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Meteorological Risk Assessment Based on Fuzzy Logic Systems for Maritime

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Abstract

In recent years, numerous casualties have been associated with a lack of safe navigation of ships. Despite advanced navigation systems and the implementation of safety management systems onboard ships, maritime safety is still one of the major concerns for the shipping industry. This research proposes a proactive modeling approach that utilizes Fuzzy Logic and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The model primarily provides continuous meteorological risk assessment for ships to improve marine navigational safety. In the study, Wind Speed, Sea Conditions, Visibility, and Day/Night Ratio are converted to meteorological risk factors using meteorological risk assessment system. Supported by ANFIS, the meteorological risk assessment system has demonstrated that the database contains details of over 180 marine casualty information involving navigation and traffic accidents. The results emphasize that environmental factors, as well as the Day/Night Ratio, significantly influence ship navigational safety. Hence, a meteorological risk assessment system can enhance navigational safety and prevent loss of life in the shipping industry. As a result, a meteorological risk assessment framework has enormous potential for preventing accidents and improving the safety and sustainability of the shipping industry. In this regard, the proposed model is a one-of-a-kind framework that will be extremely useful for mitigating and preventing the effects of maritime accidents.

Keywords: Decision support system, Fuzzy logic, Maritime accident dataset, Meteorological risk assessment, Ship navigation safety

1. Introduction

Marine science is progressing fast with the advancement of technology and engineering sciences [1]. Scientists study in various fields on advanced engineering models to tackle many issues in the marine industry [2]. Therefore, many jobs and transactions on ships are unmanned, even being planned for the future [3] and unmanned safety navigation is the most significant improvement [4]. One of the essential stages of making safety navigation unmanned is conducting the necessary risk assessments [5]. Afterward, it is possible to make safety navigation unmanned by taking the necessary action according to risk assessments [6]. From the first Day of maritime transportation, various risk assessments, such as maritime risk assessment (MARISA), have been carried out to prevent accidents and keep to a minimum risk for safety navigation [7]. However, MARISA has formed the basis for many other studies on adaptation to new technologies in shipping. This study presents a specific subject in the MARISA system in more detail, and meteorological risk assessment (MERISA) is created based on fuzzy logic and ANFIS.

There are two risk factors in the MARISA system: dynamic and static. MARISA is carried out bearing those risk factors in mind [8]. In this study, the dynamic risk factor, one of the risk factors in MARISA, has been handled with a different structure. The focus is on the meteorological risk factor. MERISA, which is the subject of this study, assesses this risk factor and is created based on detailed fuzzy logic. In this study, the dataset, which has information pertaining to 181 accidents from 1988 to 2019, is created according to

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accident reports prepared by the authorities of the United Kingdom and Turkey. MERISA has been tested on this accident dataset, and the meteorological risk factor has been created for each accident.

Experienced master mariners have previously assessed the meteorological risk for each accident. MERISA was then compared with the master mariners' assessment, and the program created by fuzzy logic was assessed.

The International Maritime Organization (IMO) has three conventions on the safety of navigation. These conventions refer to the International Convention for the Safety of Life at Sea, 1974 (SOLAS), the Convention on the International Regulations for Preventing Collisions at Sea, 1972 (COLREG), and the International Convention on Standards of Training, Certification, and Watchkeeping for Seafarers, 1978 (STCW). The IMO has also issued a series of resolutions and codes, including guidelines on navigation issues and performance standards for shipborne navigational and radiocommunications equipment. These convention codes and regulations offer seafarers standards on what to do in specific meteorological conditions. If conditions such as Wind, Sea Condition, Visibility, and Day/Night situation are considered together, it would be seen that they have a rather complex structure, and other factors such as fatigue and inexperience combine with those effects and could lead to marine accidents. A meteorological risk assessment system with a certain standard would be beneficial as a decision support tool for seafarers [9].

