining their evacuation times (including the time required to reach designated support locations plus the time needed to reach the evacuation exit)—this functionality has not been explored in the present study. This omission opens a path for future research to enhance the model by integrating these aspects, potentially improving the effectiveness of evacuation simulations.

9. Conclusion

This dissertation navigates the realm of maritime safety, focusing on the optimization of human evacuation models for passenger ships under uncertainty. The journey began with a comprehensive systematic literature review that identified gaps in the existing body of evacuation modeling research. Following this work, the exploration delved into the complexities of human evacuation, resulting in the formulation of three distinct optimization models (HEM 1, HEM 2, and HEM 3). These models address the uncertainties characteristic of maritime evacuations, including variables such as passenger walking speeds, travel distances, and exit door capacities. A key contribution of this research is the development of three uncertainty modeling techniques that are unlike uncertainty modeling techniques: *RO*, *RSSP*, and *HRSSRP*. These methods are practical in addressing the complex variables of passenger behavior under emergency conditions, such as walking speed variability, travel distances, and exit door capacity disruptions. The optimization process, facilitated by the CPLEX solver, further shows the efficacy of these models.

The models were initially developed using data from the IMO, and their validation was partially achieved through a case study on a single deck of a passenger ship. This approach has provided preliminary proof of their usefulness and robustness. Nonetheless, it is crucial to acknowledge that this validation is not yet complete. Further investigation and real-time testing are necessary to fully confirm their accuracy for broader applications, including multi-deck environments, in future studies. The incorporation of family dynamics and the optimal allocation of crew members during evacuations can demonstrate the practicality of the models and shift them toward real-world scenarios. The analysis, coupled with the development of advanced evacuation models, contributes to the field of maritime safety. It addresses some current challenges, such as uncertainty modeling and family considerations, and opens avenues for future research.

The expansion of the tourism industry demonstrates the urgent need for enhanced evacuation plans. This work is in harmony with the efforts of international organizations like the IMO and safety communities such as the MSC, driving the improvement of maritime safety standards and regulations. In conclusion, this dissertation has the potential to make a contribution to maritime safety research, providing fresh insights and solutions to protect lives at sea.

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Appendix. Paper 1 to Paper 4

This appendix presents a collection of papers (Paper 1 to Paper 4) prepared during this Ph.D. study.

Paper 1

Determinants, methods, and solutions of evacuation models for passenger ships: A systematic literature review

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Abstract

Passenger ships facilitate the mobility of people at sea and are a significant revenue stream for societies. Simultaneously, they should meet safety standards. One of the main safety pillars is offering passengers a reliable emergency evacuation plan. The International Maritime Organization (IMO) has disseminated guidelines for passenger ships to enhance the evacuation process understanding. Although the number of passenger ships is rising worldwide, implementing IMO's guidelines, particularly advance evacuation analysis, is still a young research area. Hence, this paper attempts to study previous research on human evacuation from the IMO perspective to uncover the current position of the issued guidelines in the literature. Accordingly, this research reviews 115 research publications published in scientific journals, peer-reviewed conferences, and doctoral and master dissertations from January 1999 to August 2022. As a result, the authors present the literature review of state-of-the-art papers to establish a firm foundation of past research. After identifying gaps, breakthrough points are clarified for future research about the benefits of handling uncertainty in input parameters, understanding human evacuation behavior, mutual interrelation among evacuation factors, and potential adoption of digital technologies in human evacuation from passenger ships.

Keywords: Passenger ship, Passenger behavior, Evacuation process, Methods, Solutions.

1. Introduction

During the last decade, the tourism industry significantly contributed to economic growth (Figini and Vici, 2010). Passenger ships carrying at least 12 passengers, including cruise ships and passenger ferries, make up a significant part of society's revenue. Thirty million passengers are expected to travel on cruise ships, generating over $154 billion in revenues worldwide in 2019 (Cruise Lines International Association, 2021). Conversely, traveling by sea increases the safety risk for passengers. Allianz (2021) reported 69 passenger ship losses from 2011 to 2020. In addition, see Table 1, at least 2,526 people lost their lives due to incidents from 2011 to 2018.

Table 1. Passenger ship incidents.

Year	Ship name	Type	Fatalities	Reference
2011	• MV Spice Islander	• Passenger ferry	1,529[2]	(Fundi, 2018)
2012	• Costa Concordia	• Cruise ship	32	(Vanem and Skjong, 2006)
2013	• MV ST Thomas Aquinas	• Passenger ferry	120	(Fahcruddin et al., 2019)
2014	• MV Sewol	• Passenger ferry	304	(Kim et al., 2016)
2015	• Dongfang Zhi Xing	• Cruise ship	442	(Baird, 2018)
2016	• Aung Soe Moe Kyaw 2	• Passenger ferry	99	(Christine and Bonnemains, 2018)
Total			2,526	

The facts mentioned pushing IMO to enhance safety at sea. The Maritime Safety Committee (MSC), which is primarily responsible for coping with all safety issues at sea, published principal safety regulations through different circulars (Circ.) (IMO, 2016). They aim to upgrade basic maritime safety standards for ships, first released by the International Convention for the Safety of Life at Sea (SOLAS) in 1914. Evacuation models have been integral to the issued regulations. Xie et al. (2020a) pinpoints evacuation as an effective action for lowering the casualty rate at sea. A ship evacuation process occurs in three successive distinct periods: (1) response, (2) evacuation, and (3) embarkation and launching period (IMO, 2016). Evacuation time is the central part of the evacuation process. It must not exceed the onset of circumstances threatening passengers' safety. Initially, the response period starts off noticing initial notifications (e.g., alarm) until deciding to move. Then, the evacuation period starts from the moving point to an assembly station. Afterward, the launching period commences. The mustered people in the assembly stations (or embarkation stations) must abandon the ship with a ship signal to reach a safe place. If the assembly and embarkation stations are separate, there is also a travel time between the assembly and embarkation stations.

[2] 203 passengers died, and 1,326 passengers are still missing but presumably dead.

Meanwhile, evacuation factors have a critical function during the evacuation process. Various factors influence the process, including environmental, configurational, behavioral, and human. Table 2 categorizes them according to definition (Lee et al., 2003).

Table 2. Aspects of evacuation process for passenger ships.

Aspect	Definition	Features
• Environment	• It defines the external drivers affecting the moving speed of passengers.	• Static and dynamic conditions of the ship (ship motions, transverse, and longitudinal stability) and • hazard (e.g., fire products including heat, smoke, and toxic gases)
• Configuration	• It covers the layout of a passenger ship	• The structure of evacuation routes and landing areas
• Behavior	• It encompasses the passenger's response to a situation.	• Travel speed, • family and group interactions, and • crossing flows
• Human	• It consists of passenger properties.	• Age, • gender, and • physical conditions

Fig. 1 depicts a ship evacuation process sequence considering influencing elements.

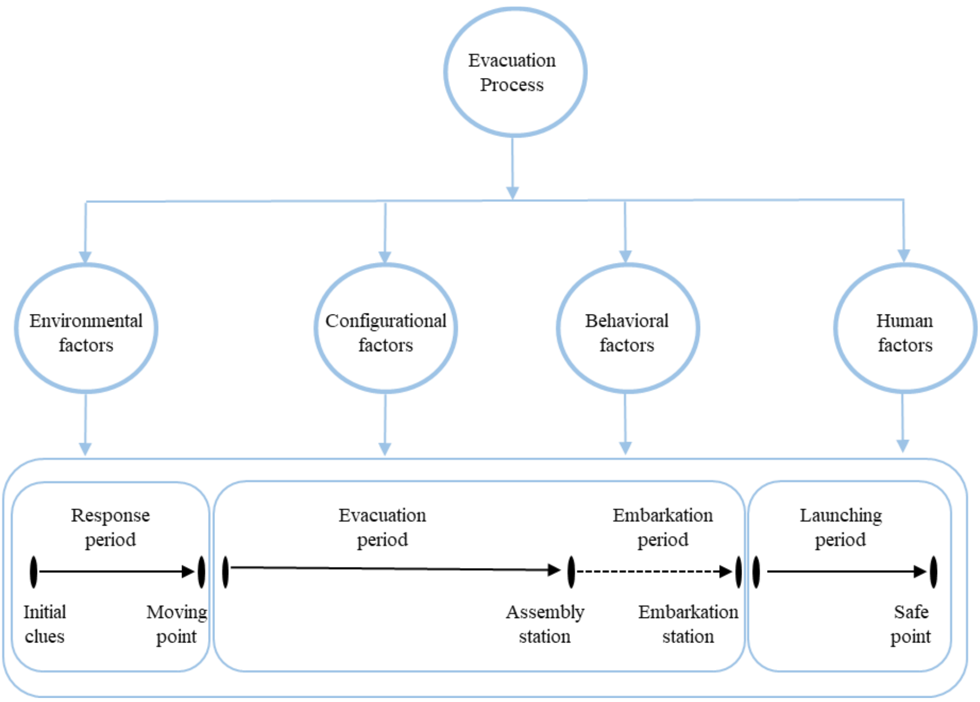

Fig. 1. Graphical representation of the evacuation process with evacuation factors.

The MSC has pushed ship designers to analyze the evacuation process by putting the evacuation factors into practice. Considering the factors in modeling at an early stage of ship design can preclude any extra safety assessment later in calculating evacuation time. Specifically, it can reduce the possibility of rebuilding ships for only satisfying new safety evacuation standards. Simplified and advanced analysis are two categories of evacuation analysis (IMO, 2016). A simplified analysis is according to a deterministic method assuming passengers as nonautonomous agents. However, the latter considers passengers autonomous agents under the uncertain influence of input parameters, such as ship motion (Nasso et al., 2019). Ship designers should implement relevant corrective actions if the evacuation time exceeds the allowed time. Existing passenger ships could also carry out appropriate evacuation actions to reach the permitted evacuation duration (IMO, 2016). Given the above discussion, two research questions arise:

- What is the current situation of evacuation models for human evacuation from passenger ships regarding evacuation factors, modeling approaches, and solution methods?
- How do evacuation factors affect human behavior in the event of an accident?

This paper presents a review to identify the current situation and create a roadmap for future research in this area. The authors have not identified any comprehensive literature overview in this domain. This paper tries to cover this gap by reviewing, categorizing, and analyzing 105 publications released between January 1999 and August 2022. The specific review choices resulting from this sample of papers are explained in detail in Section 3.1. Before coming to that section, the authors first discuss earlier review/partial-review papers in Section 2. Research methodologies are clarified in Section 3. Detailed analyses and classifications are coming in Section 4. The current gaps analysis and future research opportunities are presented and discussed in Section 5. Finally, Section 6 contains the conclusion and directions for future research.

2. Literature review

Understanding the state of the current literature establishes a firm base for advancing knowledge and uncovering novel research areas (Pignatelli et al., 2005). Therefore, the previous review/partial review papers and IMO guidelines are listed in Table 3.

Table 3. Characteristics of earlier review/partial review studies in the passenger-ship evacuation research area.

Scope	Regulatory reference	Range	Sample size	Paper
• IMO's requirements	• MSC/Circ.909	1995-2001	25	(Lee et al., 2003)
• Determinants of passenger injuries	• IMO, Athens Convention	2001-2008	20	(Yip et al., 2015)
• IMO guidelines analysis	• IMO, MSC.1/Circ.1238	2002-2015	10	(Bucci et al., 2016)
• Modeling, analysis, and planning of evacuation models	• IMO, MSC.1/Circ. 1533	1973-2017	53	(Sarvari et al., 2018)
• IMO guidelines analysis and evacuation projects description	• IMO, MSC.1/Circ. 1533	1974-2018	57	(Stefanidis et al., 2019)
• IMO guidelines analysis	• IMO, MSC.1/Circ. 1533	1999-2017	23	(Nasso et al., 2019)
• Evacuation factors, modeling approaches, and solution methods	• IMO, MSC.1/Circ. 1533	1999-2022	115	Our study

Given Table 3, the authors have been unable to identify any comprehensive review study for human evacuation analyzing state-of-the-art research papers considering evacuation factors. Most review papers in Table 3 are limited based on the scope and period. In this area, review papers are divided into two groups. The first group of review studies is based on assessing past findings and the current situation. For instance, Sarvari et al. (2018) and Yip et al. (2015) investigated a range of publications for a specific period. The second group of review papers is according to the IMO guidelines for analyzing evacuation methods for passenger ships. For example, Bucci et al. (2016), Lee et al. (2003), and Stefanidis et al. (2019) primarily focus on examining the IMO guidelines for passenger ships.

Among all mentioned papers in Table 3, Sarvari et al. (2018) almost reviewed all relevant academic journals and conference papers on human evacuation from passenger ships. Although they analyzed the influencing evacuation factors on the evacuation process, the number of publications in their analysis is low. Furthermore, covered papers were published before 2017. The current work coincidences with Sarvari et al. (2018). The reason is about 60 percent of publications are released between 1999 and 2017. Therefore, this paper attempts to include them in the database and examine them based on the defined objectives, for example clustering the collected publications according to research type, quantitative (modeling or data collection) or qualitative (questionnaire, case study description, or evacuation software analysis). In addition, although Gwynne et al. (2003) and Galea et al. (2014a), with 61 and 31 citations until March 2022, are disregarded in the review of Sarvari et al. (2018), they are reviewed in this paper since they offer a significant contribution to the process of data collection and validation for human evacuation from the passenger ships.

Moreover, 1999 was a watershed year when the IMO issued the first circular regulations of evacuation analysis for passenger ships, so 1999 is applied as the cut-off year. Following this synthesis, this study intends to present a systematic review of the influencing factors on the human evacuation process for passenger ships and appropriately determine the modeling approaches and solution methods. At the same time, this paper looks at how emerging technologies such as digital twin (DT) and virtual reality (VR) can shift the performance of the evacuation process. Fig. 2 depicts the trend in the number of publications over the study period. Although research has been active during the first decade (1999-2009), this area has received more attention over the second decade (2010-2022).

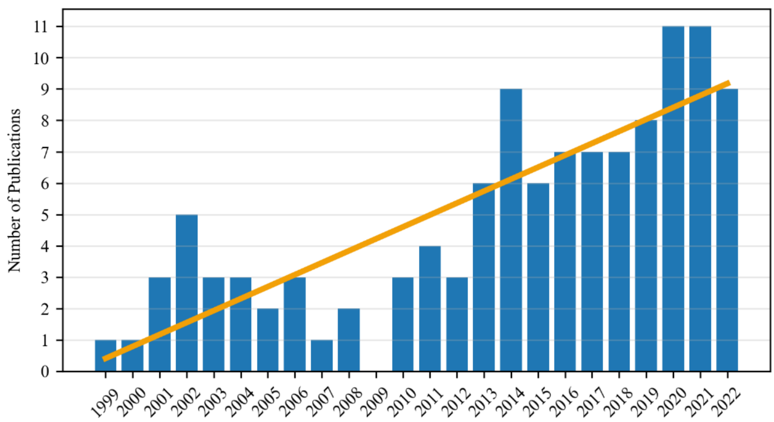

Fig. 2. Publications distribution.

3. Research methodology

This paper applies a four-step process to analyze the content in literature reviews. This process aligns with the qualitative content analysis methodology (Mayring and Brunner, 2007). It consists of (1) material collection, (2) descriptive analysis, (3) category selection, and (4) material evaluation steps portrayed in Fig. 3.

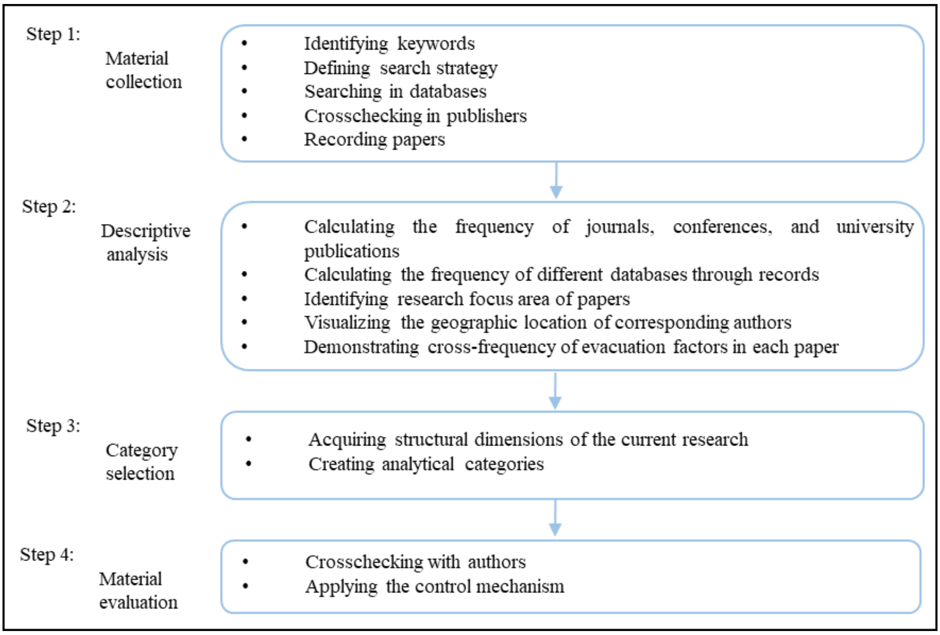

Fig. 3. Holistic workflow diagram.

3.1. Material collection

The current research was carried out from September 2021 to June 2022. This paper covers peer-reviewed papers, conference papers, and doctoral and master dissertations in scientific English language journals from January 1999 to August 2022. The material collection is conducted in five stages. The stages are as follows.

- Identifying keywords: they are referred to our research questions to identify the keywords. Therefore, the keywords are defined as" passenger ship (cruise, ferry, ocean liners), evacuation, emergency, human/passenger behavior."
- Defining search strategy: this paper pursues a search string strategy. It combines keywords, truncation symbol (keyword root + *), and boolean operators (AND to include all search terms,

OR to include alternative terms, NOT to exclude specific terms). The search is conducted in title, keywords, and abstract.

- Searching in databases: the authors selected the Web of Science (WoS) database for gathering material. Likewise, the search is carried out on the Open Access Theses and Dissertations database (OATD) to identify relevant research.
- Crosschecking in publishers: the collection is crosschecked by publishers to determine records' accuracy to include/exclude the intended keywords.
- Reporting outputs: the selection set is first transferred to Excel sheets for data cleaning and organizing collected papers. Afterward, the database is called in Python data frames for analysis and visualizations. Pandas, NumPy, and Matplotlib libraries are employed to analyze data.

Fig. 4 demonstrates the employed search strategy for retrieving relevant studies.

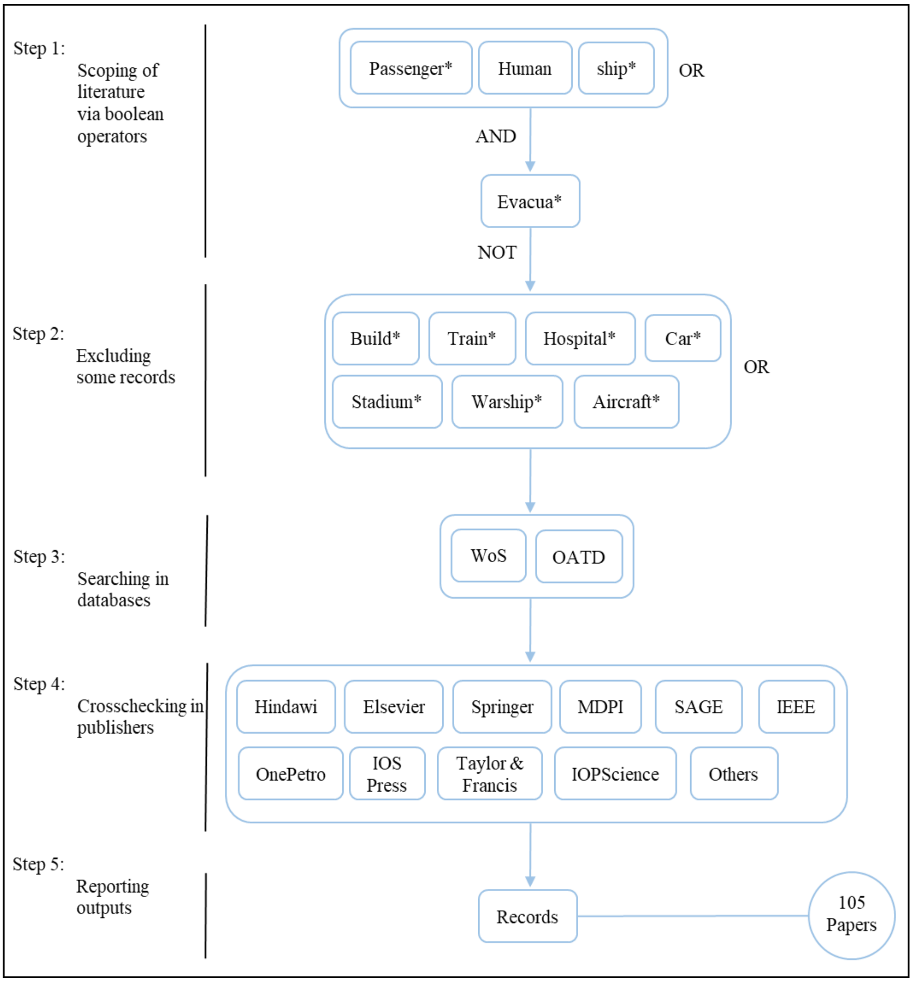

Fig 4. Records extraction.

The authors initially searched on WoS. The search yielded papers consisting of at least one of the keywords in the first step and a word from the root of evacua (evacua*). It produced 4,300 records. After that, any paper concerning evacuation from buildings, hospitals, trains, aircraft, and stadiums is excluded. The excluding strategy stood on WoS's advance search option and the authors' inspection by reading the paper's title (if necessary, the abstract is read as well). Similarly, theses and dissertations are retrieved from the OATD database. Ultimately, 115 papers are downloaded and classified. The records are distributed as 27% from Elsevier, 24% from Springer, 6% from IEEE, 4% from MDPI, 3% from Taylor & Francis, 3% from National Taiwan Ocean University, 3% from Royal Institution of Naval Architects, 2% from OnePetro, and 2% from Hindawi. Other publishers with one publication had an overall 26% contribution. Appendix A contains the list of publishers. The records' credibility in data collection, analysis, and reporting is fulfilled by the author checking (Creswell, J.W., & Miller, 2000).

3.2. Descriptive analysis

The authors found 111 journal and conference papers, two doctoral dissertations, and two master theses-115 research publications in total. The distribution of journals, conferences, and university publications is represented in Fig. 4. Those with more than two publications are described under the same name of journal/conference; however, others with one publication are allocated to the other categories named Others (Journal Papers /Conference Papers). They are listed in Appendix B. Appendix C is also constructed for the journal names' abbreviations. Fig. 4 reveals a growing tendency in evacuation studies for passenger ships. Among journals, Ocean Engineering (Ocean Eng.) and Safety Science (Saf. Sci.) have the largest number of publications, with 10 and 6, respectively. They have been more active in this area. They mainly researched passenger behavior/awareness, walking speed, safety perception, and risk analysis during a human evacuation from passenger ships. Meanwhile, the Pedestrian and Evacuation Dynamics conference published more papers than others, with seven amid conferences. The released papers not only focus on data collection concerning movement and evacuation dynamics of passengers considering ship motions, but they also have worked on the simulation and modeling of human evacuation.

Besides, Journal of Marine Science and Technology (JMST), Journal of Marine Science and Technology (J Mar Sci Technol), Physica A: Statistical Mechanics and its Applications (Phys. A: Stat. Mech. Appl.), Procedia Computer Science (Procedia Comput. Sci.), Mathematical Problems in Engineering (Math. Probl. Eng.), Reliability Engineering & System Safety (Reliab. Eng. Syst), Journal of Marine Science and Engineering (J. Mar. Sci. Eng.), and Computers in Industry (Comput Ind) with 14.8% contribution attempted to reflect new insights in this research area. They tried to develop system simulation models considering passengers' characteristics. While International Conference on Human Factors in Ship Design and Operation, Traffic and Granular Flow (TGF), and International Conference on Virtual, Augmented, and Mixed Reality (VAMR), with a 5% impact, push the research in this area forward. They are more inclined to manifest human factors into ship design. Moreover, the University of Greenwich, University of Huddersfield, Norwegian School of Economics (NHH), and Aalto University (with a 3.5% impact) generate new knowledge in this area. They devoted considerable effort to advancing the understanding of passenger behavior during a ship evacuation. Furthermore, Springer with 40 %, Elsevier with 16 %, and the Royal Institution of Naval Architects with 8% have a remarkable impact on emerging the research area of human evacuation from passenger ships. They built the foundation of knowledge by conducting questionnaires, conducting onboard experiments, and simulating/modeling the human evacuation process from passenger ships. Afterward, IEEE (6 %), National Taiwan Ocean University (6 %), Hindawi (4 %), and Taylor & Francis (2 %), along with Springer (28 %) and Elsevier (26 %), shifted the state of research in this area and yielded fresh insights into the research by analyzing advanced evacuation methodologies and taking human behavior properties into account. Since 2019, evacuation studies have received more attention from MDPI and IOS Press databases. They accelerated development in this area by applying multidisciplinary approaches, particularly computer science, mathematics, engineering, and environmental science.

