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ABSTRACT

Ship maneuvering decisions are influenced by several factors, and it is essential to prioritize the main influencing factors for efficient selection of the corresponding maneuvering decisions. Meanwhile, the autonomous ship maneuvering decision-making influencing factors constitute a typical grey system, which is suitable for research by grey relational analysis. Furthermore, in the fuzzy approach, linguistic assessment of factors is evaluated to obtain priorities numbers. Therefore, this study mainly focuses on the concept of human-like maneuvering for autonomous ships. Based on experimental data of experienced seafarers and using a simulation platform under the scenario of the Shanghai Waigaoqiao wharf, an inference model utilizing grey and fuzzy theories is proposed. The proposed model combined with expert linguistic terms in order to select the ship maneuvering decision-making main influencing factors from multi-source influencing factors (in overall and separated categories of natural environment, ship motion, force parameters, draft, and position), and to study the decision-making prioritization for maritime traffic safety for specific ship maneuvering scenarios. This method can prioritize the main factors which affect maneuvering decisions as well as guide an autonomous ship-assisted or automatic maneuvering evaluation system for the research of human-like maneuvering behavior. This study provides a new perspective on the identification of main ship maneuvering decision-making influencing factors in theory and in practice. It can be utilized for better decision-making concerning maritime traffic safety of autonomous ship maneuvering, which in turn makes shipping safer and promote the application and spreading of autonomous ships.

1. Introduction

Maritime shipping is the lifeblood of the global economy, transporting approximately 90% of international merchandise trade (ICS, 2018). According to the statistics, there are over 50,000 merchant ships trading internationally (AGCS, 2018). Therefore, the safety of vessels is a critical issue in global seaborne transport. In addition, with the development of computer science and technology, especially the rapid development of technologies and theories such as The Internet of Things (IoT), Information Technology (IT), and Artificial Intelligence (AI), the world merchandise trade is moving in the direction of informatization and intelligence. Thereupon, the study of autonomous merchant ships has become a "hot" topic internationally, as this would reduce the need for operators/seafarers onboard, and increase maritime

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Nomenclature

X	a grey relation factor set (discrete series)
X_0	a reference series
X_i	the comparative series
X_0'	the processed reference series
X_i'	the processed comparative series
S_0	the standard deviation of the reference series
S_i	the standard deviation of the comparative series
X'	the original data series
ω	the number of influencing factors
$\Delta_i(k)$	the absolute value of the difference between the reference series and each sub-series at each point
$\Delta_i(\max)$	the first-level maximum range
$\Delta_i(\min)$	the first-level minimum range
$\Delta_{\max}$	the second-level maximum range
$\Delta_{\min}$	the second-level minimum range
$\xi_i(x_0(k), x_i(k))$	the correlation coefficient between the comparative series X_i and the reference series X_0 at point k
ρ	the resolution ratio
$A = (a, b, c)$	the triangular fuzzy number corresponding to the linguistic term
β_i	the relative weights of the experts
$A(X)$	the crisp number
$\mu_A(x)$	the membership function for linguistic terms from the judgments of domain experts
γ_i	the grey relational grade
λ_k	the weight of each influencing factor
$\lambda_i(x_0(k), x_i(k))$	the relational grade between the reference series and comparative series

transport as a more environmental-friendly alternative to transport by trucks on land. Several large companies have started to test such vessels, for instance, the Advanced Autonomous Waterborne Applications Initiative (AAWA) project of Rolls-Royce Holdings plc (Rolls-Royce, 2018). In addition, for the shipping industry, advancements in Network Technology (NT), Information and Communication Technology (ICT), and Information Technology (IT) create new opportunities for developing electrical systems such as ships autonomous navigation (Lee et al., 2009; Perera et al., 2015), Integrated Bridge System (IBS), and decision support system (Pietrzykowski et al., 2017), and the level of shipping modernization has been rapidly improved (Pazouki et al., 2018). The development of autonomous ships has been technically feasible. In addition, the economy of the world is experiencing a period of slow-moving recovery; thus shipping industries are falling into the long-term overcapacity. Hence the world's major shipping companies have to shift their development planning to improve the operational efficiency and enhance the safety management of their merchant fleet, in order to reduce the seaborne transport costs and adapt to the market tendency. Moreover, the demands of ship owners and seafarers for safety and profitability of shipping are constantly increasing; it is also an essential influencing factor for the development of autonomous ships.

Furthermore, since the implementation of the international energy conservation and emission reduction rules and regulations promoted the development of autonomous ships, the EU's Monitoring, Reporting and Verification (MRV) regulations for greenhouse gas emissions of the shipping industry took effect on July 1, 2015, and began to monitor emissions according to MRV regulations on January 1, 2018. In addition, all ships larger than 5000 gross tons and berthed in EU ports are required to meet MRV regulations. Moreover, the International Maritime Organization (IMO) has the program to start emissions monitoring under the Ship Energy Efficiency Management Plan (SEEMP) on January 1, 2019 (IMO, 2018). Besides, the number of seafarers in the world is declining recently, while the wages of seafarers are rising year by year, which has become the second largest expenditure item after the fuel costs of shipping (Lun et al., 2016). At the same time, maritime accidents frequently occur, for instance, there were 2712 reported shipping incidents/casualties in 2017 (AGCS, 2018), and hull collisions and damages caused by human errors account for more than 80% of marine accidents (Hanzu-Pazara et al., 2008; Rothblum, 2000). In addition, the safety of the seafarers in extreme sea conditions in recent years has also become a problem that cannot be ignored (Xue et al., 2019a; Wang et al., 2014; Baksh et al., 2018; Aziz et al., 2019; Khan et al., 2018).

In summary, as autonomous ships have outstanding advantages in improving operational efficiency, safety management, decision-making efficiency, and energy consumption management of ships, research for autonomous ships has become an inevitable tendency for future ship development, and gained the interest of many researchers in both academia and private sectors (Goerlandt and Montewka, 2015). Furthermore, although the control technology of ships has gradually begun to change from traditional electromechanical control (Gupta et al., 2018) to the trend of networking, digitization, and automation, the ship-handling process has become a multi-functional integrated system integrating multiple automation systems, which improves the safety, profitability and management efficiency of shipping. However, the improvement of the degree of automation of ships has a certain gap from the ships with automatic perception, subjective analysis, and autonomous decision-making.

The accuracy of ship maneuvering decisions is directly related to the safety of waterway transportation. The seafarers onboard vessels, especially the officer on watch (OOW), often perform duties in circumstances where technological, environmental factors, etc., emerge which may lead to the occurrence of human failures and marine accidents (Ugurlu et al., 2015). Likewise, in the process of autonomous ships human-like decision-making, the OOW maneuvering decision-making is also influenced by multi-source information, for instance, the other ships in waterways and ports, the natural environmental factors, etc. (Kim et al., 2017), this requires ship maneuvering decision-making procedures expressed along with higher effectiveness. However, due to the limited capacity of the information acquiring and processing, OOW cannot achieve the multi-attribute or multi-source information in a particular time and space concurrently (Xue et al., 2019b). For instance, under high-intensity work pressure, the OOW cannot always ensure to make correct decisions timely when facing constantly changing factors in different navigation scenarios, thus maneuvering decisions cannot still be made accurately and quickly, which could lead to maritime traffic accidents. Therefore, the automatic acquisition and representation of maneuvering decision-making are necessary for ensuring accurate maneuvering decisions and maritime traffic safety; moreover, it is essential to identify, analyze, and prioritize the main maritime traffic safety influencing factors for efficient selection of autonomous ships from the multi-attribute or multi-source information for corresponding maneuvering decisions.

Multi-attribute decision-making is widely used in economics, society, military, and engineering technology (Liu et al., 2015). Due to the uncertainty and complexity of decision problems, the problems of multi-attribute decision-making are always combined with uncertain and fuzzy matters, so fuzziness is an essential factor to be considered in practical decision-making of real-world (Jin and Liu, 2010). In addition, when conducting the problems with poor information, the characteristics of grey (the data/information that is known partially) are also shown within the decision problems. Therefore, the decision-making problems in the real world are often fuzzy and grey, which are called the grey fuzzy multiple attribute decision-making problems (Liu et al., 2015).

Although variety of previous studies in academia have been conducted upon impact factors assessment based on the grey and fuzzy theories, they seldom take into consideration the relative importance of different influencing factors (just consider different influencing factors in the same weight) and in the absence of expertise; just consider the same weight to determine the judgments from different experts; just use the standard fuzzy number functions to evaluate the linguistic terms given from experts, however, the standard fuzzy membership function sometimes cannot determine different linguistic terms from different domain experts reasonably, on some specific situation, it treats different indexes, specifically, the same linguistic term from different domain experts, equally.

In this research, the autonomous ship human maneuvering decision factors are modeled as a typical "grey system", and fuzzy numbers of the domain experts are utilized to optimize the proposed model. The maritime traffic safety influencing factors of autonomous ship maneuvering decision-making, such as force parameters, draft, environment, motion, and position, etc., are obtained using data from a simulation platform. After collecting the judgment knowledge from domain experts, the Delphi method was utilized for comprehensively determining the fuzzy numbers of different linguistic terms combined with varying weights of each domain expert. Finally, the novel improved GRA and fuzzy theories based model is proposed for analyzing the final weights and rankings of the influencing factors. With computer assistance, the algorithm/model proposed in this paper permits an automatic conversion from the comparative series of maritime traffic safety influencing factors and the corresponding maneuvering decisions (the combination of ship telegraph and rudder order) reference series to autonomous ship maneuvering influencing factors analysis system.

The remainder of this paper is organized as follows. Firstly, Section 2 presents the literature review of grey relational analysis and fuzzy theory. Secondly, the methdology and specific steps of our proposed model are described in Section 3. Thirdly, the experimental processes are introduced in Section 4. Fourthly, Section 5 details the results of our experiment. Then, the discussions of the results are represented in Section 6. Finally, the conclusions are addressed in Section 7.

2. Literature review

There are many researches in the literature relating to grey system theory and fuzzy theory. In the sub-sections, we give an overview about these relevant contemporary studies, and identify material that contributes to our research.

2.1. Grey system theory

The grey system theory, proposed by Deng (Deng, 1982, 1989), is one of the most widely utilized models of grey system theory. As an effective pattern recognition method, it is mainly utilized to analyze the proximity of the dynamic grey process development situation, determine the primary and secondary factors in the grey system, and control the main factors affecting the system (Huang et al., 2013). Grey system theory is characterized by an uncertain system in which "partial information is known and some information is unknown". Through the research on some known information, the system can be accurately understood (Liu and Forrest, 2010).

After more than twenty years of development, the grey system theory has penetrated many scientific research fields and has been confirmed and developed. It provides a new insight into to solve system problems in the case of poor information (Li, 1996). In order to analyze the system behavior of grey systems with uncertain information, the grey system theory develops a series of comprehensive analysis methods of grey systems, such as the Grey Relational Analysis (GRA) (Fu et al., 2017; Hao et al., 2017; Lee et al., 2018; Lilly Mercy et al., 2017; Rajesh et al., 2013).

Specifically, the GRA method is suitable for the data with uncertain, multiple inputs and discrete properties; it does provide techniques for determining an appropriate solution for real-world problems. Moreover, the GRA does not require too much sample size and does not require a typical distribution law during analysis. In addition, regardless of whether the system has adequate information, the GRA could capture the impact of the relationship between the main factor and influencing factors in the system (Deng, 1989; Shen and Du, 2005). As a systematic analysis technique, the GRA is a quantitative comparative analysis method, by calculating the correlation between the target value and the influencing factors, and the ranking of the relevance, the main factors affecting the target value are sought (Deng, 1982; Liu et al., 2010). The results are corresponding to the qualitative analysis results, so the method has wide practicality (Chen and Ting, 2002; Deng, 1989).