There are numerous studies on safe navigation in the literature, but only a few were considered for this study. A systematic literature review of the studies on navigational collision risk assessment provides studies conducted close to the subject of this article [10]. However, no articles were found that specifically discussed MERISA. Thus, this is the first study to address this issue in detail. A marine accident dataset has also been created with the present study. Besides, the present study has been focused only on the sea state following meteorological variables [11]. Therefore, this study is unique in the dataset by considering Wind, Sea State, Visibility, and Day/Night Rate. There are reports on the ship-bridge collision alert system [12]. Also, some maritime studies were made using fuzzy logic on navigational safety [13-16], which mentioned meteorological conditions. For instance, a study on bad weather as one of the vulnerabilities factors was involved in the fuzzy reasoning engines to evaluate the maritime conditions and environment; it has examined bad water in the vulnerabilities module [13]. However, the meteorological risk is an important issue and should be discussed in detail for safe navigation. Vessel traffic service also considers meteorological conditions for collision avoidance, using fuzzy logic [14]. Meteorological conditions are one of the factors considered while designing a two-dimensional (2D) asymmetrical polygonal ship domain [15]. The meteorological risk factor is created and handled in 29 marine accidents in the literature [16]; however, the handling is not as detailed and specific as the present study. This study is the most comprehensive study in the literature dealing with meteorological risk assessment on marine accidents and studying them in detail.

While some of the many studies on preventing marine accidents are more general, other studies such as this are more specific. The article entitled "Identifying Factors Influencing Total-loss Marine Accidents in the World: analysis and Evaluation based on Ship Types and Sea Regions" selects the dataset on the total-loss marine accidents that occurred in the world from 1998 to 2018, involving 16 ship types and 13 main navigation sea regions and is based on an improved the entropy weight-TOPSIS model. The results show that the most influential factors in both models, for ship type and sea region, are foundering, stranding, and fires/explosions [17]. However, it has no information about meteorological factors. The article "Maritime Navigation Accidents and Risk Indicators: an Exploratory Statistical Analysis using AIS Data and Accident Reports" presents the results of statistical analyses of maritime accidents datasets and AIS data from Norwegian waters to identify conditions that are associated with navigation-related accidents (groundings and collisions) and could be used as risk indicators [18].

Weather conditions are usually handled as one variable, but other variables such as Wind Speed, Sea Conditions, Visibility, and Day/Night Ratio are also considered in the present study. Heavy weather is a factor in most marine accidents, as indicated by marine accident analysis [19]. Furthermore, a unique meteorological risk assessment was made in this study to prevent marine accidents. Therefore, the dataset formed by maritime accidents serves as the starting point of this study. The assessment in this study was carried out using a real accident dataset.

Fuzzy logic has been used in maritime science of MARISA systems and many other studies. Examples include the assessment and mapping of maritime transportation risk in the South China Sea [20]; dynamic decision-making systems for intelligent navigation strategies within inland traffic separation schemes to the base [21]; comprehensive risk estimations of maritime accidents focusing on fishing vessel accidents in Korean waters [22]. Fuzzy logic is also used to create fuzzy cognitive maps, AHP, and other fuzzy-based hybrid models. These methods are designed to address specific issues in the literature. Meteorological risk factors are generally assessed as only one factor in the literature; therefore, fuzzy logic should be used when evaluating meteorology for ship safety navigation, as in MERISA. For this reason, the MERISA system created in this study is designed based on fuzzy logic.

MERISA provides navigational safety by establishing a decision support system in this paper. A continuous meteorological risk assessment based on fuzzy logic that handles MERISA in detail will improve safety standards by ensuring full clarity of the impact of weather conditions on shipping. If the MERISA system is integrated with systems designed to ensure safe navigation, it would be possible to switch to automatic ships in a shorter amount of time.

In this article, a dataset that could be used in other maritime studies has also been created. The dataset contains 181 accident data with 15 variables. Furthermore, with the assessment of MERISA to be made in this study, a program based on fuzzy logic is compared with expert opinions and is found to provide superior results. As a result, in cases where expert opinion is essential to the operation of the ship, this program may be used in its place.

Figure 1 presents the framework of this study. Before explaining modeling, the dataset has been explained.

2. Dataset

This paper used datasets with data pre-processing stages accepted in the literature with marine accident data [23]. Data collection, data reduction, data cleaning, data transformation, and data integration were involved.

Figure 2 presents a summary of what has been done in the chapter within the scope of this study.

2.1. Data Pre-processing Stages

In the first stage, marine accident reports and annexes were collected from the Marine Accident Research Center [Marine Accident Investigation Branch (MAIB)] and the Turkish Ministry of Transport and Infrastructure, Transport Safety Investigation Center (TSIC). From the MAIB and TSIC websites, 357 files containing marine accident reports and annexes were collected. The authors have checked to ensure no duplicate reports of the same accidents.