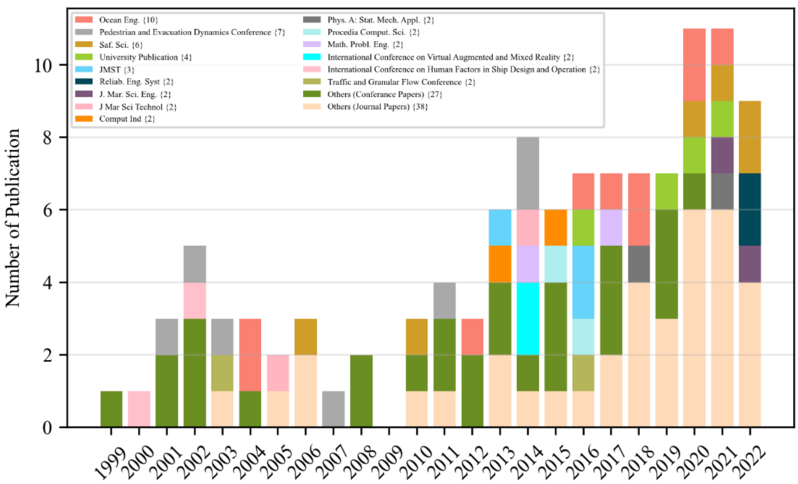

Fig. 4. Distribution of different journals, conferences, and university publications.

Further, it is essential to identify the subject areas of publications. The research area of each publication is placed using the WoS subject area feature. This identification can enable researchers to recognize the research area's focus and open new research topics for future research. According to Fig. 5, engineering with 38.3 % is more interested among researchers, followed by 36.5 % for multidisciplinary approaches. Afterward, computer science and mathematics accounted for 12.2% and 3.5 %, respectively.

Moreover, those research areas with two or fewer publications are listed in the others' category (physics, environmental science, psychology, construction building technology, neuroscience, and medicine). Interdisciplinary research pays increasing attention among scholars in this research area. The reason is the presence of different evacuation factors involved in the human evacuation process. There is a need to consider all together to fulfill IMO's requirements. Integrating techniques from other disciplines, such as engineering, environmental science, oceanography, operations research, management science, etc., augment the understanding and describing human evacuation problems from passenger ships.

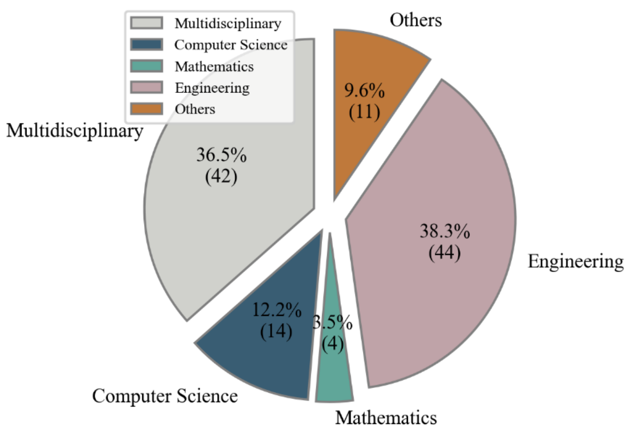

Fig. 5. Distribution of publications' research subject areas.

Next, from Fig. 6, Asia (52.2 %) and Europe (44.3 %) have the most significant academic contribution among others (Africa and South America have zero publications). Most publications in Asia are researched in Chinese and South Korean maritime institutions, with 39 and 12 papers, respectively. One of the solid reasons for the importance of this area for Chinese and South Korean scholars can be the sinking of Dongfang Zhi Xing and MV Sewol passenger ships with the loss of 442 and 304 passengers and crew, respectively (Baird, 2018; Kim et al., 2016). Hence, the Chinese and South Korean maritime sectors have inspired researchers and ship designers to reach safer evacuation solutions at sea. The UK (17 papers) and Norway (7 papers) have been more active and interested in Europe. Not only a disaster such as Costa Concordia and MS Scandinavian Star but also IMO's guidelines have pushed the maritime industry to rise in research and development activities in terms of human evacuation modeling. Other countries on the list have a 34.8 % contribution (Japan, Greece, Germany, Poland, Taiwan, Finland, Italy, Spain, Netherlands, Sweden, Canada, USA, Australia, Croatia, and Turkey). It shows that the popularity of human evacuation problems is growing among scholars in different geographic regions. Eventually, according to the first author's affiliations, Edwin Richard Galea from the University of Greenwich with seven publications, and Xinjian Wang from Dalian Maritime University with six publications, have the most considerable contribution in this research area.

Fig. 6. Geographic locations of the corresponding author.

3.3. Category selection

The structural dimensions of the current research and chief topics of analysis, including detailed analytical categories, are represented in Table 3. Each category consists of different features discussed in greater detail in Section 4. The MSC scope has various study subjects, such as updating the SOLAS convention, piracy and armed robbery against ships, and cyber security. However, the current work focuses on emergency evacuation from passenger ships. The present study targets the evacuation factors listed in Table 2 to determine underlying features. Then, the collected papers are analyzed and categorized concerning the identified features. A detailed presentation of all publications in different analytical categories is described in Appendix D to H.

Table 3. The principal analytical categories of the study.

Analytical category	Features	Appendix
Modeling approach	• Mathematical, • simulation, • experimental, • conceptual- and analytical-based, and • hybrid	D
Traffic assignment formulation	• System-optimal and • user equilibrium	E

Model parameters	• Environmental factors
	  ○ Fire products (smoke, heat, and toxic gas),
	  ○ ship stability condition,
	  ○ ship motions, and
	  ○ other external forces (wave, sea state, and time of day)
	• Configurational factors
	  ○ Ship layout, such as the layout of corridors, staircases, and doorways, and
	  ○ initial distribution of passengers and crew across the ship.
	• Human factors
	  ○ Passenger behavior, including walking speed and social relationship
	  ○ passenger age,
	  ○ passenger gender,
	  ○ passenger physical condition (agility and mobility impairment),
	  ○ passenger height,
	  ○ passenger weight, and
	  ○ passenger onboard evacuation experience.
	• Behavioral factors
	  ○ Crow behavior (family group behavior, counter and crossing flows, and crow assistance)
		F

Hazard type	• Fire, • flooding, • sinking, • storm, and • capsizing	G
Solution method	• They are presented based on methods applied in the paper, e.g., the Cellular Automata (CA) method.	H

Fig. 7 demonstrates the popularity of different modeling approaches for representing the behavior of the problem. The most significant portion of researchers prefers to apply simulation approaches for defining their model (with 52.2%). It is followed by hybrid (simulation/mathematical, simulation/experimental, simulation/questionnaire) and experimental approaches with 19.1% and 17.4%, respectively. 7% of the used methods account for the mathematical approaches. Only a minority of researchers, 4.3%, prefer to employ analytical modeling approaches. It shows the popularity of simulation techniques and increasing attention to hybrid and experimental methods.

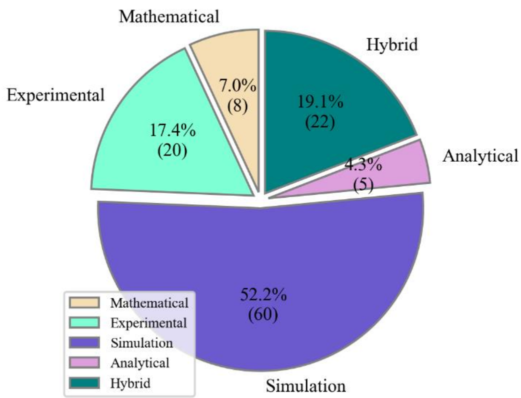

Fig. 7. Distribution of publications according to the modeling approach.

The other analytical category is traffic assignment formulation. Karabuk and Manzour (2019) classified land-based evacuation models into an optimal system formulation and a user equilibrium formulation. Their definition is considered for ship-based models—the former attempts to offer an evacuation plan to improve the main objective (macroscopic perspective). In contrast, a user equilibrium formulation generates an evacuation plan based on the characteristics of each passenger and addresses the problem at a more granular level (microscopic perspective). For example, an evacuation model can minimize the overall evacuation time with and without considering passengers' physical condition. The former can be in the first category; however, the latter focuses on every passenger's mobility. Moreover, 64.3% of researchers address their problem from a user equilibrium perspective. It shows there is increasing attention to understanding passenger behavior in this area.

Model parameters are the third analytical category. Parameters are concerned with the model's configuration. For example, the model's settings can vary according to the ship's motion mode. Fig. 8 demonstrates how many times two parameters are assessed together in the collected papers. Thirteen factors interacted more with each other among other evacuation factors. The blue circles indicate how many times two parameters are viewed in modeling simultaneously, while the green ones indicate a parameter is solely applied. For example, ship stability is repeated ten times with passenger age. Conversely, yellow squares ascertain the gaps for future research.

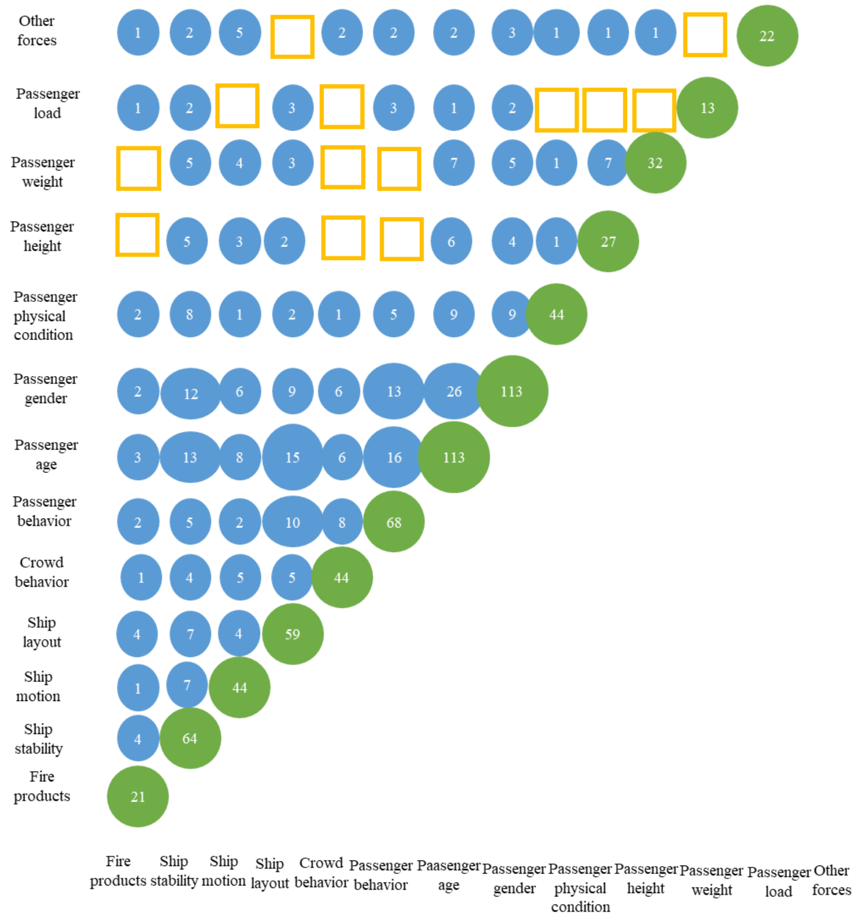

Fig. 8. Cross-frequency analysis of evacuation parameters among the collected papers.

The next category is the hazard type. Hazard refers to a potential source of damage to a passenger ship or people onboard. However, when the hazard happens, it can become a disaster (Shi, 2019). The most significant proportion of papers disregards considering the kind of hazard that threatens passengers' lives. In contrast, 21 publications consider fire as a hazard. Six research papers examine flooding and storm, with three for each. Although foundered (sunk and submerged) accidents with 54.4% of the total losses in the world ocean are the most frequent hazards that ships encountered from 2010 to 2020

(Allianz, 2021), only six papers addressed it in the literature. Three papers also take two hazards into account simultaneously. Also, Allianz reported wrecked (grounded): 19.6%, fire and explosion: 11.3%, machinery failure and damage: 5.8%, collision (involving vessels): 3.4%, hull damage (holed, cracks): 3%, and other causes (piracy and miscellaneous): 2.5% are other hazards. They can be other directions for future research to consider in formulating and analyzing human evacuation models.

Finally, the solution method category is analyzed. Applied solution methods are categorized based on the paper's objective. 31.3% of researchers used an evacuation tool to simulate the process. Some are based on discrete models allowing agents to occupy a discrete set of points in terms of space representation (such as MaritimeEXODUS and IMEX). In contrast, others are continuous models considering a constant sequence without interruption between different points in a defined space (such as VELOS and Pathfinder). Moreover, hybrid tools benefit from both models' properties (e.g., EVI and EvacSim). Appendix I lists available evacuation simulation tools in the literature.

The collected papers are thus evaluated and analyzed according to the features described in **Error! Reference source not found.**. The details of the analytical dimensions of the review study are thoroughly discussed in the following sections.

3.4. Material evaluation

The sample papers are cross-checked with another database, including Scopus whereby the authors verify the paper's properties, such as the research area. The aim is to improve the validity of the analysis. The author checking technique is consequently applied to control the credibility of the sample papers. After reading the abstract, they would be kept if they are consistent with the study objectives. Finally, the collection with 115 publications is established for further analysis.

4. Detailed analyses of the literature

This section gives the results of the analysis. The collection is studied according to analytical categories to determine the status in this research area. The gaps are identified, and the future research agenda is accordingly established. Although there can be an overlap in classification, this paper tries to categorize them according to the objective of each paper appropriately.

4.1. Problem classifications

There are various subjects in this area of study. Although the authors pursued particular aims, the papers can be classified into the following categories. Appendix J classifies papers according to their objectives.

4.1.1. Traffic assignment category

This subsection tries to classify the collected papers based on the traffic assignment analytical category. Papers with the aim of optimizing the overall performance of the egress system are placed in the evacuation time and route optimization subcategory. In comparison, the passenger behavior modeling subcategory pays attention to papers with user equilibrium formulation features.

4.1.1.1. Evacuation time and route optimization

Evacuation time optimization gains a significant portion of research objectives in the collected papers. All research subjects with the same subject matter are included in this classification (response time, assembly time, and embarkation time). The aim is to minimize the evacuation time considering evacuation factors. Furthermore, the route optimization module intends to provide safe evacuation routes in which the characteristics of passengers/crew distribution and the ship's layout are considered. The authors aim to determine the emergency evacuation routes available for evacuees or analyze the operational level considering congestion and counter-flow movements.

This kind of research has several advantages. For instance, total evacuation time calculation can be employed for updating the whole evacuation time in a real-time emergency response. Specifically, it can assist crew and passengers in handling the remaining time based on the available evacuation routes (Lin and Wu, 2018). Conversely, it has some shortcomings. For example, it lacks to consider passengers as conscious agents in a real-life case. Explicitly, how different aspects of passengers, such as the level of compliance, can affect the total evacuation time. Critically, this paper attempts to categorize them to represent a clear view of estimating the whole evacuation time in the presence of evacuation factors. This category consists of 48.7 % of studies.

4.1.1.2. Passenger behavior understanding

31.3 % of publications attempted to focus mainly on understanding passenger behavior. It is critical during evacuation as it minimizes total evacuation time and casualties in emergency maritime situations

(Finiti, 2021). Many authors attempted to advance understanding of passenger behavior by finding the most significant drivers, such as ship stability (mostly considered trim and heel angle) and disaster development (most researchers considered fire), in their reaction to the emergency. Some carried out a series of evacuation trials at sea to calculate passenger gait speed under predefined emergency scenarios. In contrast, some conducted questionnaires to explore new insights with an interactive study with passengers (Deere et al., 2012; Wang et al., 2020b; Yip et al., 2015).

The main advantage of considering passenger behavior is to design an effective emergency evacuation system to ensure safety standards (Wang et al., 2020b). Likewise, passenger behavioral responses to an emergency can enhance understanding of control efforts and crowd behavior (Li et al., 2019). While understanding the various source of uncertainty in passenger behavior calls for more investigations and quantifications in this research area. Specifically, how internal and external drivers, such as stress level and ship motions, can impact the behavior. Hence, the relevant samples are categorized to reveal the importance of evacuation factors in behaving passengers during an evacuation process.

4.1.2. Solution methods

The solution method category is the next analysis classification. It consists of three subcategories: (1) description of evacuation models, (2) data collection and validation, and (3) optimization solvers.

4.1.2.1. Description of evacuation models

Another category represents the description of evacuation models (11% of studies). Parts of the collected papers described maritime evacuation models to understand the evacuation process better. Some analyzed the current evacuation models considering simplified and advanced approaches, while others tried to evaluate evacuation simulation tools (Miyazaki et al., 2004; Sun et al., 2018a). The offered category can deliver a clear view for selecting a simulation-based evacuation tool according to the models' configuration. K V Kostas et al. (2014a) reflected the applicability of VELOS for assessing passenger and crew activities in normal and hectic conditions of evacuation operations. Also, Guarin et al. (2014) described the concept of escape and evacuation from passenger ships using the pedestrian dynamics simulation tool EVI.

Although the available simulation-based evacuation models can provide solutions, there is a need to design a real-time decision support system to track the evacuation process. It is suggested that the system can be based on a data-driven multistage optimization framework. Various real-time operation data is obtained from different agents involved in the evacuation process. They can be modeled with machine learning (ML) techniques under the uncertain development of a disaster (Roy et al., 2021).

4.1.2.2. Data collection and validation

Researchers tried to collect data through either paper-based methods, including surveys or questionnaires, interviews, or computer-based techniques such as video cameras (7% of the collected papers). Regarding questionnaire surveys, some researchers tried to analyze different points of the passengers' views during the evacuation process. They determined the impact of various factors on the evacuation process and passenger behavior. For example, Liu and Luo (2012) and Lozowicka (2021) analyzed the influence of demographic differences, including age, gender, educational level, mobility level, experience onboard, and traveling companion, on passengers' behavior and safety awareness and perception during an emergency evacuation Ro-Ro passenger ship.

Moreover, Finiti (2021) applied two different methodologies (case study and interview) as complementary tools. They attempted to understand likely passenger behavior by analyzing the collected data from some survivors of the Costa Concordia disaster in terms of gender, age, companions, and experience. Furthermore, data related to passenger behavior under different circumstances, such as ship stability angles, play an essential role in understanding the evacuation process. Actual onboard experiments can further shift our understanding of the evacuation process. A notable example is five full-scale semi-unannounced assembly trials performed at sea under the EU Seventh Framework Programme project SAFEGUARD (IMO Fire Protection Sub-Committee, 2012). The aim was to generate passenger response time data, validation, and calibration data sets for ship-based evacuation models and establish a set of fire and trim/heel scenarios. Studies with the same subject matter fall in this category. Video-based observation is another popular method for gathering data in evacuation studies (Galea et al., 2014a; Na et al., 2019; Wang et al., 2021a).

This category can deal with relations between different data collection methods and evacuation factor data. It can help researchers find a suitable database based on their problem requirements. For instance, Deere et al. (2012) is a source of human factors data for the passenger assembly process on large passenger ships. They utilized hybrid methods, including video cameras and infrared beacons. Still, there is room for measuring biological and psychological passengers' cognitive states, such as stress levels, and how they affect the evacuation process. Moreover, sociological-based data, such as cultural diversity, can give ship managers more insight into passenger behavior (Galea et al., 2015; D. Zhang et al., 2017). Therefore, they are another challenge in collecting and analyzing data in this research area.

4.1.2.3. Optimization solvers

In the simplified version of evacuation analysis, the overall performance of the evacuation system is critical, whereas, in the advanced version, the egress of each human while various factors, such as hazards and ship motions, affect the behavior is the primary objective. In doing so, two types of methodologies are provided.

On the one hand, researchers use various approaches to solve the formulated evacuation problems for passenger ships. The authors have split the applied methodologies into three main categories according to the paper's objective. Firstly, many authors use simulation and mathematical tools such as MaritimeEXODUS, VELOS, CPLEX, and MATLAB to reach a solution. Secondly, some employed optimization models to harness uncertainty of the different elements of the evacuation process, such as human evacuation behavior. They include Polynomial chaos- (PC) and Monte Carlo-based (MC). For instance, Xie et al. (2020a) applied PC expansion with Gauss quadrature to quantify the uncertainty of evacuation time for passenger ships. Furthermore, Wang et al. (2013) employed an MC-based sampling method to analyze available safety egress time under ship fire (SFAT). Thirdly, researchers applied meta-heuristic algorithms for solving real-life evacuation problems (Lozowicka, 2021). For example, Łozowicka (2010 and 2005) utilized the Genetic Algorithm (GA) to find the shortest evacuation time and route. Although GA can propose a feasible structure fitted to problem parameters, there is a possibility of falling to the local optimum for this algorithm. Also, the degree of complexity is raised by considering more evacuation factors. Therefore, it is suggested to employ hybrid techniques to escape it. For example, Kaveh and Ghobadi (2020) presented a hybrid evacuation model using the graph theory and metaheuristic algorithms to find the best evacuation route under a fire situation considering human factors.

On the other hand, passengers and crew are characterized as unique individuals with distinctive personality traits and cognitive abilities. Fifty publications applied microscopic models, including social force-based, velocity-based, acceleration-based, and CA, to work out the dynamic behavior of passengers. The most considerable contribution was seen for velocity-based models with 52%—cell-based and social force-based models comprised 26% and 14%, respectively. The minor portion stands for accelerated-based models with 8%. However, there can be a potential extension to study the influence of evacuation factors, particularly dynamic conditions of the ship, on passenger behavior within microscopic-based models (IMO, 2016). In land-based evacuation path planning, Yang et al. (2022) integrated three forces, i.e., pedestrians' self-driving force, the pedestrian's interaction force, and the interaction force between pedestrians and obstacles, in the format of a social force model. Furthermore, Fang et al. (2022a and 2022b) improved social-force models to simulate the influence of inclination on passenger walking speed. These methodologies are documented in Appendix H.

4.2. Modeling approaches

Researchers apply various modeling approaches in this research area to formulate the behavior of the problem. The collected papers can be divided into five categories according to the modeling approaches. This paper specifies which methods are more widely employed and offer more significant research advancement opportunities among these categories.

4.2.1. Simulation-based approaches

One of the popular techniques in human evacuation modeling is simulation. The reason can be financial, ethical, and safety issues posed by full-scale evacuation trials for passenger ships (Deere et al., 2012; Galea et al., 2014b). Full-scale human evacuation experiments are time-consuming (Q. Xie et al., 2020c). Therefore, researchers attempt to understand the dynamics of passenger behavior during human evacuation through simulation techniques. Balakhontceva et al. (2015), Chen and Lo (2019), and Kim et al. (2019 and 2020) addressed passenger behavior under particular environmental factors such as ship motions, heeling, trimming, and listing the ship. Moreover, Azzi et al. (2011) and Salem (2016) described passenger behavior under ship fires. They tried to understand how fire outbreaks onboard can affect the life safety of passengers and crew. They simulate the development of fire and the spread of combustion products under different fire scenarios. Furthermore, Balakhontceva et al. (2016), Ruponen et al. (2015), and Spanos and Papanikolaou (2014) simulated evacuation processes under storms and flooding. They draw an emergency response to abandon the ship. Łozowicka (2010) and Ni et al. (2018) reflect evacuees' movements and behavior in the presence of the contraflow and obstacles. Also, Brumley and Koss (2000) and Zhang et al. (2017) observed different patterns of passenger behavior according to their characteristics, such as age, gender, height, and weight, during the evacuation process.

Simulation approaches are commonly applied to modeling evacuation problems at a microscopic level. For instance, CA simulation techniques are employed to capture passenger behavior during movement (Hu and Cai, 2017; Wang et al., 2020b). However, tracking passenger behavior in the presence of other evacuation factors, such as disaster development, can generate more scenarios and accordingly produce a more complicated problem. The generated problem cannot be easily tackled with only a simulation-based approach. Therefore, it is recommended to integrate this technique with other techniques. For example, Xie et al. (2020c) recently constructed a surrogate model of passenger assembly time with response time parameters to improve the simulation time of a large-scale crowd for passenger ship fire evacuation.

4.2.2. Experimental-based approaches

Another approach to analyzing ship evacuation is based on an experiment. Researchers conduct experiments either in a simulator or onboard. They collect data regarding passenger walking speed under moving characteristics of the ship, such as heeling and trim. In this stream, Bles et al. (2001), Sun et al. (2018a), and Zhang et al. (2017) designed their experiments in a ship corridor simulator or ship operating simulator. Katuhara et al. (2003) and Liou and Chu (2016) conducted a series of onboard walking experiments to gather data in various sea conditions on training ships. Furthermore, several evacuation trials were conducted on passenger ships to validate marine-based computer models (Gwynne et al., 2003; Murayama et al., 2000; Walter et al., 2017).

