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Rapid prediction of human evacuation from passenger ships based on machine learning methods

Xinjian Wang

Navigation College, Dalian Maritime University, P.R. China. E-mail: wangxinjian@dlmu.edu.cn

Yiquan Yuan

Navigation College, Dalian Maritime University, P.R. China. E-mail: asu572@dlmu.edu.cn

Yubo Guan

Navigation College, Dalian Maritime University, P.R. China. E-mail: g15841439342@163.com

Yuhao Cao

Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, UK. E-mail: Y.Cao@ljmu.ac.uk

Huanxin Wang

Navigation College, Dalian Maritime University, P.R. China. E-mail: wanghxdmu@dlmu.edu.cn

Zhengjiang Liu

Navigation College, Dalian Maritime University, P.R. China. E-mail: liuzhengjiang@dlmu.edu.cn

Zaili Yang

Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, UK. E-mail: Z.Yang@ljmu.ac.uk

Abstracts: Compared to land-based evacuation scenarios, research on human evacuation from passenger ships presents unique challenges due to factors such as the complex geometric layout of ships, passengers' lower familiarity with the environment, and the impact of sea conditions. Rapidly predicting evacuation time is therefore important and crucial for safety of passenger ships at sea. This study aims to address the challenge of rapidly and accurately predicting human evacuation time from passenger ships using methods such as simulation modelling and predictive analysis. Firstly, the key risk factors affecting human evacuation from passenger ships are identified through literature reviews and accident report analysis, and a set of evacuation risk factors is established based on different combinations of these risk factors. Secondly, a simulation model for human evacuation from passenger ships is developed, and its reliability is verified by comparing the simulation results with actual evacuation drill outcomes. Based on this model, different evacuation scenarios are simulated using various combinations of risk factors, and the impact of key factors—such as guiding behaviour, personnel attributes and initial distribution, day/night environment, stair availability, and ship inclination—on evacuation efficiency is systematically analysed. Finally, several well-established machine learning models, including Random Forest, Support Vector Regression, and Neural Networks, are used to rapidly predict human evacuation time in different scenarios. The model with the shortest prediction time and highest accuracy is chosen. The results show that the simulation data closely align with the actual drill data. Among all the predictive models, Support Vector Regression performs the best, providing rapid and accurate predictions of human evacuation time from passenger ships. The findings make significant contributions to improve evacuation safety of passenger ships and crowd management.

Keywords: Maritime safety; Passenger ships; Emergency evacuation; Machine learning; Prediction efficiency.

1. Introduction

Unlike land-based vehicles or buildings, large passenger ships have complex structures to realize large carrying capacity while keeping their safety. In the event of an accident, it can lead to large-scale casualties. For example, in the Sewol Ferry accident, a passenger vessel carrying 476 people capsized due to overloading and improper emergency procedures by the crew, ultimately resulting in the tragic loss of 304 lives (Kim et al. 2020). To ensure the safety of passenger ships during maritime operations, the International Maritime Organization (IMO) has issued a series of evacuation analysis guidelines and standards. These guidelines require that all passenger ships built after January 1, 2020, undergo evacuation analysis.

Currently, research on shipboard evacuation can generally be divided into three main areas: passenger behaviour analysis, evacuation strategy optimization, and evacuation performance assessment (Liu et al. 2022). Research on passenger behaviour primarily focuses on practical surveys or evacuation trials. Researchers typically build experimental platforms (Fang et al. 2024) or conduct surveys using questionnaires (Liu et al. 2022). Research on evacuation strategies includes the studies on how factors such as the inclination angle and stair layout affect evacuation (Fang et al. 2023) , as well as research focused on path planning during evacuation (Deng et al. 2022). Research on evacuation performance assessment are conducted from macroscopic and microscopic perspectives. Macroscopic studies focus on analysing the crowd as a whole, for example, by treating it as a fluid (Salami et al. 2023). Microscopic studies, on the other hand, treat each passenger as an individual agent, analysing them using models such as a social force model or cellular automata (Yang et al. 2023, Ma et al. 2024).