The GRA is applied to many research domains, for example, it was adapted to study the research output and growth of countries (Javed and Liu, 2017), and utilized to investigate the nonlinear multiple-dimensional model of the social economic activities' impact on the city air pollution (Li et al., 2017). In addition, Lu et al. (2010) applied a mathematical approach and GRA to analyze the traffic situation trends of China and investigate the potential solutions for enhancing road traffic safety. Wang et al. (2007) proposed a grey model-based smoothness predictions; the results showed that the model provides promising results and is useful for evaluating the riding quality of pavement performance. Zhou and Thai (2016) utilized GRA and grey theory to evaluate the failure modes and analyze the effect for tanker equipment failure prediction; the priority ranking results show that both fuzzy theory and grey theory are quite similar and the proposed fuzzy and grey Failure Mode and Effects Analysis (FMEA) method is more practical and flexible for risk evaluation with respect to tank shipping. Rajesh et al. (2013) introduced the optimization steps to investigate the effects of different operations in the Computer Numerical Control (CNC) machine by using the GRA with entropy. Hatefi and Tamošaitienė (2018) presented a novel improved GRA method to evaluate construction projects on the basis of the sustainable development criteria in social, economic, and environmental dimensions using experts' opinions.

2.2. Fuzzy theory

The grey relational analysis is an effective algorithm for resolving uncertainty problems in the case of partial and discontinuous information (Deng, 1982). However, the traditional GRA has been largely criticized because it treats different indexes (influencing factors) equally and does not take the relative importance of different indexes into consideration. It does not fit with people's preferences for a specific index. Nevertheless, the fuzzy logic theory is a beneficial method for modeling processes which are too complicated for conventional quantitative analysis or information obtained from the process is qualitative, uncertain or inexact (Balin et al., 2018; Tseng and Cullinane, 2018; Zadeh, 1983; Zhou and Thai, 2016). Moreover, fuzzy numbers are more compatible with phrases and ambiguities; it is better to use them in real-world decision-making and reflect human thoughts (Hatefi and Tamošaitienė, 2018).

In the maritime domain, many studies using fuzzy theories have been implemented. For instance, in the aspect of shipping accident risk analysis and prevention, Senol and Sahin (2016) used the defuzzification process of fuzzy logic to transform the fuzzy numbers from Crisp Failure Possibility (CFP) to Fault Probability (FP) and proposed a dynamic real-time continuous fuzzy fault tree model for the analysis of ship collision and grounding. Balmat et al. (2011) applied a novel fuzzy technique to conduct a maritime risk assessment for the prevention of pollution on the open sea based on the decision-making system named MAritime RISk Assessment (MARISA). Yang and Wang (2015) developed an approach for analyzing engineering system risks based on a Fuzzy Evidential Reasoning (FER) method, and applied it to the safety modeling of an offshore engineering system, then performed the failure criticality analysis in a collision of a Floating, Production, Storage, and Offloading (FPSO) system with a shuttle tanker during tandem unloading operations. Celik et al. (2010) proposed a risk-based modeling algorithm on the basis of the fuzzy extended fault tree analysis to enhance the implementation process of the investigation for shipping accident; this approach allows accident stakeholders to clarify the technical failures that lead to the shipping accident. Yang et al. (2009) proposed a systematic framework to process the subjective maritime security assessment information based on the fuzzy evidential reasoning approaches. Goerlandt et al. (2015) developed a framework named: Risk-Informed ship Collision Alert System (RICAS), the result of the case-study for RICAS shows that it has an effective performance. Marken et al. (2015) used a fuzzy bow-tie analysis method to quantify the risk of delay for ships sailing in the northern sea route.

In addition, some fuzzy theory-based studies done for the reliability analysis for the human error and offshore operation issues for the shipping industry. Ung (2015) developed a novel fuzzy Cognitive Reliability and Error Analysis Methods (CREAM) methodology considering the weight of each Common Performance Condition (CPC), and validated the method using two axioms and demonstrated by the case of an oil tanker. Zhou et al. (2018) introduced a Bayesian network and fuzzy model for the quantitative analysis of human reliability of tanker shipping industry; the results show that the proposed model is up-and-coming and is in accordance with the CREAM approach. Similarly, Zhou et al. (2017) also proposed a quantitative CREAM method to estimate the human error probability in tanker operational safety using Fuzzy Analytic Hierarchy Process (FAHP) to establish a fuzzy congruous matrix. Abdussamie et al. (2018b) proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm to predict the ultimate strength reduction of locally corroded steel plates suffering from pitting corrosion for the marine structures. Abdussamie et al. (2018c) also developed a rule-based fuzzy logic model to calculate operational risk values of the transport barges and the offshore structure being loaded as well as the potential impacts on the safety of seafarers and environment. Rahman et al. (2019) proposed a robust logistics risk model based on the fuzzy and evidence theory to analyze criticality of the contributing factors for offshore oil and gas operations.

Moreover, the location selection problem is another aspect of concern in the academia. For instance, Wu et al. (2018) developed a fuzzy multiple attribute decision-making approach to select the location of an offshore wind farm in the busy waterway of the Eastern China Sea, the proposed method considered the maritime safety and economic feasibility of installation and determined an optimal site selection scheme for the wind farm. Guneri et al. (2009) conducted the shipyard location selection question based on the fuzzy analytical network process algorithm, which provided reference to the decision makers based on quantitative analysis.

Furthermore, many studies are explored by combining expert knowledge with fuzzy theories. Such as, Abdussamie et al. (2018a) presented a rule-based fuzzy set approach to deal with the uncertainty of expert knowledge used for qualitative risk assessment for the hazardous scenarios of berthing operations of Liquefied Natural Gas (LNG) carrier and Floating LNG (FLNG) in open sea. Akyuz et al. (2016) integrated fuzzy rule-based expert system into fuzzy FMEA to identify potential failure and enhance maritime safety. Kose et al. (1995) introduced an intelligent expert system for monitoring vessel safety by using the fuzzy logic inference engine. Perera et al. (2010) proposed a fuzzy inference system for collision avoidance based on the expert knowledge and the International Maritime Organization Convention on the International Regulations for Preventing and Collisions at Sea (COLREGs) under critical situations.

Also, fuzzy theories are applied to the research area of ship maneuvering and performance evaluation of the management of shipping company. Bhattacharyya et al. (2011) illustrated a mathematical fuzzy autopilot algorithm for nonlinear maneuvering of surface ships and its performance has been found acceptable. Surendran and Kiran (2007) used the fuzzy logic control algorithm to reduce the roll motions of a ship by active fins; the algorithm proved to be versatile and can be utilized for irregular sea conditions. Wei et al. (2019) put forward a fuzzy algorithm to plan the variable values for hybrid boarding system to compensate the wave disturbance in roll direction as well as other disturbances. Chou and Liang (2010) dealt with an application for the performance evaluation of shipping company through the proposed fuzzy Multiple Criteria Decision Making (MCDM) model.

3. Methodology

This paper utilizes the grey and fuzzy theories combined with quantitative and qualitative analysis, and comprehensively evaluates the maritime traffic safety influencing factors of autonomous ship maneuvering decisions. On the one hand, it can deal with the problems of imprecision and uncertainty. On the other hand, giving various weights of different experts leads to a more rational use of expert knowledge for judging the prioritization of the influencing factors. Furthermore, the evaluation results of the specific criteria of different experts on each linguistic term will be more accurate and reasonable by comprehensively utilizing the fuzzy numbers. The specific method is introduced below.

3.1. Grey relational analysis

Deng (1982) proposed the grey system theory in 1982, and then came the concept of a grey set. If white represents completely clear data/information and black represents completely unknown data/information, grey is other data/information that is known partially. If a system contains grey information, it can be called a grey system. Grey system theory is suitable for multiple inputs and uncertain data. It can be utilized to resolve uncertainty problems, under partial information and discontinuous data effectively (Kumar et al., 2018). A typical grey system concept is shown in Fig. 1.

Grey relational analysis is an analytical method based on the microscopic or macroscopic geometric approach to determine the influence degree between factors or the contribution of factors to the primary system. It is a dynamic quantitative analysis procedure, which is represented by the proximity of the geometric shape of the curve, judging by the degree of correlation. GRA can be combined with other mathematical theories for conducting uncertainty (Proske and Van Gelder, 2006).

3.2. Fuzzy sets

Fuzzy theory was introduced by Zadeh (1965) to solve uncertainty on decision-making by extending the traditional notation of sets

Fuzzy logic is a type of multi-valued logic. The truth values of variables are considered to be “fuzzy” may be any real number within the unit interval [0,1] (Novák et al., 2012). It is an effective method to design a system for decision-making, and it can be used to solve the problems related to conducting inaccurate and uncertain data (Balmat et al., 2011). Zadeh (1965) proposed the fuzzy sets in 1965, and it provides a useful mathematical tool for reliability analyses and to solve

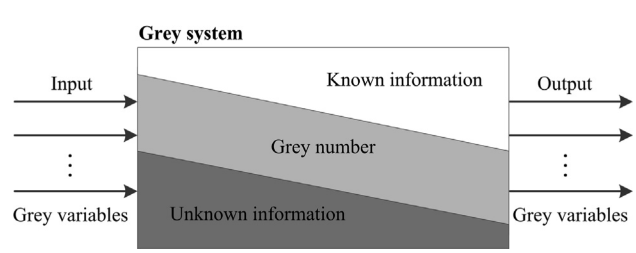

Fig. 1. The concept of the grey system.

system vagueness and uncertainty on decision-making by extending the traditional notation of sets (Zadeh, 1983). A membership function specifies and assigns a value between 0 and 1 in the usual case for each element of discourse. The assigned value is called a membership degree and determines the extent to which a given element belongs to the fuzzy set. Besides, any fuzzy set can be uniquely determined by its membership (Wang et al., 2009; Zhou et al., 2018).

Fuzzy numbers are cases of fuzzy sets, and the most commonly used fuzzy numbers are trapezoidal and triangular fuzzy numbers (Hadi-Vencheh and Mokhtarian, 2011). In addition, the triangular fuzzy numbers have the advantages of promoting representation and processing imprecise information due to its computational simplicity (Pedrycz, 1994). In practical applications, fuzzy membership functions are utilized to convert the linguistic estimations into fuzzy numbers for quantitative evaluation. The triangular membership functions are shown in Fig. 2, and respectively defined as follows:

$$\mu_A(X) = \begin{cases} 0, & x < a \\ (x-a)/(b-a), & a \leqslant x \leqslant b \\ (c-x)/(c-a), & b \leqslant x \leqslant c \\ 0, & x > c \end{cases} \tag{1}$$

3.3. The proposed model

3.3.1. Data preprocessing

Since there are differences in the dimension and magnitude of each factor in the ship's maneuvering decision system. In order to facilitate data processing, the original data need to be standardized, the dimension or the order of magnitude needs to be eliminated, and the data series need to be transformed into a comparative series due to the inconsistent dimension of various factors.

Assume X is a grey relation factor set (discrete series), $X_0 = \{x_0(k)|k = 1, 2, \cdots, m\}$ as a reference series, representing the ship maneuvering decisions, which is the combination of ship Telegraph and Rudder Order (TRO) in the research (see Fig. 7). $X_i = \{x_i(k)|k = 1, 2, \cdots, m\}(i = 1, 2, \cdots, n)$ as comparative series, representing the influencing factors, such as wind, current, and waves. Thus, the correlation mechanisms of the reference series and comparative series can be utilized to recognize the influential mechanism of four types of different factors (ship motion, natural environment, force parameters, and draft & position, shown in Table 3) for autonomous ship maneuvering.

In the analysis and calculation process of the GRA, there are three methods for the non-dimensionalization of the original data, namely, equalization, initialization, and standardization.