The advantage is that researchers can have greater control of the basic experimental setup. For example, Wang et al. (2021b) considered the test area of the experiment to be larger than the calculation area to improve the accuracy of the experimental consequences. Also, Wang et al. (2021a) calculated the walking speed of about 90 cadets in diverse sea areas and conditions on different days due to the ship's uncontrollable motion states. Nevertheless, there is a deficiency in carrying out onboard experiments by taking evacuation factors, such as disaster development (e.g., fire), ship motions (e.g., pitching), and crossing flows, into account simultaneously. Moreover, the authors found that research participants are well-trained people in onboard experiments. They understand how to act in abnormal and emergency occurrences; the results may lead to overfitting issues. Therefore, new technologies, such as VR, can raise the possibility of involving untrained passengers considering evacuation factors. VR technology is discussed later in Section 5.7.2.

4.2.3. Mathematical-based approaches

Another category of modeling is mathematical. Modelers utilize quantitative techniques to describe the relations between parameters or variables. Chu et al. (2013), Lozowicka (2021), and Xie et al. (2020c) represented the behavior of the evacuation problem using mathematical properties and arguments, such as Legendre polynomials and Leung–Ng algorithms. They dealt with evacuation times and routes. Mathematical approaches, such as the minimum cost model and the quickest path/flow, are generally employed to find an optimal lower bound for evacuation time, considering the distance to the destination and queue length (Hamacher and Tjandra, 2001). They disregard passenger behavior during the emergency. Therefore, it is suggested to integrate the mathematical model into a simulation model, such as the social force model. This integration propagates the movement law and path selection behavior of pedestrians.

4.2.4. Conceptual- and analytical-based approaches

These studies analyze practical factors to find a framework for different aspects of human evacuation studies. For example, Guarin et al. (2014) presented the concept of escape and evacuation from the point of ship design and risk management. Nevalainen et al. (2015) broke an evacuation problem into the elements and tried to work out human evacuation from the passengers' perspective. They investigated four accident reports to map environmental factors influencing passenger behavior during ship evacuation.

This type of research can give a clear view of the interaction between passengers and evacuation factors. Specifically, it can unlock passengers' perception and interpretation of the evacuation process and ship-based disasters. For instance, Finiti (2021) tried to find indications of passengers' behavior from the survivors of the Costa Concordia disaster using the Talk-Through method. Nevertheless, it is typically a challenging task to have survivors view a real-life disaster or talk with every passenger. Instead, it is recommended to analyze the passenger behavior under emergency with crew and safety engineers onboard.

4.2.5. Hybrid approaches

Some researchers combined two modeling methodologies, which are indicated as hybrid approaches. They can reinforce the precision of evacuation models and simultaneously control different aspects of the evacuation process. For instance, Chen et al. (2016), Jasionowski et al. (2011), Qiao et al. (2014), Dracos Vassalos et al. (2002), and Xie et al. (2020a) integrated simulation and mathematical modeling approaches to track the evacuation process in light of at least two evacuation factors (e.g., fire and passenger properties). They attempted to reduce the complexity of the evacuation model for a large-scale passenger ship. Meanwhile, Kang et al. (2010), Miyazaki et al. (2004), Murayama et al. (2000), and Sarvari et al. (2019) simultaneously employed simulation and experimental approaches. In addition, Brown et al. (2008) and Casareale et al. (2017) applied questionnaire approaches with simulation and experimental techniques to improve modeling efficiency.

Nevertheless, the majority of the proposed hybrid models lack generalization features. For instance, Sarvari et al. (2019) presented a user equilibrium formulation-based model for a Ro-Ro ferry boat sinking regarding evacuation time, death toll minimization, and evacuation plans. However, how effective the proposed model is while being fed with real-time data obtained from a passenger ship under the same emergency can improve the model's validity. Consequently, the potential extension includes the development of a robust hybrid modeling approach that can be operated across a variety of ship-based evacuation models is suggested.

4.3. Case study

37.4 % of the collected papers evaluated the performance of the proposed methodology within a case study. Remarkably, researchers analyzed various subjects, including understanding passenger behavior, emergency evacuation route, travel time, the influence of obstacles in cabins, social impact on evacuation behavior, passengers' walking speed and safety awareness, the concept of dynamic affordances, and the application of wireless sensor networks in the ship evacuation process. They attempted to provide managerial insights regarding passenger behavior or ship interior design to ship designers. However, researchers considered specific passenger ships, demographic, and transverse/longitudinal stability angles. Therefore, testing the proposed evacuation models by other real-life cases is suggested to increase the generalizability of results to different settings. The case studies are listed in Appendix K.

4.4. Model parameters

Parameters are quantities driving the evacuation process. Understanding these parameters can hence facilitate modeling of the evacuation process more reliably. Parameters are represented through four evacuation factors. Most publications (38.7%) considered human factors in their modeling, while 29% of authors tried to reflect the impact of environmental factors on the evacuation process. The other significant factors were configurational (20%) and behavioral, 12.3%. Hindrances and obstacles are highlighted in calculating passengers' travel speed on flat terrain and stair up/down in the advanced version of guidelines for passenger ships. Therefore, such considerations about behavioral factors are necessary and a gap in the literature. Appendix F can indicate a clear view of engaging the evacuation factors in the literature.

5. Discussion and future opportunities

This section outlines the deficiencies of the current studies and accordingly provides future research directions on human evacuation studies. Based on the classifications presented in Section 4, the authors categorize the findings into five sub-sections.

5.1. Handling uncertainty

Future research based on the identified gaps in uncertainty issues can be conducted in three category levels: (1) parametric, (2) modeling methods, and (3) solution methods. In the remainder of the paper, the term uncertainty is utilized, but it must be defined first. Wallace (2003) defined uncertainty as a lack of predictability for outcomes. It is due to the gap between the needed and available information for fulfilling a task. Emblemsvåg and Endre Kjølstad (2002) also specified that uncertainty is intertwined with the complexity of factors influencing a system.

5.1.1. Modeling uncertainties on parametric level

Availability of perfect or imperfect/partial information drives the decision-making process into certain or uncertain situations, respectively. Uncertainty is presented as randomness, hazard, and deep uncertainty. Firstly, the randomness stems from the random nature of low-impact events. To presume that input data varies randomly, the existence of sufficient and reliable historical observations for estimating the probability distribution and validity of the data are requisites (Marchau et al., 2019). Secondly, low-probability peculiar events with high impact characterize hazard. Thirdly, the deep uncertainty comes from insufficient information to estimate the objective or subjective probability of plausible future events (Marchau et al., 2019). Besides, Obaidurrahman et al. (2021) classified uncertainty into fuzziness and epistemic uncertainty. The former is related to flexibility in constraints and goals. The latter concerns a lack of knowledge of the input data and is often presented as linguistic attributes.

Passenger behavior, ship motion, and disaster development can be possible sources of uncertainty in a ship evacuation process. They can be classified according to the uncertainty type. Under the second research question, this paper discusses the uncertain influence of evacuation factors on human behavior. Passenger behavior is the main element in managing an evacuation process (Wang and Wu, 2020a). One's behavior is simultaneously influenced by environmental factors, such as disaster products, and physiological, psychological-, and sociological-based factors, for instance, physical condition and cultural differences (Nevalainen et al., 2015). Finding the correct type of uncertainty considering passengers' behavior can approach ship managers to have a more reliable evacuation plan. Disaster development is another source of uncertainty that affects the evacuation process, particularly passenger behavior. Disaster develops over time, and exposure to a threat makes the cognitive function of decision-making more challenging, and one's choices become limited. Depending on the disaster type, the uncertainty assessment process can vary. For example, a fire progresses and may need a different realization than flooding. Ship motions are another uncertain driver affecting evacuees. They are movements that a ship can witness in different directions by forces, such as waves and storms. Each move can affect passengers' behavior in other ways (Wang et al., 2021a).

There is room for further progress in uncertainty assessment for human evacuation studies at a parametric level. Moreover, taking these uncertainties into modeling paves the way to represent reality, minimize risk, bring remarkable competitive merit for ship designers, and enhance usability (Van Reedt Dortland et al., 2014).

5.1.2. Uncertainty modeling methods

After identifying the uncertainties, the next step is to model them. As the problem variables mentioned above constantly change and it is questioning to find their clear values, uncertainty modeling can harness their fluctuations. Uncertainty modeling approaches can deal with this type of problem. They include robust optimization, stochastic programming, Bayesian-based network (BN), MC-based simulation, ML-based, and hybrid techniques. This section presents more explanations regarding these approaches and how they can handle an evacuation problem.

5.1.2.1. Robust optimization

Robust optimization (RO) is a methodology for handling optimization problems under uncertainty. RO calls data from an uncertainty set instead of running a specific probability distribution. As objective function and constraints are assumed to belong to a given uncertainty set, the decision-maker establishes a feasible solution for any realization of the uncertainty (Bertsimas and Sim, 2003). RO-based methodologies have a significant drawback. The proposed solution can be highly conservative as this methodology aims to harness all possible worst-case realizations of the uncertainty (Bertsimas et al., 2012). Another challenge is that while mathematically finding an optimum is relatively straightforward once all the parameters are defined, proving that this optimum is a global optimum for real-life satiation is an entirely different and far more challenging aspect. However, this is where the robustness comes into play and lessens this challenge, albeit not eliminating it completely.

In contrast, they offer two main merits that can be appropriate for evacuation problems. First, the robust counterpart, a deterministic equivalent of the original model, is still computationally tractable regardless of the number of uncertain parameters. Second, experts' opinions can be involved in constructing uncertainty sets (Bertsimas et al., 2012). Ship motions and disaster development intertwine and affect passenger behavior. They can be established in an uncertainty set. At the same time, maritime experts and ship designers can provide their views to specify the boundaries of uncertainty set. Although researchers apply this technique in a land-based situation (Rabbani et al., 2018), investigating the influence of RO-based approaches on human evacuation models is recommended in ship evacuation.

5.1.2.2. Stochastic programming

Another approach is stochastic programming. This modeling paradigm can provide decision-makers with the expected objective value subject to various constraints over uncertainty realizations in a sequential decision-making process (Birge and Louveaux, 2011). Although this tool fulfills the objective functions, it needs an accurate estimation of the probability distribution of the random variables (Bertsimas et al., 2012). Insufficient verified data in this area of research can hinder estimating an accurate probabilistic description of the random variables.

The ship evacuation process can also be formulated as a multi-stage stochastic programming model. For example, based on a two-stage stochastic programming model, the first-stage decisions can be related to the availability of evacuation routes at the beginning of the disaster event. Passengers' behavior is realized after knowing which routes are available under disaster developments or ship motions scenarios. Each scenario can correspond to how a hazard or ship motion can affect the ship's availability or passenger behavior. Afterward, recourse decisions are made to determine which evacuation routes are still available and what corresponding travel time is. Therefore, further studies focusing on stochastic-based approaches are suggested to assess the simultaneous influence of disaster development and ship motion on the ship evacuation process.

5.1.2.3. BN-based approaches

BN is a robust potential method to address decision-making in uncertain situations where variables are highly interlinked (Marcot and Penman, 2019). However, this approach increases the computational cost when variables rise. Another drawback of this methodology is that translating variables' dependencies into the mathematical formulation can be tricky and produce misleading results (Robert, 2007). A BN can formulate an evacuation guidance model with conditional dependencies among input parameters. For instance, when different ship motions meet other hazards, an evacuation plan can be distinct based on how the combination will affect human evacuation behavior. Specifically, the roll motion of a ship in the presence of a fire accident can result in different passengers' walking speeds compared to pitch motion combined with flooding. Accordingly, passengers demand different evacuation routes depending on how fast they move. Therefore, a BN technique can model the dependency among influencing drivers on human evacuation behavior.

Moreover, there is a feature within BN techniques that facilitates representing maritime specialists' knowledge in modeling. This feature can cover the lack of sufficient verified data in this area of research. Although Sarshar et al. (2013a and 2014) applied BN-based methods through evacuation modeling under uncertainty, additional studies will be needed to develop a complete picture of this technique.

5.1.2.4. MC-based simulation approaches

MC simulation technique has been commonly used to explore uncertainty analysis of the random inputs in ship-based evacuation models. It is a reliable and cost-effective technique (J. Wang et al., 2013). Nevertheless, MC-based methods require many scenarios due to the slow convergent rate. The more scenario you design, the higher complexity the problems face (Matala, 2008). To overcome the first issue, researchers tried to fuse evacuation models with Latin hypercube sampling in the ship-based evacuation problems. Xie et al. (2020a) proposed PC expansion based on the corresponding distribution of random variables to reduce the number of evaluation samples.

Surrogate-based models, such as the Gaussian process, can also be integrated into MC techniques and reduce the run time. Furthermore, variance reduction techniques can improve the computational efficiency of MC simulations (Turner and Davis, 2013). Another main drawback of MC-based techniques is the necessity of knowing an accurate probability distribution of the random variables. One of the main requirements to estimate an exact distribution is access to a large amount of historical data, which, undoubtedly, many projects face data scarcity. In this regard, examining methods, such as the bootstrapping technique, can lessen the amount of data. Another solution to escape data scarcity is applying the fuzzy analysis method. Fuzzy numbers are employed to track the effect of uncertainty. Kong et al. (2014) presented a framework of fuzzy assessment for a building under fire. They determined fire development rate and pre-evacuation time using fuzzy numbers to describe the uncertainty associated with fire development. Future works could study the influence of these extensions on MC-based approaches.

5.1.2.5. ML-based approaches

ML-based techniques can also model uncertainty in decision-making processes. Bayesian deep learning, ensemble learning, and neural network-based techniques are three widely-used types of uncertainty quantification methods that can significantly increase the reliability of results (Abdar et al., 2021). In a land-based evacuation, Zhao et al. (2020) leveraged the random forest technique to estimate people's emergency behavior based on social and environmental factors during the pre-evacuation stage. Also, Katzilieris et al. (2022) developed logistic regression models and ML-based techniques to analyze the evacuees' response behavior in communities under the emergence of wildfires. Moreover, researchers tried to apply deep learning-based techniques to deal with evacuation problems. Zhang et al. (2021) proposed a deep reinforcement learning algorithm with a social force model to train agents to find the fastest evacuation route in an evacuation of a room with obstacles. Future research can consider the potential effects of ML-based algorithms more carefully.

5.1.2.6. Hybrid approaches

Some researchers consider simultaneously macroscopic and microscopic models in describing evacuation problems to formulate an emergency evacuation problem closer to a real-life situation. They apply hybrid approaches. Hassanpour et al. (2022) modeled human evacuation behavior and the building's interior design using a hierarchical hybrid agent-based framework combining CA and graph-based models in a land-based problem. Zhang and Jia (2021) proposed a hybrid multiscale approach to work out the movement of followers, the guidance behavior of leaders, and the follower-leader interaction. IMO (2016) pays attention to environmental aspects of the evacuation plan together with geometrical, population, and procedural elements. Future research can be devoted to developing hybrid approaches to bring these aspects into play. A hybrid robust-stochastic programming approach can be a potential solution. Disaster development can be described through various stochastic scenarios, and uncertainty sets can be established for defining different ship motions.

5.1.3. Uncertainty solution approaches

Researchers deployed different solution methods to tackle a modeled evacuation problem under uncertainty. Many benefits from simulation tools. While a few scholars have used general solvers such as CPLEX and MATLAB to test evacuation problems. Furthermore, some employed metaheuristic algorithms, such as GA to improve the performance and quality of solutions. However, the above-mentioned methods focus mainly on human behavior under fire situations. Future research can focus on applying simulation technology, such as DT, or metaheuristic algorithms, such as a tabu search, to model sources of uncertainty affecting passenger and crew behavior, evacuation time, and escape routes. New guidelines for an advanced evacuation analysis document that a congestion region is not precisely known in advance. Applying uncertainty analysis techniques, such as the Benders decomposition algorithm and ML-based techniques, can close us to more quality solutions beforehand in a reasonable time based on various scenarios affecting the congestion points density (Romanski and Van Hentenryck, 2016).

5.2. Multi-objective optimization modeling

Future studies can also consider multi-objective optimization modeling direction in this research area. Multi-objective models can provide solutions for different objectives in one single run. Also, they can reduce the number of assumptions about the problem and near modeling to a real-life situation (Pilát, 2010). For instance, minimizing evacuation time, maximizing crew assistance, and passengers' satisfaction levels subject to the ship layout configuration can be formulated as a multi-objective evacuation model. Meanwhile, multi-criteria decision-making techniques, such as the Analytic Hierarchy Process (AHP) or the analytic network process, can be applied to analyze the weights of the multiple factors affecting objectives. Afterward, weights are employed in formulating a multi-objective evacuation model. Ping et al. (2018) proposed a quantitative analysis model in an offshore incident by integrating BN and fuzzy AHP to calculate the probability of successful escape, evacuation, and rescue in light of experts' opinions.

5.3. Human evacuation behavior understanding

Human behavior is a central ingredient for analyzing and designing an egress system. Modeling human behavior and two psychological properties regarding human behavior named passenger compliance behavior and risk perception are considered the potential research directions. In doing so, they are analyzed in this subsection, and suggestions for a better understanding of these topics are provided.

5.3.1. Modeling human evacuation behavior

Passenger behavior is a complex phenomenon affected by various environmental, human, and behavioral factors. Taking these elements into modeling subject to different constraints such as configurational factors has been a challenging research question in this area. Researchers primarily attempt to harness passenger behavior with the help of social force-, velocity-, acceleration-based, and CA models. The social-force models are based on complex rules; they do not provide satisfactory calculation efficiency (Ni et al., 2018). CA-based models are discrete in space, time, and state variables; they do not track the dynamic behavior of passengers varying instantly (Ha et al., 2012). Velocity- and acceleration-based models cannot take the behavior pressure from the crowd into consideration (Cho et al., 2016). Surrogate-based models can be, therefore, a solution for covering challenges. They can estimate outputs of simulations across the whole design space, substituting the original (more expensive and time-consuming) model and improving the computational efficiency (Dias et al., 2019). Xie et al. (2020c) developed a surrogate-based model of passenger assembly time using the Legendre PC expansion. They predicted the optimal time for the issuance of evacuation orders. Future studies can pay more attention to this technique for approximating the projections of the original model.

In addition, researchers can employ ML-based algorithms to predict human evacuation behavior. Ning and You (2019) elucidated the integration of a data-driven with a mathematical-based optimization model. An ML model interacts with a mathematical model. Concretely, information is circulated between the two models in an iterative process, improving the output's performance and reliability. These two models can be integrated using the loss function in the ML model and the objective function in the mathematical model. On the ML side, evacuation factors can be represented as features per passenger, while the mathematical side can minimize the total evacuation time.

5.3.2. Passenger compliance behavior

Understanding the compliance psychology of passengers can be a critical part of more effectively tracking the evacuation process. Also, it aligns with the advanced evacuation analysis guidelines that consider passengers as sentiment agents. Compliance behavior is the coincidence of human behavior with what they should do based on rules, instructions, and others' advice (Chu et al., 2017). Human factors (e.g., cultural differences), and environmental factors (e.g., crowd behavior), can influence the compliancy level (Hamad et al., 2003). Furthermore, Karabuk and Manzour (2019) categorized compliance behavior in a land-based evacuation situation into three classes: (1) hard, (2) soft, and (3) non-compliance behavior. Ditlev Jorgensen and May (2002) empirically studied the attitudes and behavior of passengers regarding non-compliance with instructions and how it can affect assembly time in case of an emergency on ferries. In a land-based evacuation, Chu et al. (2017) proposed a bi-level optimization methodology for modeling the compliance behavior of evacuees under environmental factors. Therefore, understanding this human attribute according to evacuees' compliance class can be another future direction in this research area.

5.3.3. Passenger risk perception

During the response period, the critical point is the decision of passengers whether to move after they have noticed initial cues. This decision mainly depends on passengers' risk perception (RP) (Kinateder et al., 2015). RP originates from ambiguity in the evacuation process and passengers' subjective judgments about the probability of negative occurrences such as death. Taking RP into account aids in understanding the human cognitive process and may minimize the total evacuation time (Kinateder et al., 2015). In land-based fire evacuation, researchers attempted to theoretically frame the RP and discover its role during the evacuation process (Kinateder et al., 2014), while there is still a significant gap in the ship-based evacuation process to modulate RP. This lack can be owing to the absence of insufficient actual evacuation at sea.

Viking Sky cruise ship is a successful rescue operation in Norway. She faced an engine failure, which led the system to shut down the engines. She next started listing in the stormy weather. Meanwhile, 1,373 passengers and crew passengers perceived uncertainty about what was going on and judged subjectively about the likelihood of unfavorable events, such as incidents (Ibrion et al., 2021). This interpretation might foster the pilot to issue the evacuation order at the best possible time. Analysis of disasters such as the Viking Sky passenger ship can smooth the path to understanding the evacuation process at sea. There is no single study in this stream to analyze the impact of passengers' RP on the evacuation process. This topic can be, therefore, another research direction.

5.4. Mutual interrelations

A significant research opportunity is investigating the relationships among evacuation parameters and how their concurrent existence can affect the human evacuation process from passenger ships. Some opportunities are listed in **Error! Reference source not found.** as cross-frequency analyses of two p arameters.

However, additional opportunities can be when there are more than two parameters in analyzing the evacuation plan. Table 4 indicates the simultaneous influence of three parameters on the evacuation process. For example, three papers (Brown, 2016; Sarshar et al., 2014, 2013c) performed the evacuation analysis by considering the coexistence of three parameters during the evacuation process, including fire, ship layout, and physical condition. In contrast, there is no study to analyze the interplay of fire, counterflow movements, and passenger walking speed. These future directions are listed in **Error! R eference source not found.**. Furthermore, considering four elements or even more is also applicable; however, it could be more complicated (such as counter and crossing flows, passenger physical conditions, fire, and flooding).

Table 4. Mutual interrelation among evacuation factors.

	Fire		Passenger physical condition
(Ship layout, passenger physical condition)	3	(Ship motion, crowd behavior)	0
(Ship layout, crowd behavior)	0	(Ship motion, hazard)	0
(Passenger physical condition, other forces)	0	(Walking speed, counter and crossing flows)	0
(Ship motion, passenger physical condition)	0	(Walking speed, family group behavior)	0
(Passenger walking speed, counter and crossing flows)	0		

As a result, this study reveals that such mutual interrelations are necessary and a gap in the literature.

5.5. Digital transformation

This section tries to introduce two enabling technologies that may enhance safety and emergency response in human evacuation from passenger ships.

5.5.1. DT technology

DT is a virtual model for a physical object. It mirrors the behavior of a physical counterpart using a simulation/optimization model (Kaur et al., 2020). A bi-directional data flow is crucial in communicating between the object and the model. Data is collected from Internet of Things-based (IoT) devices such as sensors installed in the physical asset and transmitted to the model in real-time. Afterward, the model is run, tested, and validated on a DT. Then, faults are diagnosed, and possible improvements will accordingly be produced. Finally, the solutions are transmitted back to the physical object. Although the application of a DT is witnessed in other industries, such as the manufacturing industry (Tao et al., 2019), there is no passenger ship-based DT. This absence can be due to many reasons. Firstly, it can be owning to the lack of a cost-effectiveness evaluation for creating a DT of a passenger ship. Specifically, this technology targets academia and industry for teaching purposes and as a source of income. Academics and ship managers need to meet their financial requirements regarding this technology for applying it through their activities. Secondly, the absence of a data-driven simulation/optimization model can be another reason. Data-driven decision-making for the evacuation process demands exponentially many data points. At the same time, human evacuation behavior is a central ingredient for analyzing and designing an evacuation model. In this regard, the simulation/optimization model should be fed with data concerning human properties such as age, gender, and stress. Therefore, data privacy issues are the third sign restricting the creation of a DT in this area. Fourthly, even though a DT can be built by tackling the challenges mentioned above, how to generalize and transfer findings from a specific demographic on a passenger ship to others can cause additional concerns.

On the other hand, a DT can benefit the maritime industry, especially when maritime transport is approaching the era of autonomous shipping. It can highlight real-time collaboration between a ship and its digital counterpart. This connection can remove human errors and improve safety at sea by establishing a correct relationship among parties, such as passengers and crew, during evacuation.

5.5.2. VR technology

VR is a three-dimensional simulated environment where the agents can feel a spatial sense (Huang et al., 2022). The applicability of VR is presented in many fields, for instance, tourism (Beck et al., 2019). In this stream, Vukelic et al. (2021) evaluated the possibility of adopting new technologies to the human evacuation process, including VR. There is an opportunity to expand the VR application in passenger ship-based emergency circumstances. Precisely, it can be employed for data collection purposes, such as passenger walking speed. Not only conducting an actual full-scale onboard experiment is time-consuming and costly, but it also can be dangerous for passengers while sailing. In this regard, a set of onboard experiments can be designed in the presence of virtual reality devices like headsets. Headsets can be programmed based on the influence of a disaster on human behavior. Similarly, this technology can transport participants to an interactive digital world considering ship motions. Then, how participants react to a virtual hazard or ship motions can affect their evacuation behavior and speed. Therefore, further research can be undertaken to investigate the application of VR in a passenger ship-based data collection process, especially in a spatial environment while a ship berths.