To support the analysis of human evacuation from passenger ships, the European Union (EU) conducted the SAFEGAURD project, which involved large-scale evacuation experiments on passenger ships and provided relevant datasets. However, organizing a similar evacuation experiment is not only costly but also entails certain risks. In recent years, with the development of computer software technology, evacuation simulation modelling has become a key research tool for evacuation analysis. Applying evacuation simulation modelling to shipboard evacuation allows for the selection of appropriate scenarios and parameters. The simulation model can easily construct large-scale human evacuation scenarios from passenger ships, significantly reducing experimental costs and improving efficiency (Ronchi 2013). However, evacuation analysis based on simulation modelling is time-consuming and cannot provide rapid predictions of evacuation times.

In recent years, the rapid development of machine learning, particularly its advantages in prediction, has enabled fast evacuation time predictions. Therefore, this study uses the Pathfinder simulation software to build a simulation model for human evacuation from passenger ships, obtaining evacuation results under different combinations of risk factors. This study then applies various machine learning models to predict evacuation time across different scenarios, selecting the model with the shortest prediction time and highest accuracy to achieve rapid and accurate predictions of human evacuation time from passenger ships.

The structure of this paper is organized as follows. Section 2 describes the simulation model and machine learning models used in this study. Section 3 evaluates the experimental results. Section 4 discusses the experimental findings. Finally, Section 5 provides a summary of the paper and suggests directions for future research.

2. Methodology

2.1. *Evacuation simulation tool*

Pathfinder is an efficient and accurate intelligent emergency evacuation assessment system (Wang et al. 2023). The system integrates collision avoidance and steering mechanisms, simulating individual movement graphically by considering both collision avoidance behaviour and dynamic steering paths. It enables evacuation route planning and precise evacuation time calculations. Compared to other simulation software, such as AnyLogic and Evi, Pathfinder demonstrates significant advantages in terms of accuracy (Fang et al. 2023).

This study uses the Pathfinder simulation tool along with ship data from the EU's SAFEGAURD project and the CAD drawings from SGVDS 2 to construct a model of the "Ocean Jewel" cruise ship. The ship has a gross tonnage of 90,090 tons, a length of 293.25 meters, and a width of 32.2 meters. It features four assembly stations, twelve decks, and forty stairways, with a complex and well-equipped interior capable of accommodating a large number of passengers. Its intricate assembly layout and high passenger capacity provide ideal conditions for constructing an emergency evacuation simulation model for passenger ships. By using this cruise ship model for evacuation simulations, this study can realistically replicate the evacuation process in emergency situations, fully meeting the research requirements for evacuation under complex scenarios.

2.2. *Simulation parameter settings*

In evacuation simulations, the total number of the evacuated people is a key influencing factor. Based on the maximum passenger capacity of the "Ocean Jewel" cruise ship, this study sets the simulation range from 900 to 1,900 people, with increments of 200 people at a step, resulting in six different scenarios. In addition, the day-night difference is another important factor, as passenger distribution and response time vary significantly between day and night. To comprehensively assess the impact, this study also considers the presence or absence of guidance and the ship's inclined angle (ranging from 0° to 25°, with increments of 5° at a step, totalling six conditions) on the evacuation process. According to relevant studies(Fang et al. 2023), the movement speed of passengers under inclined conditions can be described by Eq. (1), where v represents the individual walking speed, V represents the individual walking speed considering the inclined factor, and k is the speed attenuation factor. The specific values of k are shown in Table 1.

$$V = k \cdot v \tag{1}$$

A holistic consideration of these factors provides a scientific basis for analysing passenger behaviour and evacuation efficiency to reflect complex evacuation scenarios in the real world.

Table 1. Attenuation factor for individual walking speed at different inclined angles

Angle	0°	5°	10°	15°	20°	25°
k	1	0.98	0.92	0.86	0.73	0.39

The cruise ship has a total of 12 stairways, but not all are usable in the event of an emergency. During a fire, stairwells can become filled with smoke and toxic gases, potentially leading to passenger suffocation. Additionally, in the case of ship inclination, as the inclined angle increases, stairway areas may become blocked by fallen objects, hindering passage. Therefore, the availability of stairways is one of the key risk factors influencing evacuation efficiency during an emergency. Several scenarios with varying stairway availability are designed for the experiment, with the specific settings shown in Table 2.