Equalization First, the average value of each series is calculated separately, and then the original data in the corresponding series is divided by the average value, that is, the new data column obtained by the mean transformation.

$$X_0' = \left\{ nx_0(k) / \sum_{k=1}^{m} x_0(k) | k = 1, 2, \cdots, m \right\} \tag{2}$$

$$X_i' = \left\{ nx_i(k) / \sum_{k=1}^{m} x_i(k) | k = 1, 2, \cdots, m \right\} (i = 1, 2, 3, \cdots, n) \tag{3}$$

Initialization The data of the same series is divided by the subsequent original data to obtain new multiple series, which is an initial valued series.

$$X_0' = \{x_0(k)/x_0(1)|k = 1, 2, \cdots, m\} \tag{4}$$

$$X_i' = \{x_i(k)/x_i(1)|k = 1, 2, \cdots, m\}(i = 1, 2, 3, ..., n) \tag{5}$$

Standardization Firstly, the average value and standard deviation of each trait are respectively determined, and then the original data is subtracted from the average value and then divided by the standard deviation so that the new data column obtained is the standardized series.

$$X_0' = \left\{ \left[x_0(k) - \frac{1}{m} \sum_{k=1}^{m} x_0(k) \right] / S_0 | k = 1, 2, \cdots, m \right\} \tag{6}$$

$$X_i' = \left\{ \left[x_i(k) - \frac{1}{m} \sum_{k=1}^{m} x_i(k) \right] / S_i | k = 1, 2, \cdots, m \right\} (i = 1, 2, 3, ..., n) \tag{7}$$

where X'_0 is a non-dimensionalized reference series; X'_i is a dimensionless comparative series; S_0 and S_i are the standard deviation of the reference series and the comparative series, respectively.

The original data series can be described by

$$X' = \begin{pmatrix} X_0' \\ X_1' \\ X_2' \\ \vdots \\ X_\omega' \end{pmatrix} = \begin{bmatrix} x_{01}' & x_{02}' & \cdots & x_{0m}' \\ x_{11}' & x_{12}' & \cdots & x_{1m}' \\ x_{21}' & x_{22}' & \cdots & x_{2m}' \\ \vdots & \vdots & \ddots & \vdots \\ x_{\omega 1}' & x_{\omega 2}' & \cdots & x_{\omega m}' \end{bmatrix} \Rightarrow \begin{bmatrix} \text{TRO} \\ \text{InfluenceFactor1} \\ \text{InfluenceFactor2} \\ \vdots \\ \text{InfluenceFactor}\omega \end{bmatrix} \tag{8}$$

where ω is the number of influencing factors.

3.3.2. Range analyzing

First, calculate $\Delta_i(k)$, that is, the absolute value of the difference between the reference series and each sub-series at each point:

$$\Delta_i(k) = |x_0(k) - x_i(k)| \tag{9}$$

among them, $k = 1, 2, \cdots, m$, $i = 1, 2, \cdots, n$.

Then find the two-level maximum range and the two-level minimum range. First, calculate the first-level maximum range and the first-level minimum range:

$$\Delta_i(\max) = \max_k \Delta_i(k) \tag{10}$$

$$\Delta_i(\min) = \min_k \Delta_i(k) \tag{11}$$

Then calculate the second-level maximum range:

$$\Delta_{\max} = \max_i \max_k \Delta_i(k) \tag{12}$$

Similarly, the second-level minimum range is given by:

$$\Delta_{\min} = \min_i \min_k \Delta_i(k) \tag{13}$$

3.3.3. Relational coefficient calculating

The relational coefficient is used to measure the geometric difference between the comparative series and the reference series at each point. The relational coefficient of X_i to X_0 is:

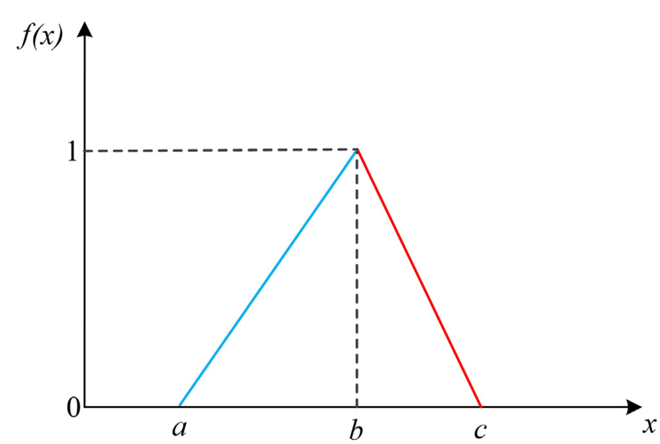

Fig. 2. Triangular membership functions.

$$\xi_i(x_0(k), x_i(k)) = \frac{\Delta_{\min} + \rho\cdot\Delta_{\max}}{\Delta_i(k) + \rho\cdot\Delta_{\max}} \tag{14}$$

where $\xi_i(x_0(k), x_i(k))$ represents the correlation coefficient between the comparative series X_i and the reference series X_0 at point k; ρ is a resolution ratio, in (0, 1), if ρ is small, the greater the difference between the relationship coefficient, the stronger the ability to distinguish, and ρ usually takes a value of 0.5 (Wang et al., 2014); $k = 1, 2, \cdots, m$, $i = 1, 2, \cdots, n$.

3.3.4. Fuzzy membership functions of linguistic terms establishing

The traditional GRA does not fit with people's preference for a specific index. In order to overcome this shortcoming, this paper considers the relative importance weights of the influencing factors, but it is difficult to be precisely determined. Moreover, in many situations, the information and experts' expertise are uncertain or vague. However, fussy sets provides a useful mathematical tool for directly working with the linguistic expression in reliability analyses (Lin and Wang, 1997; Page and Perry, 1994), and it is better to utilize fuzzy numbers in real-world decision-making to reflect human thoughts (Hatefi and Tamošaitienė, 2018). Therefore, we utilize fuzzy numbers of the domain experts to optimize our proposed model. The four domain experts are characterized as follows:

- **Expert No.1**: An experienced captain with more than 15 years of experience on the operation of board ships (classes of certificates: class A, ≥ 3000 gross tons, unlimited voyages).
- **Expert No.2**: A professor engaged in maritime research for more than ten years with particular reference to the ship operations.
- **Expert No.3**: A senior officer in charge of safety management of port operations of Yangtze River Three Gorges Navigation Authority.
- **Expert No.4**: A senior officer in charge of safety regulation of Shanghai Port from China Maritime Safety Administration.

The triangular fuzzy number, corresponding to linguistic terms, can be determined from domain expert knowledge based on the Delphi method (Ishikawa et al., 1993). Assuming that there are n experts, the i-th expert is assigned with the relative weight β_i ($i = 1,\ldots$,m), satisfying $\sum_{i=1}^{m}\beta_i = 1$ and $\beta_i > 0$ for $i = 1,\ldots$,m. And the fuzzy judgment linguistic term for the specific influencing factors is $x_i = (a_i, b_i, c_i)$, then according to the experts' judgment, the triangular fuzzy number $A = (a, b, c)$ corresponding to the fuzzy linguistic term of the variable can be summarized according to Eqs. (15)–(17).

$$a = \sum_{i=1}^{n}\beta_i a_i \tag{15}$$

$$b = \sum_{i=1}^{n}\beta_i b_i \tag{16}$$

$$c = \sum_{i=1}^{n}\beta_i c_i \tag{17}$$

This study defines the maritime traffic safety influencing factors of autonomous ship maneuvering using five linguistic terms, namely, Very Low (VL), Low (L), Medium (M), High (H), Very High (VH). Different from each linguistic term utilized in the same separation distance, for instance, the corresponding midpoint or the b in triangular fuzzy number A of each linguistic term Very Low (VL), Low (L), Medium (M), High (H), Very High (VH) is 0, 0.25, 0.5, 0.75, 1, respectively (Wang et al., 2009; Wu et al., 2018). In this research, the triangular fuzzy number of different linguistic terms is determined by the domain expert knowledge, and the weight of each expert is taken into consideration, as shown in Table 1. Hence, the fuzzy membership function of each linguistic term can be represented more rationally because we take into account the different evaluation criteria of each expert for various linguistic terms comprehensively. Fuzzy membership degrees of quantitative indexes can be obtained from Fig. 3. Experts are invited to define the triangular fuzzy number of each linguistic term based their judgment, then the triangular fuzzy numbers of different linguistic terms are calculated through Eqs. (15)–(17), and the results are shown in Table 1.

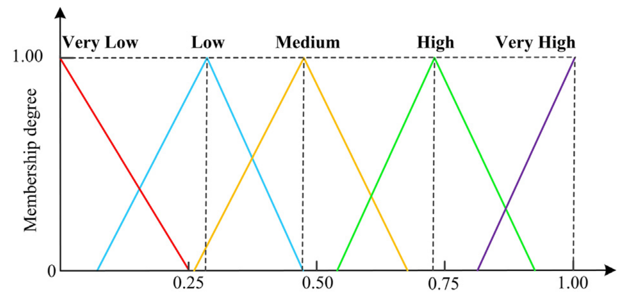

Fig. 3. Triangular membership functions of different linguistic terms.

The specific process of utilizing fuzzy logic of this step is as follows:

(i) The maritime traffic safety influencing factors of autonomous ship maneuvering decisions are evaluated by the experts using the linguistic terms defined in Table 1;
(ii) The linguistic terms based on the judgments of domain expert are represented by the triangular fuzzy numbers, then the comprehensive evaluation fuzzy set of the weight of each influencing factor is established;
(iii) The relative weights β_i for each domain expert are taken into consideration. Specifically, the relative weights of experts are assigned based on their experience with the following relative weights: 0.30, 0.25, 0.20, and 0.25, respectively, then the optimized comprehensive evaluation fuzzy set is obtained;
(iv) The comprehensive evaluation weight of each influencing factor of autonomous ship maneuvering decisions is calculated.

3.3.5. Defuzzification

The linguistic terms from the judgments of domain experts need to be transformed into crisp values before further calculation. In other words, the fuzzy numbers should be converted into crisp numbers for priority ranking or comparison purpose, this process of transformation is called defuzzification. The defuzzification of fuzzy numbers is an

Table 1
Triangular fuzzy numbers of different linguistic terms.

Expert No.	Weights (β_i)	Triangular fuzzy numbers of different linguistic terms				
		Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
1	0.30	(0, 0, 0.25)	(0, 0.25, 0.50)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1)	(0.75, 1, 1)
2	0.25	(0, 0, 0.20)	(0, 0.20, 0.40)	(0.20, 0.40, 0.60)	(0.40, 0.60,0.80)	(0.80, 1, 1)
3	0.20	(0, 0, 0.25)	(0.10, 0.30, 0.50)	(0.30, 0.50, 0.70)	(0.70, 0.90, 1)	(0.90, 1, 1)
4	0.25	(0, 0, 0.30)	(0.20, 0.40, 0.50)	(0.30, 0.50, 0.65)	(0.60, 0.70, 0.90)	(0.85, 1, 1)
Total	1	(0, 0, 0.25)	(0.07, 0.29, 0.48)	(0.26, 0.48,0.68)	(0.54, 0.73, 0.93)	(0.82, 1, 1)

important process, and it is the basis of applying the grey relational theory. Defuzzification can be conducted in many different ways, such as max criterion, center of gravity (COG), mean of maximum (MOM) methods, etc (Akyuz et al., 2016; Balmat et al., 2011; Braae and Rutherford, 1978; Lee, 1990; Senol and Sahin, 2016).

The center of gravity (COG) method, which also is known as center of area (COA), is the most extensively used technique developed by Sugeno (1999) as it is relatively accurate and takes the total output distribution into consideration (Patel and Mohan, 2002). Hence, the COG method can yield a better steady-state performance (Lee, 1990). This COG method can be used as a centroid defuzzification method to find the center of gravity point of the fuzzy set (Kumar et al., 2018).

The linguistic terms from the judgments of domain experts for maritime traffic safety influencing factors of autonomous ship maneuvering decisions can be defuzzified according to the fuzzy membership function; the crisp number can be calculated as follows:

$$A(X) = \frac{\int_X x\mu_A(x)dx}{\int_X \mu_A(x)dx} \tag{18}$$

where *A(X)* denotes the crisp value, x is the output variable, and $\mu_A(x)$ is the membership function for linguistic terms from the judgments of domain experts, as shown in Fig. 3.

Specifically, the defuzzification of a triangular fuzzy number based the Eq. (18) can be calculated as follows:

$$A(X) = \frac{\int_a^b x\frac{x-a}{b-a}dx + \int_b^c x\frac{c-x}{c-b}dx}{\int_a^b \frac{x-a}{b-a}dx + \int_b^c \frac{c-x}{c-b}dx} = \frac{1}{3}(a+b+c) \tag{19}$$

Then, we can get a crisp number of different linguistic terms as shown in Table 2.