6. Conclusion

This paper comprehensively summarizes recent and state-of-the-art publications on human evacuation. 115 studies in scientific journals, peer-reviewed conference papers, and doctoral and master dissertations are selected and reviewed between January 1999 and August 2022. Afterward, the authors analyzed the collected studies regarding evacuation factors, modeling approaches, and solution methods. Finally, future gaps and research opportunities are outlined in three aspects: uncertainty analysis of evacuation parameters, passenger characteristics, and digital transformation adaptation. Employing modeling approaches, including RO, stochastic optimization, BN, MC-based, AI-based, and hybrid approaches, are identified as future opportunities in formulating uncertainty. Accordingly, possible future directions are provided regarding algorithms for tackling the modeled evacuation problems under uncertainty. Other future suggestions include paying attention to multi-objective optimization problems and employing the corresponding approaches.

Further, mutual interrelations evacuation parameters propose future trends in the problem classifications. Also, surrogate-based models are recommended for estimating the underlying model to ease the complexity of evacuation problems. Moreover, opportunities associated with passengers' compliance psychology and risk perception are offered. Ultimately, the possibility of adapting the two latest enabling technologies named DT and VR is suggested for this research area. The authors attempt to conduct the current study as a comprehensive literature review as possible; however, there are still some shortcomings. For instance, the number of the collected publications is not large, and the results of the visual network analysis may not be comprehensive. Hence, scholars can also examine the released investigation report from different maritime accidents, such as the Costa Concordia disaster and the MV Viking Sky, and how the literature can study them from an advanced evacuation analysis perspective. Also, most non-English publications have an English summary section. Therefore, they can be represented in the review analysis.

CRediT authorship contribution statement

Hossein Arshad: Conceptualization, Investigation, Visualization, Methodology, Writing- original draft, review, and editing, Software. Jan Emblemsvåg: Conceptualization, Supervision, Resources, Writing- review and editing. Guoyuan Li: Supervision, Writing- review and editing. Runar Ostnes: Supervision, Writing- review and editing.

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Appendix A. Publishers

Table A.1. List of publishers.

Paper	Publisher
List of publishers with a minimum of two publications.	
(Azizpour et al., 2022; Balakhontceva et al., 2016; Fang et al., 2022a; Grandison et al., 2017; Ha et al., 2012; Kim et al., 2004, 2019; Lee et al., 2004, 2022; Liu et al., 2022b; Park et al., 2004, 2015; Salem, 2016; Sun et al., 2018b, 2018a; Vanem and Ellis, 2010; Vanem and Skjong, 2006; Wang et al., 2020b; Wang et al., 2021c, 2021b, 2021a, 2022a; Wu et al., 2018; Xie et al., 2020c, 2020b, 2020a; Yip et al., 2015; Yue et al., 2022)	Elsevier
(Balakhontceva et al., 2016; Boulougouris and Papanikolaou, 2002; Casareale et al., 2017; Chen et al., 2016; Fukuchi and Imamura, 2005; Galea et al., 2014a, 2011; Guarin et al., 2014; Gwynne et al., 2003; Hu et al., 2019; Jasionowski et al., 2011; Katuhara et al., 2003; K V Kostas et al., 2014; K V Kostas et al., 2014a; Kwee-Meier et al., 2017; Łozowicka,	Springer

2005; Luo, 2019; Meyer-König et al., 2002, 2007; Ng et al., 2021; Sarshar et al., 2014; Spanos and Papanikolaou, 2014; Sun et al., 2018b; Dracos Vassalos et al., 2002; Walter et al., 2017; Wang et al., 2013; Wang et al., 2020b)	
(Chen and Lo, 2019; Ma et al., 2020; Qiao et al., 2014; Sarshar et al., 2013a, 2013b; Sun et al., 2019; D. Zhang et al., 2017)	IEEE
(Hu and Cai, 2020; Nevalainen et al., 2015; Sarvari et al., 2019)	Taylor & Francis
(Brumley and Koss, 2000; Ditlev Jorgensen and May, 2002; Y. Li et al., 2021; Rutgersson and Tsychkova, 1999)	Royal Institution of Naval Architects
(Hu et al., 2019; Hu and Cai, 2022; Kim et al., 2020; Liu et al., 2021; Liu et al., 2022a)	MDPI
(Cho et al., 2016; Chu et al., 2013; Liou and Chu, 2016)	National Taiwan Ocean University
(Galea et al., 2013; Wang and Wu, 2020a)	OnePetro
(Fang et al., 2022b; Montecchiari et al., 2018)	SAGE
(Ni et al., 2017b; Yuan et al., 2014)	Hindawi
List of publishers with one publication.	
(Finiti, 2021)	University of Huddersfield
(Bellas et al., 2020)	Palmdale, CA: Tech Science Press
(Brown, 2016)	University of Greenwich
(Vilen, 2020)	Aalto University
(Azzi et al., 2011)	Fire and Evacuation Modeling Technical Conference
(Boulougouris and Papanikolaou, 2002)	Proceedings of the 10th International Congress of the International Maritime Association of the Mediterranean
(Brown et al., 2008)	International Conference on Ocean, Offshore, and Arctic Engineering
(Kang et al., 2010)	Marine Technology Society
(Łozowicka, 2010)	Akademia Morska w Szczecinie
(Miyazaki et al., 2004)	Maritime Research Institute, Japan
(A. López Piñeiro et al., 2005)	Spanish Society of Maritime Research
(D. Vassalos et al., 2002)	Safety at Sea and Marine Equipment exhibition (SASMEX)
(Liu and Luo, 2012)	Shanghai Maritime University
(Lozowicka, 2021)	the Public Library of Science
(Na et al., 2019)	Medico Legal Update
(Murayama et al., 2000)	Research Institute of Marine Engineering, Japan
(Zhang et al., 2016)	ORES
(Deere et al., 2006)	International Journal of Maritime Engineering
(Galea et al., 2014b)	State Key Laboratory of Fire Science
(Hu and Cai, 2017)	Atlantis Press
(Luo, 2019)	NHH Norwegian School of Economics
(Deere et al., 2012)	RINA SAFEGUARD Passenger Evacuation Seminar
(Meyer-König et al., 2002)	Gerhard-Mercator-Universität
(Ruponen et al., 2015)	University of Strathclyde
(Ni et al., 2017a)	Gdansk University of Technology

(Vukelic et al., 2021)	Scientific Journals Zeszyty Naukowe of the Maritime University of Szczecin
(Ni et al., 2018)	IOPScience
(Montecchiari et al., 2021)	IOS Press

Appendix B. Journals and conferences

Table B.1. List of journals, conferences, and master/doctoral publications by paper.

Paper	Journal Title
List of journals with a minimum of two publications.	
(Grandison et al., 2017; Ha et al., 2012; Lee et al., 2004; Park et al., 2004; Salem, 2016; Sun et al., 2018a; Wang et al., 2021a; Wu et al., 2018; Q. Xie et al., 2020d, 2020c)	Ocean Engineering
(Azizpour et al., 2022; Fang et al., 2022a; Vanem and Ellis, 2010; Vanem and Skjong, 2006; Wang et al., 2021c; Wang et al., 2020a)	Safety Science
(Cho et al., 2016; Chu et al., 2013; Liou and Chu, 2016)	Journal of Marine Science and Technology
(Sun et al., 2018b; Wang et al., 2021b)	Physica A: Statistical Mechanics and its Applications
(Balakhontceva et al., 2016)	Procedia Computer Science
(Ha et al., 2012; Park et al., 2015)	Computers in Industry
(Fukuchi and Imamura, 2005; Spanos and Papanikolaou, 2014)	Journal of Marine Science and Technology
(Ni et al., 2017b; Yuan et al., 2014)	Mathematical Problems in Engineering
List of conferences with a minimum of two publications.	
(Galea et al., 2014a, 2011, 2003; K V Kostas et al., 2014; Meyer-König et al., 2007; Sun et al., 2018b; Dracos Vassalos et al., 2002)	Pedestrian and Evacuation Dynamics
(Brumley and Koss, 2000; Ditlev Jorgensen and May, 2002)	International Conference on Human Factors in Ship Design and Operation
(Guarin et al., 2014; K V Kostas et al., 2014b)	International Conference on Virtual, Augmented, and Mixed Reality
(Liu et al., 2022b; Wang et al., 2022)	Reliability Engineering & System Safety
(Chen et al., 2016; Katuhara et al., 2003)	Traffic and Granular Flow Conference
List of university publications.	
(Brown, 2016; Finiti, 2021)	Doctoral Dissertation
(Luo, 2019; Vilen, 2020)	Master Thesis
List of journals/conferences with one publication.	
(Kim et al., 2019)	International Journal of Naval Architecture and Ocean Engineering
(Ng et al., 2021)	Annals of Operations Research
(Park et al., 2015)	Procedia Engineering
(Sarshar et al., 2013a)	IEEE Symposium on Computational Intelligence in Dynamic and Uncertain Environments
(Casareale et al., 2017)	Building Simulation
(D. Zhang et al., 2017)	IEEE International Conference on Networking, Sensing, and Control
(Qiao et al., 2014)	IEEE International Conference on Systems, Man and Cybernetics
(Montecchiari et al., 2018)	Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability
(Bellas et al., 2020)	Computer Modeling in Engineering & Sciences
(Liu et al., 2021)	Journal of Marine Science and Engineering
(Sun et al., 2019)	International Conference on Fire Science and Fire Protection Engineering
(Sarvari et al., 2019)	Maritime Policy & Management
(Azzi et al., 2011)	Fire and Evacuation Modeling Technical Conference
(Boulougouris and Papanikolaou, 2002)	Proceedings of the 10th International Congress of the International Maritime Association of the Mediterranean

(Brown et al., 2008)	International Conference on Ocean, Offshore, and Arctic Engineering
(Galea et al., 2013)	Journal of Ship Research
(Kang et al., 2010)	Marine Technology Society Journal
(Klüpfel et al., 2001)	Theory and Practical Issues on CA
(Łozowicka, 2010)	Akademia Morska w Szczecinie
(Miyazaki et al., 2004)	Maritime Research Institute, Japan
(Nevalainen et al., 2015)	Proceedings of Marine Design
(A. López Piñeiro et al., 2005)	Journal of Maritime Research
(D. Vassalos et al., 2002)	Safety at Sea and Marine Equipment Exhibition (SASMEX)
(Rutgersson and Tsychkova, 1999)	Proceedings of RINA Conference on Learning from Marine Incidents
(Liu and Luo, 2012)	Journal of Shanghai Maritime University
(Sun et al., 2020)	International Conference on Big Data Analytics for Cyber-Physical-Systems
(Wang et al., 2020b)	Journal of Shanghai Jiaotong University (Science)
(Chen et al., 2011)	Journal of Marine Science and Application
(Gwynne et al., 2003)	Fire Technology
(Łozowicka, 2005)	International Journal of Automation and Computing
(Couasnon et al., 2019)	International Symposium on Web and Wireless Geographical Information Systems
(Sarshar et al., 2014)	Transactions on Engineering Technologies
(Kwee-Meier et al., 2017)	Advances in Human Aspects of Transportation
(K V Kostas et al., 2014a)	Virtual Realities
(Jasionowski et al., 2011)	Contemporary Ideas on Ship Stability and Capsizing in Waves
(Q. Xie et al., 2020a)	Applied Ocean Research
(Lozowicka, 2021)	Plos One
(Na et al., 2019)	Medico Legal Update
(Walter et al., 2017)	Experimental Brain Research
(Murayama et al., 2000)	Research Institute of Marine Engineering, Japan
(Zhang et al., 2016)	Xitong Gongcheng Lilun yu Shijian/System Engineering Theory and Practice
(Deere et al., 2006)	International Journal of Maritime Engineering
(J. Wang et al., 2013)	China Ocean Engineering
(Sarshar et al., 2013b)	International Conference on Innovative Computing Technology
(Galea et al., 2014b)	Fire Safety Science
(Hu and Cai, 2020)	International Journal of Computers and Applications
(Hu and Cai, 2017)	Advances in Computer Science Research
(Hu et al., 2019)	Symmetry
(Kim et al., 2004)	Computers & Industrial Engineering
(Deere et al., 2012)	RINA SAFEGUARD Passenger Evacuation Seminar
(Yip et al., 2015)	Accident Analysis & Prevention
(Meyer-König et al., 2002)	Gerhard-Mercator-Universität
(Ruponen et al., 2015)	Stability of ships and ocean vehicles
(Wang and Wu, 2020a)	Journal of Ship Production and Design
(Ni et al., 2018)	Journal of Statistical Mechanics: Theory and Experiment
(Ni et al., 2017a)	Polish Maritime Research
(Y. Li et al., 2021)	International Journal of Maritime Engineering
(Montecchiari et al., 2021)	International Shipbuilding Progress
(Chen and Lo, 2019)	International Conference on Fire Science and Fire Protection Engineering

(Yue et al., 2022)	Process Safety and Environmental Protection
(Liu et al., 2022a)	Journal of Marine Science and Engineering
(Kim et al., 2020)	International Journal of Environmental Research and Public Health
(Ma et al., 2020)	IEEE Access

Appendix C. Abbreviations

Table C.1. Journal and conference title abbreviations.

Journal/conference	Abbreviation
Ocean Engineering	Ocean Eng.
International Journal of Naval Architecture and Ocean Engineering	Int. J. Nav. Archit. Ocean Eng.
Annals of Operations Research	Ann. Oper. Res.
Safety Science	Saf. Sci.
Procedia Engineering	Procedia Eng.
IEEE Symposium on Computational Intelligence in Dynamic and Uncertain Environments	IEEE CIDUE
Physica A: Statistical Mechanics and its Applications	Phys. A: Stat. Mech. Appl.
Procedia Computer Science	Procedia Comput. Sci.
Building Simulation	Build. Simul.
Journal of Marine Science and Technology (Taiwan)	JMST
IEEE International Conference on Networking, Sensing, and Control	IEEE ICNSC
IEEE International Conference on Systems, Man and Cybernetics	IEEE SMC
Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability	Proc Inst Mech Eng
Computer Modeling in Engineering & Sciences	Comput Model Eng Sci
Reliability Engineering & System Safety	Reliab. Eng. Syst. Saf.
Journal of Marine Science and Engineering	J. Mar. Sci. Eng.
International Conference on Fire Science and Fire Protection Engineering	ICFSFPE
Maritime Policy & Management	Marit. Policy Manag.
Fire and Evacuation Modeling Technical Conference	FEMTC
International Conference on Ocean, Offshore, and Arctic Engineering	OMAE
Journal of Ship Research	J. Sh. Res.
Marine Technology Society Journal	Mar. Technol. Soc. J.
Journal of Maritime Research	JMR
Mathematical Problems in Engineering	Math. Probl. Eng.
International Conference on Big Data Analytics for Cyber-Physical-Systems	BDCPS
International Conference on Virtual, Augmented, and Mixed Reality	VAMR
Journal of Shanghai Jiaotong University (Science)	J. Shanghai Jiaotong Univ. (Sci.)
Pedestrian and Evacuation Dynamics	PED
Journal of Marine Science and Application	JMSA
Fire Technology	Fire Technol.
International Journal of Automation and Computing	Int. J. Autom. Comput.
Journal of Marine Science and Technology (Springer)	J Mar Sci Technol
International Symposium on Web and Wireless Geographical Information Systems	W2GIS
Transactions on Engineering Technologies	Trans. Eng. Technol.
Advances in Human Aspects of Transportation	AHFE
Traffic and Granular Flow Conference	TGF
Virtual Realities	Virtual Real.
Applied Ocean Research	Appl. Ocean Res.
Computers in Industry	Comput Ind

Plos one	Plos one
Medico Legal Update	Med.-Leg. Update
Experimental Brain Research	Exp. Brain Res.
International Journal of Maritime Engineering	IJME
China Ocean Engineering	China Ocean Eng.
International Conference on Innovative Computing Technology	ICICC
Fire Safety Science	Fire Saf. Sci.
International Journal of Computers and Applications	Int. J. Comput. Appl.
Advances in Computer Science Research	Adv. Comput. Sci. Res.
Symmetry	Symmetry
Computers & Industrial Engineering	Comput Ind Eng
Process Safety and Environmental Protection	Process Saf Environ Prot
Accident Analysis & Prevention	Accid Anal Prev
Journal of Ship Production and Design	J. Ship Prod. Des.
Journal of Statistical Mechanics: Theory and Experiment	JSTAT
Polish Maritime Research	Pol. Marit. Res.
International Journal of Maritime Engineering	IJME
International Shipbuilding Progress	Int. Shipbuild. Prog
International Conference on Fire Science and Fire Protection Engineering	ICFSFPE
International journal of environmental research and public health	Int. J. Environ. Res. Public Health
Journal of Statistical Mechanics: Theory and Experiment	J. Stat. Mech. Theory Exp.
Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment	P I MECH ENG M-J ENG
Journal of Marine Science and Engineering	J. Mar. Sci. Eng.
Applied Sciences	Appl. Sci

Appendix D. Modeling approach

Table D.1. List of publications categorized by modeling approach analytical category.

Paper	Modeling Approach
(Azizpour et al., 2022; Azzi et al., 2011; Balakhontceva et al., 2016; Bellas et al., 2020; Boulougouris and Papanikolaou, 2002; Brumley and Koss, 2000; Chen and Lo, 2019; Cho et al., 2016; Couasnon et al., 2019; Deere et al., 2006; Ditlev Jorgensen and May, 2002; Fang et al., 2022b, 2022a; Fukuchi and Imamura, 2005; Galea et al., 2013, 2003; Ha et al., 2012; Hu and Cai, 2022, 2017; Katuhara et al., 2003; Kim et al., 2019, 2020; Klüpfel et al., 2001; K V Kostas et al., 2014a; Lee et al., 2022; Li et al., 2021; Liou and Chu, 2016; Liu et al., 2022b; Łozowicka, 2010; Meyer-König et al., 2002; Montecchiari et al., 2018; Ni et al., 2018, 2017b, 2017a; Park et al., 2004; Piñeiro et al., 2005; Roh and Ha, 2013; Ruponen et al., 2015; Rutgersson and Tsychkova, 1999; Salem, 2016; Sarshar et al., 2014, 2013a; Spanos and Papanikolaou, 2014; Sun et al., 2020; Vanem and Skjong, 2006; Vassalos et al., 2002; Vassalos et al., 2002; Vilen, 2020; Wang et al., 2013, 2014, 2022a; Wang et al., 2020a; Wu et al., 2018; Xie et al., 2020b; Yuan et al., 2014; Zhang et al., 2017, 2016)	Simulation
(Bles et al., 2001; Deere et al., 2012; Galea et al., 2014b, 2014a, 2011; Grandison et al., 2017; K V Kostas et al., 2014; Kwee-Meier et al., 2017; Lee et al., 2004; Meyer-König et al., 2007; Na et al., 2019; Park et al., 2015; Sun et al., 2019, 2018b, 2018a; Walter et al., 2017; Wang and Wu, 2020a; Wang et al., 2021a, 2021b; Yip et al., 2015)	Experimental
(Brown, 2016; Brown et al., 2008; Casareale et al., 2017; Chen et al., 2016, 2011; Gwynne et al., 2003; Hu et al., 2019; Hu and Cai, 2020; Jasionowski et al., 2011; Kang et al., 2010; Luo, 2019; Ma et al., 2020; Miyazaki et al., 2004; Montecchiari et al., 2021; Murayama et al., 2000; Qiao et al., 2014; Sarshar et al., 2013b; Sarvari et al., 2019; Q. Xie et al., 2020a)	Hybrid (Simulation/Mathematical, Simulation/Experimental, Simulation/Questionnaire, and Experimental/Questionnaire)
(Chu et al., 2013; K V Kostas et al., 2014b; Liu and Luo, 2012; Liu et al., 2021; Lozowicka, 2021; Łozowicka, 2005; Ng et al., 2021; Xie et al., 2020c)	Mathematical
(Guarin et al., 2014; Kim et al., 2004; Nevalainen et al., 2015; Vanem and Ellis, 2010; Vukelic et al., 2021)	Analytical
(Finiti, 2021; Wang et al., 2021c; Wang et al., 2020c)	Questionnaire and Interview

Appendix E. Traffic assignment formulation

Table 16. List of publications categorized by traffic assignment formulation analytical category.

Paper	Model type
User equilibrium formulation	
(Azizpour et al., 2022; Bellas et al., 2020; Bles et al., 2001; Brown et al., 2008; Brumley and Koss, 2000; Casareale et al., 2017; Chen et al., 2016; Cho et al., 2016; Chu et al., 2013; Couasnon et al., 2019; Deere et al., 2006, 2012; Ditlev Jorgensen and May, 2002; Fang et al., 2022a, 2022b; Finiti, 2021; Fukuchi and Imamura, 2005; Galea et al., 2014a, 2014b, 2013; Ha et al., 2012; Hu et al., 2019; Hu and Cai, 2022, 2020; Kang et al., 2010; Katuhara et al., 2003; Kim et al., 2019, 2020; K V Kostas et al., 2014a; Kwee-Meier et al., 2017; Lee et al., 2004, 2022; Liou and Chu, 2016; Liu et al., 2021; Liu et al., 2022a; Liu et al., 2022b; Meyer-König et al., 2002; Miyazaki et al., 2004; Montecchiari et al., 2021; Murayama et al., 2000; Na et al., 2019; Ng et al., 2021; Ni et al., 2018; Park et al., 2015; Qiao et al., 2014; Roh and Ha, 2013; Rutgersson and Tsychkova, 1999; Sarshar et al., 2013b, 2013a; Sun et al., 2020, 2019, 2018a; Walter et al., 2017; Wang et al., 2020a; Wang et al., 2022, 2021a, 2021c; X. Wang et al., 2020; Wu et al., 2018; Yue et al., 2022; Zhang et al., 2017)	Microscopic
(Azzi et al., 2011; Balakhontceva et al., 2016, 2015; Brown, 2016; Chen et al., 2011; Gwynne et al., 2003; Hu and Cai, 2017; Klüpfel et al., 2001; Li et al., 2021; Montecchiari et al., 2018; Ni et al., 2017b, 2017a; Sarshar et al., 2014; Sarvari et al., 2019; Sun et al., 2018b; Vassalos et al., 2002; Vilen, 2020; Wang et al., 2014, 2021b; Yuan et al., 2014)	Microscopic and Macroscopic
System-optimal formulation	
(Chen and Lo, 2019; Galea et al., 2011, 2003; Grandison et al., 2017; Jasionowski et al., 2011; Lozowicka, 2021; Łozowicka, 2005; Luo, 2019; Ma et al., 2020; Park et al., 2004; Ruponen et al., 2015; Salem, 2016; Spanos and Papanikolaou, 2014; Vanem and Skjong, 2006; Wang and Wu, 2020a; Wang et al., 2013; Xie et al., 2020a, 2020c, 2020b)	Macroscopic
Not available	
(Boulougouris and Papanikolaou, 2002; Guarin et al., 2014; Kim et al., 2004; K V Kostas et al., 2014; K V Kostas et al., 2014b; Liu and Luo, 2012; Łozowicka, 2010; Meyer-König et al., 2007; Nevalainen et al., 2015; Piñeiro et al., 2005; Vanem and Ellis, 2010; Vassalos et al., 2002; Yip et al., 2015; Zhang et al., 2016)(Vukelic et al., 2021)	NA

Appendix F. Model parameter

Table F.1. List of publications categorized by model parameter analytical category.

