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REDUCTION OF NAVIGATION RISKS BY USING FUZZY LOGIC TO AUTOMATE CONTROL PROCESSES UNDER UNCERTAINTY

Abstract. The article highlights the significance of the automation of control processes in maritime transport, in particular from the point of view of maintaining the safety of navigation. The authors take into account the influence of various navigational risks, such as weather conditions, vessel maneuverability, traffic and the actions of operators-masters and emphasize the need for the development of automated systems for data processing and assessment of the skills of captains in real time.

As a result of the analysis of the scientific literature, the authors determine that the human factor becomes a determining obstacle for ensuring the safety of navigation and optimizing the control of ship's handling. As a result, the use of automated control systems based on fuzzy inference systems is proposed to improve navigation safety and reduce the impact of the human factor.

Based on the results of the research, a model was developed that allows to assess the level of qualification of ship captains in conditions of uncertainty. The use of the model contributes to maritime navigation in various directions, including the assessment of captains' actions, the identification of needs for renewed knowledge, risk management and support for scenario planning.

It is assumed that the software implementation in the application of the model should be used as a supplement to the improvement of the professional experience of ship captains, and not their replacement. A model-based decision support system is an additional resource that enhances maritime safety, contributing to the goals of life safety, environmental protection and maritime industry stability.

Highlighting the importance of fuzzy inference systems, attention is drawn to the potential of these systems as an element of artificial intelligence for implementation in automated management systems. This approach, in the future, allows for the creation of a maritime safety forecasting system that will provide forecasts considering a vast number of conditions and factors.

In general, this research in the field of automation of marine transport management is an important step in the development of new methods to improve the safety of navigation and the efficiency of decision-making in the conditions of navigational risks.

Keywords: safety of navigation, automated system, fuzzy logic, human factor, navigation risks, forecasting, artificial intelligence.

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ЗМЕНШЕННЯ НАВІГАЦІЙНИХ РИЗИКІВ ШЛЯХОМ ВИКОРИСТАННЯ НЕЧІТКОЇ ЛОГІКИ ДЛЯ АВТОМАТИЗАЦІЇ ПРОЦЕСІВ КЕРУВАННЯ В УМОВАХ НЕВИЗНАЧЕНОСТІ

Анотація. Стаття висвітлює значущість автоматизації процесів керування в морському транспорті, зокрема з погляду підтримки безпеки судноводіння. Автори враховують вплив різних навігаційних ризиків, таких як погодні умови, маневреність судна, трафік і дії операторів-судноводіїв та наголошують на необхідності розробки автоматизованих систем для обробки даних та оцінки кваліфікації капітанів у режимі реального часу.

В результаті аналізу наукової літератури, автори визначають, що людський чинник стає визначальною перешкодою для забезпечення безпеки судноводіння і оптимізації керування рухом суден. Як результат, запропоновано використання автоматизованих систем управління, які базуються на системах нечіткого виводу для покращення безпеки судноводіння та зменшення впливу людського фактору.

За результатами дослідження було розроблено модель, яка дозволяє оцінювати рівень кваліфікації капітанів суден в умовах невизначеності. Використання моделі сприяє морській навігації в різних напрямках, включаючи оцінку дій капітанів, ідентифікацію потреб у відновлені знань, управління ризиками та підтримку сценарного планування.

Передбачається що програмна реалізація у застосуванні моделі має бути використана як доповнення до вдосконалення професійного досвіду капітанів суден, а не їх заміна. Система підтримки прийняття рішень на основі моделі є додатковим ресурсом, який посилює рівень безпеки судноводіння, сприяючи досягненню цілей збереження життя, охорони довкілля та стабільності морської галузі.

Зазначивши важливість використання систем нечіткого виводу, звертається увага на потенціал цих систем як елементу штучного інтелекту для впровадження в автоматизовані системи управління. Зазначений підхід у перспективі дозволяє створити систему прогнозування безпеки судноплавства, яка надаватиме прогнози, враховуючи велику кількість умов та факторів.

Загалом, дане дослідження в галузі автоматизації управління морським транспортом є важливим кроком у розробці нових методів для підвищення безпеки судноводіння та ефективності прийняття рішень в умовах навігаційних ризиків.

Ключові слова: безпека судноводіння, автоматизована система, нечітка логіка, людський фактор, навігаційний ризик, прогнозування, штучний інтелект.