3.3.6. Relational grade ranking

Calculating the traditional grey relational grade according to the Eq. (20):

$$\gamma_i = \frac{1}{m}\sum_{k=1}^{m}\xi_i(x_0(k), x_i(k)) \tag{20}$$

where $k = 1, 2, \cdots, m$, $i = 1, 2, \cdots, n$.

Since the influence degree from each maritime traffic safety influencing factor of autonomous ship maneuvering decisions varies, assuming that the weight of each influencing factor is λ_k, then the relational grade between the reference series and comparative series can be obtained by the Eq. (21):

$$\lambda_i(x_0(k), x_i(k)) = \frac{1}{m}\sum_{k=1}^{m}\lambda_k(\xi_i(x_0(k), x_i(k))) \tag{21}$$

where $\sum_{k=1}^{m}\lambda_k = 1$, λ_k can be determined by fuzzy sets based the domain expert knowledge.

When determining the relational grade, each sub-series of Y1-Y33 is compared to the reference series of TRO. Hence, the relationship between each sub-series and the reference series is sorted. Thereby, the main maritime traffic safety influencing factors of the autonomous ship maneuvering decisions in the specific navigational scenario are prioritized and identified.

The framework of our proposed model is shown graphically in Fig. 4 that briefly illustrates the maritime traffic safety influencing factors of autonomous ship maneuvering decisions prioritizing procedure of the proposed GRA and fuzzy theories based methodology. The right-hand part of Fig. 4 shows the steps of obtaining the weights for different influencing factors; the middle part presents the process of applying the traditional GRA theory, while the left-hand part provides the priority ranking and analyzing procedure of the maritime traffic safety influencing factors analysis system for autonomous ship maneuvering. And the logic framework for applying the proposed model is shown in Fig. 5.

4. Experiments

4.1. Scenario design

In our experiment, the Shanghai Waigaoqiao wharf was designed to be the scenario, and the ship was downstream of the berthing into the port. We use the ship OS1 as our experimental ship. The initial and end boundary line in the electronic chart and the experimental scene are shown in Fig. 6.

4.2. Data collection and processing

We collect the data from the simulator of Navi-Trainer Professional 5000, which conforms to the IMO STCW78/10 convention and the Det Norske Veritas (DNV) from the Maneuvering Simulator Laboratory.

The operational data from the exercises and assessment exams of unlimited navigational class seafarers are collected as our experimental data. In this experiment, there are 96 skilled maneuvering level captain/chief officer. The mean age of OOW is 38.76 years, minimum age is 32.00 years, maximum age is 45.00 years; the mean number of years of piloting experience for OOW is 8.89 years. It should be noted that, in our case, the OOW is the captain or chief officer. Although, in the real situation, the captain is not on duty. The captain will go to the bridge only in special circumstances, and if necessary, the captain may take over the duty of the OOW to maneuver the ship, but it is an assessment and evaluation scenario in our experiment; therefore, the captain also acts as the OOW.

The multisource information of ship maneuvering traffic environment were collected. For instance, the location (longitude, latitude), environment (wind, current, etc.), control (rudder order, marine telegraph), ship movement (heading, roll rate, etc.), the ship's draft, tugs, mechanical contact force-related parameters, and other related parameters. The above factors, such as the environment, the control, location and the relevant parameters of the tug and other factors (see Tables 3 and 4), were selected from the weakly related parameters. Table 4 lists some of the training samples.

According to the scenario shown in Fig. 6, the principle of the rudder angle and the propeller speed are defined based on the data collected from the simulator and the navigation experience. Fig. 7 and Table 5 show 64 possible maneuvering decisions based on various standardization principle of speed control (propeller state) and course control (rudder angle).

The OOW maneuvers the ship by operating different TROs to change ship's speed and direction. Fig. 7 shows TROs of ship OS1 and the Table 5 shows the combining TROs; this control procedure is a multi-dynamic process. Moreover, it should be noted that, in combination with the actual situation of the experimental scenario. Unlike the ship sailing on the open sea, the OOW needs to call the TROs frequently in the inbound decision-making ship handing process; therefore, in this

Table 2
The crisp number of different linguistic terms.

Name	The triangular fuzzy number and crisp number of different linguistic terms				
Linguistic term	Very Low (VL)	Low (L)	Meium (M)	High (H)	Very High (VH)
Fuzzy number	(0, 0, 0.25)	(0.07, 0.29, 0.48)	(0.26, 0.48, 0.68)	(0.54, 0.73, 0.93)	(0.82, 1, 1)
Crisp number	0.0833	0.2800	0.4733	0.7333	0.9400

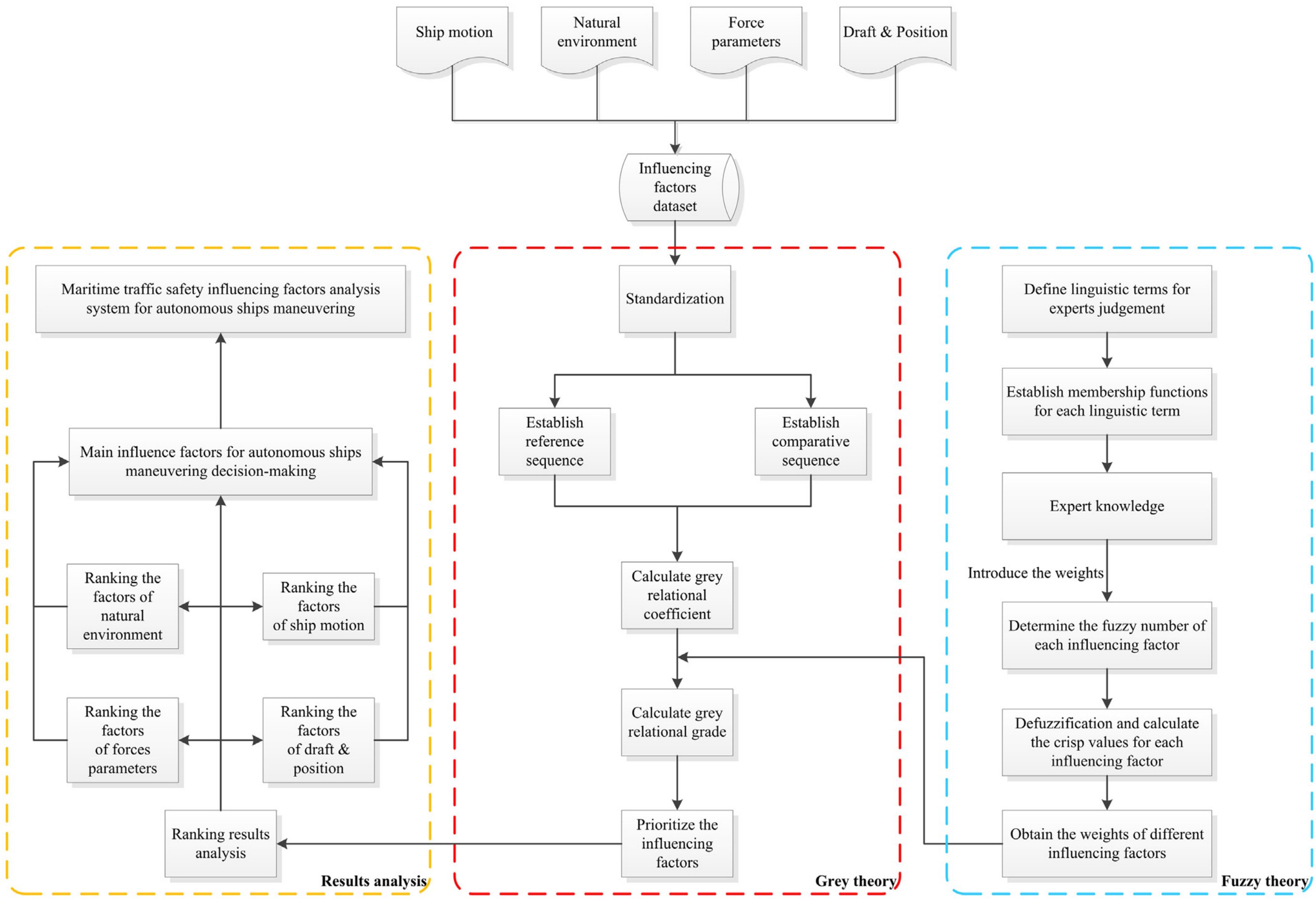

Fig. 4. The framework of the proposed model using grey and fuzzy theory.

paper, we do not consider "Stop engine" and "Midships" regardless of the rudder angle and if the power output is 0. Table 5 shows the standardization principle for output maneuvering decision-making factor.

5. Results

In our experiment, we select X and the related parameters Y1-Y33 to apply the proposed model, among them, X is the main factor and reference series, which consists of the 64 possible maneuvering decisions (the OOW's actual operation in the simulator, a different combination of TROs, see Table 5). Y1-Y33 are the influencing factors, and their values constitute the comparative series, such as the environment, ships, and other influencing factors. In addition, we collected a total of 20,534 samples as our data set.

5.1. Standardizing of the original data set

In this paper, X presents the percentage of the number of each maneuvering decision of X1- X64 in a total number of the data set records. Limited to space, Table 6 lists only a part of multiple measured data. The data in Table 6 are standardized according to the principle of standardization of maneuvering decision-making influencing factors in Table 5 and the non-dimensionalization method of standardization (see Eqs. (6) and (7)).

5.2. Applying the proposed analysis model

According to the ranking criteria of the grey relational grade, the greater the grey relational grade of the comparative series, the greater the relevance of the comparative series to the reference series, the greater the degree of influence on the reference series, and the higher the ranking of the influencing factors. The GRA method is able to quantitatively describe the similarity and consistency degree between each comparative series and reference series and uses relational grades to complete the matching order of influencing factors. We use the original data matrix as defined by Eq. (22).

$$X' = \begin{pmatrix} X_0' \\ X_1' \\ X_2' \\ \vdots \\ X_\omega' \end{pmatrix} = \begin{bmatrix} x_{01}' & x_{02}' & \cdots & x_{0m}' \\ x_{11}' & x_{12}' & \cdots & x_{1m}' \\ x_{21}' & x_{22}' & \cdots & x_{2m}' \\ \vdots & \vdots & \ddots & \vdots \\ x_{\omega 1}' & x_{\omega 2}' & \cdots & x_{\omega m}' \end{bmatrix} \Rightarrow \begin{bmatrix} \text{TRO} \\ \text{InfluenceFactor1} \\ \text{InfluenceFactor2} \\ \vdots \\ \text{InfluenceFactor}\omega \end{bmatrix} \Rightarrow \begin{bmatrix} \text{X} \\ \text{Y1} \\ \text{Y2} \\ \vdots \\ \text{Y33} \end{bmatrix} \tag{22}$$

This way, we obtain the original data series. Since there is a case where the initial value is zero w.r.t the influencing factors. Considering the value of the denominator should not be zero in a division operation; thus it is not suitable for the calculation based on Eq. (5). Moreover, the standardization method may genuinely reflect the relevance of the influencing factors to ship maneuvering decisions. Therefore, we use the standardization methods to explore the results of the interaction between ship maneuvering decisions and various influencing factors.

From Table A.1 and Eqs. (9)–(13), we can get the extreme values $\Delta_{\max} = \mathbf{56.71438286}$, $\Delta_{\min} = \mathbf{6.03501}\boldsymbol{E} - \mathbf{06}$, and we can calculate the grey relational coefficient based on the Eq. (14), then calculating the traditional grey relational grade according to the Eq. (20), the results are shown in Table A.2.