Paper	Parameter
(Q. Xie et al., 2020d)	• Fire (heat, smoke, and toxic gases) and • ship layout (stairs, assembly stations, and different functional zones including seating zone, general area, bar zone, locker zone, restaurant zone, and retail zone)
(Azizpour et al., 2022)	• Ship stability (heeling angle (0, 10, 15, and 20 degrees), • passenger age (18-72), • passenger gender (male and female), • passenger height (154-195), • passenger weight (48-123), • other forces (thermal protective immersion suits)
(Fang et al., 2022a)	• Ship stability (trim angles from −30 to 30 degrees and heeling angles from 0 to 30 degrees)
(Wang et al., 2022)	• Passenger age, • passenger gender, • passenger physical condition, • exit and staircase layout
(Kim et al., 2019)	• Ship stability (heeling angle (0,30,52.2 degrees)), • passenger load (human density) • passenger gender (crew, male, female), and • crowd behavior (counter flow)
(Liu et al., 2022b)	• Ship layout (passage, exit, and number of corners in a deck)
(Fang et al., 2022b)	• Ship stability (inclination angles (0,5,10,15,20 degree), • passenger gender (male, female), • passenger age

(Yue et al., 2022)	• Passenger gender, • passenger age, • passenger size, • passenger mass, • other factors (neighborhood radius, information value, information threshold, information attenuation ratio, location in a two-dimensional (2D) environmental network, physical quality, and psychological quality)
(Hu and Cai, 2022)	• Passenger age, • passenger gender
(Lee et al., 2022)	• Passenger age, • passenger gender, • passenger physical condition, • ship layout, • ship stability (heel and trim angle (0-30 degree))
(Ng et al., 2021)	• Passenger age (children, women, and seniors)
(Wang et al., 2021b)	• Ship stability (heeling angle of 15–20 degrees), • ship motion (ship berthing and sailing operations), • passenger age (25.8+-10,5), • passenger height (175.3 cm ± 6.6 cm), • passenger weight (71.3 kg ± 8.6 kg.), and • passenger physical condition
(Ha et al., 2012)	• Ship layout (corridors, staircase), • crowd behavior (counter flow), and • passenger behavior
(Finiti, 2021)	• Passenger age, • passenger gender, and • passenger behavior (individually based on companions and experience)
(Vanem and Skjong, 2006)	• Fire (starting point of fire within each fire zone), • ship stability (list direction), • ship layout, and • passenger and crew load
(Wang et al., 2014)	• Ship layout (staircase and restaurant)
(Sun et al., 2018a)	• Ship stability (heeling (between -15 and +15 degrees), trimming (-20 and 20 degrees), and both), • ship layout (corridors (10m1.8m2.2m)), • passenger age (24.6+-1.45), • passenger gender, • passenger weight (60.5+-9.1), and • passenger height (167.7+-6.4cm)
(Sarshar et al., 2013a)	• Fire (fire location, fire condition (controllable/uncontrollable), • ship stability (trim and heel) • passenger age, • passenger gender, and • passenger physical condition
(Sun et al., 2018b)	• Ship stability (trim and heeling), • ship layout (corridors (10m(Length)*1.8m(Width)*2.2m(Height))), • passenger age (23-26), • passenger gender, • passenger weight (45-72 kg), and • passenger height (157-185cm)
(Balakhontceva et al., 2015)	• Passenger age, • passenger gender, and • passenger physical condition, and • other external forces (intensity of waves (5, 7, 9 sea forces), rate of sailing (0, 5, 15, 25 knots))
(Casareale et al., 2017)	• Passenger behavior (familiarity with emergencies, such as disaster and drills experience, seek for emergency procedures information (e.g., emergency plan, emergency signs, and path escape routes), interacting with unknown people (e.g., social attachment), leaving immediately after the alarm or ignore it (risk denial))

(Chu et al., 2013)	• Ship layout (corridors, doorways, and stairs)
(D. Zhang et al., 2017)	• Ship motion (rolling), • passenger age (21-40), • passenger gender, • passenger height (160-187 cm), • passenger weight (50-95 kg), and • other external forces (wind-wave dynamics)
(Wu et al., 2018)	• Fire (smoke and temperature (fire growth rate is 0.0029,0.0117,0.0469,0.1846 kw/s^2) and • ship layout (corridors (initial speed is 1.2 m/s), stair descent (1.0 m/s), stair ascent (0.8 m/s))
(Qiao et al., 2014)	• Ship layout (stairs, corridors, and doorways), • passenger age (23-26), • passenger gender, • passenger height (157-185cm), and • passenger weight (45-72 kg),
(Liou and Chu, 2016)	• Ship layout (corridors and stairway), • passenger behavior (walking speed), • passenger age, and • passenger gender
(Montecchiari et al., 2018)	• Crow behavior (counter flow)
(Bellas et al., 2020)	• Ship layout (the location of corridors, doors, stairways, and ladders along with the ship), • passenger age, and • passenger gender • passenger behavior (walking speed)
(Brown, 2016)	• Fire (heat, smoke, toxic products), • ship stability (heel and trim), • passenger age, • passenger gender, • passenger physical condition (agility and mobility impairment), • passenger behavior (experience and walking speed)
(Liu et al., 2021)	• Crowd behavior (crowd density) and • passenger behavior (passenger walking speed)
(Vilen, 2020)	• Ship layout (the topology and geometry of the ship), • passenger age, and • passenger gender
(Sun et al., 2019)	• Passenger stability (heeling (-15 to +15 degrees), trim (-20 to +20 degrees), • passenger age (21-26), • passenger height (157-173 cm), and • passenger weight (45-78)
(Sarvari et al., 2019)	• Ship stability (trim and heel -20 to +20 degrees)
(Azzi et al., 2011)	• NA
(Cho et al., 2016)	• Crowd behavior (flock behavior, emergency behavior (counter flow), and other is a leader following behavior), • passenger behavior (and individual behavior (body shape, walking speed, walking direction, and rotation of each passenger), • ship layout (corridor and staircase), • passenger age (around 30 to older than 50), and • passenger gender
(Boulougouris and Papanikolaou, 2002)	• Passenger age (children, adults, and elderly)
(Brown et al., 2008)	• Passenger age, • passenger gender, • passenger height, • passenger weight
(Brumley and Koss, 2000)	• Ship layout (ship corridors and on stairs), • passenger age, • passenger gender, and • passenger physical condition (degree of handicap)
(Galea et al., 2013)	• NA
(Ditlev Jorgensen and May, 2002)	• Ship layout,

	• passenger behavior (non-compliance with instructions), and • passenger physical condition (disabled, asthmatic, heart trouble, and hearing impaired)
(Kang et al., 2010)	• NA
(Klüpfel et al., 2001)	• Crowd behavior (crowd motion)
(Łozowicka, 2010)	• Crowd behavior (counter flow)
(Miyazaki et al., 2004)	• Passenger gender, • passenger physical condition (disabled people and wheelchair), • passenger behavior (kind mental state, (non-)competitive spirits or mean mental state)
(Nevalainen et al., 2015)	• Ship layout (spaces such as staircases, objects such as escape routes), • passenger behavior (perception, decision making, passenger activities)
(Piñeiro et al., 2005)	• Passenger age, • passenger gender, • passenger behavior (walking speed), • passenger and crew load
(Vanem and Ellis, 2010)	• NA
(Vassalos et al., 2002)	• Passenger behavior
(Rutgersson and Tsychkova, 1999)	• Passenger behavior (Human factors) and • other external forces (environment factors, guidance systems, arrangements onboard, and technical equipment)
(Ni et al., 2017b)	• Ship layout (interior layout of passenger ship cabins (tables and stools) and obstacles) • passenger behavior (interaction forces between the individual and crew)
(Liu and Luo, 2012)	• NA
(Sun et al., 2020)	• Passenger age (30-50)
(Guarin et al., 2014)	• Other external forces (sea State, time of day) • human and organizational factors and crew emergency)
(Wang et al., 2020b)	• NA
(Galea et al., 2014a)	• NA
(Chen et al., 2011)	• NA
(Gwynne et al., 2003)	• Ship stability (tilting (20 degrees left), listing (20 degrees right)), • crowd behavior (contra-flow situation) • passenger physical condition
(Łozowicka, 2005)	• NA
(Spanos and Papanikolaou, 2014)	• Ship layout (hull breach and ship's loading)
(Fukuchi and Imamura, 2005)	• Fire (smoke and fire) • ship layout (enclosure layout, the number and type of exits, corridor widths, and travel distances) • passenger age (children, youth, elderly) • passenger behavior (evacuation movements and the reaction of emotions and action)
(Couasnon et al., 2019)	• Passenger behavior (crew members, disoriented passengers, and "normal" passengers)
(Galea et al., 2011)	• Passenger age (exclude children under the age of 12)
(Sarshar et al., 2014)	• Ship layout (the structure of the ship), • passenger age • passenger gender, • passenger behavior (panic)
(Kwee-Meier et al., 2017)	• Passenger age (mean age = 24.31), • ship stability (a treadmill at 0°, 7°, and 14° with and without applied mental and emotional stressors, i.e., time limit and acoustic background noise)
(Katuhara et al., 2003)	• Passenger behavior (getting information using a sense of sight, hearing, and smell), Influence of Imaginary • distances, and walking speed) • passenger age (an adult, a child, an elderly), • passenger physical condition (disabled persons)
(K V Kostas et al., 2014b)	• NA

(K V Kostas et al., 2014a)	• Fire (with and without a concurrent fire event), • ship motion (and 90-degree ship heading (beam seas)) • crow behavior (with and without crew assistance) • other external forces (No Waves, 4 m significant wave height, 11 s peak period)
(Jasionowski et al., 2011)	• Other external forces (wave (length, amplitude, elevation), flooding), • ship stability (heel and trim), and • ship motion (water accumulation and heave motion)
(K V Kostas et al., 2014)	• Ship motion (with and without ship motions), • crowd behavior
(Q. Xie et al., 2020a)	• NA
(Balakhontceva et al., 2016)	• Ship motion (ship roll and pitch angles under the influence of sea waves), • passenger age, • passenger gender, • passenger physical condition, and • other external forces (sea waves dynamics)
(Park et al., 2015)	• Ship layout (corridors, staircase, ship layout, (11 tests specified in IMO MSC/Circ. 1238 were performed), • passenger age (age (younger than 30 and older than 50))
(Grandison et al., 2017)	• NA
(Roh and Ha, 2013)	• Ship layout (corridors, staircase, ship layout, (11 tests specified in IMO MSC/Circ. 1238 were performed), • passenger age (age (younger than 30 and older than 50)), • crowd behavior (counterflow-avoiding behavior), and • passenger behavior
(Lozowicka, 2021)	• NA
(Wang et al., 2021a)	• Ship motions (rolling (0,1,3,5,9) & pitch (less than 1)), • ship layout (flat terrains and staircases, corridors (L7.4m, W5.4m, H1.2m)), • passenger age (20-53), • passenger weight (55-96kg), and • passenger gender
(Bles et al., 2001)	• Ship motion (dynamic ship motion) • ship layout (stairs and corridors), • ship stability (ship listing), and • passenger age (age (18 - 83))
(Lee et al., 2004)	• Ship motion (roll angle between 3 and 4 degrees and pitch motions), • passenger behavior, • crowd behavior, • ship layout (corridors (10m*1.2m*1.9m)), and • ship stability (trim angle between -20 and +20 and heel angle between 0 and 20)
(Meyer-König et al., 2007)	• Ship stability (heel (0-15 and 15- 35 degrees)) and • ship motion (roll motion)
(Na et al., 2019)	• Ship motion (roll angular magnitude (1 degree)), • ship stability(berthing), • passenger age, and • passenger gender
(Walter et al., 2017)	• Ship motion (roll and pitch), • passenger age (20-72), and • passenger gender
(Wang et al., 2021c)	• Passenger age (16-61 and above), • passenger gender, • passenger behavior (educational level, mobility level, experience on board), • crowd behavior (family group experience in evacuation education)
(Wang et al., 2020c)	• Passenger age (16-61 and above), • passenger gender, • passenger behavior (educational level, mobility level, experience on board),

	• crowd behavior (family group experience in evacuation education)
(Q. Xie et al., 2020c)	• Passenger load (initial passenger density) and • ship layout (stairs, different functional zones in this passenger ship including bar, general area, retail, seating, restaurant, and locker zone)
(Murayama et al., 2000)	• Ship stability (fore and aft inclination (+20 to -20 degrees)) and • ship motion (roll and pitch cycle (10 degrees and for 5 and 10 seconds), • passenger height (1.56 to 1.81 cm), and • passenger weight (51 to 90 kg)
(Zhang et al., 2016)	• Ship motion (different rolling angle) and • other external forces (wave scales)
(Chen et al., 2016)	• Ship motion (water motion)
(Deere et al., 2006)	• NA
(Vassalos et al., 2002)	• Ship motions
(J. Wang et al., 2013)	• Fire (oxygen concentration, smoker layer height, and temperature)
(Sarshar et al., 2013b)	• Fire (fire location, hat, and smoke exposure), • passenger age, • passenger gender, and • passenger physical condition
(Galea et al., 2014b)	• NA
(Hu and Cai, 2020)	• Ship layout (cabins)
(Yuan et al., 2014)	• Ship stability (heel (0 to 35 degrees) and trim (-20 to 20 degrees) • ship layout (door sizes (0-8m))
(Hu and Cai, 2017)	• Crowd behavior (the attraction of the mainstream crowd and the repulsion impact and static and dynamic floor fields)
(Luo, 2019)	• Ship layout (cabin, a hall, a doorway, and an intersection of corridors), • passenger load, and • passenger behavior
(Hu et al., 2019)	• Ship stability (listing, trimming (-30 to +40 degrees), and heeling), • passenger age (30 and younger to 50 and older), • passenger gender, • passenger behavior (walking speed), and • passenger physical condition (mobility-impaired people)
(Galea et al., 2003)	• Fire (smoke)
(Kim et al., 2004)	• Ship stability (listing), • ship motion, • crowd behavior (crowd density), • passenger behavior (cultural differences and behavior under panic), • passenger age, and • passenger gender
(Park et al., 2004)	• Ship motion, • ship layout (exit doors width), and • passenger behavior
(Deere et al., 2012)	• NA
(Salem, 2016)	• Fire (fire toxicity, heat, and smoke) and • ship layout (stairwell, corridor, and cabin)
(Yip et al., 2015)	• NA
(Meyer-König et al., 2002)	• Passenger age, • passenger gender, and • passenger behavior (the patience and stamina)
(Ruponen et al., 2015)	• Ship stability (heeling angle (-5 to 20)),
(Wang and Wu, 2020a)	• Ship layout (stairs, corridors, and doors)
(Ni et al., 2018)	• Crowd behavior (counter flow)
(Ni et al., 2017a)	• Crowd behavior (crowd movement), • passenger behavior (agent (perception, decision-making, walking speed, and locomotion)), • passenger gender (male and female), and • passenger age

(Y. Li et al., 2021)	• Ship layout (stairs, corridors, and doors) and • passenger behavior (layout familiarity and social relationship)
(Montecchiari et al., 2021)	• Crowd behavior (counter flow), • passenger age, and • passenger gender
(Chen and Lo, 2019)	• Ship stability (trim angle (-0.38,0, +0.38 degrees), rolling rate, and Influence of fore-aft direction) and • ship motion (pitching rate and yaw rate, and sway)
(Kim et al., 2020)	• Ship stability (heeling angle (0, 5, 10, 15, 20, 25, and 30 degrees), • passenger age, and • passenger gender
(Ma et al., 2020)	• Ship stability (heeling angle and trim angle) and • passenger behavior (passenger walking speed and reduction factor of the walking speed)

Appendix G. Hazard type

Table G.1. List of publications categorized by hazard type analytical category.

Paper	Hazard Type
(Azzi et al., 2011; Bellas et al., 2020; Brown, 2016; Fukuchi and Imamura, 2005; Galea et al., 2003; K V Kostas et al., 2014a; Liu and Luo, 2012; Liu et al., 2022a; Łozowicka, 2010; Luo, 2019; Miyazaki et al., 2004; Salem, 2016; Sarshar et al., 2014, 2013a, 2013b; Sarvari et al., 2019; Wang et al., 2013; Wu et al., 2018; Xie et al., 2020b, 2020c, 2020a)	Fire
(Casareale et al., 2017; Finiti, 2021; Kim et al., 2019, 2020; Ma et al., 2020; Piñeiro et al., 2005)	Foundered (capsizing and sinking)
(Jasionowski et al., 2011; Ruponen et al., 2015; Spanos and Papanikolaou, 2014)	Flooding
(Balakhontceva et al., 2016, 2015; Zhang et al., 2016)	Storm
(Vanem and Skjong, 2006)	Fire and sinking
(Vassalos et al., 2002)	Fire and flooding
(Yip et al., 2015)	Fire, grounding, flooding, and sinking
(Azizpour et al., 2022; Bles et al., 2001; Boulougouris and Papanikolaou, 2002; Brown et al., 2008; Brumley and Koss, 2000; Chen et al., 2016, 2011; Chen and Lo, 2019; Cho et al., 2016; Chu et al., 2013; Couasnon et al., 2019; Deere et al., 2006, 2012; Ditlev Jorgensen and May, 2002; Fang et al., 2022b, 2022a; Galea et al., 2014a, 2014b, 2013, 2011; Grandison et al., 2017; Guarin et al., 2014; Gwynne et al., 2003; Ha et al., 2012; Hu et al., 2019; Hu and Cai, 2022, 2020, 2017; Kang et al., 2010; Katuhara et al., 2003; Kim et al., 2004; Klüpfel et al., 2001; K V Kostas et al., 2014; K V Kostas et al., 2014b; Kwee-Meier et al., 2017; Lee et al., 2004, 2022; Li et al., 2021; Liou and Chu, 2016; Liu et al., 2021; Liu et al., 2022b; Lozowicka, 2021; Łozowicka, 2005; Meyer-König et al., 2007, 2002; Montecchiari et al., 2021, 2018; Murayama et al., 2000; Na et al., 2019; Nevalainen et al., 2015; Ng et al., 2021; Ni et al., 2018, 2017a, 2017b; Park et al., 2004, 2015; Qiao et al., 2014; Roh and Ha, 2013; Rutgersson and Tsychkova, 1999; Sun et al., 2020, 2019, 2018a, 2018b; Vanem and Ellis, 2010; Vassalos et al., 2002; Vilen, 2020; Vukelic et al., 2021; Walter et al., 2017; Wang and Wu, 2020; Wang et al., 2020a; Wang et al., 2014, 2022, 2021c, 2021a, 2021b; Wang et al., 2020b; Yuan et al., 2014; Yue et al., 2022; Zhang et al., 2017)	NA

Appendix H. Solution method

Table H.1. List of publications categorized by solution method analytical category.

Paper	Objective
Velocity-based Model	
(Kim et al., 2019)	Analyzing the influence of heel angle on passenger walking speed during the sinking
(Vilen, 2020)	Calculating reaction time, travel time, congestion time, and completion time
(Sun et al., 2019)	Calculating the correlation between passenger walking speed and gait parameters of individuals on board
(Sarvari et al., 2019)	Designing real-time decision support for estimating evacuation time and the death toll
(Azzi et al., 2011)	Evacuation time minimization
(Cho et al., 2016)	Passenger behavior analysis during ship evacuation
(Boulougouris and Papanikolaou, 2002)	Route finding

(Brown et al., 2008)	Abandonment of passenger vessels with untrained and ambulatory subjects	
(Sun et al., 2018a)	Analyzing the influence of heel/trim angle on passenger walking speed during ship evacuation	
(Bellas et al., 2020)	Evacuation time minimization	
(Brown, 2016)	Data production, human performance understanding, and passenger response time calculation	
(Galea et al., 2013)	Finding passenger response times, starting locations, end locations, and arrival times in the assembly stations	
(Vassalos et al., 2002)	Calculating the cumulative probability distribution (CDF) of evacuation time under uncertainties regarding human behavior	
(Sun et al., 2020)	Determining the number of passengers assembled	
(Guarin et al., 2014)	Developing a pedestrian dynamics simulation tool	
(Galea et al., 2014a)	Determining response time, starting locations, arrival time at the designated assembly stations, and the paths taken	
(K V Kostas et al., 2014b)	Description of the enhanced crowd modeling approaches in VELOS	
(K V Kostas et al., 2014a)	Description of VELOS' components and functionalities	
(Deere et al., 2006)	Passenger response time calculation	
(Vassalos et al., 2002)	Passenger behavior and movement analysis	
(Galea et al., 2014b)	Data validation related to response times, starting locations, end locations, and arrival times in the assembly stations	
(Galea et al., 2003)	Assembly time determination	
(K V Kostas et al., 2014)	Analyzing the effect of ship motions on passengers and/or crew movements	
(Kim et al., 2004)	Meeting requirements of IMO and current research works for evacuation from the ship	
(Park et al., 2004)	Distance walking time determination	
(Gwynne et al., 2003)	Number of evacuees calculation, evacuation time minimization, and data collection	
Cell-based Model		
(Ha et al., 2012)	Passenger behavior understanding	
(Klüpfel et al., 2001)	Crowd motion description	
(A. López Piñeiro et al., 2005)	Conceptual design, evacuation models during ship emergency	
(Hu and Cai, 2020)	Evacuation time minimization	
(Hu and Cai, 2017)	Evacuation time minimization	
(Meyer-König et al., 2007)	Analyzing the influence of ship motion on passenger walking speed	
(Hu et al., 2019)	Evacuation time minimization	
(Wang et al., 2020b)	Path planning of passenger ships	
(Chen et al., 2011)	Continuity of the passengers' track and evacuation time steps	
(Meyer-König et al., 2002)	Pedestrians' movements analysis	
(Roh and Ha, 2013)	Evacuation time minimization	
Social Force-based Model		
(Ni et al., 2017b)	Evacuation time minimization	
(Fang et al., 2022a)	Pedestrians' movements analysis	
(Fang et al., 2022b)	Evacuation time calculation in the presence of inclination angle	
(Balakhontceva et al., 2016)	Estimating evacuation time under environmental conditions	
(Chen et al., 2016)	Analyzing the effect of ship swaying on pedestrian evacuation efficiency	
(Ni et al., 2018)	Life jacket's location determination	
(Ni et al., 2017a)	Agent's target and shortest path determination	
(Balakhontceva et al., 2015)	Estimating evacuation time under ship motions	
(Montecchiari et al., 2021)	Real-time human participation implementation using virtual reality	
Acceleration-based Model		
(Casareale et al., 2017)	Risk perception analysis, passenger behavior analysis, and finding the similarities between building and cruises evacuation processes	
(D. Zhang et al., 2017)	Human behavior under different ship rolling angles, the data on adjustment actions, walking pauses, and the influence of rolling angle on walking speed.	
(Montecchiari et al., 2018)	Testing real-time people participation through immersive virtual reality during ship evacuation	
(Zhang et al., 2016)	Analyzing the impact of adjustment action, pause phenomenon, and linear velocity on pedestrian walking speed	
Other Techniques		
(Q. Xie et al., 2020d)	Passenger Response Time Calculation under ship Fires	PC expansion and GA

(Y. Li et al., 2021)	Route choice	Agent-based modeling technique
(Azizpour et al., 2022)	Assessing the impact of survival suit on passenger walking speeds	Regression analysis
(Yue et al., 2022)	Evaluation of passenger evacuation capacity	AnyLogic software
(Liu et al., 2022a)	Evacuation time minimization	PyroSim software
(Wang et al., 2022)	Assessing the effects of the passenger population composition on evacuation time	FDS + EVAC
(Liu et al., 2022b)	Realizing spatial modeling of the spatial-temporal characteristics of evacuation	Geographic information system
(Hu and Cai, 2022)	Analysis of the passenger characteristics	AnyLogic software
(Lee et al., 2022)	Passenger walking speed calculation and analysis	UNITY engine
(Vukelic et al., 2021)	Assessing the possibility of adopting new technologies to the human evacuation process	Literature analysis method
(Ng et al., 2021)	Evacuation time minimization	Dynamic programming
(Wang et al., 2021b)	Analyzing the influence of ship motion on passenger walking speed	Collecting data with a camera
(Finiti, 2021)	Data production and understanding of human performance	Behavioral sequence Analysis, talk-through, and comparison methods
(Vanem and Skjong, 2006)	Evacuation time minimization and number of fatalities calculation	Risk-based technique
(Wang et al., 2014)	Finding the number of the assembled passengers	An agent-based microscopic evacuation model—city flow-M
(Sarshar et al., 2013a)	Evacuation time minimization under ship fire	Simulation tool
(Sun et al., 2018b)	Analyzing the influence of heel/trim angle on passenger walking speed during ship evacuation (athwartship and fore-aft walking)	Electrical monitoring system with four cameras (AVI format, 25 fps)
(Chu et al., 2013)	finding Evacuation route, travel distance, the number of people moving from node i to node j	Mathematical tool
(Wu et al., 2018)	ASET and RSET calculation	Simulation tool
(Qiao et al., 2014)	Finding optimum evacuation route	Simulation tool
(Liou and Chu, 2016)	Evacuation time minimization ((1) walking speed, (2) the number of cadets turning to the left or right at T junctions, and (3) the number of cadets moving forward or aft in the corridors.)	Developed program
(Liu et al., 2021)	Evacuation time minimization and Developing Evacuation route planning	Improved ant colony system and flow method-based cardinal number
(Brumley and Koss, 2000)	Observations on passenger walking speed in ship corridors and on stairs	Simulation tool
(Ditlev Jorgensen and May, 2002)	Analyzing the attitudes and behavior of passengers about wayfinding, reactions to alarms, effects of “group binding,” and non-compliance with instructions on assembly time	Simulation tool
(Kang et al., 2010)	Real-time location recognition and escape route determination	Simulation tool
(Łozowicka, 2010)	Opposite flow analysis	GA
(Miyazaki et al., 2004)	Estimating Evacuation time and optimal evacuation routes	Video camera for collecting data
(Nevalainen et al., 2015)	Human-environment interaction investigation (Source of stimuli, human behavior, Spatial environment, social environment)	NA
(Vanem and Ellis, 2010)	Evaluation of a Monitoring System according to RFID technology in terms of the cost-effectiveness for passenger ships	Risk-based
(Rutgersson and Tsychkova, 1999)	Simulate the mustering operation	NA
(Liu and Luo, 2012)	Evacuation routes determination	Mathematical tool
(Łozowicka, 2005)	Finding evacuation time as a function of the initial distribution of passengers and Evacuation routes	GA
(Spanos and Papanikolaou, 2014)	Estimation of the probability to capsize	MC method
(Fukuchi and Imamura, 2005)	Analyzing smoke diffusion state, evacuation movements, and risk index analysis under ship fires	Analytical model
(Couasnon et al., 2019)	Developing an evacuation simulation model	Mathematical tool
(Galea et al., 2011)	Determining response time, starting locations, arrival time at the designated assembly stations, and the paths taken	31 Infra-Red beacons
(Sarshar et al., 2014)	Congestion prediction	Simulation tool