Based on the simulation model and the various influencing factors listed in Table 2, 1,152 simulation scenarios are constructed. These scenarios effectively consider different combinations of risk factors, providing a rich data foundation for studying evacuation process in complex situations. Through systematic analysis of these simulation results, a human evacuation time prediction model for the passenger ships can be developed, enabling rapid and accurate predictions of evacuation times under different scenarios.

Table 2. The evacuation parameters for simulation model.

NO.	Influencing factor	Scene setting	Quantity
1	Total number of evacuees	900,1100,1300,1500, 1700,1900	6
2	Diurnal difference	Day, Night	2
3	Tilt Angle	0,5,10,15,20,25,	6
4	Number of unusable stairs	None 5th deck only 6th deck only 7th deck only 8th deck only 9th deck only 10th deck only 11th deck only	8
5	Guiding behaviour	Guided, Undirected	2

2.3. *Simulation model validation*

In accordance with the requirements of the EU project and relevant literature (Galea et al. 2013), this study uses the following three deviation evaluation parameters to assess the reliability of the simulation results. These parameters are evaluated based on the dataset SGVDS 2, generated from the simulated evacuation experiments conducted on the "Ocean Jewel" cruise ship. By analysing these parameters, the accuracy of the simulation model results and their consistency with actual conditions can be ensured, thus validating the model.

The Error Rate Deviation (ERD) is used to quantify the difference between the experimental data (E_i) and the model prediction data (m_i), with the calculation formula provided in Eq. (1).

$$ERD = \frac{\sqrt{\sum_{i=1}^{n}(E_i - m_i)^2}}{\sqrt{\sum_{i=1}^{n}(E_i)^2}} \tag{1}$$

The Error Proportionality Coefficient (EPC) is used to calculate a specific factor that, when multiplied by each data point (m_i) in the model, minimizes the distance between the model vector (m) and the experimental vector (E). The calculation formula is provided in Eq. (2).

$$EPC = \frac{\langle E, \mathrm{m} \rangle}{\|m\|^2} = \frac{\sum_{i=1}^{n} E_i m_i}{\sum_{i=1}^{n} m_i^2} \tag{2}$$

The Shape Coefficient (SC) provides a measure of the degree to which the model data curve matches the experimental data curve in shape. The calculation formula is provided in Eq. (3). When selecting an appropriate value for s, the number of data points, n, in the dataset must be considered. According to the project documentation, the ratio of parameter s to the number of data points n should be set to 0.03, ensuring a reasonable correspondence between the accuracy of shape matching and the scale of the dataset.

$$SC = \frac{\langle E, m \rangle}{\|E\|\|m\|} = \frac{\sum_{i=s+1}^{n} \frac{(E_i - E_{i-s})(m_i - m_{i-s})}{s^2(t_i - t_{i-1})}}{\sqrt{\sum_{i=s+1}^{n} \frac{(E_i - E_{i-s})^2}{s^2(t_i - t_{i-1})} \sum_{i=s+1}^{n} \frac{(m_i - m_{i-s})^2}{s^2(t_i - t_{i-1})}}} \tag{3}$$

The acceptance criteria for these three indicators are shown in Table 3. By comparing the simulation results with these standards, the reliability of the results can be assessed, providing a foundation for further model optimization and application. These standards provide a clear reference framework for evaluating the model's consistency and adaptability with experimental data.

Table 3. Qualification criteria for deviation assessment parameters

Evaluation parameter	ERD	EPC	SC
Standard	ERD≤0.25	0.8≤EPC≤1.2	SC ≥0.8

2.4. *Machine learning methods*

This study selected three of the most commonly used machine learning models for the rapid prediction of evacuation times. The selected models are the Backpropagation Neural Network (BPNN), Support Vector Regression (SVR), and Random Forest (RF). The three models and their characteristics are shown in Table 4.

