Prediction of human-machine interface (HMI) operational errors for maritime autonomous surface ships (MASS)

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Abstract

The human factor is a hot topic for the maritime industry since more than 80 percent of maritime accidents are due to human error. Minimizing human error contributions in maritime transportation is vital to enhance safety levels. At this point, the Maritime Autonomous Surface Ships (MASS) concept has become one of the most significant aspects to minimize human errors. The objective of this research is to predict the human-machine interface (HMI) based operational errors in autonomous ships to improve safety control levels. At this point, the interaction between shore-based operator and controlling system (cockpits) can be monitored and potential HMI operational errors can be predicted. This research utilizes a Success Likelihood Index Method (SLIM) under an interval type-2 fuzzy sets (IT2FSs) approach. While the SLIM provides a prediction of the human-machine interface (HMI) operational errors, the IT2FSs tackles uncertainty and vagueness in the decision-making process. The findings of this paper are expected to highlight the importance of human-machine interface (HMI) operational errors in autonomous ships not only for designers but also for operational aspects.

Keywords: Autonomous surface ships, human factor, human error, human-machine interface (HMI).

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1. Introduction

Technological developments have brought innovations in the field of transportation as well as in many industries. Maritime transportation has also been affected by these developments. When changes of sea transportation from the past to the present are examined, the celestial navigation made by using the sextant has been replaced by devices such as a magnetic compass, gyrocompass, RDF, GPS, ARPA RADAR, AIS, ECDIS, etc. that facilitate navigation at sea [1]. With industry 4.0, which is the latest stage of technological developments, the aim is to perform the work carried out with manpower autonomously by communicating with each other by technological devices. As Fan et al. [2] stated, developments in autonomous ships have increased in recent years. Among the most important reasons for this increase are to prevent the seafarers shortage stated in the BIMCO [3] report shortly, to reduce transportation costs, and to reduce emission values. For unmanned ships, the removal of the accommodation space can save cost, weight, and space, as well as allow the ship to carry more cargo [4]. Besides, when maritime accidents are analyzed statistically, the result shows that more than 80 percent of them are due to human error [5-8]. Introducing autonomous ships is expected to reduce maritime accidents and enhance safety by minimizing human involvements [9].

For the definition and level of automation, the researchers specified different definitions and autonomous levels [10-13]. The International Maritime Organisation (IMO) defines MASS (Maritime Autonomous Surface Ships) as a vessel that can operate independently of human interaction and consists of four different levels to avoid ambiguity and vagueness about autonomous ships in 2018 [14]. In each of the levels, human beings have different roles and interactions in ship systems and functioning. These levels are ships with automated processes and decision support (level 1), where the seafarers are on board for the operation and control of shipboard systems and functions; a remotely controlled ship with seafarers on board (level 2); a remotely controlled ship ashore without seafarers on-board (level 3) and fully autonomous ship (level 4). [15].

From literature reviewing, the researches about autonomous ship have gradually expanded over the past few years [16-22]. The effort being made to focus on human factors in autonomous ships has remained limited since most of the researches are discussing navigational and operational risks, digitalization, and management [23-25]. Giving advanced automation systems the ability to make decisions and having such a ship operate in a complex and regulated environment like the maritime one is a real challenge, not only from the technological perspective but also from the regulatory point of view. Although certain risks can be reduced due to the benefits of technology, obviously it also brings some new risks [26].

Human factor contribution is increasing for level 2 and level 3 types of MASS where a human error might appear. In this context, human error contribution is paramount for risk analysis in maritime safety, in particular MASS operation. This paper aims to predict human-machine interface (HMI) operational errors for a remotely controlled ship ashore (level 3) to enhance safety control levels. A systematical human error prediction for designated tasks is performed and to required safety control levels are determined for a remotely controlled ship. This paper adopts a robust methodological approach utilizing a Success Likelihood Index Method (SLIM) under an interval type-2 fuzzy sets (IT2FSs) environment. As SLIM enables to quantification of HMI operational errors, the IT2FSs deals with uncertainty and vagueness in decision-making. This paper adopts the SLIM which can aggregate expert estimates on (HEP) in a formal way and obtain more reliable results in human error prediction in such situation. The method is also simple and flexible and is a robust method for estimating HEPs from the experts judgment. Its fundamental rationale is that the success likelihood of a task depends on the combined effects of a set of PSFs. [26 -27].

In this context, this paper is organized as follows. Section 1 expresses the aim of the paper, scope, literature reviewing about autonomous ships, and operational process of the MASS. Section 2 describes methods and how they are integrated. Section 3 quantifies (HMI) operational errors systematically. Section 4 concludes the paper and advises future research. At this point, the next part introduces the MASS and operational process.

1.1 Maritime autonomous surface ships (MASS)

The development of MASS needs to go through functional stages represented by enhanced navigation, assisted navigation, remote navigation, and autonomous navigation. The number of seafarers on board will gradually decrease reducing the participation of humans in the control process. Different from autonomous ships at autonomy levels 1 or 2, the L3 MASS would change the control location, enabling remote-control and operation without seafarers on board, the ship is supervised and operated from a shore-based control center, there might be no or fewer seafarers on board. Human factors are expected to be reduced improving navigation safety by liberating people from repetitive work, which could accumulate practical experience to provide the reference for fully autonomous operation in the future.

Remote operation mainly includes three modes of operations: (a) Follow-up servo mode. Direct instructions of propeller and rudder orders are given from shore-based operators via a communication network and fulfilled by the onboard equipment. (b) Task assignment mode. navigation tasks like the course and speed orders are given by shore-based operators and interpreted by the ship-based controllers to equipment orders. (c) Remote autonomous control. Shore-based operators give high abstracted orders like sailing to certain destinations while the ship-based autonomous system performs accordingly. At present, autonomous control technology has not yet come to reality. Remote-control mode based on the task assignment such as course and speed is more in line with the routine ship steering habits and the relevant provisions of the maritime laws and regulations.

Maritime autonomous surface ships at autonomy level 3 break through geographical and time constraints, online/offline monitoring, and analysis methods are applied to realize the optimal allocation and sharing of distributed resources. The task assignment mode will be the routine. A ship will perceive and analyze the navigation environment and encountered traffic through onboard sensors, providing operational data, ship states, and other information for the remote-control operator to realize the situations to make proper judgments and decisions. According to the remotely assigned tasks, the ship-based controller generates the orders to the propulsion and steering systems of the ship. When a ship sails in restricted areas or encounters an emergency, where and when consistent remote monitor and control is needed, the remote-control operator may take over with the follow-up control model. The operation process is shown in Figure 1.

<Figure 1> is inserted here

2. Research Methodology

This study presents a hybrid approach combining interval type-2 fuzzy sets and SLIM techniques to quantify Human Error Probability (HEP) values systematically in the event of a human-machine interface (HMI) operational errors for maritime autonomous surface ships (MASS). The definition of both methodologies is briefly presented in the next section.