(Kwee-Meier et al., 2017)	Analyzing the influence of physical demands on escape routes, i.e., uphill grades, and mental and emotional stress influence decision-making in terms of decision times?	Analysis of variance
(Katuhara et al., 2003)	Evacuation route selection and evacuation time minimization	Twenty video cameras
(Jasionowski et al., 2011)	Predicting ship survival time	Envelope process technique
(Q. Xie et al., 2020a)	Analysis of evacuation time, travel time, and safety factor	PC expansion
(Park et al., 2015)	Evacuation time minimization	Simulation tool
(Couasnon et al., 2019)	Developing an evacuation simulation model	Mathematical tool
(Grandison et al., 2017)	Determining the confidence interval of evacuation time	Binomial-distribution technique
(Lozowicka, 2021)	Analyzing the arrangement of evacuation routes, and evacuation time minimization	GA
(Wang et al., 2021a)	Analyzing the influence of ship rolling on passenger walking speed	Video camera for collecting data
(Bles et al., 2001)	Analyzing the influence of ship motion on passenger walking speed	TNO ship motion simulator
(Lee et al., 2004)	Passenger walking speed analysis	Camera and ship motion measuring for collecting data
(Na et al., 2019)	Passenger walking speed analysis	CCTV cameras for collecting data
(Walter et al., 2017)	Passenger walking speed analysis in athwart and fore-aft directions	Video camera for collecting data
(Wang et al., 2021c)	Illustrating the status of ship passengers' safety awareness, the perception of Evacuation wayfinding tools, and the demographic differences regarding safety awareness and perception.	Regression model
(Wang et al., 2020c)	Passenger behavior according to demographic differences during the human evacuation	Regression model
(Q. Xie et al., 2020c)	Travel time determination under ship fires	PC expansion
(Murayama et al., 2000)	Determining assembly time and passenger walking speed	27 Video cameras for collecting data
(J. Wang et al., 2013)	Uncertainty analysis for ASET under ship fire	MC method
(Sarshar et al., 2013b)	Panic quantification and modeling	Simulation tool
(Yuan et al., 2014)	Evacuation time minimization	Mathematical tool
(Deere et al., 2012)	Data collection related to response times, Starting locations, end locations, and arrival times in the assembly stations	Infra-red and video cameras
(Salem, 2016)	ASET calculation	MC method
(Yip et al., 2015)	Determinants of the crew and passenger injuries in passenger vessel accidents	Regression model
(Ruponen et al., 2015)	Assessment of the survivability of the people onboard, evaluation of the survivability of the people onboard, breach detection	124 level sensors for collecting data
(Wang and Wu, 2020a)	Total evacuation time and congestion points determination	NA
(Chen and Lo, 2019)	Determining pedestrian movement dynamics subject to ship motion	NA
(Kim et al., 2020)	Analyzing the occupants' moving speeds according to the inclination of the ship, and evacuation time minimization	Mathematical tool
(Ma et al., 2020)	Determining path length, user escape time, navigation success ratio, and minimum distance to hazardous regions	26 sensors for collecting data, and ANT (a deadline-aware adaptive emergency navigation strategy)

Appendix I. Evacuation tools

Table I.1 Evacuation simulation tools

Name	Year	Field	Space representation	Purpose	Reference
Simulex	1995	• Maritime, • Civil Engineering	• Discrete	• Evacuation time estimation • Calculation of individuals' walking speed	(Thompson and Marchant, 1995)
EVAC	1999	• Maritime	• Continuous	• Simulation of mustering operation	(Rutgersson and Tsychkova, 1999)
AnyLogic	2000	• A broad range, including maritime	• Hybrid	• Combined discrete-continuous simulation,	(AnyLogic, 2000)

				• Agent-based modeling, • System dynamic simulation	
SMARTFIRE		• Maritime, • Aerospace, and • Civil Engineering	• Continuous	• Simulation of the fire environment	(Galea et al., 2004)
MaritimeEXODUS	2003	• Maritime	• Discrete	• Simulation of evacuation behaviors and • Pedestrian dynamics	(Gwynne et al., 2003)
IMEX	2004	• Maritime, • Aerospace, and • Civil Engineering	• Discrete	• Pedestrian dynamics and • Human behavior simulation	(Park et al., 2004)
ODIGO	2000-2005	• Maritime, • Aerospace and • Civil Engineering	• Continuous	• Crowd motion simulation	(Pradillon, 2004)
FDS+Evac	2007	• Civil Engineering	• Continuous	• Simultaneous simulation of fire and Evacuation process	(Korhonen et al., 2010)
AENEAS/PedGo	2007	• Maritime	• Discrete	• Distribution of passengers and • Route definition/evacuation simulation	(Meyer-König et al., 2007)
UNITY engine	2008	• A broad range, including maritime	• Hybrid	• Simulation	(Unity, 2008)
VELOS	2010	• Maritime	• Continuous	• Assessment of passenger and crew activities	(Ginnis et al., 2010)
Pathfinder	2011	• Civil Engineering	• Continuous	• Simulation of human behavior and interactions	(Thunderhead Engineering, 2021)
EVI	2011	• Maritime	• Hybrid	• Pedestrian movement simulation	(Guarin et al., 2014)
SIMPEV	2012	• Maritime	• Discrete	• Evacuation analysis based on human behavior	(Roh and Ha, 2013)
EvacSim	2013	• Civil Engineering	• Hybrid	• Simulation of pedestrian egress	(Murphy et al., 2013)

Appendix J. Problem type

Table J.1. List of publications categorized by problem type.

Paper	Category
(Azzi et al., 2011; Balakhontceva et al., 2016, 2015; Bellas et al., 2020; Boulougouris and Papanikolaou, 2002; Chen et al., 2011; Chu et al., 2013; Deere et al., 2006; Fang et al., 2022b; Galea et al., 2003, 2013; Grandison et al., 2017; Gwynne et al., 2003; Hu et al., 2019; Hu and Cai, 2020, 2017; Jasionowski et al., 2011; Kang et al., 2010; Katuhara et al., 2003; Kim et al., 2020; Kwee-Meier et al., 2017; Li et al., 2021; Liou and Chu, 2016; Liu and Luo, 2012; Liu et al., 2021; Liu et al., 2022a; Liu et al., 2022b; Lozowicka, 2021; Łozowicka, 2005; Luo, 2019; Ma et al., 2020; Miyazaki et al., 2004; Murayama et al., 2000; Ng et al., 2021; Ni et al., 2017a, 2017b; Park et al., 2015; Qiao et al., 2014; Roh and Ha, 2013; Rutgersson and Tsychkova, 1999; Salem, 2016; Sarshar et al., 2014, 2013a; Sarvari et al., 2019; Spanos and Papanikolaou, 2014; Sun et al., 2020; Vanem and Skjong, 2006; Vilen, 2020; Wang and Wu, 2020; Wang et al., 2013, 2022b; P. Wang et al., 2020; Wu et al., 2018; Xie et al., 2020a, 2020b, 2020c; Yuan et al., 2014; Yue et al., 2022)	Evacuation time optimization

(Bles et al., 2001; Brown et al., 2008; Brumley and Koss, 2000; Casareale et al., 2017; Chen et al., 2016; Chen and Lo, 2019; Cho et al., 2016; Ditlev Jorgensen and May, 2002; Fang et al., 2022a; Fukuchi and Imamura, 2005; Ha et al., 2012; Hu and Cai, 2022; Kim et al., 2019; K V Kostas et al., 2014; Lee et al., 2004; Łozowicka, 2010; Meyer-König et al., 2007, 2002; Na et al., 2019; Nevalainen et al., 2015; Ni et al., 2018; Park et al., 2004; Sarshar et al., 2013b; Sun et al., 2019, 2018a, 2018b; Vassalos et al., 2002; Vassalos et al., 2002; Walter et al., 2017; Wang et al., 2021b, 2021a, 2021c; Wang et al., 2020b; Zhang et al., 2017, 2016)	Passenger behavior understanding
(Couasnon et al., 2019; Guarin et al., 2014; Kim et al., 2004; Klüpfel et al., 2001; Konstantinos V Kostas et al., 2014b, 2014a; Montecchiari et al., 2021, 2018; Piñeiro et al., 2005; Ruponen et al., 2015; Vanem and Ellis, 2010; Yip et al., 2015)	Evacuation models description
(Brown, 2016; Deere et al., 2012; Finiti, 2021; Galea et al., 2014b, 2014a, 2011; Wang et al., 2014)	Data collection and validation

Appendix K. Case studies

Table K.1. List of case studies.

Paper	Emergency evacuation environment
(Fang et al., 2022a)	• Training vessel "YUKUN" of Dalian Maritime University
(Wang et al., 2022)	• Ro-Ro passenger ship "Yong Xing Dao"
(Liu et al., 2022b)	• Training vessel "YUKUN" of Dalian Maritime University
(Q. Xie et al., 2020d)	• 3-storey passenger ship
(Finiti, 2021)	• Costa Concordia cruise ship
(Wang et al., 2014)	• 3-storey passenger ship
(Balakhontceva et al., 2015)	• MS Costa Allegra cruise ship
(Casareale et al., 2017)	• Costa Concordia ccccruise ship (Deck 4)
(Chu et al., 2013)	• Ro-Ro passenger ferry (TAI WHA)
(Liou and Chu, 2016)	• Training ship (Yu-Ying No. 2)
(Brown, 2016)	• Ferry without/with cabins (RoPax ferry) and • Cruise ship
(Liu et al., 2021)	• 3-tier cruise ship
(Vilen, 2020)	• Ferry without/with cabins (RoPax ferry) and • Cruise ship
(Sarvari et al., 2019)	• Ro-Ro ferryboat (Osman Gazi)
(Galea et al., 2013)	• Ferry without/with Cabins (Ro-Pax ferry) and • Cruise ship
(Ditlev Jorgensen and May, 2002)	• MS Kronprins Frederik Ro-Ro ferry vessel
(Miyazaki et al., 2004)	• Ferryboat (Yuukari)
(Ni et al., 2017b)	• Restaurant area in a passenger ship
(Sun et al., 2020)	• Ferry without/with cabins (Ro-Pax ferry) and • Cruise ship
(Wang et al., 2020b)	• An exhibition hall in a large cruise ship
(Galea et al., 2014a)	• Large RO-Pax ferry
(Gwynne et al., 2003)	• Passenger/tour boat
(Spanos and Papanikolaou, 2014)	• Ro-Ro ferry and • Panamax cruise ship
(Galea et al., 2011)	• RO-Pax ferry super speed
(Katuhara et al., 2003)	• Training ship (Seiun-maru)
(Q. Xie et al., 2020a)	• Two hypothetical main vertical zones of passenger ships
(Balakhontceva et al., 2016)	• MS Costa Allegra cruise ship
(Park et al., 2015)	• Large RO-Pax ferry
(Roh and Ha, 2013)	• Car ferry
(Na et al., 2019)	• Ro-Pax cruise ship
(Walter et al., 2017)	• Research vessel (Thomas G. Thompson)
(Wang et al., 2021c)	• Ro-Ro passenger vessel
(Wang et al., 2020c)	• Ro-Ro passenger vessel
(Q. Xie et al., 2020c)	• 3-storey passenger ship
(Murayama et al., 2000)	• Passenger ferry
(Vassalos et al., 2002)	• Ro-Pax cruise ship
(Galea et al., 2014b)	• Ferry without/with cabins (Ro-Pax ferry) and • Cruise ship
(Deere et al., 2012)	• Ferry without/with cabins (Ro-Pax ferry) and • Cruise ship

(Salem, 2016)	• Ro-Ro passenger ship and • Cruise ship
(Ruponen et al., 2015)	• Large passenger ship
(Wang and Wu, 2020a)	• Ro-Ro passenger ship (MV Tai Hwa)
(Ni et al., 2018)	• Deck 5 of a passenger ship
(Kim et al., 2020)	• MV Sewol vehicle-passenger ferry
(Ma et al., 2020)	• Passenger ship (Yangtze Gold 7)

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Paper 2

Multi-period human evacuation model for passenger ships under walking speed uncertainty

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This paper is under review for publication and is therefore not included.

Paper 3

A data-driven, scenario-based human evacuation model for passenger ships addressing hybrid uncertainty

Abstract

In a disaster at sea, the safe and timely removal of passengers from the ship is paramount. Here, a human evacuation plan enables passengers to be swiftly displaced from a risk area to one less so. Despite existing research on evacuation planning, there is a need for a more comprehensive model that considers various uncertainties and factors. This paper proposes an optimization evacuation model that balances uncertain variables, including passenger walking speed and travel distance, and deterministic factors like deck layout, door capacity, initial density, and corridor traffic flow. The model also accounts for varying starting locations and two levels of awareness—alert and non-alert. The model utilizes a data-driven technique, i.e., the k-means algorithm, to cluster historical data on speeds and generate scenarios. An adjustment scheme is applied to account for the ship's rolling motion, affecting passenger speeds during the evacuation planning period. Travel distance scenarios are produced to capture the impact of different route choices per passenger. A risk-neutral two-stage programming model is constructed to handle uncertainties. The model is tested on multiple problems for a passenger ship deck in day and night modes, revealing valuable managerial insights for the maritime safety sector.

Keywords: Passenger ship, Walking Speed, Travel Distance, Evacuation Model, Data-driven Optimization, Scenario-based Approach.

1. Introduction

In maritime emergencies, the importance of executing a prompt and precise human evacuation cannot be overstated, as it is vital for minimizing casualties and averting significant loss of life (Montewka et al., 2014). Acknowledging this necessity, the Maritime Safety Committee (MSC) protects individuals at sea from potential hazards by emphasizing the development and implementation of proper and efficient evacuation strategies, ultimately benefiting all stakeholders, including passengers, crew members, ship owners, maritime authorities, and emergency response teams. Human evacuation is a common strategy to ensure safety during emergencies, relocating individuals from high-risk areas to safer locations. Planning evacuations for passenger ships poses a challenge, as it requires addressing four essential aspects: human, behavioral, environmental, and configurational factors (Lee et al., 2003). Research in this field often targets evacuation time (ET) minimization, route optimization, understanding human behavior, and determining walking speeds (Arshad et al., 2022).

Upon initiating the evacuation process with an alarm notification, a passenger's alertness level can significantly impact preparation and ETs (Mossberg et al., 2022). Notably, individuals who are not fully aware (e.g., asleep, eating, or on the phone) may necessitate more time to evacuate than their alert counterparts.

Subsequently, updated guidelines for evacuation analysis of passenger ships highlight the importance of passenger load and initial distribution across decks. Individuals' starting locations at the time of alarms are crucial for successful evacuation (IMO, 2016). Simultaneously, managing the initial passenger density across various locations can alleviate congestion at the onset of the evacuation process, ultimately influencing ET and facilitating a smoother, more controlled emergency response (Deng et al., 2022).

Additionally, the new regulations emphasize passengers' walking speed, which impacts ship layout, corridor, and cabin capacity, and ET (Aghabayk et al., 2021). Furthermore, as passengers begin to move, they face a confusing array of routes and directions (Ni et al., 2017b). Some may need to adjust their paths upon encountering obstacles, such as displaced furniture and appliances, while others can jump over them or have clear routes. The ship's motion may also force particular passengers to reduce their speed as it causes their bodies to sway. Consequently, these two factors (i.e., speed and travel distance) are sources of uncertainty, making it essential to consider them when developing a human evacuation plan (G. Zhang et al., 2017). This consideration enables decision-makers to anticipate and identify potential evacuation measures based on varying passenger speed and travel distance representations. One approach for handling such uncertainties is generating scenarios using selections from historical data (Kaut, 2021). Scenarios can enhance the model's flexibility and robustness by accounting for multiple potential ET outcomes from hybrid uncertainty, which combines uncertainties in walking speed and travel distance within a single optimization framework to enhance the model's adaptability to complex real-world evacuation scenarios (Liu, 2010). Analyzing historical data can reveal patterns, trends, and correlations, enabling the creation of informed and targeted scenarios and ultimately improving model quality and effectiveness while exploring potential outcomes based on past events.

The k-means algorithm is a data-driven technique for clustering historical walking speed data and representing each cluster as a specific scenario according to the clusters' means (Hartigan and Wong, 1979; K. Wang et al., 2023). It stands out for its computational efficiency and ability to handle large datasets. It can rapidly converge to distinct clusters and suit scenarios requiring quick insights from large-scale data. Besides, its inertia metric aids in pinpointing the optimal cluster count for a dataset (Jain, 2010). Data-driven scenario generation can improve the model's scalability and accuracy by analyzing vast amounts of data (Bounitsis et al., 2022). It is followed by adjusting the scenarios process to regulate the speed of the evacuation process. Specifically, the speed will be affected by the ship’s rolling motions, which increasingly diminish the speed as the evacuation duration extends. Scenario adjustment can ensure the evacuation remains updated by changing the evacuation situation dynamically and providing an updated solution for the evacuation plan (Cameron et al., 2011). Regarding travel distance, a number of scenarios are generated to understand the influence of different spaces between the initial position and destination. Scenarios represent possible outcomes for the distance traveled by each passenger between the starting point and the exit door (Bode and Codling, 2013; Daamen et al., 2005).

Managing traffic flow is crucial once individuals have traversed the corridor during an evacuation. International Maritime Organization (IMO [5]) determines passenger flow based on the type of evacuation route, such as a corridor. Traffic congestion arises when demand surpasses corridor capacity, leading to queue formation near bottlenecks (Na, 2019). By controlling evacuation traffic flow after individuals leave their initial area, it is possible to maintain steady movement along the evacuation route, minimize bottleneck occurrences, and reduce evacuation delays.

Besides, exit doors have limited capacity, restricting the number of passengers who can pass through during a single period. As a result, the evacuation process occurs across multiple periods. Further, the value of speed changes over time and is subjected to traversed distance; the objective function, consequently, minimizes the ET of all passengers over the entire process. As the total ET optimization is the core objective of the evacuation process and is considered the average minimization of the entire passengers' ET (i.e., general expectation), a risk-neutral perspective can be beneficial for coping with uncertainty. Risk-neutral assumption handles the randomness of uncertain parameters on the entire scenario set instead of focusing on the worst-case scenario and becoming conservative (Bayram and Yaman, 2018; Liang et al., 2019). IMO [5] computed the total ET under day and night modes, considering passenger load and initial distribution. Accordingly, eight cases are generated to calculate ET based on passengers' initial positions and awareness levels. Afterward, evacuee scheduling is organized from their cabins to the right exit door, considering factors such as speed, proximity to the nearest exit stair, traffic flow, and passengers' current locations.

Drawing from the aforementioned analysis and MSC guidelines, this study strives to quantify uncertainties and devise an optimization model for human evacuation. This initiative is essential for addressing critical safety concerns that stakeholders face during passenger ship evacuation operations. In summary, this research contributes to the literature by:

- Developing a risk-neutral, two-stage, scenario-based mixed-integer programming (MIP) model for planning human evacuation under uncertainty.
- Applying a data-driven approach for generating scenarios from historical data on passenger speeds and travel distance scenarios, along with an adjustment scheme for speed based on the ship's rolling motion.
- Incorporating factors such as passenger starting locations, situational awareness, corridor traffic flow, and initial density at each location into the proposed model.

The remainder of this paper is organized as follows: Section 2 provides an overview of relevant studies on human evacuation plans for passenger ships. Section 3 describes the problem, and Section 4 formulates the optimization model. Section 5 details the solution process for the developed MIP model. Computational results are presented in Section 6, while Section 7 discusses the relevant managerial insights, notes limitations, and suggests potential directions for future research. Finally, Section 8 highlights the contributions and the primary findings.

2. Summary of relevant literature

A human evacuation plan is a safety measure that regards emergency issues while considering the time aspect. Over the past few years, researchers have investigated human evacuation planning extensively across various contexts, including on land and at sea. Arshad et al. [3] summarize the research on human evacuation models for passenger ships. They identified one of the most pressing problems in this field is the need to understand human evacuation plans under uncertainty. It enhances decision-making efficiency in an emergency, the accuracy of ET calculation, and resource allocation (e.g., crew allocation) by considering different possible outcomes (Doyle et al., 2014). Furthermore, although initial distribution, density, and traffic flow of passengers have been accounted for in calculating ET within the revised guidelines on evacuation analysis for passenger ships, these parameters need to receive more attention in modeling. In doing so, this literature review elaborates on human evacuation modeling in the presence of uncertainty sources and evacuation parameters.

Uncertainty can be described as the inability to understand certain circumstances fully. Uncertainty modeling methods attempt to model the input's variability and predict the outcome to compensate for this weakness (Canavero, 2019). Several techniques have driven researchers to handle uncertainty in evacuation planning problems, including stochastic programming (SP), scenario-based optimization (SO), Monte Carlo (MC), fuzzy programming (FP), and robust optimization (RO). A large amount of archived data has already been collected, allowing researchers to implement SP and SO in this field of study. SO is a technique that involves generating a set of scenarios and then optimizing decision-making based on the probabilities assigned to each scenario. This method does not presume that the uncertainty in the problem can be modeled using a probability distribution (Rocchetta and Crespo, 2021). In contrast, SP is best applied to situations where uncertainty can be managed by fitting a probability distribution to the input data (Schkufza et al., 2016).

In this study, SO is used to explicitly analyze a variety of alternative outcomes and their related probabilities, as the probability distributions for passenger walking pace and travel distance are unavailable. Giuliani et al. [25] and Lv et al. [24] have employed SO modeling to cope with multiple uncertainties during a land-based emergency evacuation. Their findings demonstrated that the model's effectiveness and decision-making during the evacuation process have been improved. In a land-based case study, Pourrahmani et al. (Pourrahmani et al., 2015) applied fuzzy credibility theory to handle uncertainty in demand (number of evacuees), which is a type of robust optimization approach where demand is modeled as a fuzzy number belonging to a convex set. The genetic algorithm then optimizes the evacuation routing based on this fuzzy demand information.

Wang et al. [26] presented a framework of uncertainty analysis for available safety egress time (SFAT) under ship fires. They developed an evacuation model handling uncertainties from fire parameters, including heat release rate, fire growth coefficient and ventilation, a thermal detector, auto-sprinkler, and manual extinguisher. Lovreglio et al. [27] investigated the influence of human behavior uncertainty on experimental and simulation data. In this regard, they introduced an evacuation model validation procedure to study the impact of behavioral uncertainty in ship fires. They applied functional analysis operators and statistical testing for converging the evacuation simulation and experimental data. Salem [28] offered a model to characterize the impact of stochastic input factors on the distribution of uncertainty when estimating the available safe escape time (ASET). They resulted in the fact that ASET is always affected by uncertainties propagated from random inputs. The time to reach an untenable condition owing to fire toxicity is the most severely influenced output in almost all studied cases. Xie et al. [29] proposed an uncertainty analysis technique to quantify the uncertainty of passenger travel time affected by the initial passenger density. They constructed a polynomial chaos expansion and a Gaussian quadrature rule to deal with the uncertainty. Further, Xie et al. (Q. Xie et al., 2020c) improved their model efficiency by applying a nested sampling method. They decreased the number of evacuation simulations for calculating passenger travel time for a ship under fire.

Passenger walking speed directly impacts ET in an emergency, which varies considerably by age, gender, health, and other factors. In this respect, researchers investigated the impact of different drivers, such as ship motions, on speed quality in great detail. Sun et al. [31] designed a ship corridor simulator to examine how heeling and trimming influence one's speed while walking freely and fast. They observed that increasing heeling and/or trim angles could significantly reduce average individual walking speed. Wang et al. [32] deduced the effects of ships docking and sailing by measuring how fast people moved in experiments. They found that, during the sailing, an individual's speed reduction ratio was between 86.0 and 96.2 percent, and the value decreased as the deck height grew. Wang et al. [33] examined human behavior in emergencies based on responding to evacuation alarms, observing others' actions, following evacuation instructions, obeying the crew, queuing patiently, returning to the cabin when their families are left behind, and being cooperative rather than competitive. They indicated that older passengers who have limited mobility, have more experience aboard ships, and are part of a larger group will be more likely to confirm the authenticity of evacuation events proactively. In land based setting, Alam et al. (Alam et al., 2022) investigated the resources and traffic operation requirements for evacuating persons with mobility needs. The study crucially pilots emergency planners and engineers to improve mass evacuation strategies for individuals with disabilities, especially those needing mobility assistance.

Further, another important factor is the distance traveled to reach a safe location during evacuation. It can affect the route choice and total ET. In this regard, Zhang et al. [34] proposed a probabilistic occupant evacuation model for fire emergencies. They modeled the distance occupants traveled from the initial point to a safe point in the land-based setting. Li et al. [35] proposed an agent-based simulation model with a route choice process to predict crowd behaviors. The paper concluded that passenger characteristics of layout familiarity and social relationships in the evacuation process on board caused route choice behaviors. Qiao et al. [36] proposed a method to select an optimum evacuation route. They offered each evacuee an escape route considering the length of the passage, actual congestion, and individual complex behavior attributes.

Understanding the initial density and traffic flow of passengers play a critical role in designing human evacuation plans. A safe and swift evacuation can be the byproduct of considering these two elements in modeling (Moriarty et al., 2007). Piñeiro et al. [38] researched the movement of people in complex and size-limited scenarios in terms of traffic flow. They presented a unique requirement to use findings on ship emergency evacuation simulations.

Lastly, assuring that passengers in the affected area are made aware of the emergency is critical. In doing so, it is crucial to consider the awareness component in modeling the human evacuation plan; otherwise, passengers will be treated at the same level of consciousness in modeling, which is unrealistic. Wang et al. [39] demonstrated the demographic variations in safety awareness and perception, the understanding of emergency wayfinding tools, and the demographic differences regarding safety awareness and perception. Table 1 showcases the distinctiveness of this study compared to existing literature, considering factors such as initial density (ID), traffic flow (TF), different starting locations (DSL), night and day mode (NDM), uncertainty, solution method (SM), and objective function (OF).