Table 4. The machine learning models used in this study and their characteristics

Name	Core	Peculiarity	Reference
BPNN	The weights are adjusted through error backpropagation to minimize prediction error.	It fits nonlinear relationships and demonstrates strong adaptability.	(Miao et al. 2024)
SVR	The optimal hyperplane is identified to separate the	It handles high-dimensional data and	(Zhu et al. 2024)

	samples, enhancing generalization capability.	reduces overfitting.	
RF	Robustness is enhanced through the ensemble of multiple decision trees.	It avoids overfitting by voting or averaging the output results.	(Yan et al. 2024)

To assess the accuracy of the machine learning models, the coefficient of determination (R^2) and Relative Error (RE) (Uhlík et al. 2024) are commonly used for evaluation. R^2 is a statistical measure of the model's predictive ability, indicating the extent to which the model explains the variation in the data. Its value ranges from 0 to 1, with values closer to 1 indicating better model fit. RE, on the other hand, is used to evaluate prediction accuracy by representing the ratio of the prediction error to the actual value. It is particularly useful for tasks of varying scales, as it measures the relative degree of the model's error within the prediction range.

3. Results

3.1. *Evacuation simulation results*

To ensure data stability, the simulations are repeated 50 times, and the average evacuation data are calculated to minimize the influence of unexpected factors. The results are compared with the EU experimental dataset, and relevant graphs are generated, as shown in Figs. 1 and 2. The evacuation patterns from the simulation closely match those in the dataset. Therefore, the simulation data from this study are considered reliable.

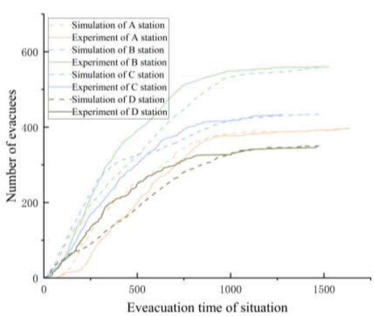

Fig. 1. Experimental and simulation results for stations A-D.

To further validate the reliability and accuracy of the simulation model, the deviation assessment parameters are calculated using Eqs. (2), (3), and (4), with the results shown in Table 5.

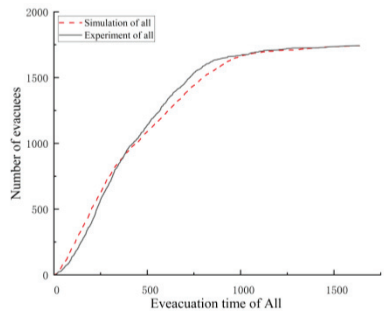

Fig. 2. The experimental and simulation results for overall evacuation process.

Table 5. The numerical values of deviation assessment parameters.

Area	ERD	EPC	SC
Station A	0.1505	1.1247	0.9649
Station B	0.2135	0.8327	0.9134
Station C	0.1681	0.9961	0.8510
Station D	0.2331	0.8492	0.8894
Overall	0.0837	0.9441	0.9782

As shown in Table 5, the simulation data output by the Pathfinder software closely match the actual situations, demonstrating that the constructed simulation model effectively meets the requirements for human evacuation simulations.

3.2. *Machine learning performance*

Based on the established simulation model, 1,152 simulation scenarios are conducted to obtain evacuation data for various scenarios. The data are then input into the machine learning models described in Section 2.3 for training. During training, the data are randomly split into training and test sets, with 80% used for model training and 20% for evaluating the model's predictive performance (Yang and Ding 2023).

The trained model is tested using the test set, and the degree of fit between its predictions and the simulation results is shown in Fig. 3.

As shown in Fig. 3, the predictions of all three models exhibit a high degree of fit with the simulation data, with relatively small fitting errors. The specific performance of each model is presented in Table 6.