2.1 Success Likelihood Index Methodology

Success Likelihood Index Methodology (SLIM) is a rating-oriented model. It has been applied in other sectors such as chemistry and transportation, primarily the nuclear regulatory commission [27]. The method enables the user to evaluate failure during a task or action. It is applied in maintenance, operational, or event analysis. The SLIM is quite practical in HEP estimation since it is always difficult to capture human error data [28]. According to expert opinion, human factors-based performance is taken into consideration. [29]. In the literature where researchers analyzed human error in maritime transport, the SLIM has been successfully applied for calculating human errors [30,31]. The occurrence probabilities of human error are based on numerous factors, defined as performance shaping factors (PSFs), which affect human performance. Stress, task difficulty, level of preparation (preparation), experience level (experience), fatigue, event-related factors (event factors), etc. are some of the PSFs and can be considered as operational errors for MASS. It is possible to quantify the PSF, which has a major influence on human performance, in SLIM and convert it into a preference index type. Thus, a Success Likelihood Index (SLI) is elicited by using expert assessment. To compute the HEP value, the SLI is calibrated with existing human error data. The SLIM involves some implementation steps such as task analysis, scenario definition, PSF derivation, PSF rating, weighting of PSF, calculating SLI, and HEP calculation.

2.2 Interval type-2 fuzzy sets

Type 2 fuzzy sets have been proposed as an extension of the principle of type 1 fuzzy sets by Zadeh in 1975 [32]. The extensive use of generalized type-2 fuzzy systems has not occurred, because generalized type-2 fuzzy sets involve complicated and enormous, computationally burdensome activities. Due to their simplicity and reduced computing effort concerning general type-2 fuzzy sets, interval type-2 fuzzy sets (IT2FS) are the most widely used type-2 fuzzy sets [33]. The IT2FS has been successfully applied in different industries such as petrochemical [34], offshore structure [35,36], logistic [37], and maritime transport [38-39] where insufficient data, the subjectivity of analysis and uncertainty exist. Besides, the theory of linguistic variables is useful to tackle complex situations. Linguistic variables are used in fuzzy sets to determine the ratings of different parameters and alternatives in real-case applications. The fuzzy sets often denote linguistic values and make more sense than specific numbers [40], . The IT2FSs are more suitable for the usage of linguistic variables to represent uncertainties [41]. For IT2FSs that derive from type-1 fuzzy sets [42] different linguistic variables are created. To address the difficulty and ambiguity of the data collection process, linguistic variables are used for determining parameters. In the proposed method, while the SLIM is used to calculate HEP, the IT2FS deals with the vagueness of expert judgments and expression in decision-making during the PSF weighting process. It should also be emphasized that IT2FSs tackles more uncertainty and generate more precise data. The IT2FSs will be used in this article instead of type-1 fuzzy sets due to its superiority. Here some mathematical operations between two IT2FSs are presented for further calculations.

The addition operation:

$$\tilde{\tilde{A}}_1 = \left(\tilde{A}_1^U, \tilde{A}_1^L\right) = \left(\left(a_{11}^U, a_{12}^U, a_{13}^U, a_{14}^U; H_1\left(\tilde{A}_1^U\right), H_2\left(\tilde{A}_1^U\right)\right), \left(a_{11}^L, a_{12}^L, a_{13}^L, a_{14}^L; H_1\left(\tilde{A}_1^L\right), H_2\left(\tilde{A}_1^L\right)\right)\right)$$

$$\tilde{\tilde{A}}_2 = \left(\tilde{A}_2^U, \tilde{A}_2^L\right) = \left(\left(a_{21}^U, a_{22}^U, a_{23}^U, a_{24}^U; H_1\left(\tilde{A}_2^U\right), H_2\left(\tilde{A}_2^U\right)\right), \left(a_{21}^L, a_{22}^L, a_{23}^L, a_{24}^L; H_1\left(\tilde{A}_2^L\right), H_2\left(\tilde{A}_2^L\right)\right)\right)$$

$$\tilde{A}_1 \oplus \tilde{A}_2 = \left(\tilde{A}_1^U, \tilde{A}_1^L\right) \oplus \left(\tilde{A}_2^U, \tilde{A}_2^L\right) = \begin{pmatrix} \left(a_{11}^U + a_{21}^U, a_{12}^U + a_{22}^U, a_{13}^U + a_{23}^U, a_{14}^U + a_{24}^U; \min\left(H_1\left(\tilde{A}_1^U\right), H_1\left(\tilde{A}_2^U\right)\right), \min\left(H_2\left(\tilde{A}_1^U\right), H_2\left(\tilde{A}_2^U\right)\right)\right), \\ \left(a_{11}^L + a_{21}^L, a_{12}^L + a_{22}^L, a_{13}^L + a_{23}^L, a_{14}^L + a_{24}^L; \min\left(H_1\left(\tilde{A}_1^L\right), H_1\left(\tilde{A}_2^L\right)\right), \min\left(H_2\left(\tilde{A}_1^L\right), H_2\left(\tilde{A}_2^L\right)\right)\right) \end{pmatrix} \quad (1)$$

The subtraction operation:

$$\tilde{A}_1 \Theta \tilde{A}_2 = \left(\tilde{A}_1^U, \tilde{A}_1^L\right) \Theta \left(\tilde{A}_2^U, \tilde{A}_2^L\right) = \begin{pmatrix} \left(a_{11}^U - a_{21}^U, a_{12}^U - a_{22}^U, a_{13}^U - a_{23}^U, a_{14}^U - a_{24}^U; \min\left(H_1\left(\tilde{A}_1^U\right), H_1\left(\tilde{A}_2^U\right)\right), \min\left(H_2\left(\tilde{A}_1^U\right), H_2\left(\tilde{A}_2^U\right)\right)\right), \\ \left(a_{11}^L - a_{21}^L, a_{12}^L - a_{22}^L, a_{13}^L - a_{23}^L, a_{14}^L - a_{24}^L; \min\left(H_1\left(\tilde{A}_1^L\right), H_1\left(\tilde{A}_2^L\right)\right), \min\left(H_2\left(\tilde{A}_1^L\right), H_2\left(\tilde{A}_2^L\right)\right)\right) \end{pmatrix} \quad (2)$$

The multiplication operation:

$$\tilde{A}_1 \otimes \tilde{A}_2 = \left(\tilde{A}_1^U, \tilde{A}_1^L\right) \otimes \left(\tilde{A}_2^U, \tilde{A}_2^L\right) = \begin{pmatrix} \left(a_{11}^U \times a_{21}^U, a_{12}^U \times a_{22}^U, a_{13}^U \times a_{23}^U, a_{14}^U \times a_{24}^U; \min\left(H_1\left(\tilde{A}_1^U\right), H_1\left(\tilde{A}_2^U\right)\right), \min\left(H_2\left(\tilde{A}_1^U\right), H_2\left(\tilde{A}_2^U\right)\right)\right), \\ \left(a_{11}^L \times a_{21}^L, a_{12}^L \times a_{22}^L, a_{13}^L \times a_{23}^L, a_{14}^L \times a_{24}^L; \min\left(H_1\left(\tilde{A}_1^L\right), H_1\left(\tilde{A}_2^L\right)\right), \min\left(H_2\left(\tilde{A}_1^L\right), H_2\left(\tilde{A}_2^L\right)\right)\right) \end{pmatrix} \quad (3)$$