The convenient fuzzy numbers are defined for making pairwise comparisons shown in Table 1. Table A.3 shows the linguistic terms

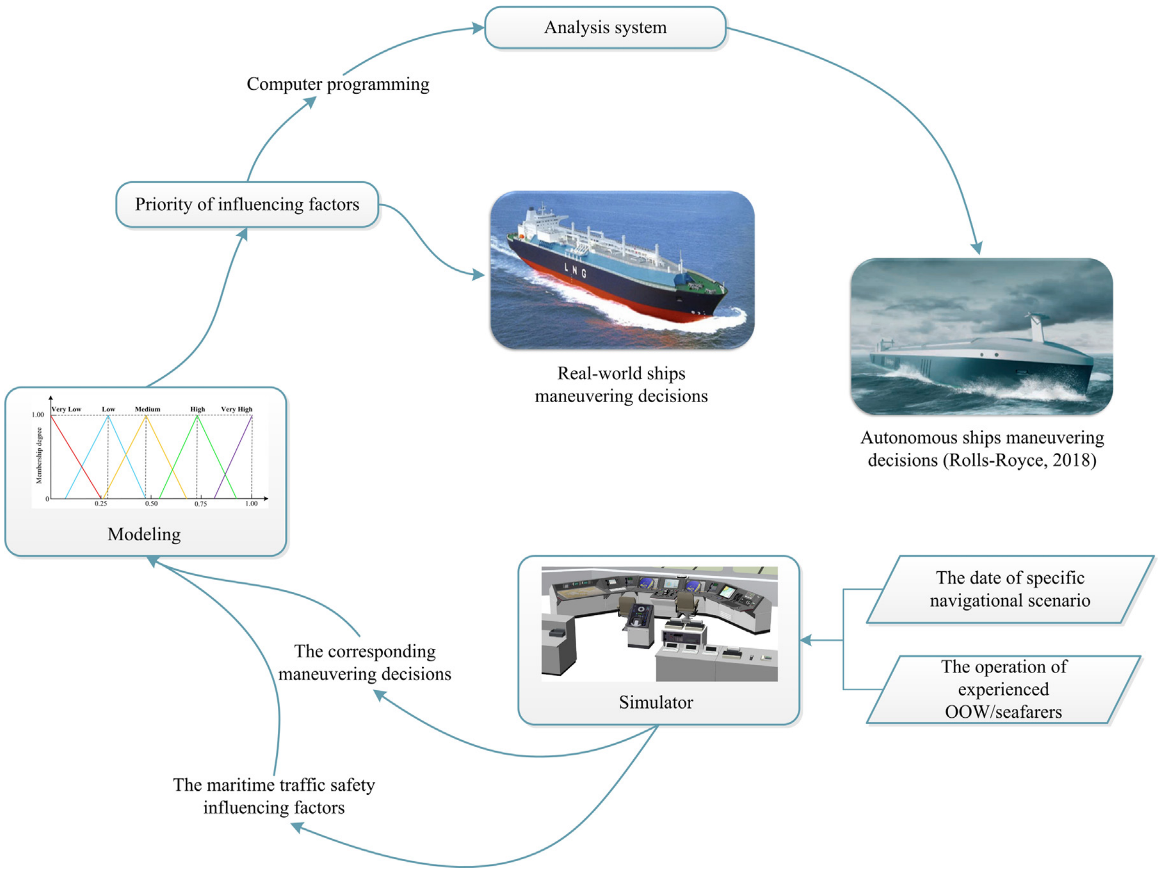

Fig. 5. The logic framework for applying the proposed model.

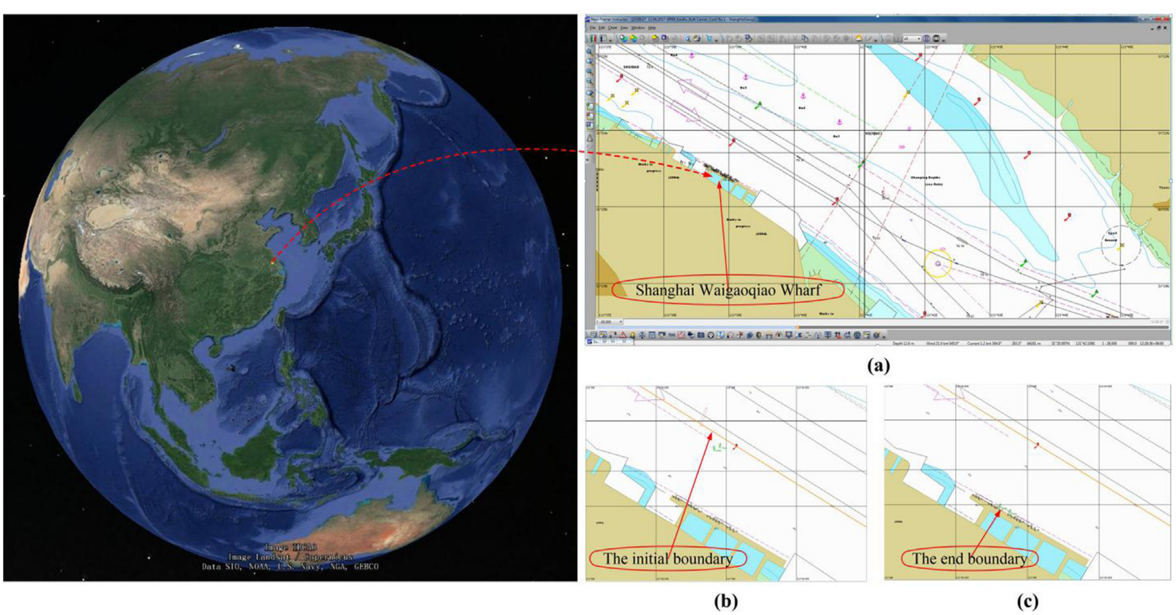

Fig. 6. The designed experimental scenario.

survey results from the four experts, and the crisp number and weights of different maneuvering influencing factors.

Then the defuzzification procedure is conducted based on Eq. (19) and Table 2. The crisp number of different influencing factors are calculated with the relative weights β_i, then λ_k, the weights of different maneuvering influencing factors can be determined, the results are shown in Table A.3.

Finally, using Eqs. (20) and (21), and the results of grey relational coefficient from Table A.2, the priority ranking results of comparing grey algorithm with our proposed model are obtained, as shown in Table 7.

The rankings of ship maneuvering decision-making influencing factors are shown in Table 7, ranking result number 3. Furthermore, the result of grey method are sorted based the ranking result number 1. As can be observed that the common seven influencing factors in the top ten most influential factors of both two methods are: Y15 (Summary

Table 3
The category of influencing factors.

Influencing factors	Meaning	Units	Category	Influencing factors	Meaning	Units	Category
Y1	Current draft at ship bow	Meters	Draft	Y18	Longitudinal force of mooring lines	Tonne-force	Force Parameters
Y2	Current draft at ship stern	Meters	Draft	Y19	Summary force of mooring lines	Tonne-force	Force Parameters
Y3	Under keel clearance aft	Meters	Draft	Y20	Vertical force of mooring lines	Tonne-force	Force Parameters
Y4	Under keel clearance fwd	Meters	Draft	Y21	Heading	Degrees	Motion
Y5	Current direction	Degrees	Environment	Y22	Height above the water	Meters	Motion
Y6	Current speed	Knots	Environment	Y23	Lateral speed	Knots	Motion
Y7	Relative current direction	Degrees	Environment	Y24	Longitudinal speed	Knots	Motion
Y8	Relative wave direction	Degrees	Environment	Y25	Pitch angle	Degrees	Motion
Y9	Relative wind direction	Degrees	Environment	Y26	Pitch rate	Degrees/min	Motion
Y10	Relative wind speed	Knots	Environment	Y27	Rate of turn	Degrees/min	Motion
Y11	Water depth	Meters	Environment	Y28	Roll angle	Degrees	Motion
Y12	Wave height	Meters	Environment	Y29	Roll rate	Degrees/min	Motion
Y13	Lateral force	Tonne-force	Force Parameters	Y30	Vertical speed	Knots	Motion
Y14	Longitudinal force	Tonne-force	Force Parameters	Y31	Yaw rate	Degrees/min	Motion
Y15	Summary force	Tonne-force	Force Parameters	Y32	Latitude	Degrees	Position
Y16	Vertical force	Tonne-force	Force Parameters	Y33	Longitude	Degrees	Position
Y17	Lateral force of mooring lines	Tonne-force	Force Parameters	–	–	–	–

force), Y19 (Summary force of mooring lines), Y8 (Relative wave direction), Y17 (Lateral force of mooring lines), Y18 (Longitudinal force of mooring lines), Y13 (Lateral force), Y14 (Longitudinal force), which should be taken more attention when making decisions in ship maneuvering process. Furthermore, the result of top ten most influential factors sorted through our optimal model shows that: Y19 (Summary force of mooring lines) has risen four places to second place; Y8 (Relative wave direction) has risen five places to third place; Y10 (Relative wind speed) has risen seven places to fourth place; Y9 (Relative wind direction) has risen thirteen places to ninth place; Y7 (Relative current direction) has risen two places to tenth place. Y10, Y9, and Y7 became the new factors in the top ten of autonomous ship maneuvering decision process, which is corresponding to the judgment/operation of experienced seafarers in the real word shipping: when the seafarer (OOW) maneuvering the ship inbound the port, they need to pay more attention to the influencing factors of forces (e.g. forces of mooring lines and tugs), relative wave direction, relative wind direction, relative current direction, relative wind speed etc., so as to ensure the safety of ship and cargo. Therefore, the results indicate that our proposed model can identify the influencing factors of autonomous ship maneuvering decisions under real word maritime traffic safety context, and the priority ranking results are more reasonable than the original GRA method.

To compare the results from the proposed method and the GRA method more intuitively and clearly, we settle different coordinate systems in the same specific figure to compare the trend of different graphics. The x-axis denotes the number of influencing factors, and the y-axis represents the grey relational grade get from grey method or the modeling grade get from our proposed method. The ranking results of comparing grey algorithm with our proposed model are visualized in Fig. 8. Meanwhile, the priority ranking analysis for four types of influencing factors is shown in Fig. 9.

As can be seen from Fig. 8, the changing tendency of the curves for the GRA method and our proposed model are the same basically, however the fluctuation trend of the curve of our proposed model is more evident than the GRA method (the dispersion of the fluctuation for GRA is 0.0137; the dispersion of the fluctuation for the proposed model is 0.0329), which means that the sensitivity of the prediction result of each influencing factor of our proposed model is higher than GRA method. Meanwhile, the curve of the original GRA method is relatively flat (especially for the influencing factors w.r.t. force parameters of Y13-Y20), which also proves the drawbacks of the traditional GRA method: it treats different indexes (influencing factors) equally and takes no account of the relative importance of them. Moreover, it does not fit with people's preferences for a specific index.

In addition, as shown in Fig. 8, the comparing results of the histogram heights of the maritime traffic safety influencing factors Y9 (Relative wind direction), Y10 (Relative wind speed), Y23 (Lateral speed), and Y24 (Longitudinal speed) of our proposed method are obviously higher than the numbers in the GRA method, which indicates that OOW needs to take more attention about these factors when maneuvering the ship. In other words, when we design the program for the analysis system of the autonomous ship maneuvering decisions in the specific

Table 4
Original data of the studied area (partially).