Table 1. A brief review of the literature.

Reference	Model features				Uncertain parameters	SM	OF
	ID	TF	DSL	NDM			
Piñeiro et al. [38]	●	●				Simulation	Studying pedestrian movement
Wang et al. [26]					Fire parameters	Monte Carlo sampling, sensitivity analysis	Studying the SFAT under ship fires
Lovreglio et al. [27]					Human behavior	Functional analysis operators, statistical testing	Studying the evacuation simulation and experimental data
Qiao et al. [36]						Mathematical and simulation-based heuristic	Studying route choice
Salem [28]					Fire parameters	Monte Carlo Simulation, CFAST	Studying the ASET under ship fires
Sun et al. [31]						Experimental-based approach	Studying evacuation behaviors of passengers under listing conditions
Xie et al. [29]	●				Passenger travel time	Polynomial chaos, Gaussian quadrature rule	Passenger travel time optimization under ship fires
Xie et al. [30]	●				Passenger travel time	Polynomial chaos, Nested sampling	Passenger travel time optimization under ship fires
Wang et al. [33]					Human behavior	Multinomial logistic regression	Examining human evacuation behavior
Wang et al. [32]						Experimental-based approach	Studying individual walking speed under ship motion
Li et al. [35]						Simulation runs	Studying route choice behaviors
Azizpour et al. [40]						Regression modeling and simulation runs	Studying individual walking speed under thermal protective suit and heeling angle
The research	●	●	●	●	Passenger walking speed, travel distance	Data-driven, risk-neutral, scenario-based	Minimizing the total ET

Designing a human evacuation plan considering the combined influence of passenger walking speed and travel distance uncertainties has been largely unexplored in the existing literature. This study is the first to address the effects of factors such as initial density, passenger traffic flow, diverse starting locations, and situational awareness in both day and night conditions on the total ET. Moreover, our research is unique in utilizing machine learning techniques to generate data-driven scenarios that partition passenger walking speed observations into distinct clusters for ship-based human evacuation planning.

3. Problem description

This section is split into two parts: (1) the problem statement and (2) the framework of the solution methodology.

3.1. Problem statement

This section outlines the optimization problem of emergency human evacuation planning tackled in this research. In the event of a potential or actual threat to passengers, they should prepare to leave the ship. The ship's crew and emergency personnel give an obligatory evacuation order when the projected effect is destructive and costly. A single deck of a passenger ship is explored in this research. The deck plan is depicted as a network graph comprising nodes that represent various functional areas such as cabins, restaurants, jacuzzi, bar, exit doors, and distinct segments along the corridor. The edges in this network graph denote the connections between these functional areas. This representation aids in visualizing the deck layout and facilitates a more informed decision-making process. A group of passengers is situated on a single deck of a passenger ship, divided into two corridors. These passengers are allocated across l cabins, represented by the set $J = \{j_1, j_2, \ldots, j_l\}$. The passenger group is diverse in several aspects:

- Age: Passengers vary in age.
- Gender: The group includes both male and female passengers.
- Physical condition: Variations in mobility levels are observed among passengers.
- Awareness level: Some passengers may be less alert due to various factors; for example, they could be asleep, eating, or engaged in a phone conversation.
- Walking speed: Individual walking speeds differ among passengers.

The set of passengers is symbolized as $P = \{p_1, p_2, \ldots, p_n\}$, where n indicates the total number of passengers. Non-alert passengers are penalized for a longer distance in their travel. Cabins' capacity is limited. They are situated on one side of each corridor. Seven exit doors, $E = \{e_1, e_2, \ldots, e_7\}$, as a means of evacuation are located at various locations throughout the corridors. The deck is also facilitated by a restaurant, bar, and jacuzzi. Furthermore, seven different starting locales are considered for starting points per passenger. Specifically, $I = \{i_1, i_2, \ldots, i_7\}$ denotes different starting locales (i_1 means passengers berth in their own cabin, and other locales are marked in Fig. 1) for each passenger depending on where he/she is located at the time of emergency. Denote (p_n^i, e_m), $\forall\, n \in N$ and $m \in \{1, 2, \ldots, 7\}$ as an edge representing evacuation route for passenger p_n located at area i traveling to exit door e_m. Fig. 1 represents the structure of the examined network in this research. It displays how different passengers, including male and female, alerted and sleeping, are distributed across the deck.

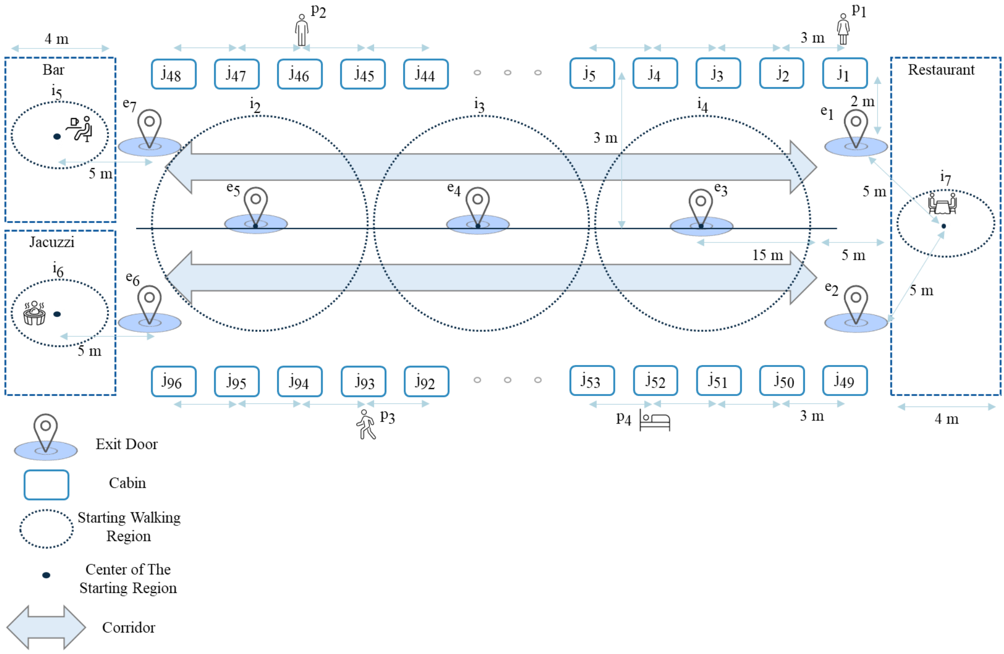


Fig. 1. Schematic structure of considered human evacuation model.

The model is formulated as an optimization model subjected to uncertain parameters, incorporating passenger walking speed and travel distance between passengers and exit doors and deterministic factors, comprising the deck's layout, doors' capacity, initial density, and traffic flow of passengers. Let $T= \{t_1,t_2,\ldots,t_o\}$ be a set of time periods for the considered evacuation planning horizon, and $o \in O$ is an optional value indicating the number of periods. Each period is ended when there is no capacity available for exit stairs. Denote cap_{et}, $\forall\ e \in E$ and $t \in T$ as the capacity of the exit stair $e \in E$ during a period $t \in T$. Each passenger is advised to travel towards a certain exit stair which the capacity allows. In this regard, the evacuation route capacity is set according to the exit stair capacity in each period. Specifically, the nominal capacity of a route may be higher than the exit stair. Lastly, the counterflow correction factor is applied to the total ET in case of disruption and corridor closure by passengers and crew activities.

3.2.Solution methodology architecture

Fig. 2 delivers a schematic representation of the proposed solution methodology. The framework consists of seven stages, detailed in subsequent sections, which encompass data clustering, scenario generation, scenario adjustment, mathematical modeling and optimization of the human evacuation model using the generated scenarios. The scenarios capture evacuation uncertainties, including passengers' walking speed and travel distance. They're adjusted and used in the optimization model to generate various outcomes. The mathematical model is formulated and optimized using the CPLEX solver within the Generic Algebraic Modeling System (GAMS) software environment. The model is backed by a series of experiments under different conditions to validate its performance. All the experiments are conducted on a computer equipped with an Intel(R) Core i5 processor running at a speed of 1.70 GHz to 2.21 GHz and a memory capacity of 16 GB of RAM.

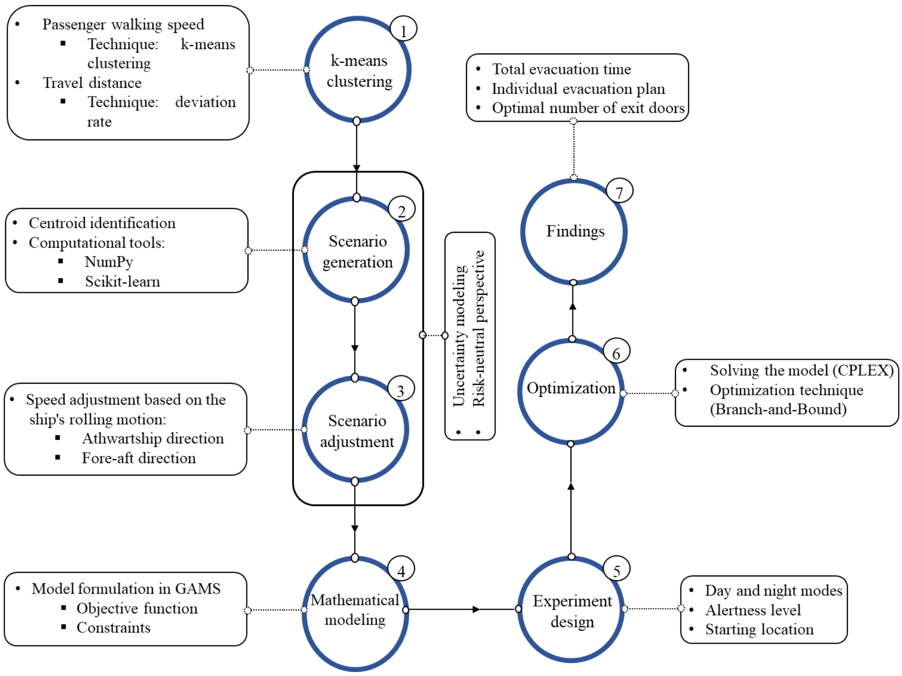


Fig. 2. Solution methodology architecture.

Operational decisions are preoccupied with formulating individualized evacuation plans to guarantee safe egress for each passenger. Tactical decisions pivot on allocating resources to optimize the throughput and efficiency of the evacuation process. On the other hand, strategic considerations involve identifying the optimal number of exit doors, thereby providing a structural framework that improves the usefulness of operational and tactical implementations.

4. Problem formulation

This section presents a mathematical formalism for the problem as an optimization model. After a verbal formulation is given, the model's notations are provided. Lastly, the mathematical optimization model is formulated.

4.1. Notations

Notations used in the mathematical model are described in Table 2.

Table 2. Mathematical notations.

Sets and indices	
P	Set of passengers, indexed by $p \in P$
E	Set of exit stairs, indexed by $e \in E$
I	Set of starting locales, indexed by $i \in I$
T	Set of periods, indexed by $t \in T$
S	Set of walking speed scenarios, indexed by $s \in S$
U	Set of travel distance scenarios, indexed by $u \in U$
J	Set of cabins, indexed by $j \in J$
Parameters	
v_{pt}	Nominal walking speed of passenger $p \in P$ in period $t \in T$ (meters/second)
v_{pt}^{s}	Walking speed of passenger $p \in P$ in period $t \in T$ in scenario $s \in S$ (meters/second)
$v_{pt}^{s'}$	Walking speed of passenger $p \in P$ in period $t \in T$ in scenario $s \in S$ adjusted by rolling angle of a ship (meters/second)

d_{pe}^{i}	Nominal travel distance by passenger $p \in P$ located in starting locale $i \in I$ to exit door $e \in E$ (meter)
d_{pe}^{iu}	Travel distance by passenger $p \in P$ located in starting locale $i \in I$ to exit door $e \in E$ in scenario $u \in U$ (meter)
cap_{et}	Capacity of exit door $e \in E$ in period $t \in T$ (per passenger)
r_{pe}^{t}	Equal to 1 if passenger $p \in P$ is in a radius of exit door $e \in E$ in period $t \in T$; 0, otherwise
θ_p	Equal to 1 if passenger $p \in P$ is fully alert; 0, otherwise
ϑ_p^i	Equal to 1 if passenger $p \in P$ is located in starting locale $i \in I$; 0, otherwise
π_s	Probability occurrence of scenario $s \in S$
π_u	Probability occurrence of scenario $u \in U$
σ_i	Availability area of locale $i \in I$ (meter^2)
ω	Corridor width (meter)
τ	Average shoulder width of passengers (meter)
ι	Non-alert distance factor
γ	Correction factor
δ	Counterflow correction factor
Decision variables	
Free variables	
ψ_{us}	The total ET in scenario $u \in U$ and $s \in S$
F_t	Traffic flow of passengers in period $t \in T$ (passengers)
D_i	Initial density of passengers in locale $i \in I$ (passengers)
Z	The total ET
Binary variables	
Y_{et}	Equal to 1 if the potential exit door $e \in E$ in period $t \in T$; 0, otherwise
X_{pet}^{su}	Equal to 1 if passenger $p \in P$ is traveling to the exit door $e \in E$ in period $t \in T$ in scenario $u \in U$ and $s \in S$; 0, otherwise

4.2. Uncertainty modeling

By incorporating a scenario for each possible outcome of the stochastic event, uncertainty is integrated into the optimization model. The researched model comprises the passenger's walking speed and distance as stochastic parameters. Clustering algorithms are practical for scenario generation because they enable data reduction, pattern discovery, and the creation of robust, flexible, and customizable scenarios that incorporate uncertainty. This leads to more informed decision-making processes and an improved understanding of complex problems while considering uncertainty (Xu and WunschII, 2005). The k-means algorithm is beneficial for clustering historical data due to its scalability, efficient handling of large datasets, and quick convergence speed. It results in being computationally efficient and creates distinct, non-overlapping clusters, which helps identify clear patterns and trends (Jain, 2010). In this regard, the k-means clustering algorithm can generate scenarios for speed. As such, each scenario contains a realization of the speed for each passenger in each period. Regarding travel distance, some scenarios that are varied enough to represent the possibilities that might happen are produced at random. In the proposed model formulation, four assumptions and simplifications are used to frame the boundaries of the research.

- Passengers' walking speed and travel distance are subjected to uncertainty.
- All passengers must be evacuated.
- The location of cabins, exit doors, and corridors' layout are fixed and predefined.
- The capacity of exit doors is known and fixed.

The described human evacuation optimization problem can be developed as a two-stage scenario-based MIP model under the risk-neutral perspective (Birge and Louveaux, 2011). In this regard, Oksuz et al. (Oksuz and Satoglu, 2020) introduced a two-stage stochastic model for the strategic placement of temporary medical centers during disasters, using stochastic optimization to accommodate uncertain parameters. The model incorporates initial decisions like the location of the centers and later decisions, such as patient load, allowing for adaptability to evolving circumstances in a terrain-oriented environment.

The decision variables are categorized into (1) the here-and-now and (2) wait-and-see.

4.2.1. Here-and-now variable

Here-and-now variables (Y_{et}, F_t and D_i) are independent of scenarios and determined based on the available information. It means that such decisions are made before the realization of uncertain parameters ($v^{s'}_{pt}$ and d^{iu}_{pe}). Y_{et}, F_t and D_i decisions are made in such a way that the model can resist the variation in passengers' walking speeds and travel distances, and accordingly, the expected ET is optimized. These first-stage decisions are not directly related to uncertain parameters, whereas they can stabilize decision-making in the first and second stages of the optimization process by enhancing the robustness of the model (Wets, 2002).

4.2.2. Wait-and-see variable

Wait-and-see decision variables (X^{su}_{pet}) depend on the realization of uncertain parameters. After deciding on the here-and-now decision variables, a random event occurs, and the values of the uncertain parameters become clearer (Li and Grossmann, 2021). In other words, determining X^{su}_{pet} is performed with flexibility and robustness. For instance, once the random parameters, including $v^{s'}_{pt}$ and d^{iu}_{pe} are realized, based on the here-and-now decisions made, the scenario-based optimization model confidently decides on allocating different passengers to different exit doors in each period $t \in T$. In other words, X^{su}_{pet} is optimally established.

4.3.Mathematical modeling

The described human evacuation problem can be formulated as follows. The objective function, a minimization optimization expression of the proposed model, offers the optimal value of Equation (1) considering the constraints.

$$\textit{Minimize (Total Evacuation Time)} = \sum_{s \in S}\sum_{u \in U} \pi_s \times \pi_u \times \psi_{us} \tag{1}$$

The objective function (1) minimizes the present value of total ET in hybrid consideration of scenario u and s affected by the likelihoods of occurrence. It represents the time passengers need to evacuate from the starting point to an exit.

$$\psi_{us} = (\delta \times \gamma) \times \sum_{p \in P}\sum_{e \in E}\sum_{t \in T}\sum_{i \in I} (d^{iu}_{pe} + (1 - \theta_p) \times \imath / v^{s'}_{pt}) \times X^{su}_{pet} \times \vartheta^{i}_{p} \quad \forall u \in U \text{ and } s \in S \tag{2}$$

Constraint (2) generates the total ET based on travel distances, non-alert travel distances, adjusted walking speed, and the current starting locale affected by the counterflow correction factor in combination consideration of s and u. To be more specific, the total travel distances are divided by the walking speed depending on where the passenger is located.

$$X^{su}_{pet} \leq Y_{et} \quad \forall p \in P, e \in E, t \in T, u \in U \text{ and } s \in S \tag{3}$$

Constraint (3) states that an exit door must be available to be passed by a passenger in each period.

$$\sum_{p \in P} X^{su}_{pet} \leq cap_{et} \times Y_{et} \quad \forall e \in E, t \in T, u \in U \text{ and } s \in S \tag{4}$$

Constraint (4) stipulates that evacuees traveling toward an exit door at each period must be less than the capacity of the corresponding facility.

$$Y_{e(t-1)} \leq Y_{et} \quad \forall e \in E \text{ and } t \in T \tag{5}$$

Constraint (5) ensures that once established, an exit door must be available by the end of the planning horizon.

$$\sum_{e \in E} \sum_{t \in T} X_{pet}^{su} = 1 \quad \forall p \in P,\ u \in U \text{ and } s \in S \tag{6}$$

Constraint (6) imposes that each passenger is evacuated only one time over the horizon period.

$$Y_{et} \le \sum_{p \in P} X_{pet}^{su} \quad \forall e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{7}$$

Constraint (7) ascertains that at least one evacuee must travel to the established exit door at each period.

$$\sum_{p \in P} (X_{pet}^{su} \times \tau) / \omega \le F_t \quad \forall e \in E,\ t \in T,\ u \in U \text{ and } s \in S \tag{8}$$

Constraint (8) assures that the number of evacuees past the corridor per unit of clear width of the corridor involved must be less than or equal the traffic flow of passengers in each period.

$$\sum_{e \in E} \sum_{t \in T} X_{pet}^{su} \times \vartheta_p^i \le D_i \times \sigma_i \quad \forall p \in P,\ u \in U \text{ and } s \in S \tag{9}$$

Constraint (9) enforces that the number of passengers available in each starting area must be less than or equal to the initial density of passengers in the corresponding area.

The developed model contains $(|P|\times|E|\times|T|\times|S|\times|U|+|E|\times|T|)$ binary decision variables, $(|I|+|T|+|S|\times|U|+1)$ free variables, and $(|P|\times|E|\times|T|\times|U|\times|S|+(3\times|P|\times|U|\times|S|)+(3\times|E|\times|T|\times|U|\times|S|)+(|U|\times|S|)+(|E|\times|T|))$ constraints.

5. Solution method

The problem was set up as a scenario-based MIP optimization model in the final part. Strategic decisions, which are challenging to change over time, are made in the proposed model. The number of exit doors, for instance, cannot be altered after installation. As such, making correct choices in the planning stages is crucial early on. Due to the high costs of inaccuracy in strategic decisions, offering an optimal solution can be beneficial. This matter leads the authors to seek an exact procedure for solving the model. The researched problem is small in scale; therefore, its computational complexity is well within the capabilities of the GAMS. The CPLEX solver in GAMS can optimize the mathematical model. Realization of the model's parameters via data is required prior to optimization. Afterward, the mathematical optimization model can represent the described model's behavior.

Two uncertain parameters, passenger walking speed and travel distance, are presented in this subsection. As an assumption, scenarios with equal probabilities of occurrence are generated.

5.1. Passenger's walking speed scenarios

IMO features passengers' walking speeds on flat ground in real-world conditions based on age, gender, and mobility. As shown in Table 3, the measured speed follows a statistically uniform distribution with a minimum and maximum.

Table 3. Walking speed on flat terrain (e.g., corridors).

Passenger's characteristics	Min. $(\frac{\text{meters}}{\text{second}})$	Max. $(\frac{\text{meters}}{\text{second}})$
Females younger than 30 years	0.93	1.50
Females 30–50 years old	0.71	1.19
Females older than 50 years	0.56	0.94
Females older than 50, mobility impaired (1)	0.43	0.71
Females older than 50, mobility impaired (2)	0.37	0.61
Males younger than 30 years	1.11	1.85
Males 30–50 years old	0.97	1.62

Males older than 50 years	0.84	1.40
Males older than 50, mobility impaired (1)	0.64	1.06
Males older than 50, mobility impaired (2)	0.55	0.91
Mobility impaired (1) and (2): limited mobility without and with the need for assistance, respectively.		

Based on the maximum and minimum values, random realizations for walking speed are generated according to Equation (10). NumPy (np), a Python library, is employed for producing $\varsigma = 1{,}000{,}000$ samples for each passenger's walking speed.

$$v_{pt}^{\{passenger's\ characteristics\}} = (\text{Max. value of speed - Min. value of speed}) \times \text{np.random.random\_sample}(\varsigma) + \text{Min. value of speed} \quad \forall p \in P \tag{10}$$

Next, the k-means algorithm, an unsupervised clustering machine-learning technique, is employed to cluster the generated data, utilizing the NumPy and scikit-learn libraries in Python. According to the inertia metric, which determines the optimal number of clusters for a given dataset, three clusters are offered. Fig. 3 illustrates that the position of the cluster centroids is chosen in such a way that minimizes the total variation sum of squares within the clusters and decreases as the number of clusters increases since the data points are split into smaller groups. The generated clusters can be as many as three scenarios (plus one scenario representing the nominal value of the passenger's speed). The center of each cluster (centroid) is considered the walking speed value under the corresponding scenario. Besides, as the generated scenarios follow the historical data in Table 3, it can prove their validity. Afterward, walking speed scenarios are represented as $S = [S_1, S_2, S_3, S_4]$ so that S_s= centroid of cluster s = 1,2,3 and S_4 is the nominal representation of the walking speed of a passenger.

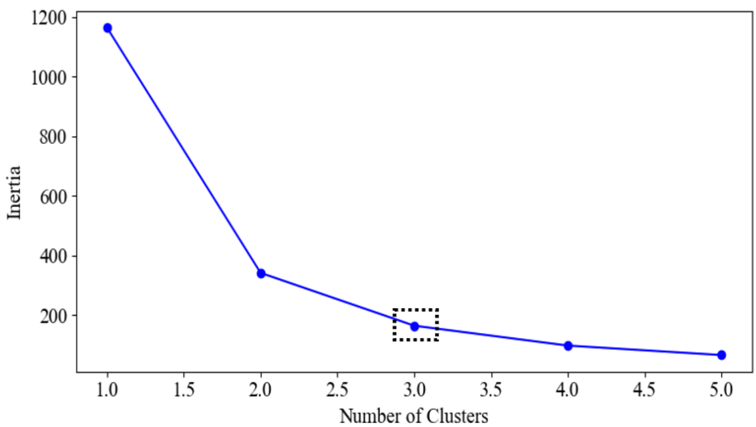


Fig. 3. Evaluation of the clustering results quality.

Ultimately, an adjustment scheme based on the ship's rolling motion is applied to adapt to current uncertainties, such as an intensified ship motion, and generate a new speed setting per passenger over the evacuation planning period ($t \in T$). By adjusting the scenarios, the model can reflect actual unforeseen circumstances and trends and provide more accurate projections (Schwartz, 2012). Wang et al. (Wang et al., 2021b) demonstrated how the ship's rolling angle (0 - 4º) could variously affect the walking speed in different walking directions (athwartship and fore-aft). As one also draws nearer to the horizon's end, Kim et al. (Kim et al., 2019) observed that one's walking speed drops more steeply. In this respect, Table 4 describes the influence rate (IR) of the rolling angle on the walking speed of passengers over the horizon. As such, the walking speed is updated in each period based on Equation (11).

$$v_{pt}^{s\,'} = v_{pt}^{s} \times (IR^{t}) \tag{11}$$

Table 4. The walking speed after adjusting to a new situation. The o is an integer value representing the number of evacuation periods.