The arithmetic operations:

$$k\tilde{\tilde{A}}_1 = \begin{pmatrix} \left(k \times a_{11}^U, k \times a_{12}^U, k \times a_{13}^U, k \times a_{14}^U; H_1\left(\tilde{A}_1^U\right), H_2\left(\tilde{A}_1^U\right)\right), \\ \left(k \times a_{11}^L, k \times a_{12}^L, k \times a_{13}^L, k \times a_{14}^L; H_1\left(\tilde{A}_1^L\right), H_2\left(\tilde{A}_1^L\right)\right) \end{pmatrix} \quad (4)$$

$$\frac{\tilde{\tilde{A}}_1}{k} = \begin{pmatrix} \left(\frac{1}{k} \times a_{11}^U, \frac{1}{k} \times a_{12}^U, \frac{1}{k} \times a_{13}^U, \frac{1}{k} \times a_{14}^U; H_1\left(\tilde{A}_1^U\right), H_2\left(\tilde{A}_1^U\right)\right), \\ \left(\frac{1}{k} \times a_{11}^L, \frac{1}{k} \times a_{12}^L, \frac{1}{k} \times a_{13}^L, \frac{1}{k} \times a_{14}^L; H_1\left(\tilde{A}_1^L\right), H_2\left(\tilde{A}_1^L\right)\right) \end{pmatrix} \quad (5)$$

2.3 Integration of methods

This section explains how the IT2FS and SLIM will be integrated for performing quantitative HEP. A flow chart of the proposed approach is illustrated in Figure 2. The main steps of the proposed approach are expressed accordingly.

<Figure 2> is inserted here.

Step 1. Task analysis

Task analysis is conducted to identify relevant steps per the scenario. It addresses tasks that must be successfully performed sequentially by the operator. The operator will not fail each task that is being performed during navigation. In compliance with Hierarchical Task Analysis (HTA), where the main task consists of sub-tasks, the task analysis is performed [43, 44].

Step 2. Operation definition

In this section, various scenarios are defined under different conditions. This scenario involves numerous conditions such as weather conditions, the working environment, fatigue, workload, stress, noise level, experience, alarm, etc.

Step 3. PSF derivation

In this section, a set of PSFs that affects human performance during the task is revealed by the expert group. Different factors such as time availability, ergonomics, task difficulty, working environment, age, etc. may be PSFs. The number of appropriate PSFs is considered about six in SLIM [28] which are the most significant factors affecting the tasks.

Step 4. PSF rating

Once PSFs are elicited by experts, each of the PSFs is assigned a value from 1 to 9 on a linear scale by experts. Evaluations made by experts are independent of the impact of other PSFs. If a PSF has a significant impact on the task, the most negative score is usually 1, with a value of 9 being optimal.

Step 5. PSF weighting

The weighting process is applied to prioritize PSF in terms of the influence on each task. Thus, the relative importance of each PSF is determined. In the conventional SLIM technique, the

PSF weighting is performed based on the direct percentage evaluation of experts. However, if experts give a percentage value directly to the linguistic expression, it may give erroneous results. This paper adopts the IT2FS expression in the percentage evaluation representation to address these limitations. The fuzzy linguistic expression can improve the accuracy of the outcome in the representation of percentage evaluation of PSFs.

In this context, the Type-2 fuzzy sets and IT2FS definitions (Celik et al., 2014; Mendel et al., 2006) are described as follows.

Definition 1: A type-2 fuzzy set $\tilde{\tilde{A}}$ in the universe of discourse *X* can be represented by a type-2 membership function $\mu_{\tilde{\tilde{A}}}$, shown as follows:

$$\tilde{\tilde{A}} = \left\{((x,u),\mu_{\tilde{\tilde{A}}}(x,u)) \middle| \forall x \in X, \forall u \in J_X \subseteq [0,1], 0 \le \mu_{\tilde{\tilde{A}}}(x,u) \le 1\right\}$$

where J_X denotes an interval in [0, 1]. Moreover, the type-2 fuzzy set $\tilde{\tilde{A}}$ also can be represented as follows:

$$\tilde{\tilde{A}} = \int_{x\in X}\int_{u\in J_X} \mu_{\tilde{\tilde{A}}}(x,u)/(x,u)$$

where $J_X \subseteq [0,1]$ and $\int\int$ denotes union overall admissible *x* and *u*.

Definition 2: Let $\tilde{\tilde{A}}$ be a type-2 fuzzy set in the universe of discourse X represented by the type-2 membership function $\mu_{\tilde{\tilde{A}}}$. If all $\mu_{\tilde{\tilde{A}}}(x,u)=1$, then $\tilde{\tilde{A}}$ is called an interval type-2 fuzzy set.

An interval type-2 fuzzy set $\tilde{\tilde{A}}$ can be regarded as a special case of a type-2 fuzzy set, represented as follows:

$$\tilde{\tilde{A}} = \int_{x\in X}\int_{u\in J_X} 1/(x,u) \quad \text{where } J_X \subseteq [0,1]$$

Definition 3: The upper membership function and the lower membership function of an interval type-2 fuzzy set are type-1 membership functions, respectively. In this paper, the IT2FSs is used to capture fuzzy multiple attributes group decision-making problems, where the reference points and the heights of the upper and the lower membership functions of IT2FSs are used to characterize interval type-2 fuzzy sets. Figure 3 shows a trapezoidal interval type-2 fuzzy set.

$$\tilde{\tilde{A}}_i = \left(\tilde{A}_i^U, \tilde{A}_i^L\right) = \left(\left(a_{i1}^U, a_{i2}^U, a_{i3}^U, a_{i4}^U; H_1\left(\tilde{A}_i^U\right), H_2\left(\tilde{A}_i^U\right)\right), \left(a_{i1}^L, a_{i2}^L, a_{i3}^L, a_{i4}^L; H_1\left(\tilde{A}_i^L\right), H_2\left(\tilde{A}_i^L\right)\right)\right)$$

, where $\tilde{A}_i^U$ and $\tilde{A}_i^L$ are type-1 fuzzy sets, $a_{i1}^U, a_{i2}^U, a_{i3}^U, a_{i4}^U, a_{i1}^L, a_{i2}^L, a_{i3}^L$ and a_{i4}^L are the reference points of the interval type-2 fuzzy $\tilde{\tilde{A}}_i$; $H_j\left(\tilde{A}_i^U\right)$ denotes the membership value of the element $a_{i(j+1)}^U$ in the upper trapezoidal membership function $\tilde{A}_i^U$; $1 \le j \le 2$, $H_j\left(\tilde{A}_i^L\right)$ denotes the membership value of the element $a_{i(j+1)}^L$ in the lower trapezoidal membership function $\tilde{A}_i^L$; $1 \le j \le 2$, $H_j\left(\tilde{A}_i^L\right)$

$H_1\left(\tilde{A}_i^U\right) \in [0,1]$, $H_2\left(\tilde{A}_i^U\right) \in [0,1]$, $H_1\left(\tilde{A}_i^L\right) \in [0,1]$, $H_2\left(\tilde{A}_i^L\right) \in [0,1]$ and $1 \le i \le n$.

<Figure 3> is inserted here.