No.	X		Y1 (Meters)	Y2 (Meters)	Y3 (Meters)	Y4 (Meters)	…	Y33 (Degrees)
	Rudders Order (Degrees)	Telegraphs Order (%)						
1	−1.0000	50.0000	10.1766	10.8138	4.2631	4.8818	…	121.6474
2	−1.0000	50.0000	10.1812	10.8184	4.2574	4.8783	…	121.6474
3	−1.0000	50.0000	10.1898	10.8270	4.2478	4.8706	…	121.6474
4	−1.0000	50.0000	10.2095	10.8468	4.2267	4.8523	…	121.6473
5	−1.0000	50.0000	10.2152	10.8526	4.2200	4.8474	…	121.6473
6	−1.0000	46.2955	10.1926	10.8300	4.2411	4.8714	…	121.6473
7	−1.0000	40.0000	10.1809	10.8183	4.2521	4.8837	…	121.6473
8	−1.0000	40.0000	10.1915	10.8290	4.2398	4.8748	…	121.6473
9	−1.0000	40.0000	10.2082	10.8457	4.2220	4.8591	…	121.6473
10	−1.0000	40.0000	10.2006	10.8381	4.2284	4.8678	…	121.6472
11	−3.3119	40.0000	10.1846	10.8221	4.2431	4.8849	…	121.6472
12	−11.2792	40.0000	10.1958	10.8334	4.2307	4.8747	…	121.6472
13	−11.9016	40.0000	10.2208	10.8584	4.2045	4.8507	…	121.6472
…	…	…	…	…	…	…	…	…

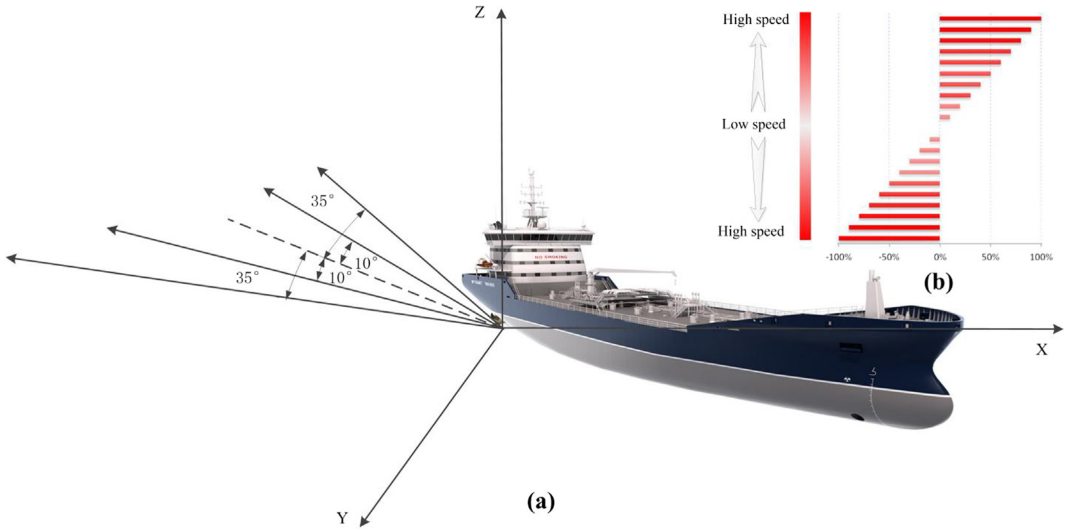

Fig. 7. The telegraph and rudder orders of ship OS1 (Xue et al., 2019b).

scenarios, we should assign a larger weight for these influencing factors than the original weight obtained from the grey method. Similarly, we should assign a smaller weight for the influencing factors Y12 (Wave height), Y21 (Heading), Y22 (Height above the water), Y30 (Vertical speed), and Y33 (Longitude) considering their histogram heights are obviously lower than the numbers in the GRA method.

It should be noted that, for the influencing factors of the same property, we may get different grey relational grades in different

Table 5
Ship maneuvering decision-making factors and standardization principle, abridged from Xue et al. (2019b).

Attributes	Speed control			Course control		
	Symbolic principle	Status	Symbol	Symbolic principle	Status	Symbol
Variety	$a_{i+1} - a_i \neq 0$	Changed	C1	$b_{i+1} - b_i \neq 0$	Changed	C2
	$a_{i+1} - a_i = 0$	Unchanged	U1	$b_{i+1} - b_i = 0$	Unchanged	U2
Value	$[-100\%, -50\%] \cup [50\%, 100\%]$	Fast	F1	$[-35, -10] \cup [10, 35]$	Large	L2
	$(-50\%, 0) \cup (0, 50\%)$	Slow	S1	$(-10, 0) \cup (0, 10)$	Small	S2
Direction	$a_i > 0$	Ahead	D1	$b_i > 0$	Starboard	D2
	$a_i < 0$	Astern	T1	$b_i < 0$	Port	T2
Maneuvering factors	**Decisions**		**Symbols**	**Decisions**		**Symbols**
X(Dimensionless)	U1F1D1U2L2T2		X1	U1F1D1C2L2T2		X33
	U1F1D1U2S2T2		X2	U1F1D1C2S2T2		X34
	U1S1D1U2L2T2		X3	U1S1D1C2L2T2		X35
	U1S1D1U2S2T2		X4	U1S1D1C2S2T2		X36
	U1F1T1U2L2T2		X5	U1F1T1C2L2T2		X37
	U1F1T1U2S2T2		X6	U1F1T1C2S2T2		X38
	U1S1T1U2L2T2		X7	U1S1T1C2L2T2		X39
	U1S1T1U2S2T2		X8	U1S1T1C2S2T2		X40
	U1F1D1U2L2D2		X9	U1F1D1C2L2D2		X41
	U1F1D1U2S2D2		X10	U1F1D1C2S2D2		X42
	U1S1D1U2L2D2		X11	U1S1D1C2L2D2		X43
	U1S1D1U2S2D2		X12	U1S1D1C2S2D2		X44
	U1F1T1U2L2D2		X13	U1F1T1C2L2D2		X45
	U1F1T1U2S2D2		X14	U1F1T1C2S2D2		X46
	U1S1T1U2L2D2		X15	U1S1T1C2L2D2		X47
	U1S1T1U2S2D2		X16	U1S1T1C2S2D2		X48
	C1F1D1C2L2T2		X17	C1F1D1U2L2T2		X49
	C1F1D1C2S2T2		X18	C1F1D1U2S2T2		X50
	C1S1D1C2L2T2		X19	C1S1D1U2L2T2		X51
	C1S1D1C2S2T2		X20	C1S1D1U2S2T2		X52
	C1F1T1C2L2T2		X21	C1F1T1U2L2T2		X53
	C1F1T1C2S2T2		X22	C1F1T1U2S2T2		X54
	C1S1T1C2L2T2		X23	C1S1T1U2L2T2		X55
	C1S1T1C2S2T2		X24	C1S1T1U2S2T2		X56
	C1F1D1C2L2D2		X25	C1F1D1U2L2D2		X57
	C1F1D1C2S2D2		X26	C1F1D1U2S2D2		X58
	U1S1D1C2L2D2		X27	C1S1D1U2L2D2		X59
	C1S1D1C2S2D2		X28	C1S1D1U2S2D2		X60
	C1F1T1C2L2D2		X29	C1F1T1U2L2D2		X61
	C1F1T1C2S2D2		X30	C1F1T1U2S2D2		X62
	C1D1T1C2L2D2		X31	C1S1T1U2L2D2		X63
	C1D1T1C2S2D2		X32	C1S1T1U2S2D2		X64

Table 6
Dataset with the principle of standardization (partially).

No.	X			Y1	Y2	Y3	…	Y33
	Symbols	Proportion	Standardization					
1	X2	0.0300	−0.9848	0.5448	0.6840	−0.4284	…	0.7903
2	X2	0.0300	−0.9848	0.6719	0.7840	−0.4414	…	0.7782
3	X2	0.0300	−0.9848	0.9643	1.0135	−0.4704	…	0.7684
4	X2	0.0300	−0.9848	1.0498	1.0807	−0.4795	…	0.7555
5	X52	0.0196	−1.0784	0.7140	0.8186	−0.4506	…	0.7433
6	X52	0.0196	−1.0784	0.5404	0.6830	−0.4356	…	0.7320
7	X4	0.2955	1.4108	0.6975	0.8064	−0.4524	…	0.7214
8	X4	0.2955	1.4108	0.9452	1.0003	−0.4768	…	0.7100
9	X4	0.2955	1.4108	0.8325	0.9122	−0.4681	…	0.6986
10	X36	0.0098	−1.1667	0.5955	0.7270	−0.4479	…	0.6865
11	X35	0.0062	−1.1992	0.7622	0.8576	−0.4649	…	0.6744
12	X35	0.0062	−0.9848	0.5448	0.6840	−0.4284	…	0.7903
13	X35	0.0062	−0.9848	0.6719	0.7840	−0.4414	…	0.7782
…	…	…		…	…	…	…	…

Table 7
Results of comparing grey method with our proposed model.

Influencing factors	Grey method				Our proposed model			
	Grey relational grade	Rank No. 1	Category	Rank No. 2	Modeling grade	Rank No. 3	Category	Rank No. 4
Y1	0.963331321	18	Draft	3	0.022296521	26	Draft	4
Y2	0.963022501	21	Draft	4	0.028357107	22	Draft	2
Y3	0.964702382	13	Draft	1	0.031169444	17	Draft	1
Y4	0.964360060	15	Draft	2	0.025634601	24	Draft	3
Y32	0.955548915	33	Position	6	0.016264792	30	Position	6
Y33	0.962805458	23	Position	5	0.018028349	28	Position	5
Y5	0.962321061	26	Environment	7	0.022824349	25	Environment	6
Y6	0.962607649	24	Environment	6	0.022279772	27	Environment	7
Y7	0.964744459	12	Environment	3	0.036003278	10	Environment	4
Y8	0.967877544	8	Environment	1	0.040086883	3	Environment	1
Y9	0.962919694	22	Environment	5	0.037689118	9	Environment	3
Y10	0.964861416	11	Environment	2	0.039961964	4	Environment	2
Y11	0.964247007	16	Environment	4	0.033350178	14	Environment	5
Y12	0.961966953	27	Environment	8	0.012658338	31	Environment	8
Y13	0.968696019	3	Forces	3	0.037915206	7	Forces	5
Y14	0.968659475	4	Forces	4	0.037913776	8	Forces	6
Y15	0.969245754	1	Forces	1	0.040143551	1	Forces	1
Y16	0.969236192	2	Forces	2	0.033081376	15	Forces	7
Y17	0.968609094	5	Forces	5	0.038352880	5	Forces	3
Y18	0.968266306	7	Forces	7	0.038339307	6	Forces	4
Y19	0.968451261	6	Forces	6	0.040110645	2	Forces	2
Y20	0.967668141	9	Forces	8	0.029048175	18	Forces	8
Y21	0.957594808	31	Motion	10	0.007249314	33	Motion	11
Y22	0.957995484	29	Motion	8	0.007667484	32	Motion	10
Y23	0.957976209	30	Motion	9	0.035314460	12	Motion	2
Y24	0.955638214	32	Motion	11	0.035228273	13	Motion	3
Y25	0.962322084	25	Motion	6	0.028887693	21	Motion	7
Y26	0.964491499	14	Motion	2	0.035554637	11	Motion	1
Y27	0.963209744	20	Motion	5	0.028914340	20	Motion	6
Y28	0.964126732	17	Motion	3	0.028941867	19	Motion	5
Y29	0.965110499	10	Motion	1	0.031182631	16	Motion	4
Y30	0.961761784	28	Motion	7	0.018008806	29	Motion	9
Y31	0.963209766	19	Motion	4	0.026155744	23	Motion	8

maritime traffic scenarios. For instance, in the specific experimental navigation scenario of Shanghai Waigaoqiao wharf, the ship's position of longitude did not change basically, and it's just a change in the position of latitude when it was berthing into the port, so the grey method gives us the different grey relational grades for the same property of longitude and latitude. However, when it is extended to the real general word maritime traffic scenarios or other domains, in common sense, the change of longitude and latitude always coincide. Thus the results are consistent with the proposed model. Therefore, the results displayed in Fig. 8 are reasonable and meaningful, and the traditional GRA approach can sort the maneuvering influencing factors efficiently so that the OOW can get the main maritime traffic safety influencing factors intuitively through the correction and optimization of expert judgment knowledge and fuzzy theory. Then through the proposed model, the influencing factors affecting the ship maneuvering decisions are obtained in a more general widespread applicability way.