Problem Statement. Ensuring the safety of navigation, a cornerstone of modern sea transport, fundamentally rests on the interaction of various elements including weather conditions, vessel maneuverability, traffic density, and crucially, the competence of ship captains [1,2]. This intricate mesh of factors, when effectively managed, ensures safety and efficiency in sea transport. However, the sheer complexity of these variables necessitates the development of specialized automated systems for data processing and real-time assessment of shipmasters' qualifications.

Such automated systems promise a significant enhancement to maritime safety by enabling the prediction of the impact of captains' training levels safety of navigation across various scenarios navigation risks. By using fuzzy logic, these automated systems can realistically assess maritime safety, taking into account a multitude of factors ranging from the captain's level of training to current navigation risks [3].

As international trade and transportation volumes continue to surge, the complexities within maritime transport escalate concurrently, increasing the propensity for accidents and incidents related to the human factor. Therefore, research focusing on identifying and analyzing safety-affecting factors, such as positional errors, inadequate emergency response, system failures, and safety rule violations, is of paramount importance [4]. The findings from such investigations can guide shipping companies, ship owners, port authorities, and international organizations to develop and implement refined procedures, standards, and technologies that bolster maritime safety [5].

Moreover, the pressing need for competent personnel training for ship crews, including navigators, captains, and sailors, underscores the relevance of this research direction. Coupled with the necessity for stronger international cooperation and experience exchange in maritime safety and accident prevention, this research direction becomes indispensable for the future safety of navigation.

Analysis of Recent Research and Publications. The role of human factors in safety of navigation is thoroughly discussed in the study by [6], where the authors delve into the myriad of potential navigation risks, including ship positional inaccuracies, navigation system failures, inadequate emergency responses, and communication loss with other vessels and organizations. Concurrently, the research by [7] provides an in-depth examination of technologies and automated systems employed in collision prevention within aviation and maritime transport. Their exploration extends to the limitations and potentials of these technologies in enhancing safety of navigation, with a particular emphasis on the consequences of international safety standard violations.

Furthermore, human factors accidents leading to shipwrecks and ship collisions are carefully investigate by international organizations such as EMSA

(European Maritime Safety Agency) [8,9]. These investigation examine navigational risks and the human factor, ranging from sudden changes in weather and sea conditions to positioning errors and navigation system failures. The authors' analyses provide valuable insights into the nature and root causes of these maritime mishaps, offering critical inputs for the development of more effective safety measures and automated systems.

Purpose of the Article is to explore and elucidate the potential of automated management systems, particularly those based on fuzzy inference systems, for enhancing maritime navigation safety, reducing human error, and facilitating efficient decision-making under complex and uncertain conditions.

Problem Definition. Drawing from the literature reviewed, it is evident that navigators' errors stand as a significant challenge in ensuring maritime safety and efficiency. These errors can be broadly categorized into the following key areas:

1. Inadequate rapid response in emergency situations: Navigators' lack of preparedness for decision-making and actions under extreme conditions can potentially escalate to severe accidents, injuries, and even loss of lives.

2. Communication loss with other vessels and organizations: Inattention to calls and requests can disrupt coordination with other vessels, port authorities, and organizations, thereby compromising the safety of the ship and the overall efficiency of navigation.

3. Violation of international safety rules and standards: Non-compliance with critical safety standards, such as the COLREGS-72, can lead to disastrous consequences, including ship collisions, accidents, and hefty fines. Moreover, such violations can severely tarnish the reputation of the ship and its owner.

4. Lack of proper record-keeping: If a navigator fails to document navigational events and significant decisions, it can result in insufficient control and communication issues among crew members. This, in turn, can negatively impact safety of navigation and efficiency.

Collectively, these errors underscore the critical need for robust measures to minimize navigational risks, thereby enhancing safety of navigation and efficiency.

Approaches to Problem Solving. Given the challenges outlined in the problem definition, addressing the underlying issues associated with maritime safety and human factors calls for innovative and technologically advanced solutions. Automated and intelligent management systems, as discussed in various studies [10], can provide significant assistance in this endeavor. Several potential applications of these systems include:

- Navigation System Enhancement: The integration of artificial intelligence and machine learning into navigation automated systems can increase positional accuracy and reduce error likelihood, addressing one of the primary navigational challenges previously identified.