Definition 4: In this part, an extended center of area method is used to defuzzify and rank IT2FSs. At this point, equation (1) is applied for defuzzification of the IT2FSs [33]

$$Defuzzified\left(\tilde{\tilde{A}}_i\right) = \frac{\dfrac{\left(a_{i4}^U - a_{i1}^U\right) + \left(H_1\left(\tilde{A}_i^U\right) * a_{i2}^U - a_{i1}^U\right) + \left(H_2\left(\tilde{A}_i^U\right) * a_{i3}^U - a_{i1}^U\right)}{4} + a_{i1}^U + \dfrac{\left(a_{i4}^L - a_{i1}^L\right) + \left(H_1\left(\tilde{A}_i^L\right) * a_{i2}^L - a_{i1}^L\right) + \left(H_2\left(\tilde{A}_i^L\right) * a_{i3}^L - a_{i1}^L\right)}{4} + a_{i1}^L}{2} \tag{6}$$

Step 6. SLI determination and HEP calculation

The SLI can be calculated as per equation (7) once PSF ranking and weighting values are calculated. It estimates the probability of situations in which numerous human errors may occur. The calculated SLI values can be converted into HEP values by using equation (8). The SLI values are calibrated by using constant a and b values in the equation [45,39]

$$SLI = \sum_{i=1}^{n} r_i w_i \,, \quad 0 \le SLI \le 1 \tag{7}$$

$$Log\ (HEP) = aSLI + b \qquad a, b = const. \tag{8}$$

3. Prediction of human-machine interface (HMI) operational errors

This section conducts an empirical analysis to predict HMI operational errors for MASS to enhance safety and operational reliability in maritime transportation, providing a methodological extension through the integration of the SLIM into the IT2FSs.

3.1 Problem statement

Adapting automation systems to the maritime industry is a tough challenge since even routine ship operations involve complicated operations monitored by a great number of regulators. Not only from a technical perspective but also for policymakers, autonomous ships present a significant challenge.Therefore, the possibility to evaluate human errors related to MASS operation is a much-needed capability, able to help the industry assessing the validity of their concepts, and to allow regulatory organizations. In this context, human (operator) error assessment addressing remote-control autonomous ships with human– autonomy collaboration is of paramount importance for detecting deficiencies during operation. Hence, this paper predicts the human-machine interface (HMI) based operational errors in MASS to improve safety control level.

3.2 A virtual-shipboard operational environment and task analysis

Hierarchical task analysis for the virtual-shipboard operational environment of remote-control operations is demonstrated in Table 1. It should be noted that the process is set based on contemporary navigation procedures and an assumption of the future remote-control procedures. It is assumed that the remote-control operations are performed through commands given from onshore operators and execution of commands by the onboard system as discussed in Section 1.1. The procedure of three main tasks, which are i) Before remote-control operations for a certain route (preparation and leave the harbor), ii) During navigation in the sea, iii) Harbor entrance and docking.

<Table 1 > is inserted here.

During each route, the operational scenarios vary with weather conditions, traffic density, schedule, etc. leading to changes in fatigue, workload, stress, etc. of the operators. Thus, the operators will embrace a different working environment and experience during each shift. Accordingly, the possibilities of human errors may change. Since there are no remote-control ships available in routine, the analysis is limited to the knowledge of the authors during remote-control tests and demonstrations.

3.3 PSF derivation and rating

The PSF derivation is one of the critical parts of the implementation stage of the method. In this paper, six PFS derivations were derived by maritime experts who are dealing with MASS. In the elicitation process, the experts were chosen from the ship management companies and universities. They are wide knowledge and experience about ship handling since the experts are ocean going Masters (6), chief officers(3) and safety inspectors (3). The rest of them (4 experts) are academicians who are working on remote-control mode ships (MASS). After having performed a brainstorming, the ERT selected the best appropriate PSFs affecting MASS operation. The elicited PFSs are stress, complexity, training, environmental factors, communication, and fatigue respectively. In the view of the PSFs, the excel sheet prepared for the survey was sent to marine experts. They were asked to evaluate the rating of PSFs based on a 1-9 liner scale introduced by method for each sub-task. To simplify the calculations, five marine experts (3 Ocean going Master and 2 academcian) were asked to complete an excel survey. Once the judgments were gathered, the geometric means of them are taken. In this context, Table 2 shows PSF ratings by marine expert judgments.

<Table 2 > is inserted here.

3.4 PSF weighting

The weighting process is performed to prioritize the PSFs under IT2F linguistic scale. Five marine experts evaluated the importance weight of the PSFs according to the scale of Lee and Chen [42] Table 3 shows the IT2FSs numbers associated with the linguistic terms for calculating the importance weight of PSFs. Table 4 shows fuzzy linguistic statements of five marine experts to evaluate PSFs weights. Furthermore, the marine experts' linguistic statements are converted to the IT2FSs and then those transformed into one judgment by using addition operation and arithmetic operation (Eq. 1, 4, and 5). In this context, Table 5 illustrates calculated average IT2FSs values.

<Table 3 > is inserted here.

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The defuzzified IT2FSs values are calculated by using equation (6) once the average IT2FSs values are determined for each PSFs. Since the PSF weights are being between 0.0-1.0, they must be converted to normalized values. Accordingly, table 6 gives crisp and normalized values of PSF weights under IT2FSs approach.

<Table 6 > is inserted here.

3.5 Determination SLI and calculating HEP

After having determined the weights for each PSF, the SLI values are determined concerning the equation (7) for each task addressing to MASS operational process. The HEP values for each task are calculated by using the equation (8). In the equation, *a* and *b* are the constant numbers and calculated from the highest and the lowest SLI values [46,47]. In this context, Table 7 shows the SLI and HEP values for each task of remote-control MASS operation.

<Table 7> is inserted here.

3.6 Comparison with an cognitive approach

The IT2FSs-SLIM approach is compared to CREAM (Cognitive reliability and error analysis method) which was developed by Hollnagel [48] to calculate the probability of human errors for completion of a specific task. The method provides retrospective and prospective analysis. The basis steps of the extended CREAM method involve; i.) Assessment of common performance conditions (CPCs), ii.) identify the context influence index (CII), iii.) determining performance influence index (PII), iv.) calculating cognitive failure probability (CFP) [43,47]. Once the occurrence probability of the task is calculated, the following equations are used to transform the probability into HEP [47].

$$\log\left(\frac{CFP}{CFP_0}\right) = k.CII, \tag{9}$$

where k gives a constant coefficient and can be derived from equations (4) and (5) respectively [47].

$$\log(\mathrm{CFP}_{\mathrm{max}}/\mathrm{CFP}_0) = k.CII_{max},$$
$$\log(\mathrm{CFP}_{\mathrm{min}}/\mathrm{CFP}_0) = k.CII_{min}, \quad (10)$$

$$k = \log(\mathrm{CFP}_{\mathrm{max}}/\mathrm{CFP}_{\mathrm{min}})/(\mathrm{CII}_{\mathrm{max}} - \mathrm{CII}_{\mathrm{min}}) \quad (11)$$

$$\mathrm{CFP}_0 = \mathrm{CFP}_{\mathrm{max}}/10^{\mathrm{k.CII_{max}}} \quad (12)$$

Based-on the specific control modes and CII values, the maximum CII value can be calculated 9 and the minimum CII is -7. In the equation, the $\mathrm{CFP}_{\mathrm{max.}}$ is accepted as 1.0000 (maximum HEP value), which defines the certainty for human error probability. The $\mathrm{CFP}_{\mathrm{min}}$ is accepted as 0.00005 (minimum HEP value), which presents almost impossibility. In this context, k is figured out 0.26. In conclusion, the following equation can be applied to calculate the adjusted CFP (HEP) value in case of a definite CII value [43, 47].

$$CFP = CFP_0 \; x \; 10^{0.26.CII} \quad (13)$$

In the view of above, Table 8 gives a comparison of human error probabilities calculated by using the CREAM methodology for each task of remote-control MASS operation. Five marine experts (3 Masters and 2 academicians) were participated for assessment. The consensus of marinex perts judgements were gathered during calculation process. After having perfoemd calculation through CREAM, it can be observed that the HEP values for each task calculated in both approaches are almost similar. The CREAM verifies the results of the IT2FSs – SLIM approach.