As shown in Fig. 9, the diagrams of four categories of influencing factors are drawn independently (the histogram depicts the variation tendency of the proposed method and the scatter diagram in the form of a smooth curve represents the variation tendency of the GRA method). Overall, the changing tendency of each diagram for the GRA method and our proposed model are the same basically, but there are some

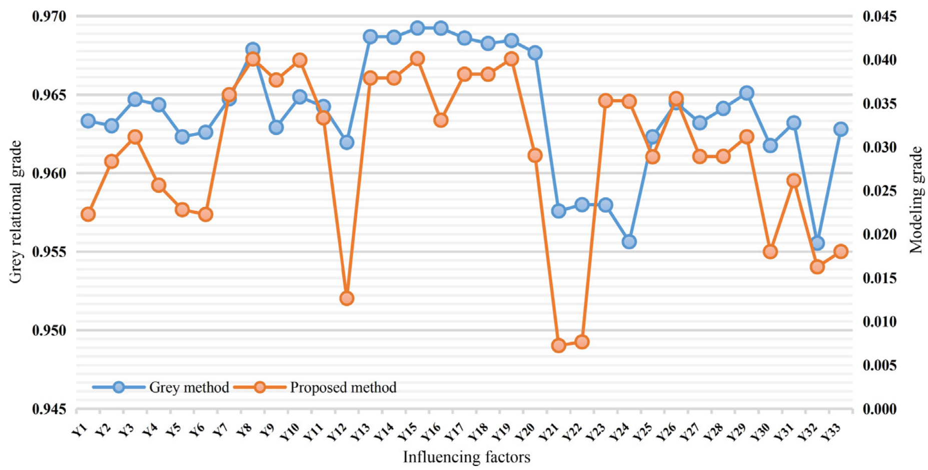

Fig. 8. The results of comparing the grey method with our proposed model.

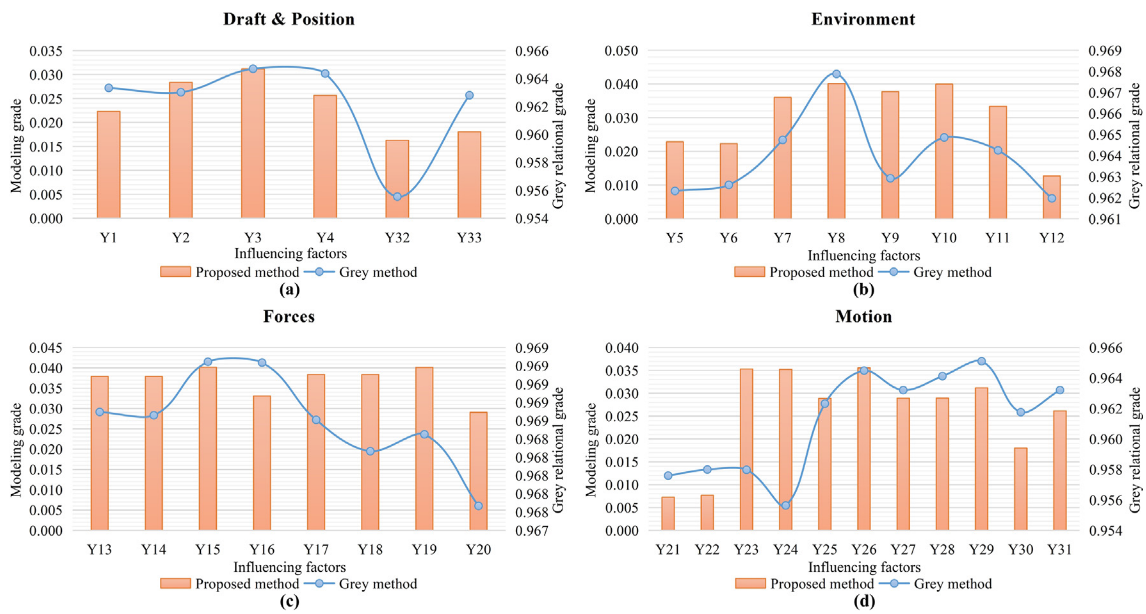

Fig. 9. The ranking results analysis for four types of influencing factors.

details/differences which need to be described and explained.

Draft & Position: It can be seen from Fig. 9(a), compared with the diagram of the grey method and the proposed method, the most influential factor within draft and position aspects is Y3 (Under keel clearance aft), it indicates that the OOW needs to take more attention about the under-keel clearance aft within the influencing factors of draft and position. Meanwhile, when we design the program for the analysis system of the autonomous ship maneuvering decisions in the specific scenarios considering maritime traffic safety, we should assign a larger weight for the keel clearance aft. Similarly, when it comes to the influencing factors longitude and latitude, the specific weight of Y32 (Latitude) has been increased, and the weight of Y33 (Longitude) has been reduced. As the above analysis, in the proposed method, the weight of latitude is higher, and the weight of longitude is lower than the original weight obtained via the grey method, that indicates the proposed model has a property of general flexibility for the analysis of the maritime traffic safety influencing factors for the ship maneuvering decisions.

Natural environment: As shown in Fig. 9(b), Y8 (Relative wave direction) and Y10 (Relative wind speed) are the top two most influential factors in both the grey method and the proposed method, which indicates the OOW needs to focus on the relative wave direction and relative wind speed when it comes to the natural environment. In addition, the Y9 (Relative wind direction), Y10 (Relative wind speed), and Y11 (Water depth) have been increased in the results of proposed method. Among them, the increase of Y9 is greatest, which indicates that, in the scope of natural environment, according to the judgments of domain experts based the fuzzy theory, the OOW should pay more attention to the relative wind direction when maneuvering the ship. Furthermore, it is similar to the program design for the analysis system, the heavy weight of relative wave direction and relative wind speed need to be given. Moreover, the weight of influencing factor of relative wind direction needs to be increased.

Force parameters: According to Figs. 9(c) and 8, the ranking and grade of force parameters maintain a relatively stable trend in various influencing factors, meanwhile, all the force parameters keep a high ranking and grade in both two methods (all remain in the top 18, seen from Table 7). It indicates that all the force parameters play a crucial role in autonomous ship maneuvering decision-making in the specific scenario. Besides, it is also corresponding to the operation of experienced seafarers in the real world shipping, the force parameters is the crucial and direct influencing factors for the maneuvering of ships and maritime traffic safety. Furthermore, we can see that the most influential factor of force parameters is Y15 (Summary force); Y17 (Lateral

Table A1
The extreme values of our data set (the bold values indicate the extreme values, that is, the second-level maximum range shown in Eqs. (12) and (13)).

Influencing factors	Standardization	
	Δ_i(max)	Δ_i(min)
Y1	10.75723437	0.000149400
Y2	9.286000215	2.97525E-05
Y3	6.670632875	0.000162331
Y4	4.939213846	0.000240429
Y5	2.677718534	0.001937135
Y6	2.607298241	0.002782460
Y7	4.896570329	4.70016E-05
Y8	6.238392243	0.000341300
Y9	5.742657263	0.000149654
Y10	2.699055325	4.80284E-05
Y11	6.230599999	0.000794324
Y12	8.023167652	0.000179697
Y13	45.23686934	0.001040272
Y14	37.19534450	0.010007617
Y15	36.16702220	0.006453297
Y16	**56.71438286**	0.005779491
Y17	26.88140323	0.001041084
Y18	26.76096695	0.029507153
Y19	25.52296248	0.005543666
Y20	31.57740192	0.041646945
Y21	6.406334561	3.47088E-05
Y22	4.576141174	0.000154554
Y23	4.212766847	0.000149660
Y24	5.285008067	0.000186862
Y25	13.21063113	7.98433E-05
Y26	24.45508796	0.001488166
Y27	6.267063219	0.000109524
Y28	10.38202823	9.73156E-05
Y29	12.12034909	6.66299E-05
Y30	8.602456594	0.000166826
Y31	6.267064612	0.000108035
Y32	3.862857951	**6.03501E-06**
Y33	4.661142861	2.04946E-05

Table A2
The grey relational coefficient (partially).

Influencing factors	Grey Relational Coefficient (Standardization)								Grey Grade
	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	…	No. 20,534	
Y1	0.948821333	0.944800559	0.935685389	0.933054446	0.940548179	0.945995493	…	0.936525683	0.963331321
Y2	0.944422670	0.941285170	0.934169836	0.932105721	0.937298072	0.941518452	…	0.930200250	0.963022501
Y3	0.980756009	0.981198262	0.982182514	0.982491117	0.978341825	0.977832987	…	0.985724706	0.964702382
Y4	0.984269772	0.984635896	0.985511601	0.985748630	0.981409613	0.980825559	…	0.926098511	0.964360060
Y5	0.958719718	0.958719718	0.958719718	0.958719718	0.955695626	0.955695626	…	0.915302540	0.962321061
Y6	0.940306134	0.940306134	0.940306134	0.940306134	0.937396914	0.937396914	…	0.915797346	0.962607649
Y7	0.977801220	0.977891825	0.977931508	0.977993022	0.974925396	0.974957017	…	0.941043104	0.964744459
Y8	0.971251135	0.971392017	0.971608734	0.971735174	0.974998194	0.975095592	…	0.973872465	0.967877544
…	…	…	…	…	…	…	…		…
Y28	0.966142965	0.966234013	0.966354440	0.966462437	0.963518894	0.963701914	…	0.941754820	0.964126732
Y29	0.966915878	0.966277561	0.966579003	0.966698608	0.963888008	0.964242401	…	0.951127489	0.965110499
Y30	0.970562344	0.972582036	0.973802135	0.958892072	0.950538172	0.968438806	…	0.952762326	0.961761784
Y31	0.993807833	0.993415906	0.992347753	0.991987132	0.988237248	0.987176821	…	0.968141097	0.963209766
Y32	0.902638993	0.902687368	0.902726071	0.902784132	0.900150231	0.900198339	…	0.919241512	0.955548915
Y33	0.941088142	0.941467051	0.941775139	0.942178328	0.939634966	0.939989087	…	0.977156185	0.962805458

force of mooring lines), Y18 (Lateral force of mooring lines), and Y19 (Lateral force of mooring lines) has been increased and occupy a heavyweight, and Y16 (Vertical force) has been decreased. Similarly, it is reasonable for the real word shipping, especially for the inbound scenario. For instance, when a ship inbound a port, the pilots always call the tugs for assistance, the tugs push (there is no vertical force in this procedure) or pull through the mooring lines then assist the ship get into the port, this has great influence on the maneuvering of ships. For another example, when the ship is close to the berth, the ship usually use the mooring winch to assist the berthing, so the forces from mooring lines is the main influencing factors for ship maneuvering and maritime traffic safety. Therefore, when the program design for the analysis system of the influencing factors of autonomous ship maneuvering decisions in the specific scenario, the force parameters should take into consideration and attach the heavyweights.

Ship motion: It is observed from Fig. 9(d) that the most influential factor of ship motion is Y26 (Pitch rate); Y23 (Lateral speed) and Y24 (Longitudinal speed) has been increased, and Y30 (Vertical speed) has been decreased. In addition, the changing tendency of each influencing factor for the GRA method and our proposed model are the same

Table A3
The linguistic terms from the experts and the crisp number and weights of different maneuvering influencing factors.