- Weather and Sea Condition Forecasting: Automated systems capable of delivering timely and accurate weather and sea condition forecasts can support captains in making informed decisions regarding route planning and vessel management.
- Navigation Systems Monitoring and Control: The implementation of intelligent systems for the continuous monitoring of navigational instruments can facilitate early detection of failures and prompt maintenance, thereby improving reliability and safety.
- Emergency Situation Resolution Automation: Intelligent systems designed for rapid analysis of emergency situation data can provide action recommendations and automatically execute maneuvers to mitigate navigation risks, addressing the need for prompt response in crisis scenarios.
- Personnel Training and Education: The introduction of intelligent systems and simulators can enhance the quality of training for sailors, navigators, and captains, bolstering their skills and knowledge in maritime safety.

Incorporating these approaches in addressing the identified problems can significantly improve maritime safety, mitigate human errors, and enhance the efficiency of sea transport operations.

Presentation of the Main Material. Fuzzy inference systems are an important tool in the field of artificial intelligence and are applied in numerous applications [11-13]. Here are five of the most well-known fuzzy inference systems:

Mamdani Model:

The Mamdani model uses fuzzy implication to determine the output fuzzy set. Let R_i $(i=1,...,n)$ denote the fuzzy rule, then the output fuzzy set B_i can be defined as: $B_i = A_i \otimes C_i$

where A_i is the input fuzzy set, C_i is the output fuzzy set, and $\otimes$ is the fuzzy implication operator.

Takagi-Sugeno-Kang (TSK) Model:

The TSK model uses a linear combination of input variables instead of output fuzzy sets. For each rule *i*, the output signal y_i is expressed as:

$$y_i = k_i + p_i x_1 + q_i x_2 + ... + r_i x_n,$$

where k_i, p_i, q_i, r_i are the parameters of the linear function, and x_1, x_2, x_n are the input variables.

Larsen Model:

The Larsen model uses a scaling method for aggregating fuzzy rules. The output fuzzy set B_i is defined as: $B_i = \mu_{A_{i(x)C_i}}$,

where $\mu_{A_{i(x)C_i}}$ is the degree of membership of the input value *x* to the fuzzy set A_i, and C_i is the output fuzzy set.

Tsukamoto Model:

The Tsukamoto model is a special case of the TSK model and uses exponential membership functions. The output signal y_i is determined as: $y_i = \exp^{\alpha_i x}$,

where α_i is the parameter of the exponential membership function, and x is the input variable.

Gupta-Nawat-Gaptonavatkun (GAP) Model:

The GAP model combines the logic of Mamdani and Takagi-Sugeno. The output fuzzy set B_i is defined as: $B_i = A_i \otimes (C_i + k_i)$,

where A_i is the input fuzzy set, C_i is the output fuzzy set, $\otimes$ is the fuzzy implication operator, and k_i is the parameter of the linear function associated with the output fuzzy set.

In all fuzzy inference models, the main parameters include the following elements:

Fuzzy Sets: Definition of membership functions for input and output variables, which are used to represent fuzzy information in the system.

Fuzzy sets are characterized by membership functions, which define the degree of membership of each element from a certain universal set to a given fuzzy set.

Let X be the universal set, then a fuzzy set A on X is defined by the membership function $\mu_A : X \rightarrow [0,1]$, which indicates the degree of membership of each element $x \in X$ to the set A.

The mathematical description of a fuzzy set A can be represented as a set of pairs:

$$A = \left\{ \left(x, \mu_{A(x)} \mid x \in X \right) \right\},$$

where x is an element of the universal set X, and $\mu_{A(x)}$ is the degree of membership of element x to the fuzzy set A.

The membership function can be chosen according to a specific application and can have different forms, considering that the research is in the initial stage, let's adopt a triangular shape.

A computer program in the Python programming language has been developed for modeling fuzzy sets:

```
1. Import Libraries
   ├── numpy as np
   └── matplotlib.pyplot as plt

2. Define Functions
   ├── membership_low(x, low, mid)
   ├── membership_medium(x, low, mid, high)
   └── membership_high(x, mid, high)
```

```
3. Define Parameters
        ├── "Knowledge of rules and regulations"
        ├── "Communication skills"
        ├── "Knowledge of data communication systems"
        ├── "Seafaring experience"
        ├── "Ability to make decisions"
        ├── "Computer skills"
        └── "Organizational and leadership skills"

4. Generate X Values
        └── x_values = np.linspace(0, 100, 1000)

5. Define Low, Mid, High Values
        └── low_mid_high = [(18, 36, 67) for _ in range(7)]

6. Iterate over Parameters
        ├── for i, parameter in enumerate(parameters):
                ├── Get low, mid, high values for the current parameter
                ├── Calculate memberships for low, medium, and high
                │       ├── low_membership = [membership_low(x, low, mid) for x in x_values]
                │       ├── medium_membership = [membership_medium(x, low, mid, high) for x
in x_values]
                │       └── high_membership = [membership_high(x, mid, high) for x in x_values]
                ├── Plot memberships
                │       ├── Create a new figure
                │       ├── Plot low_membership
                │       ├── Plot medium_membership
                │       ├── Plot high_membership
                │       ├── Set xlabel as parameter
                │       ├── Set ylabel as 'Membership degree'
                │       ├── Add legend
                │       └── Set title as f'Membership functions for a parameter "{parameter}"'

7. Show Plots
        └── plt.show()
```