<Table 8> is inserted here.

3.7 Findings and discussion

The findings of the research show that, for Task 1 (Preparation for departure), sub-task 1.6 (Set target route and update system configurations based on the route) is the most significant sub-task where HEP (1.71E-01) reached the highest value for the remote-control MASS operation and increase the risk of collision with other ships. This task requires utmost human-machine interaction since setting a target route and updating system configuration is quite complex and needed for effective operator control. In this task, the HEP value is quite high compared to others. The reason behind that is complexity, stress, and fatigue. This is most likely to be overwork, long and irregular hours resulting in lack of rest. Stress and fatigue may cause failure to adjust the target route (course) and failure to update the system correctly. Failure to set target route and update system configurations may lead to ship deviate from the course and increase the risk of collision with other ships. Thence, safety recommendations for operators have been elaborated, pertaining to potential ways of mitigating hazards. In order to prevent the operator from making errors due to fatigue, it should be ensured that the working hours of the operator are determined and rested sufficiently. Operators should receive advanced training to conduct complex operations more safely, and the stress factors of experienced operators can be considered more seriously. In addition to these measures, an early warning alert system can be installed in the operator control room to detect the fatigue levels of the operators.

For Task 2 (Navigation at sea), the sub-task 2.4 (Perform a continuous collision avoidance where course and engine requirements are given from the shore to the ship) has the second-highest HEP value (1.49E-01). Insufficient practical training and lack of communication for the remote-control MASS can be a cause of failure. Specifically, continuous communication systems in the cockpit pose a critical role to enhance navigational safety and prevent collision avoidance. At this point, a high-level HMI system for a vessel could include alarm and status signals to minimize human-based errors. In order to prevent failures determined in this task, operators should be given training on collision avoidance and effective communication with the remote-control MASS. In addition, a decision support system that early perceives the collision and makes suggestions of possible collision avoidance action can be developed.

The third highest HEP value (1.11E-01) is related to Task 3 (Harbour entrance and docking) and is found in sub-task 3.1 (Reporting time to arrival, tug assistance requirement, etc. to the harbor) having the highest HEP values. Lack of communication is one of the main reasons for the increased probability of human error for this task. It may cause to fail berthing, harbor arrangements, and tugs assistance (if required). Timely and correct planning can be ensured with good communication and prevent errors that may occur in berthing, harbor arrangements, and tugs assistance. In order to make the timely planning, a system can be developed to determine automatic reporting ETA, berthing arrangements to inform the harbor. In this context, Figure 4 shows the PSF deviation chart for sub-tasks which are having the highest HEP values.

<Figure 4> is inserted here.

The rest of the sub-tasks have lower HEPs for a remote-control MASS operation since the average value is 2.85E-02 which is quite low. It shows that operator performance reliability is satisfactory and typically following planned procedures as some provisional deviation is still possible. On the other hand, Figure 5 illustrates a comparison of calculated HEP in IT2FS-SLIM approach and CREAM. The graph shows HEP value distributions throughout sub-tasks. In the view of the figure, the observed HEPs are almost similar in tasks and this proves that the research outcomes are consistent and reasonable.

<Figure 5> is inserted here.

4. Conclusion

HMI system is a critical component in the operation of remote-control MASS. The effectiveness of the HMI system can affect the operation process of the entire system. At this point, human performance becomes a critical concern since human errors are key attributes of safety and reliability engineering [49,50]. The expectation is to complete tasks for the operational process of the system without any failures [51]. This paper aims to predict HMI operational errors of remote control MASS to enhance safety. The paper deals with the quantification of human error probability applied to a remote-control MASS. To address this concern, comprehensive research has been performed by using the IT2FS-SLIM approach. Whilst the SLIM calculated HMI operational errors for a remote-control MASS, the ITFS coped with uncertainty and vagueness in decision-making.

The findings of the paper show that setting the target route and update system configurations, performing continuous collision avoidance, and reporting ship arrival are the critical operational tasks in which HEP values increase. The results reveal that the impact of the errors associated with HMI is much more significant than its basic functionality. To verify the results of the research, the proposed approach is compared with CREAM. It is noted that the HEP values for each task calculated in both approaches are similar. The uncertainty is one of the significant limitations of this study since uncertainties are inherent in all scientific undertakings. Physical constraints or lack of resources are the main contributing factors for data scarcity [52, 53]. In the paper, there is uncertainty during HEP calculation due to data scarcity in MASS operation. The potential limitation of the proposed model is using 1-9 liner numeric scale instead of fuzzy sets. The further research will try to tackle with aforementioned limitation since it is not capable of capturing entire assessment.

In conclusion, the findings of this paper are expected to highlight the importance of human-machine interface (HMI) operational errors in remote-control MASS not only for designers but also for operational aspects. Further researches will be focused on the real dataset obtained by the operation of autonomous ships in the open seas and will be compared and updated on the outcomes.

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Table 1 . HTA of virtual-shipboard operational environment for remote-control MASS operation.

Remote-control operation process for a certain route
1. Prior to remote-control operations for a certain route
1.1 Check if the remote-control operator is suitable to proceed.
1.2 Check if the facilities and equipment in the virtual shipboard operational environment are operational.
1.3 Check the shore-ship communication status.
1.4 Perform a routine sail out check of the on-board machines and systems.
1.5 Check the navigation plan, weather conditions, time schedule, etc.
1.6 Set target route and update system configurations based on the route.
1.7 Call tug assistance if it is necessary.
1.8 Undock and sail out.
2. During navigation in sea
2.1 Set an autopilot and continuous watch while sailing.
2.2 Perform monitor and deal with alerts
2.3 Intervene when the environment perception system detects risks.
2.4 Perform a continuous collision avoidance where course and engine requirements are given from the shore to the ship.
2.5 Check the operation status feedback from the ship to see if the commands are fulfilled.
2.6 Back to autopilot when the risks are rest.
2.7 Repeat the above procedures till the target harbour.
3. Harbour entrance and docking
3.1 Report time to arrival, tug assistance requirement etc. to the harbour.
3.2 Remote-control operator takes continuous control instead of autopilot.
3.3 Communicate with the pilot and/or tugs if it is necessary.
3.4 Perform docking control with full cautions.
3.5 Cool down the machineries and set to the system for standby.
3.6 Perform diagnosis of the route operations to see if any mistake was made and how to avoid it in the future routes.