Influencing factors	Expert No. 1		Expert No. 2		Expert No. 3		Expert No. 4		Crisp numbers (with β_i)	Weights (λ_k)
	Linguistic terms	Crisp numbers	Linguistic terms	Crisp numbers	Linguistic terms	Crisp numbers	Linguistic terms	Crisp numbers		
Y1	M	0.4733	M	0.4733	H	0.7333	M	0.4733	0.5253	0.0231
Y2	H	0.7333	M	0.4733	H	0.7333	H	0.7333	0.6683	0.0294
Y3	H	0.7333	H	0.7333	H	0.7333	H	0.7333	0.7333	0.0323
Y4	H	0.7333	M	0.4733	H	0.7333	M	0.4733	0.6033	0.0266
Y5	M	0.4733	M	0.4733	M	0.4733	H	0.7333	0.5383	0.0237
Y6	M	0.4733	M	0.4733	H	0.7333	M	0.4733	0.5253	0.0231
Y7	VH	0.9400	H	0.7333	H	0.7333	VH	0.9400	0.8470	0.0373
Y8	VH	0.9400	VH	0.9400	VH	0.9400	VH	0.9400	0.9400	0.0414
Y9	VH	0.9400	VH	0.9400	VH	0.9400	H	0.7333	0.8883	0.0391
Y10	VH	0.9400	VH	0.9400	VH	0.9400	VH	0.9400	0.9400	0.0414
Y11	H	0.7333	VH	0.9400	H	0.7333	H	0.7333	0.7850	0.0346
Y12	M	0.4733	L	0.2800	VL	0.0833	L	0.2800	0.2987	0.0132
Y13	VH	0.9400	VH	0.9400	VH	0.9400	H	0.7333	0.8883	0.0391
Y14	VH	0.9400	VH	0.9400	VH	0.9400	H	0.7333	0.8883	0.0391
Y15	VH	0.9400	VH	0.9400	VH	0.9400	VH	0.9400	0.9400	0.0414
Y16	H	0.7333	H	0.7333	VH	0.9400	H	0.7333	0.7746	0.0341
Y17	VH	0.9400	VH	0.9400	H	0.7333	VH	0.9400	0.8987	0.0396
Y18	VH	0.9400	VH	0.9400	H	0.7333	VH	0.9400	0.8987	0.0396
Y19	VH	0.9400	VH	0.9400	VH	0.9400	VH	0.9400	0.9400	0.0414
Y20	H	0.7333	H	0.7333	M	0.4733	H	0.7333	0.6813	0.0300
Y21	VL	0.0833	L	0.2800	L	0.2800	VL	0.0833	0.1718	0.0076
Y22	L	0.2800	VL	0.0833	L	0.2800	VL	0.0833	0.1817	0.0080
Y23	H	0.7333	VH	0.9400	H	0.7333	VH	0.9400	0.8367	0.0369
Y24	H	0.7333	VH	0.9400	H	0.7333	VH	0.9400	0.8367	0.0369
Y25	H	0.7333	H	0.7333	M	0.4733	H	0.7333	0.6813	0.0300
Y26	H	0.7333	VH	0.9400	H	0.7333	VH	0.9400	0.8367	0.0369
Y27	H	0.7333	H	0.7333	M	0.4733	H	0.7333	0.6813	0.0300
Y28	H	0.7333	H	0.7333	M	0.4733	H	0.7333	0.6813	0.0300
Y29	H	0.7333	H	0.7333	H	0.7333	H	0.7333	0.7333	0.0323
Y30	M	0.4733	M	0.4733	M	0.4733	L	0.2800	0.4250	0.0187
Y31	H	0.7333	M	0.4733	M	0.4733	H	0.7333	0.6163	0.0272
Y32	M	0.4733	L	0.2800	L	0.2800	M	0.4733	0.3863	0.0170
Y33	M	0.4733	L	0.2800	M	0.4733	M	0.4733	0.4250	0.0187
Weights (β_i)	–	0.30	–	0.25	–	0.20	–	0.25	–	**Sum = 1**

basically, except Y 23 and Y24. The changes are reasonable and meaningful in the real word shipping and traffic safety domain. When the ship berthing to the port, the OOW/pilot needs to pay attention to the lateral and longitudinal speed at all times, thus to ensure the safety of ship and cargo. For instance, if the ship has an obvious lateral speed, it would do damage for the berth and port; if the ship has a greater longitudinal speed, it will cause the collision with the ships before, and after the berth. However, the vertical speed usually is not considered to be the significant influencing factor of maritime safety when a ship is berthing into the port. Hence, when the OOW maneuvering the ship, the lateral and longitudinal speed, as well as pitch rate, should be given more attention, as the same to the program design for the analysis system of the autonomous ship maneuvering decisions for the evaluation of maritime traffic safety influencing factors.

6. Discussion

Ship maneuvering decision-making is influenced by multi-source information, such as the information from the aspects of people, ships, environment, and it has an interaction with various influencing factors, and each factor plays a different role in the ship maneuvering decision-making process. At the same time, some factors interact with each other (e.g. when Y21 (Heading) of the ship changed, then Y8 (relative wave direction) changed correspondingly; when the position changed, i.e. Y32 (Latitude) and Y33 (Longitude) changed, then Y11 (Water depth) changed correspondingly) to form a grey system with clear and partially unclear information, thus constitute a typical “grey system”. In this paper, the maritime traffic safety influencing factors of autonomous ship maneuvering decision-making are identified and classified into four aspects: “Draft & Position”, “Natural environment”, “Force parameters”, “Ship motion”. Then the proposed grey and fuzzy algorithms are applied to prioritize these influencing factors using the linguistic terms of the judgments of domain experts; among these procedures, the relative importance of the linguistic terms of experts judgments is also taken into consideration.

The results from the grey relational analysis showed that the values of grey relational grade for different influencing factors are relatively large (the minimum value is over 0.95), moreover, the values of grey relational grade between the reference series TRO and comparative series of different influencing factors are different, which indicates that the ship maneuvering decision-making is affected by different influencing factors and each influencing factor plays different roles.

Furthermore, grey relational analysis combines with the fuzzy theory is a simple and practical method. The model elaborated in this innovative paper is utilized to prioritize the influencing factors of autonomous ship maneuvering decision-making. The top ten most influential factors in the proposed method are Y15 (Summary force), Y19 (Summary force of mooring lines), Y8 (Relative wave direction), Y10 (Relative wind speed), Y17 (Lateral force of mooring lines), Y18 (Longitudinal force of mooring lines), Y13 (Lateral force), Y14 (Longitudinal force), Y9 (Relative wind direction), and Y7 (Relative current direction). In addition, among the four categories of influencing factors, the most influential factor within each aspect are Y3 (Under keel clearance aft), Y8 (Relative wave direction), Y15 (Summary force), and Y26 (Pitch rate), respectively. The results are corresponding to the judgment/operation of experienced seafarers in the real world shipping. Likewise, they are reasonable and meaningful in the specific navigational scenarios under maritime traffic safety domain.

Therefore, in the process of ship maneuvering decision-making, as well as the program design for the analysis system of the influencing factors of autonomous ship maneuvering decision-making in specific scenarios, the above ten factors should be taken as the main influencing factors considerations. At the same time, the most influential factor in each category also needs to be paid particular attention, especially when the OOW/operators considering the impact of a certain type of influencing factors on ship maneuvering decision-making or the engineers design the maneuvering decisions programs for autonomous ships in specific maritime traffic scenarios. Furthermore, the degree of influence of various factors and the actual economic cost of ships operation should be further considered, thus to promote the development of autonomous merchant shipping reduce transportation costs and improve transportation efficiency and maritime traffic safety.

Though the proposed grey and fuzzy model is a promising model, this paper still has some shortcomings as follows, which should be solved in future research. In the specific experimental navigation scenario, as the above description and analysis for Figs. 8 and 9(c) in Section 4, our proposed model is rational and widely applicable to the analysis of the maritime traffic safety influencing factors for the ship maneuvering decisions. However, when in a specific navigational scenario, for instance, the influencing factors of longitude and latitude do not change correspondingly, there still has some shortcomings when adding the general expert knowledge using general common sense; in this case, the accuracy of our proposed model for analyzing these influencing factors is affected. Therefore, although the traditional grey theory has been largely criticized for the reason that it treats different indexes (influencing factors) equally and takes no account of the relative importance of them, and does not fit with people's preferences for a specific index, it still has the accuracy and sensitivity in specific experimental scenario for particular factors, so it is better to combine with the results from traditional grey method when we apply the proposed model. Hence, further research is needed to find out more influencing factors and navigational scenarios that can conduct a more comprehensive analysis of traffic safety influencing factors which affecting autonomous ship maneuvering decision-making.

7. Conclusions

With the development of modern science and technology, the improvement of autonomous ships has been technically feasible. However, autonomous ship maneuvering decisions are influenced by several influencing factors. The main purpose of our study is to select/prioritize the main influencing factors from all the decision-making influencing factors, thereby establishing the decision-making model efficiently for our subsequent autonomous ships human-like decision-making algorithm studies.

In this paper, the standardization principle of ship maneuvering is introduced, and an innovative grey and fuzzy theories based inference model combined with the expert linguistic terms with different weights is proposed. This model can recognize the main decision-making factors of ship maneuvering from multi-source influencing factors, so as to study the decision-making prioritization for maritime traffic safety in specific ship maneuvering scenario accurately and efficiently, and it also can provide the theoretical basis for the decision-making of OOW and improve the maritime traffic safety as well as the program design for the analysis system of the influencing factors of autonomous ship maneuvering decisions in specific scenarios.

In this study, the overall influencing factors and four categories of influencing factors are analyzed and prioritized separately. The result provides guidance for the OOW's attention to different navigational information for ship maneuvering decision-making under specific maritime traffic scenarios. It not only emphasizes the main influencing factors in the overall attributes but also pays attention to the maritime traffic safety influencing factors and their dynamic change features in each category. The results of the proposed model are more related to real word shipping scenarios and are found to be satisfactory.

Furthermore, the fuzzy number functions are utilized to apply expert knowledge to the process of the main influencing factors selecting/prioritizing of autonomous ship maneuvering decisions, which realizes the identification of the main influencing factors. Moreover, through using the fuzzy theory with expert knowledge, the order of the ranking results of various influencing factors obtained from the traditional grey relational analysis is changed. The results show that the proposed model improves the ranking results of the influencing factors, it is more rational and applicable. Likewise, it provides guidance for autonomous ship maneuvering decisions. In addition, with computer assistance, the model proposed in this paper permits an automatic conversion from the comparative series of maritime traffic safety influencing factors and the corresponding maneuvering decisions (the combination of ship telegraph and rudder order) reference series to autonomous ship maneuvering influencing factors analysis system. The proposed algorithm solves the computational problem of complex fuzzy systems under big data by computer programming (computing advantage), which is of great significance to the development of autonomous ship maneuvering decisions analysis system.

Overall, this paper proposes a prioritizing model for the influencing factors of autonomous ship maneuvering decision-making using grey and fuzzy theories. Based on the actual operation data of the experienced seafarers collected from the simulator, a reference series is established by using the combination of ship telegraph and rudder orders which directly corresponding to the control of a ship. Likewise, establish the comparative series for various influencing factors of ship motion, natural and traffic environment which affect ship maneuvering decision-making. Moreover, combined with the expert knowledge, the proposed model is further optimized to ensure the rationality, accuracy, and generalizability of it, to select/prioritize the main maritime traffic safety influencing factors of the autonomous ship maneuvering decisions in the specific navigational scenario. The proposed model has the following fourfold advantages:

(i) Applying the expert knowledge to the process of autonomous ship maneuvering decisions influencing factors prioritizing, furthermore, by establishing fuzzy linguistic terms sets and the corresponding fuzzy numbers, the basis for qualitative evaluation of the influencing factors of the autonomous ship maneuvering decision-making is provided.
(ii) Through the procedure of defuzzification, the fuzzy numbers are transformed into crisp numbers for priority ranking and comparison purpose. Therefore, the analysis of maritime traffic safety influencing factors for autonomous ship maneuvering decision-making can be conducted. Thereby improving accuracy and rationality as well as expanding the application scope of the proposed model.
(iii) The weight of each expert and the weight of each influencing factor in the whole grey system both being introduced to rank and compare the order of various influencing factors more reasonable and more accurately. Hence, the importance degree of each influencing factor and the preference of decision makers are comprehensively considered according to the actual situation.
(iv) The simulator used in this research can simulate various actual navigational scenarios in different ports all over the world, combining with the actual operation data of experienced seafarers, thus, it can provide meaningful guidance for the selection/prioritization of the maritime traffic safety influencing factors of the autonomous ship maneuvering decisions and promote the development of autonomous ships.

The results of this research provide theoretical and practical insights for prioritizing/evaluating the influencing factors in the autonomous ship maneuvering and maritime safety management for the shipping industry. The model can be further applied to the more general widespread way of the analysis system for autonomous ships human-like decision-making in specific scenarios. In further research, we will explore more about the optimization method for the selection/prioritization of influencing factors and use different data sets to compare the research findings. Moreover, we need to illustrate and combine the expert knowledge for various specific navigational scenarios when we apply our proposed model.

Supplementary materials

Supplementary material (including the process data) associated with this article can be found at https://doi.org/10.4121/uuid:a9b0458d-a6d8-4758-97a6-a09b0efbd085.

Appendix A

See Tables A1–A3.

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