As a result of the program's operation, graphs of fuzzy membership functions were obtained for each of the parameters. Additionally, a multivariate membership function was constructed (Fig. 1).

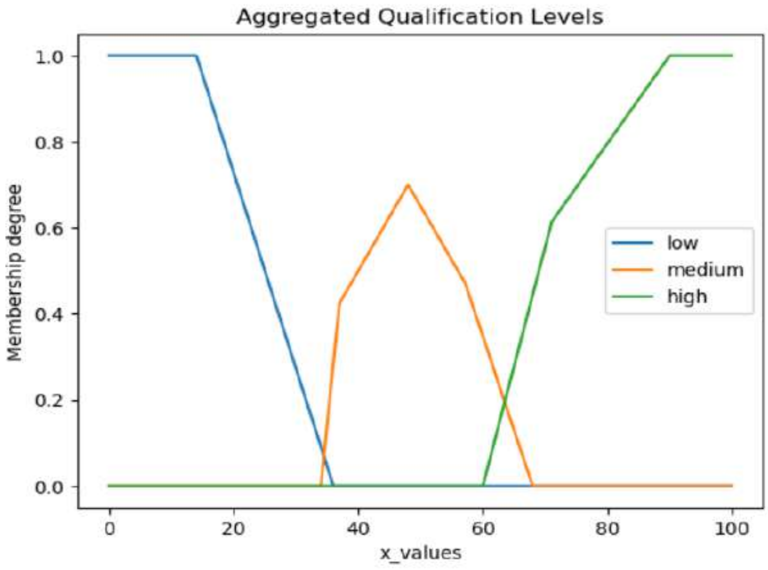

Fig. 1. *Membership function of the qualification of the i-th shipmaster*

Having detailed the key fuzzy inference systems and their parameters, the study now shifts towards an application-focused approach. The aforementioned fuzzy systems, including Mamdani, Takagi-Sugeno-Kang (TSK), Larsen, Tsukamoto, and Gupta-Nawat-Gaptonavatkun (GAP) models, provide a robust theoretical foundation for implementing fuzzy logic in practical scenarios. Specifically, these systems, with their unique capabilities of handling imprecise and fuzzy information, are positioned to address the complexities associated with maritime safety forecasting.

The second phase of this research pivots towards leveraging the power of these fuzzy inference systems and expert knowledge to construct a rule-based forecasting system for maritime safety. Such a system would be flexible, capable of adapting to dynamic maritime conditions and providing real-time information to support decision-making processes on board. The subsequent section will delve into the operational steps of this proposed system, encompassing the determination of input variables, fuzzification of data, rule activation, rule aggregation, and defuzzification, thereby providing a comprehensive blueprint for maritime safety forecasting.

The rule base can be compiled based on expert knowledge and experience, taking into account various scenarios related to maritime navigation. This will enable the creation of a flexible system capable of adapting to changing conditions and providing up-to-date information to support the ship captain's decision-making process [14].

Maritime safety forecasting using such a system may include the following steps:

- Determining input variables such as visibility, traffic density, vessel maneuverability, background lighting, weather conditions, precipitation, depth, radar effectiveness, and the captain's level of training.

- Fuzzification of input data, transforming them into degrees of membership in corresponding fuzzy sets.

- Evaluating the degree of activation of each rule based on input variables and the rule base.

- Aggregation of rules to obtain output fuzzy sets representing the safety level in each scenario.

- Defuzzification, transforming fuzzy output values into crisp numerical values representing the safety level in each scenario.

For modeling, let's consider the International Regulations for Preventing Collisions at Sea (COLREGs) Rule 6: Safe Speed. It states that every vessel must always proceed at a safe speed so that it can take proper and effective action to avoid collision and be stopped within a distance appropriate to the prevailing circumstances and conditions.

To create a fuzzy system for assessing maritime safety based on Rule 6, let's define input and output variables.