<Table 2. PSF ratings based on the marine experts' assessment>

		PSFs					
Task	Sub-task	Stress	Complexity	Training	Environmental factors	Fatigue	Communication
1.							
	1.1	5	7	4	4	4	6
	1.2	4	7	4	4	4	5
	1.3	4	7	6	4	4	6
	1.4	4	6	4	3	4	5
	1.5	4	5	3	4	4	5
	1.6	4	5	3	3	4	4
	1.7	4	5	4	3	5	3
	1.8	4	6	5	4	4	5
2.							
	2.1	4	5	5	4	4	4
	2.2	5	6	5	4	4	4
	2.3	5	6	5	5	4	6
	2.4	5	3	5	3	3	5
	2.5	5	6	5	4	5	5
	2.6	4	6	6	5	5	4
	2.7	4	7	5	4	5	5
3.							
	3.1	3	4	4	4	4	5
	3.2	5	5	5	3	4	5
	3.3	4	5	5	4	4	5
	3.4	5	7	6	5	5	6
	3.5	3	5	5	4	5	6
	3.6	3	5	5	4	5	5

<Table 3. Linguistic terms for rating of criteria>

Linguistic terms	Interval type-2 fuzzy sets
Very Low (VL)	((0;0;0;0.1;1;1),(0;0;0;0.05;0.9;0.9))
Low (L)	((0;0.1;0.1;0.3;1;1),(0.05;0.1;0.1;0.2;0.9;0.9))
Medium Low (ML)	((0.1;0.3;0.3;0.5;1;1),(0.2;0.3;0.3;0.4;0.9;0.9))
Medium (M)	((0.3;0.5;0.5;0.7;1;1),(0.4;0.5;0.5;0.6;0.9;0.9))
Medium High (MH)	((0.5;0.7;0.7;0.9;1;1),(0.6;0.7;0.7;0.8;0.9;0.9))
High (H)	((0.7;0.9;0.9;1;1;1),(0.8;0.9;0.9;0.95;0.9;0.9))
Very High (VH)	((0.9;1;1;1;1;1),(0.95;1;1;1;0.9;0.9))

<Table 4. Fuzzy linguistic statement of marine experts>

	Marine experts				
PSF	Exp.1	Exp.2	Exp.3	Exp.4	Exp.5
Stress	L	M	M	VL	L
Complexity	VH	MH	MH	VH	M
Training	H	H	ML	M	H
Environmental factors	MH	MH	M	MH	M
Communication	L	VH	VH	VH	MH
Fatigue	H	H	VL	H	VL

<Table 5. Calculated average IT2FSs values >

PSF	Average fuzzy sets values												Average interval type-2 fuzzy sets
Stress	0.30	0.44	0.44	0.60	1.00	1.00	0.37	0.44	0.44	0.52	0.90	0.90	((0.3;0.44;0.44;0.6;1;1), (0.37;0.44;0.44;0.52;0.9;0.9))
Complexity	0.70	0.86	0.86	0.94	1.00	1.00	0.78	0.86	0.86	0.90	0.90	0.90	((0.7;0.86;0.86;0.94;1;1), (0.78;0.86;0.86;0.9;0.9;0.9))
Training	0.62	0.82	0.82	0.94	1.00	1.00	0.72	0.82	0.82	0.88	0.90	0.90	((0.62;0.82;0.82;0.94;1;1), (0.72;0.82;0.82;0.88;0.9;0.9))
Environmental factors	0.54	0.74	0.74	0.88	1.00	1.00	0.64	0.74	0.74	0.81	0.90	0.90	((0.54;0.74;0.74;0.88;1;1), (0.64;0.74;0.74;0.81;0.9;0.9))
Communication	0.68	0.80	0.80	0.86	1.00	1.00	0.74	0.80	0.80	0.83	0.90	0.90	((0.68;0.8;0.8;0.86;1;1), (0.74;0.8;0,8;0.83;0.9;0.9))
Fatigue	0.78	0.94	0.94	1.00	1.00	1.00	0.86	0.94	0.94	0.97	0.90	0.90	((0.78;0.94;0.94;1;1;1), (0.86;0.94;0.94;0.97;0.9;0.9))

<Table 6. Crisp and normalised values of PSF weights >

PSF	Crisp values	Normalised values
Stress	0.49	0.10
Complexity	0.87	0.18
Training	0.85	0.18
Environmental factors	0.78	0.16
Communication	0.81	0.17
Fatigue	0.95	0.20

<Table 7. SLI and HEP values for each task of remote-control MASS operation.>

Task	Sub-task	SLI	log-HEP	HEP
1.				
	1.1	4.96	-2.815	1.53E-03
	1.2	4.77	-2.448	3.56E-03
	1.3	5.10	-3.092	8.10E-04
	1.4	4.44	-1.784	1.64E-02
	1.5	4.21	-1.323	4.75E-02
	1.6	3.93	-0.767	1.71E-01
	1.7	4.21	-1.328	4.69E-02
	1.8	4.81	-2.519	3.03E-03
2.				
	2.1	4.56	-2.029	9.35E-03
	2.2	4.77	-2.434	3.68E-03
	2.3	5.05	-3.006	9.86E-04
	2.4	3.96	-0.826	1.49E-01
	2.5	5.01	-2.925	1.19E-03
	2.6	4.97	-2.841	1.44E-03
	2.7	5.06	-3.029	9.36E-04
3.				
	3.1	4.03	-0.956	1.11E-01
	3.2	4.46	-1.820	1.51E-02
	3.3	4.71	-2.314	4.86E-03
	3.4	5.88	-4.660	2.19E-05
	3.5	4.82	-2.535	2.92E-03
	3.6	4.62	-2.133	7.35E-03

<Table 8. Comparison of calculated HEP in IT2FS-SLIM approach and CREAM.>

Task	Sub-task	HEP (IT2FS-SLIM)	HEP (CREAM)
1.			
	1.1	1.53E-03	1.43E-03
	1.2	3.56E-03	4.30E-03
	1.3	8.10E-04	4.30E-03
	1.4	1.64E-02	1.43E-02
	1.5	4.75E-02	1.43E-02
	1.6	1.71E-01	2.86E-01
	1.7	4.69E-02	1.43E-02
	1.8	3.03E-03	2.17E-04
2.			
	2.1	9.35E-03	2.17E-04
	2.2	3.68E-03	2.17E-05
	2.3	9.86E-04	6.50E-04
	2.4	1.49E-01	1.62E-01
	2.5	1.19E-03	1.00E-04
	2.6	1.44E-03	6.38E-03
	2.7	9.36E-04	6.38E-03
3.			
	3.1	1.11E-01	8.20E-02
	3.2	1.51E-02	1.82E-02
	3.3	4.86E-03	6.38E-03
	3.4	2.19E-05	2.74E-05
	3.5	2.92E-03	2.74E-04
	3.6	7.35E-03	2.74E-04

Figure 1. Operational process of remote-control MASS.