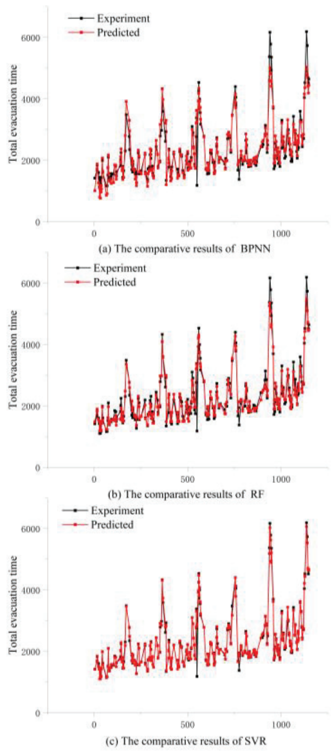

Fig. 3. The fit curve of prediction and simulation results for different machine learning models.

Table 6. The prediction performances of three machine learning models

Model	R^2	RE	time
BPNN	0.95624858	0.04021030	26.15 s
SVR	0.97965071	0.02648534	15.37 s
RF	0.94103509	0.04508456	5.12 s

As shown in Table 6, SVR achieves the highest accuracy with moderate training speed, performing the best overall. BPNN has relatively high prediction accuracy but requires longer training time, at 26.15 seconds. RF, while having lower prediction accuracy, trains more quickly, completing training in just 5.12 seconds.

Comparative analysis reveals that the BPNN model requires extensive matrix computations due to its algorithmic nature, resulting in a high computational load. Additionally, the BPNN model may not fully utilize its potential when working with smaller datasets. On the other hand, the RF model benefits from decision tree advantages, allowing for parallel processing. However, due to its relatively simple structure, the RF model exhibits lower accuracy.

4. Discussion

This study uses a Pathfinder simulation tool, based on the actual layout of passenger ships, to model various evacuation scenarios and apply machine learning models to predict total evacuation times. The goal is to enhance emergency response and on-site decision-making for passenger ships. By integrating simulations with machine learning, evacuation time for various emergencies can be predicted within seconds. Machine learning significantly improves computational efficiency and provides practical decision support, surpassing traditional simulation methods in both speed and accuracy. This finding further demonstrates the new contributions of this study from a theoretical perspective.

At a macro level, machine learning models evaluate evacuation time based on factors such as the real-time environment, personnel attributes, vessel condition, and facility availability. These predictions help operators and emergency managers optimize evacuation strategies, ensuring passengers evacuate via the most efficient routes, thereby improving both response efficiency and safety. At a micro level, machine learning predicts evacuation times for individual passengers or specific areas (e.g., cabins or corridors), considering factors such as passenger density, facility availability, and guiding behaviour. This helps managers adjust plans for specific areas, optimize evacuation routes, and reduce congestion. Such managerial implications emphasise the findings' real-world insights in practice.

This study also enhances the understanding of passenger behaviour and crowd dynamics. By simulating evacuation scenarios and analysing data, the impact of guidance on evacuation efficiency is shown to be significant. The results indicate that guiding behaviour positively influences evacuation efficiency, offering managers insights on focusing on guidance dynamics and optimizing evacuation routes.

In high-density areas or at the beginning of evacuation, delays may occur due to confusion or passengers searching for family members. Machine learning models can predict these issues in advance, enabling managers to adjust guidance strategies to prevent delays.

This dual-level analysis—optimizing the overall strategy at the macro level and adjusting individual behaviours at the micro level—enhances evacuation efficiency and reduces risks. This study provides a scientific, rapid, and reliable insight for emergency management, enabling faster and more efficient human evacuation from passenger ships, ensuring the safety of both passengers and crew. The model can also quickly predict overall evacuation times based on factors such as environment, passenger distribution, and facility availability, providing key data for emergency decision-making.

5. Conclusion

This study utilizes a passenger ship from the EU's SAFEGAURD project public dataset as the research object. A human evacuation model for the "Ocean Jewel" ship is established using a Pathfinder tool for simulation and validation purposes. By considering key factors affecting human evacuation from passenger ships, 1,152 different evacuation scenarios are constructed, and simulations are conducted using the model.