Input variables:

Visibility condition (V): poor (V_p), average (V_m), good (V_g)

Traffic density (D): low (D_l), medium (D_m), high (D_h)

Vessel maneuverability (M): poor (M_p), average (M_m), good (M_g)

Lighting background (L): weak (L_w), medium (L_m), strong (L_s)

Weather conditions (W): calm (W_c), variable (W_v), stormy (W_s)

Draught and depth (S): small (S_s), medium (S_m), large (S_l)

Radar efficiency (R): low (R_l), medium (R_m), high (R_h)

Output variable:

Navigational safety (Saf): unsafe (Saf_u), moderately safe (Saf_m), safe (Saf_s)

Now, let's formulate fuzzy rules:

IF V is V_p AND D is D_h THEN Saf is Saf_u

IF V is V_g AND D is D_l AND M is M_g THEN Saf is Saf_s

IF M is M_p AND W is W_s THEN Saf is Saf_u

IF L is L_s AND R is R_l THEN Saf is Saf_m

IF S is S_s AND W is W_c AND R is R_h THEN Saf is Saf_s.

These rules suggest that navigational safety depends on a combination of various factors, such as visibility, traffic density, vessel maneuverability, lighting background, weather conditions, draught and depth, as well as radar efficiency. The fuzzy system will use these rules to analyze the situation and provide a navigational safety assessment.

Within the modeling framework, we consider three scenarios with different navigational conditions:

Scenario 1: Navigational route through dense fogs in the San Francisco area

In this scenario, vessels navigate through an area with poor visibility due to dense fogs in the San Francisco area. In this situation, the following input variables may have a greater impact on navigational safety:

Visibility condition (V): poor (V_p)

Lighting background (L): weak (L_w) or medium (L_m), depending on the time of day

Scenario 2: Navigational route through a high traffic density zone in the Suez Canal area

Here, vessels navigate through a high traffic density zone in the Suez Canal area. In this situation, the following input variables may have a greater impact on navigational safety:

Traffic density (D): high (D_h)

Vessel maneuverability (M): poor (M_p), medium (M_m), or good (M_g), depending on the type of vessel

Scenario 3: Navigational route through a stormy zone in the North Atlantic

In this scenario, vessels encounter strong winds and high waves in a stormy zone of the North Atlantic. In this situation, the following input variables may have a greater impact on navigational safety:

Weather condition (W): stormy (W_s)

Draught and depth (S): small (S_s), medium (S_m), or large (S_l), depending on the route depth and vessel draught.

The structure of the computer program in the Python language will be as follows:

Importing necessary libraries:

- numpy for working with numbers and arrays
- matplotlib.pyplot for creating plots
- tkinter for creating a graphical interface

Defining functions:

- gaussian_mf() - Gaussian function for determining the degree of membership
- safety_scenario() - function for calculating the degree of safety membership depending on the scenario and captain's skills
- plot_graph() - function for plotting safety degree graphs for each scenario and type of captain

Defining variables:

- safety - array of safety levels
- saf_u, saf_m, saf_s - arrays of membership degrees for each scenario
- captain_L, captain_M, captain_H - dictionaries with the skills of captains of different qualification levels

Creating a graphical interface:

- initializing the main window root
- creating a plot_button for calling the plotting function
- launching the main tkinter event handling loop

This program creates a simple graphical interface with a "Plot Graph" button. When this button is pressed, the program plots safety membership degree graphs for different scenarios and captains with varying skills.

The program constructs safety graphs for three different captains with varying levels of training in three different maritime navigation scenarios. It uses a Gaussian membership function to determine the degree of safety for each captain in each scenario. The captains' training levels are set manually by inputting parameters for visibility (V), traffic density (D), vessel maneuverability (M), background lighting (L), weather conditions (W), draught and depth (S), and radar effectiveness (R).

Let us consider the modeling of the fuzzy membership function of navigational safety relative to each scenario in terms of complexity (Fig. 2-4).