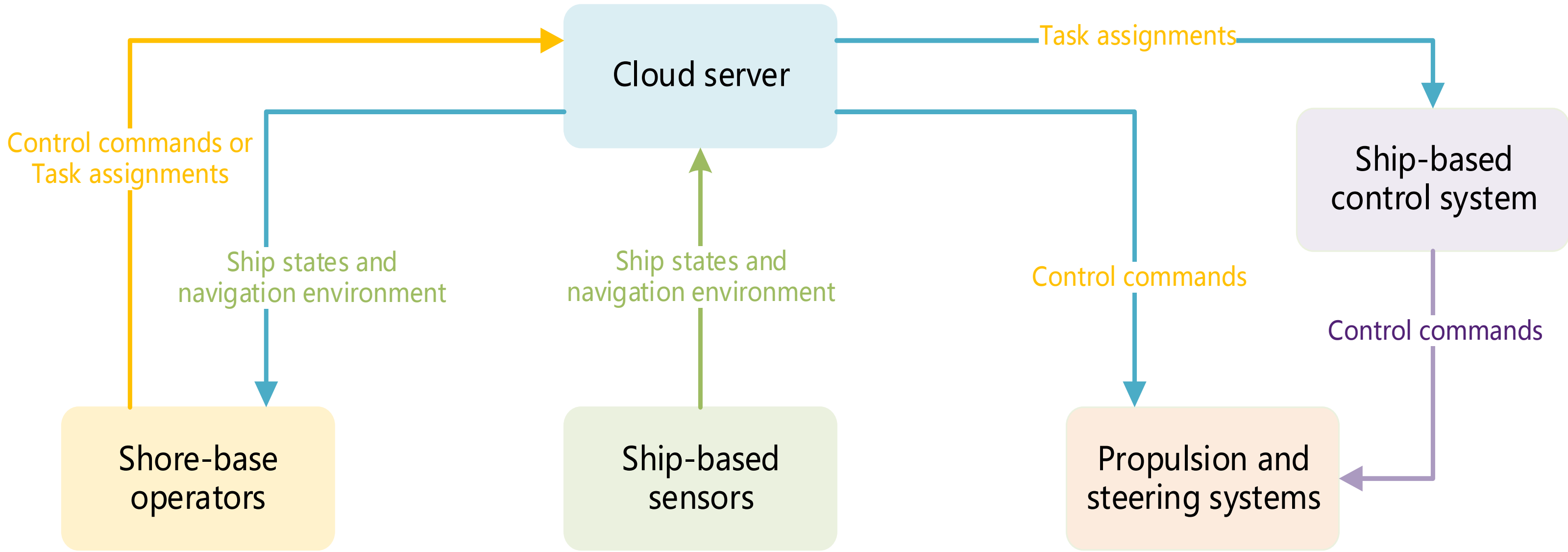
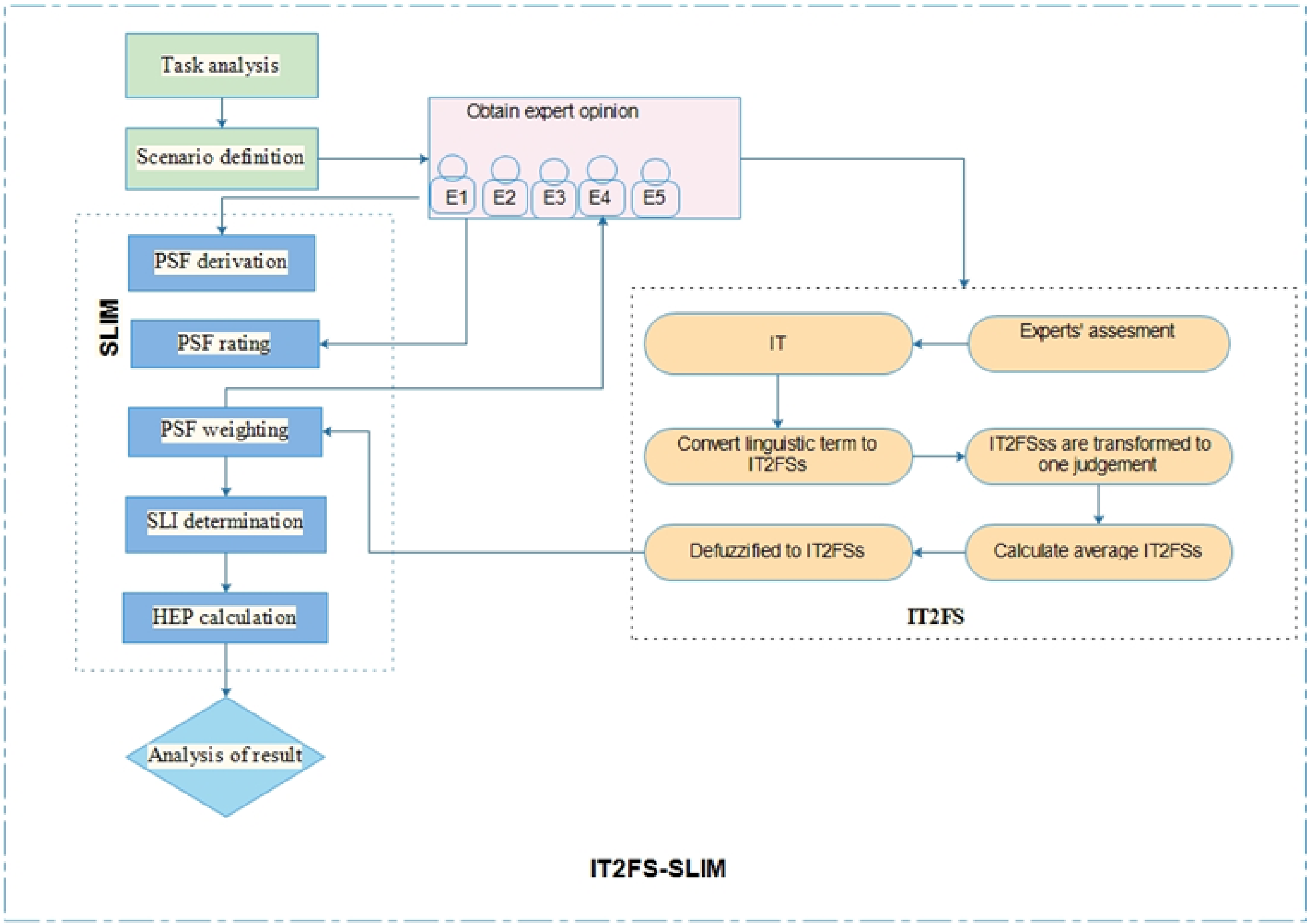
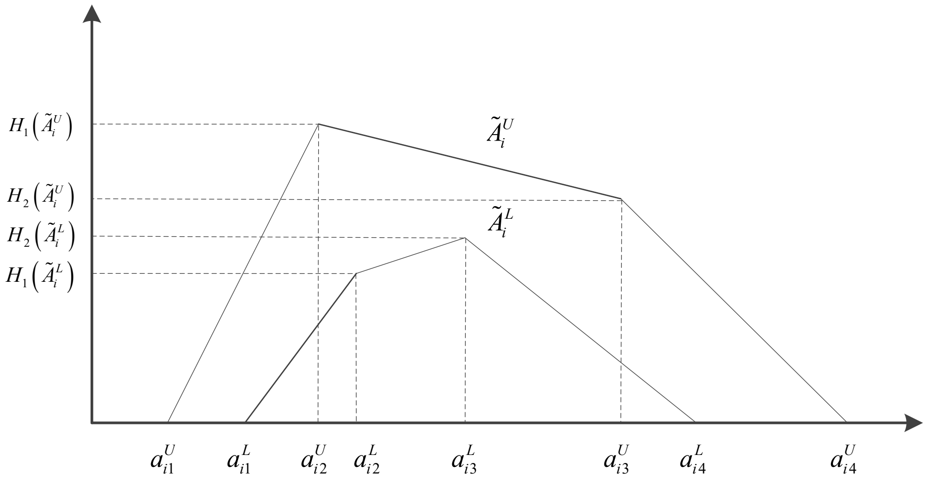