	IR	t_1	t_2	...	t_o
Rolling 0 - 4º (athwartship)	0.9295	$v^{s\,'}_{pt^1} = v^{s}_{pt^1} \times (0.9295^1)$	$v^{s\,'}_{pt^2} = v^{s}_{pt^2} \times (0.9295^2)$	...	$v^{s\,'}_{pt^o} = v^{s}_{pt^o} \times (0.9295^o)$
Rolling 0 - 4º (fore-aft)	0.9114	$v^{s\,'}_{pt^1} = v^{s}_{pt^1} \times (0.9114^1)$	$v^{s\,'}_{pt^2} = v^{s}_{pt^2} \times (0.9114^2)$	...	$v^{s\,'}_{pt^o} = v^{s}_{pt^o} \times (0.9114^o)$

5.2. Passenger's travel distance scenarios

Distance is measured according to how far a passenger is from different potential exit doors, which are assumed to be in 7 possible locations. Scenarios for the travel distances for passengers are produced using a deviation rate (dr_{u_k}) applied to the nominal values of distance. The unit of dr_{u_k} is the meter and adds up to the nominal value of the travel distance. The travel distance scenarios are produced as Equation (12) so that Equation (13) generates the travel distance scenarios. Equation (14) produces five scenarios for each passenger's travel distance.

$$dr_{u_k} = U_k \quad \text{for } k = 1, 2, 3, \ldots, K \tag{12}$$

$$\text{travel distance under scenario } U_k = dr_{u_k} + \text{nominal value of travel distance} \tag{13}$$

$$d^{iu}_{pe} = dr_{u_k} + d^{i}_{pe} \quad \text{and } dr_{u_{k\in[1,2,3,4,5]}} = \left[dr_{u_1}=7,\ dr_{u_2}=5,\ dr_{u_3}=3,\ dr_{u_4}=1,\ dr_{u_5}=0\right] \tag{14}$$

The provided $dr_{u_{k\in[1,2,3,4,5]}}$ are illustrative examples of how uncertainties can influence travel distance. In scenarios U_1 to U_5, route choice uncertainties add 7, 5, 3, 1, 0 units to the nominal distance.

5.3. Deterministic parameters

All other model's parameters are listed in Table 5.

Table 5. deterministic parameters.

Parameter	Value
ω	3 meters
τ	0.42 meter
ρ	1.74 meters
ι	1.5 meters
γ	2
δ	1
cap_{et}	5 passengers

6. Computational results

Based on the nature of the evacuation process and various factors, such as passengers' visibility and alertness, a series of experiments are set up before the results are presented.

6.1. Experiment design

Eight cases (C) are designed depending on the day and night modes, initial distribution of passengers (ϑ^i_p), and passengers' alertness situation (θ_p) (IMO, 2016; Nasso et al., 2019). The cases can offer a better understanding of evacuation times under varying initial conditions and passenger awareness situations. Table 6 illustrates how eight different cases are set.

Table 6. Experiment's setting. Passengers' walking speed is affected by the rolling motion of the ship (0 to 4º - athwartship walking direction)

Case	Day	Night	ϑ^i_p	θ_p
C_1		•	All passengers berth in i_1	all passengers are non-alert ($\theta_p = 0$)
C_2		•	All passengers berth in i_1	25% are alert ($\theta_p = 1$) and 75% are non-alert ($\theta_p = 0$)
C_3	•		10% berth in i_1 and 90% in other locales	95% are alert ($\theta_p = 1$) and 5% are non-alert ($\theta_p = 0$)

C_4	●		1% berth in i_1 and 99% in other locales	99% are alert (θ_p= 1) and 1% are non-alert (θ_p= 0)
C_5		●	All passengers berth in i_1	50% are alert (θ_p= 1) and 50% are non-alert (θ_p= 0)
C_6	●		50% berth in i_1 and 50% in other locales	80% are alert (θ_p= 1) and 20% are non-alert (θ_p= 0)
C_7	●		All passengers are in other locales	all passengers are alert (θ_p= 1)
C_8	●		All passengers are in other locales	all passengers are non-alert (θ_p= 0)

In each case under consideration, 396 passengers are distributed across 96 cabins.

6.2.Findings

Depending on the described cases, eight test problems (TP) are tailored to demonstrate the performance of the proposed solution approach. In Table 7, the size of each test problem, computational time (CT), number of iterations, and nodes to obtain optimal value are presented. The number of iterations refers to the number of steps performed by CPLEX to acquire the optimal solution.

Table 7. Performance of the solution method.

	Input						Output			
Test Problem	Case	$\|P\|$	$\|E\|$	$\|I\|$	$\|S\|$	$\|U\|$	$\|T\|$	CT (second)	Iterations	Nodes
TP_1	C_1	396	7	7	4	5	15	≈3,731	306,602	3,931
TP_2	C_2	396	7	7	4	5	15	≈4,001	218,475	3,145
TP_3	C_3	396	7	7	4	5	15	≈3,406	294,491	3,471
TP_4	C_4	396	7	7	4	5	15	≈4,298	200,069	3,052
TP_5	C_5	396	7	7	4	5	15	≈4,637	261,014	3,318
TP_6	C_6	396	7	7	4	5	15	≈4,007	245,604	3,209
TP_7	C_7	396	7	7	4	5	15	≈3,834	214,968	3,273
TP_8	C_8	396	7	7	4	5	15	≈4,082	313,307	3,528

The given data in Table 7 shows that the computational complexity varies significantly across the different TPs. TP_5 demanded the highest computational time of approximately 4,637 seconds. In contrast, TP_3 was the least time-consuming, requiring about 3,406 seconds. It indicates that TP_5 present a more intricate challenge for the solver, while TP_3 appears relatively simpler. Moreover, in terms of iterations, TP_8 leads with 313,307 iterations, whereas TP_4 necessitates the least, with 200,069 iterations. This disparity in iterations can be viewed as a measure of the solver's effort in pinpointing the optimal solution. A higher iteration count implies a more complex search space. Regarding the number of nodes traversed by the solver, TP_8 also dominates with the most nodes at 3,528. Meanwhile, TP_4 has the least, with 3,052 nodes. Given that each node in the tree structure corresponds to a subproblem, the data suggests that TP_8 has a greater number of subproblems to explore and solve.

Fig. 4 reveals that TP_1takes the longest time, followed closely by TP_2, while TP_6 has the shortest evacuation duration. The sequence of total ETs in different TP progresses as: TP_1, TP_2, TP_8, TP_5, TP_7, TP_4, TP_3, and finally TP_6. ETs are predominantly influenced by the time of day, passenger distribution, and alertness. Specifically, scenarios conducted during the night, such as TP_1, TP_2, and TP_5, typically experience longer evacuation times, ranking them at 1, 2, and 4, respectively. The location of passengers further impacts evacuation times. When all passengers are situated in i_1 during nighttime scenarios (as observed in TP_1 and TP_2), the evacuation duration is notably extended. As the proportion of passengers in i_1 diminishes, a corresponding decrease in evacuation time is generally observed.

Furthermore, the level of passenger alertness also holds significance. TPs with a higher prevalence of alert passengers, such as TP_3, TP_4, and TP_7, tend to finalize evacuation procedures more promptly compared to their counterparts with lesser alert passengers, like TP_1 and TP_8. After solving TPs, the optimization model established all seven potential exit doors to evacuate all passengers as quickly and safely as possible in all tests. They are located as marked in Fig. 1.

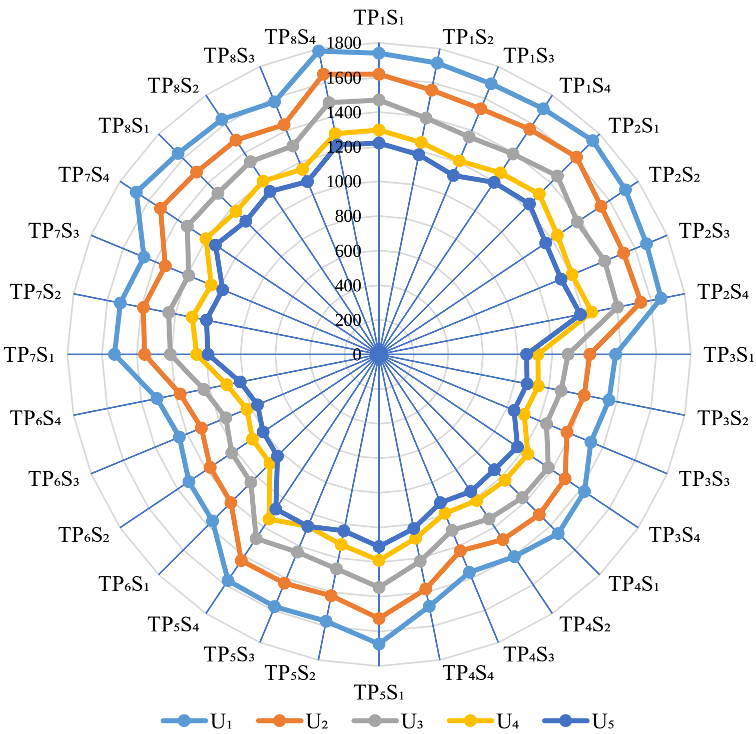
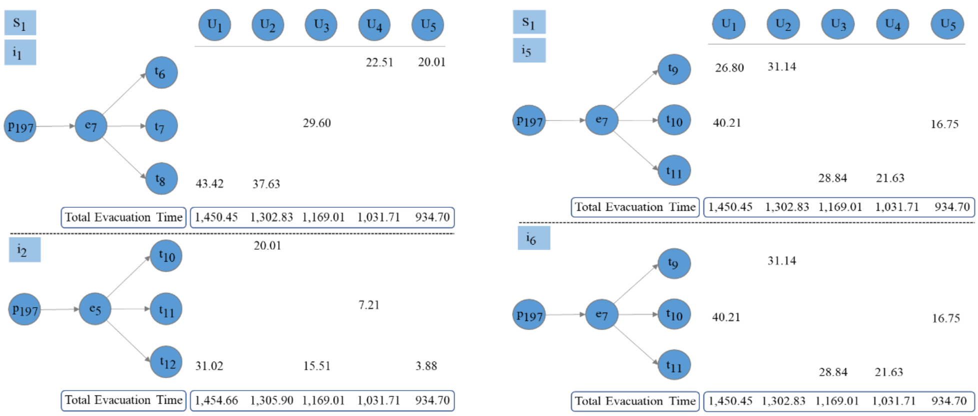


Fig. 4. ET through different cases and scenarios.

Under the circumstances of U_1, passengers travel more distance to reach their nearest exit doors. In this regard, the optimization model reflects it (Fig.4 conveys it). This critical scenario needs special attention as it corresponds to the worst-case scenario.

Seven more TPs are implemented for a specific passenger (p_{197} and $\theta_{197} = 1$) to figure out how starting point can affect the total ET. Fig. 5 displays the way passenger's starting locale affects the total ET in different scenarios.



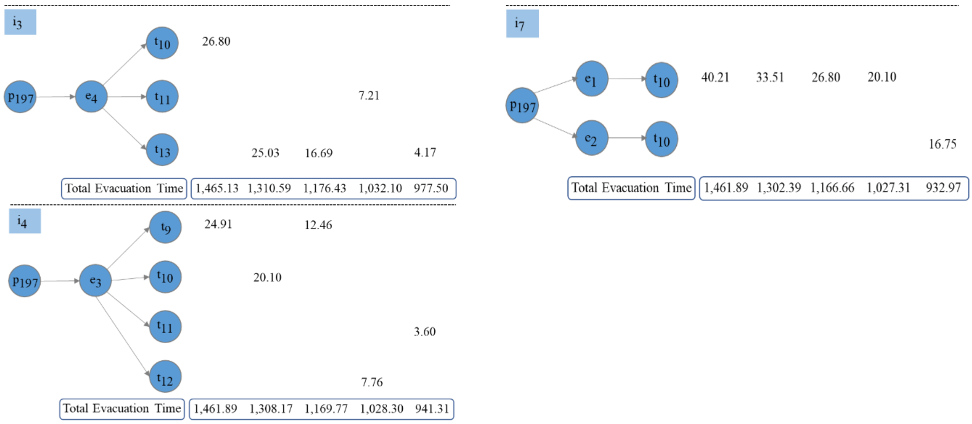


Fig. 5. The impact of passenger's starting placements on ET and passenger's plan under C_4.

As seen in Fig. 5, varying a passenger's starting location causes different plans for the corresponding passenger to be formulated and alter the tactical and operational decisions.

The identification of the slowest passengers is another major observation. It helps prioritize assistance and allocate appropriate personnel and emergency services to those who require them immediately, such as aged, disabled, or limited-mobility individuals. Moreover, identifying the slowest passengers can minimize the likelihood of bottlenecks and implement a staged evacuation process where the slowest passengers are evacuated first, followed by the remainder of the occupants. Fig. 6 marks the passengers with the highest ET under the different scenarios in C_2. The slowest passengers are clustered based on their proximity during evacuation in each scenario.

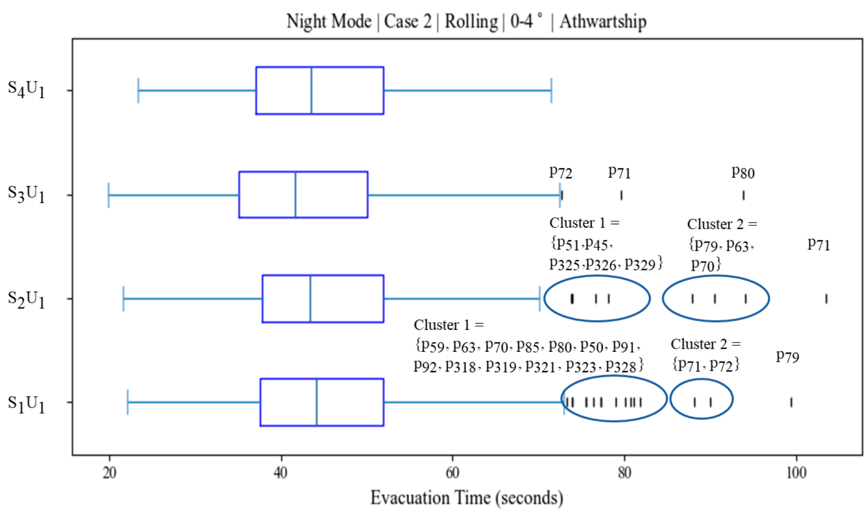


Fig. 6. The statistical visualization of the slowest passengers.

Considering S_1U_1 and cluster 1, the distribution of the corresponding passengers is illustrated in Fig. 7.

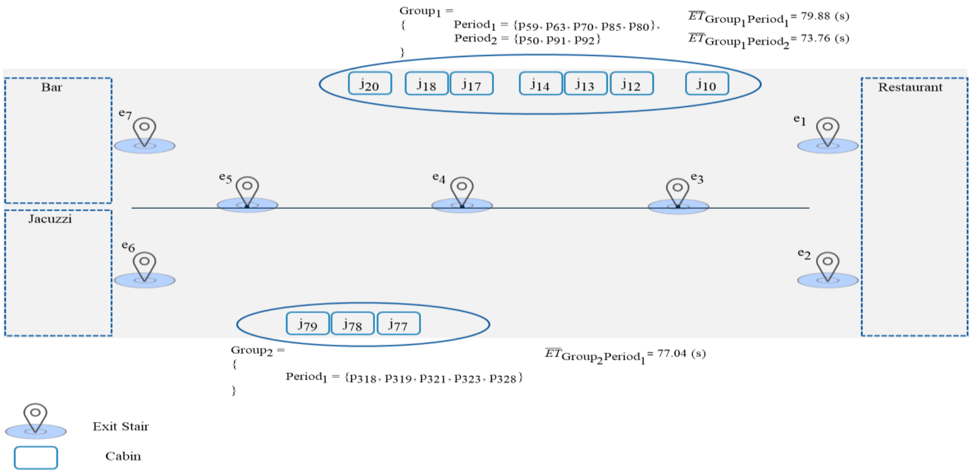


Fig. 7. The graphical illustration of the slowest passengers in cluster 1 evacuated in periods 1 and 2.

Passengers in group 1 belong to the female category, aged 30–50 or older than 50, with mobility impairments (1) and (2). While group 2 represents females over the age of 50 who are in good physical condition. Fig 7 displays that group 1 passengers took an average of 79.88 (period 1) and 73.76 (period 2) seconds to evacuate, whereas group 2 passengers traveled an average of 77.04 (period 1) seconds. In addition, the average walking speeds for periods 1 and 2 are 0.75 and 0.78 meters per second for groups 1 and 2, respectively. Thus, the emergency response team may tailor targeted training programs and evacuation drills considering these individuals' specific needs and limitations, guaranteeing they are better prepared for an emergency. The timeframe it will take to evacuate each group of people safely, for instance, may be roughly estimated.

According to IMO regulations, the corridor passenger density must be less than 3.5, which is reported by the optimization model. For a specific TP, $\underset{i\in[i_2,\, i_3,\, i_4]}{D_i} = [0.04, 0.08, 0.04]$ and for other locales than corridors, including cabins, bar, jacuzzi, and restaurant, $\underset{i\in[i_1,\, i_5,\, i_6,\, i_7]}{D_i} = [1.1, 0.16, 0.21, 0.27]$ at the beginning of an emergency situation onboard. Safety planners can pinpoint areas where congestion will probably ensue during an evacuation by gauging the initial density in corridors. This information can enable them to design alternative routes (for existing passenger ships) or install more exit points (for new passenger ships) to ease congestion.

The optimization model also regulates the flow of passengers across the corridors to ensure the evacuation is safe, efficient, and comfortable for passengers in each period. This value for the developed model accounts for 0.56 in each period, depending on the clear width of the corridor and passengers' shoulders.

7. Discussion

Advanced evacuation analysis involves the use of computer-based standards to construct detailed models of the evacuation process. These models incorporate a multitude of evacuation factors such as passenger walking speed, physical obstructions, ship layout, and environmental conditions (e.g., ship motions). These models optimize evacuation plans by enabling the exploration of various scenarios and evacuation features. Besides this, they may provide more precise estimates of ET and the number of individuals at risk by evaluating the inherent uncertainty and variability in evacuation constituents like passenger speed and travel distance.

In this study, we delved into these aspects by proposing a mathematically optimized model for formulating human evacuation plans for passenger ships, prioritizing the safe and efficient removal of all occupants from a ship's deck during emergencies while taking uncertainty into account.

7.1.Managerial insights

The outcomes generated numerous valuable managerial insights.

Managerial insight 1: how can the developed human evacuation model for passenger ships enhance safety at sea?

The proposed human evacuation optimization model can enhance the evacuation process by

1. enabling dynamic decision-making based on the current location of passengers, guaranteeing that guidance stays relevant and practical as the circumstances evolve.
2. minimizing congestion by strategically distributing passengers across multiple exit routes and safety areas, the model prevents bottlenecks and overcrowding, which can slow down the evacuation process.
3. providing customized instructions by delivering tailored guidance for different groups of passengers, such as those with mobility impairments, and
4. coordinating crew member responsibilities by assigning evacuation roles and duties to crew members, for example, managing the use of life-saving equipment and enabling the crew to focus on particular tasks, allowing targeted training, and better emergency preparedness.

The model can offer clear guidance to passengers, reducing disorganization during emergencies and ensuring a timely and efficient evacuation. The designed optimization model can determine the optimal number of exit doors and evacuation routes by taking into account the current location of passengers, the ship's layout, passenger walking speed, passenger travel distance, passenger awareness situation, rolling motion of the ship, and day and night mode. This can help minimize the time required for evacuation and the risk of injury or loss of life.

Managerial insight 2: how can uncertainty management in this research improve the robustness of human evacuation on passenger ships?

By hybrid consideration of uncertainty in passengers' walking speed and travel distance, the evacuation model can be more effective in the decision-making process during an emergency. It can provide a complete picture of the potential outcomes and risks of a particular decision. Crew and safety engineers can weigh the risks and benefits more effectively and make more informed decisions by understanding the uncertainty level of different walking speeds, travel distances, age groups, fitness levels, and mobility conditions. Furthermore, uncertainty modeling can assist safety managers and engineers onboard better handling risks by developing the relevant strategies for corresponding risks, for example, allocating critical resources, such as experienced crew, to the worst-case scenarios where the number of slowest passengers is high and needs special assistance. Moreover, by incorporating uncertainty management into the human evacuation model, it can account for the variability in passenger speed and movement and simulate different scenarios that may occur during an evacuation. This allows the crew to identify potential bottlenecks and evaluate the effectiveness of varying evacuation strategies, such as the placement of exits, the use of alternative routes, or the provision of clear guidance and communication.

The generated data-driven scenarios for passenger walking speed have been used to assess the impact of passenger performance on different emergencies. They are representative of a cluster of similar walking speed data per passenger. By clustering similar data points together, the k-means algorithm can help identify patterns that might not be immediately obvious by examining the data as a whole. For example, it can assist in identifying groups with similar physical behavior of each passenger in a large dataset, which can then be used to tailor evacuation strategies or offerings to each cluster. The applied adjustment scheme on speed allowed the optimization model to be more resilient to unexpected changes in speed.

Managerial insight 3: how can the considered situational awareness of passengers better the human evacuation model?

By considering situational awareness, evacuation models can better represent how humans perceive and react to the environment during an evacuation, improving the model's accuracy and reliability. It involves the perception and understanding of the current situation, potential hazards, and available options for action. For example, when a passenger is fully alert, the response time will go down, and the risk of injury will be minimized. In this regard, it can optimally offer the closest exit door considering other passengers. The considered feature in this research enables the model to apply smart sensors and accordingly define a more precise non-alert distance factor for calculating ET. As advanced evacuation analysis concentrates on the sentimental side of passengers, the awareness attribute can represent passengers' feelings more precisely and lead safety engineers to conceive appropriate post-event analysis, such as allocating proper crew to the feared and confused passengers.

Managerial insight 4: how can the imposed constraints on the initial density and traffic flow of passengers in this paper improve the human evacuation procedure?

As initial walking speed depends on the density of passengers on a passenger ship (IMO, 2016), the determined D_i in each starting point can help calculate the optimal capacity for each locale area i. for instance, the number of passengers who are being served in a restaurant or bar must be restricted. Besides, if it exceeds a threshold, consider proactive resilient measures such as allocating more crew to the spot. Constraint (8) and capacity of exit doors handle the traffic flow of passengers to reduce congestion in critical areas such as corridors and exits. These make it easier for passengers to move quickly and smoothly toward the exits, mitigating the risk of bottlenecks and delays.

Managerial insight 5: how can the optimized human evacuation model contribute to the design of a passenger ship?

The developed model can optimize the capacity and layout of different areas of the ship and doors and identify areas that may be overcrowded or difficult to navigate. This can inform decisions about the size and configuration of different areas of the ship to ensure they can accommodate an appropriate number of passengers during an emergency.

7.2. Limitations and future works

Despite its contributions, the study recognizes certain limitations. The binary representation of passengers' situational awareness could be refined using intelligent sensors to provide a continuous measure between zero and one, leading to more accurate modeling of passenger behavior. Moreover, while the current model focuses on a single deck of a passenger ship, its applicability could be extended to a multi-deck human evacuation framework for enhanced realism. Additionally, the exploration of ship roll's impact on walking directionality was limited, an aspect that is crucial for understanding speed changes due to ship rolling and presents a promising avenue for future research.

8. Conclusion

This research develops a data-driven, risk-neutral, scenario-based optimization framework for the human evacuation model under hybrid uncertainty. Passenger walking speeds and travel distances are described as scenarios representing the centroids of the clusters and random scenarios, respectively. The k-means algorithm generates data-driven scenarios (i.e., derived from historical data) for passenger walking speed, and a deviation rate is applied for generating travel distance scenarios. The effects of ship rolling motions on the evacuation process further compound the scenario. The model adjusts scenarios to update the evacuation plan based on changing situations. Primarily, the adjusted scenarios are fed into an MIP mathematical model, which is in charge of minimizing the total evacuation time of the whole passenger over the planning horizon. The formulated model not only determines the optimal number of exit stairs but also allocates and schedules passengers across multiple periods. The passengers' starting locations and awareness are considered to shift the model to real-life settings. Besides, a traffic flow constraint is applied to control the risk of bottlenecks and delays across the corridors and exit doors. In addition, seven locales are considered starting points for passengers to represent their current location. In this regard, the density of passengers is regulated in these locations.

Analysis of the multiple test problems reveals those factors like passenger walking speed, travel distance, alertness, and starting location influence the total evacuation time. Furthermore, extended distances and passengers' lack of alertness significantly augment the total evacuation time. It demonstrates the imperative for immediate attention and aid during an emergency. The model identifies passengers with protracted evacuation time. It signals those who might need specialized assistance. Moreover, a passenger's specific locale can markedly alter their evacuation plan (i.e., evacuation time and exit period and door) amidst varying uncertainties.

CRediT authorship contribution statement

Hossein Arshad: Conceptualization, Modeling, Visualization, Methodology, Writing- original draft, review, and editing, Software- programming. Jan Emblemsvåg: Conceptualization, Supervision, Resources, Writing- review, and editing. Xilei Zhao: Conceptualization, Supervision, Resources, Writing- review, and editing.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly and ChatGPT to improve the paper's language and readability. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Paper 4

Stochastic-robust human evacuation planning for individual and family travelers: A Ro-Ro passenger ship

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