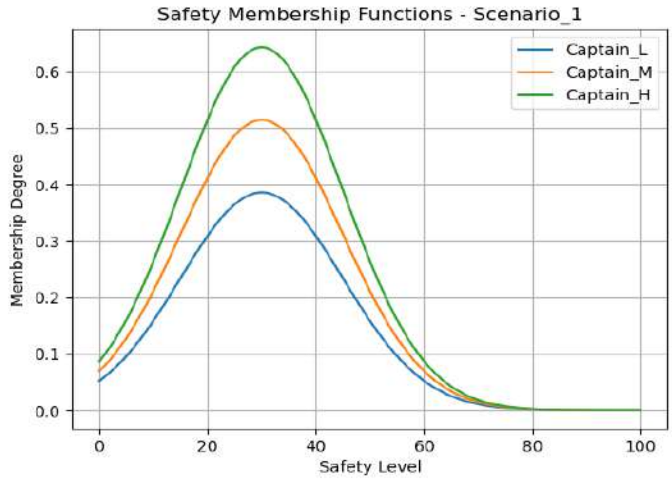

Fig. 2. *Modeling for Scenario No. 1 "Fog in San Francisco"*

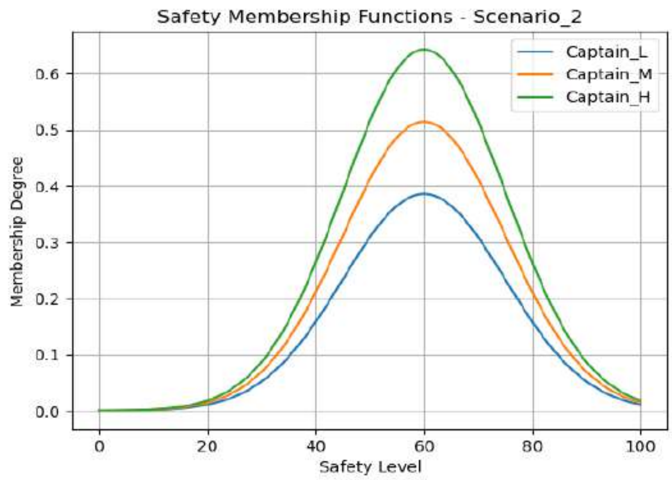

Fig. 3. *Modeling for Scenario No. 2 "Dense Traffic in the Suez Canal"*

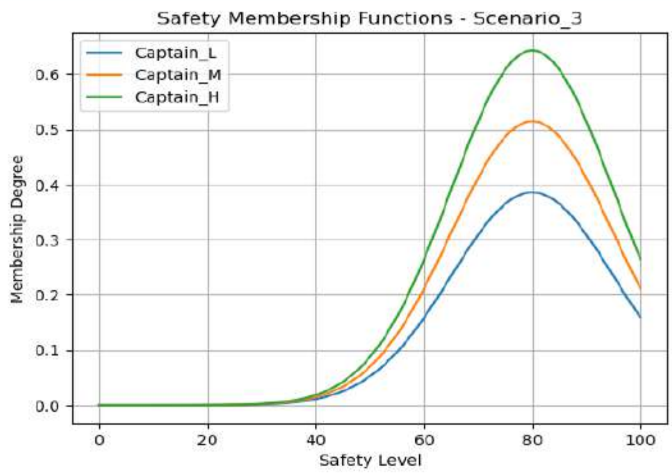

Fig. 3. *Modeling for Scenario No. 3 "Stormy Zone in the North Atlantic"*

As can be seen, when the program is launched, it constructs safety charts for each of the three captains in each scenario. This allows for a clear visualization of how different levels of captains' preparation affect their ability to ensure safety in various maritime conditions [15].

Conclusions. The results of this research underscore the significance of integrating fuzzy inference systems and automated management systems in enhancing safety of navigation and mitigating human factors. By identifying the adequacy level of shipmasters' qualifications under conditions of uncertainty, the developed model serves as a vital tool in the ever-complex field of maritime navigation.

Navigational risks, including lack of rapid response, violation of international safety norms, and improper record-keeping, pose substantial threats to maritime safety. These challenges can be effectively addressed using automated and intelligent management systems, which offer applications such as automated emergency response and advanced personnel training using intelligent systems and simulators.

The study further highlights the potential of fuzzy inference systems, a key tool in artificial intelligence, to implement these automated management systems. By utilizing these systems, a fuzzy logic-based maritime safety prediction system can be established, capable of providing detailed safety forecasts considering an array of conditions and factors. This assists maritime professionals, especially ship captains, in making informed decisions, thereby promoting the safety and efficiency of maritime transportation.

The implemented program can significantly contribute to maritime navigation in several ways. It can facilitate the assessment of captains based on varied parameters, aid in identifying training needs, assist in managing maritime safety-related risks, and support scenario planning for comprehensive 'what-if' analyses. However, it's essential to consider this program as a tool for analysis and evaluation, complementing, not replacing, the professional experience and knowledge of captains. It serves as an additional resource bolstering decision-making in safety of navigation, furthering the goals of life preservation, environmental safety, and economic stability in the maritime industry.

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