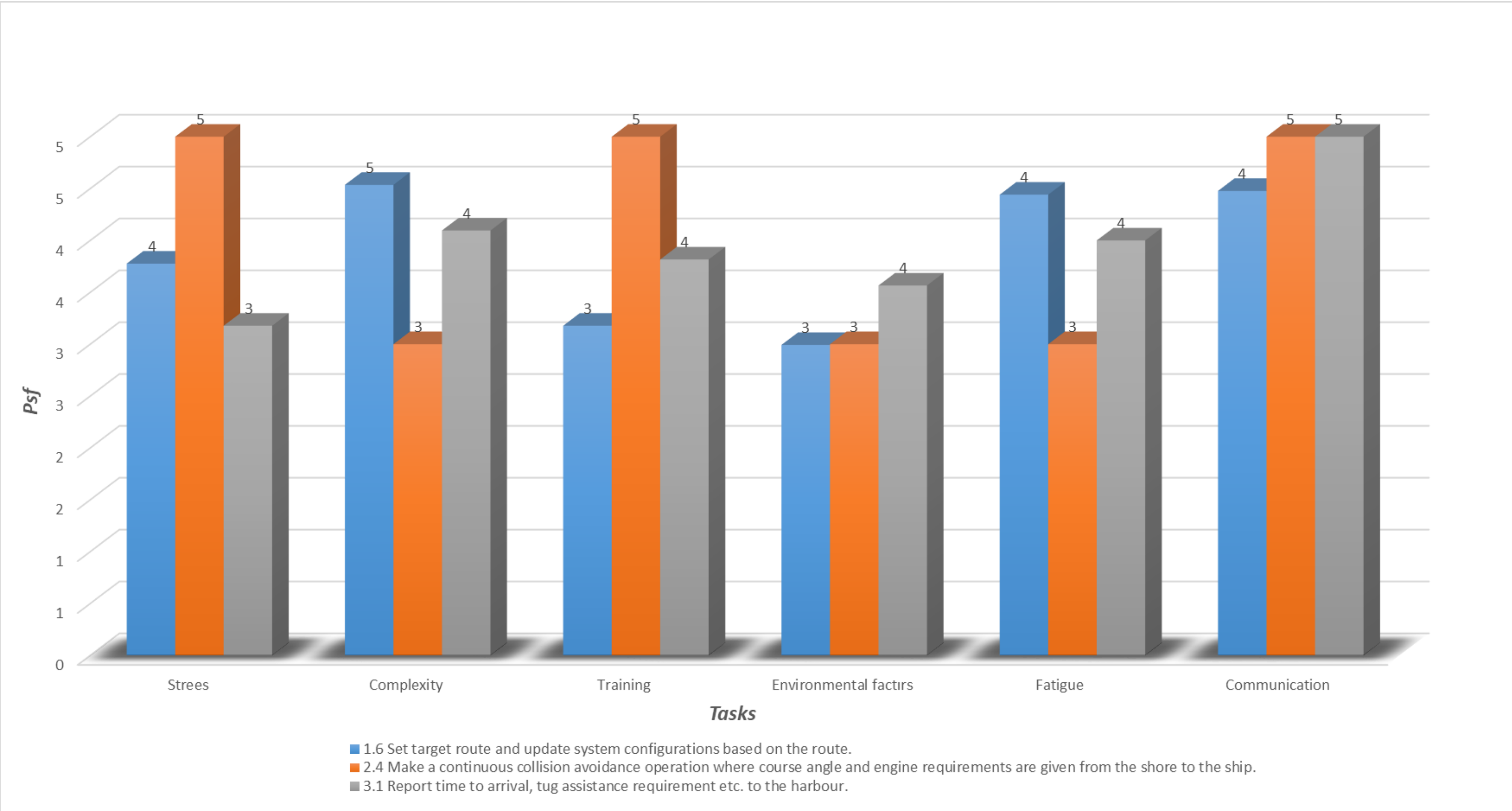
Figure 2. A flow chart of the proposed approach.



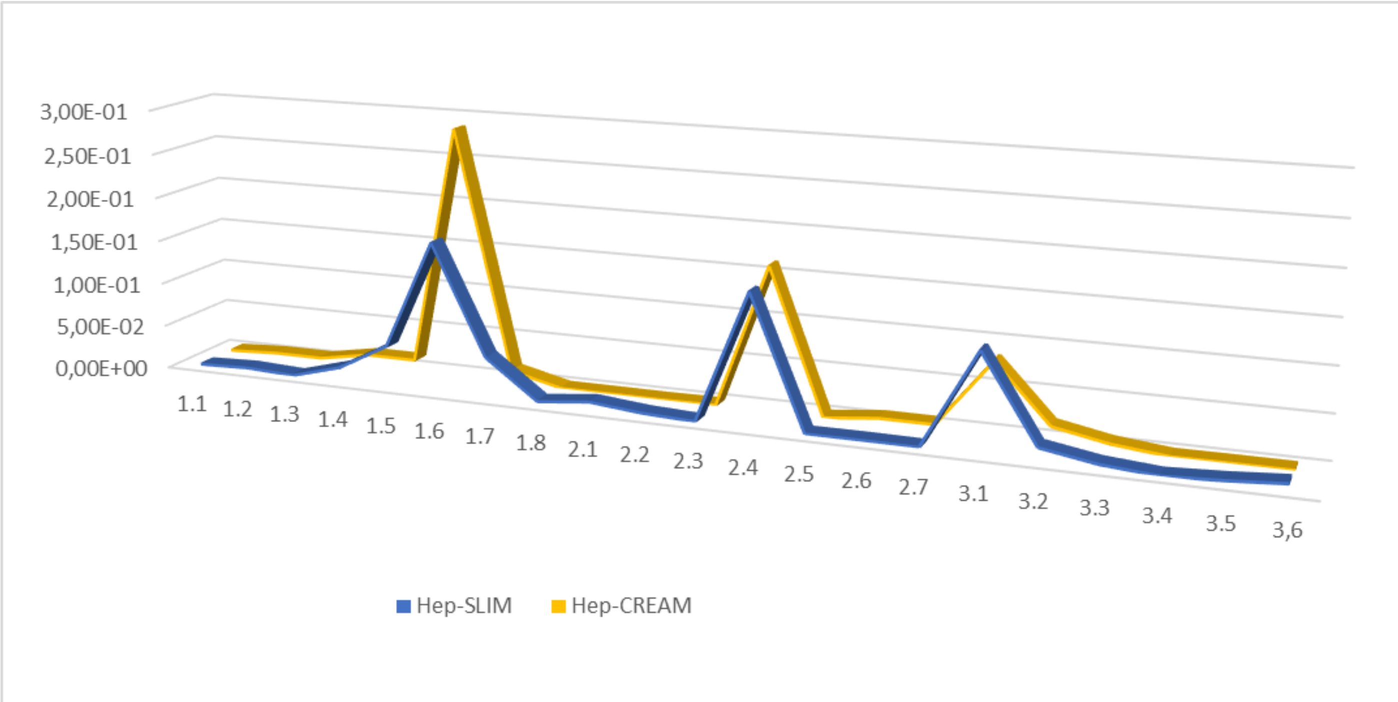
<Figure 3. The trapezoidal membership function >



<Figure 4. PSF deviation chart for subtasks with the highest HEP value >



<Figure 5. HEP values distributions in IT2FS-SLIM and CREAM >



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