The model developed in this study comprehensively takes into account factors such as the number of passengers, evacuation time, facility availability, ship inclination, and the guidance behaviour. Then, three machine learning models are employed to train and predict evacuation times for passengers. The results reveal that Support Vector Regression (SVR) performs excellently in terms of prediction accuracy, making it suitable for medium- to long-term evacuation planning. Random Forest (RF), with its fast computation speed, is well-suited for meeting the rapid prediction needs of emergency management during sudden accidents.

The human evacuation from passenger ships model developed in this study still has certain limitations. Factors such as ship rolling, small groups, and panic behaviour shall be investigated in terms of their impacts. If they are significant, future research should integrate these factors, optimize evacuation scenarios, and collect more comprehensive training data to achieve more accurate prediction results, thus providing a solid scientific basis for real-world evacuation strategies.

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References

Kim, Imgyu, Hyuncheol Kim, and Soonhung Han, "An Evacuation Simulation for Hazard Analysis of Isolation at Sea during Passenger Ship Heeling," *International Journal of Environmental Research and Public Health 17*, no. 24 (2020): 9393.

Liu, Kezhong et al., "A survey of crowd evacuation on passenger ships: Recent advances and future challenges," *Ocean Engineering 263* (2022): 112403.

Fang, Siming et al., "Experimental study on human evacuation onboard passenger ships considering heeling angle and opposite directions," *Ocean Engineering 308* (2024): 118256.

Fang, Siming et al., "A quantitative study of the factors influencing human evacuation from ships," *Ocean Engineering 285* (2023): 115156.

Deng, Kunxiang et al., "Optimal Emergency Evacuation Route Planning Model Based on Fire Prediction Data," *Mathematics 10*, no. 17 (2022): 3146.

Salami, Oluwafemi B. et al., "Underground mining fire hazards and the optimization of emergency evacuation strategies (EES): The issues, existing methodology and limitations, and way forward," *Process Safety and Environmental Protection 177* (2023): 617-34.

Yang, Xiaoxia et al., "Multi-Objective Optimization of Evacuation Route for Heterogeneous Passengers in the Metro Station Considering Node Efficiency," *IEEE Transactions on Intelligent Transportation Systems 24*, no. 11 (2023): 12448-61.

Ma, Yaping, Gangqiang Zhang, and Feizhou Huo, "An evacuation model considering pedestrian fall behavior in an inclined passenger ship," *Physica A: Statistical Mechanics and its Applications 643* (2024): 129794.

Ronchi, Enrico, "Testing the predictive capabilities of evacuation models for tunnel fire safety analysis," *Safety Science 59*(2013): 141-53.

Wang, Yi et al., "Modelling and interpreting evacuation time and exit choice for large-scale ancient architectural complex using machine learning," *Journal of Building Engineering 80* (2023): 108133.

Galea, Edwin Richard et al., "An Experimental Validation of an Evacuation Model using Data Sets Generated from Two Large Passenger Ships," *Journal of Ship Research 57*, no. 3 (2013): 155-70.

Miao, Xu, Bingcheng Chen, and Yuxi Zhao, "Prediction of compressive strength of glass powder concrete based on artificial intelligence," *Journal of Building Engineering 91* (2024): 109377.

Zhu, Defu et al., "Fusion of finite element and machine learning methods to predict rock shear strength parameters," *Journal of Geophysics and Engineering 21*, no. 4 (2024): 1183-93.

Yan, Tie et al., "A real-time intelligent lithology identification method based on a dynamic felling strategy weighted random forest algorithm," *Petroleum Science 21*, no. 2 (2024): 1135-48.

Uhlík, Ondřej et al., "Real-time RSET prediction across three types of geometries and simulation training dataset: A comparative study of machine learning models," *Developments in the Built Environment 18* (2024): 100461.

Yang, Lixuan and Ning Ding, "Evacuation behavior under violent attacks in classrooms based on experiments and interpretable machine learning method," *Safety Science 166* (2023): 106243.