In the second stage for data reduction, It was decided to create 15 variables in the dataset by examining all accident reports and annexes. These variables are vessel details, accident classification, accident type, vessel type, flag, latitude, longitude, location of incident, date/hours, injuries/fatalities, damage/environmental impact, wind, sea state, visibility, and weather conditions. This dataset of the 181 accidents was directly taken as written in the accident reports and annexes, and the relevant accident data now makes up a dataset of 181 accidents with 15 variables. This dataset will be helpful in many fields of marine science.

This study aims to assess meteorological risk, where 15 variables should have been reduced for clear and effective work. According to the literature [6-8,16], Wind Speed, Sea Condition, Visibility, and Day/Night ratio variables are widely used for meteorological risk assessment. Thus, the dataset is divided into four variables and contains 181 accidents. Due to the absence of marine accident reports and annexes, 40 accidents data were not included as meteorological variables in this dataset. Hence, 40 errors were removed from the dataset at the third stage as a data cleaning. The dataset was then organized by including four variables and 141 accidents.

MERISA is a meteorological risk assessment, so it is a specific assessment and has been tested on only marine accidents in

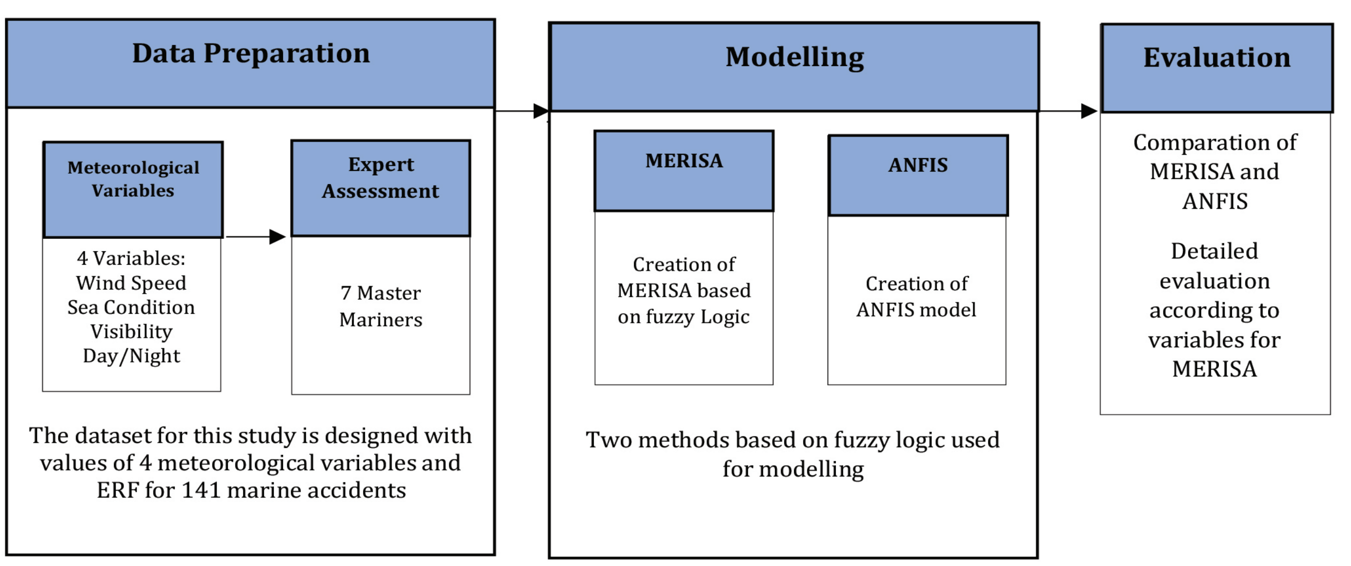

Figure 1. The framework of this study

this study. Weather conditions may not be directly related to accidents, but it is safe to say that meteorology always has an indirect effect. In order to clear up any doubts, before removing 11 variables in the data cleaning stage, the distribution of the dataset according to maritime accident types is examined, and the resulting graph is shown in Figure 3.

For a simple and effective study, making a constant conversion for each variable unit is necessary. Wind speed and sea condition variables had to be converted to constant according to the Meteorological Beaufort Scale, the Visibility variable had to be converted to standard values in the optical range Table, and the Day/Night variables had to be converted to standard values in the range of numbers

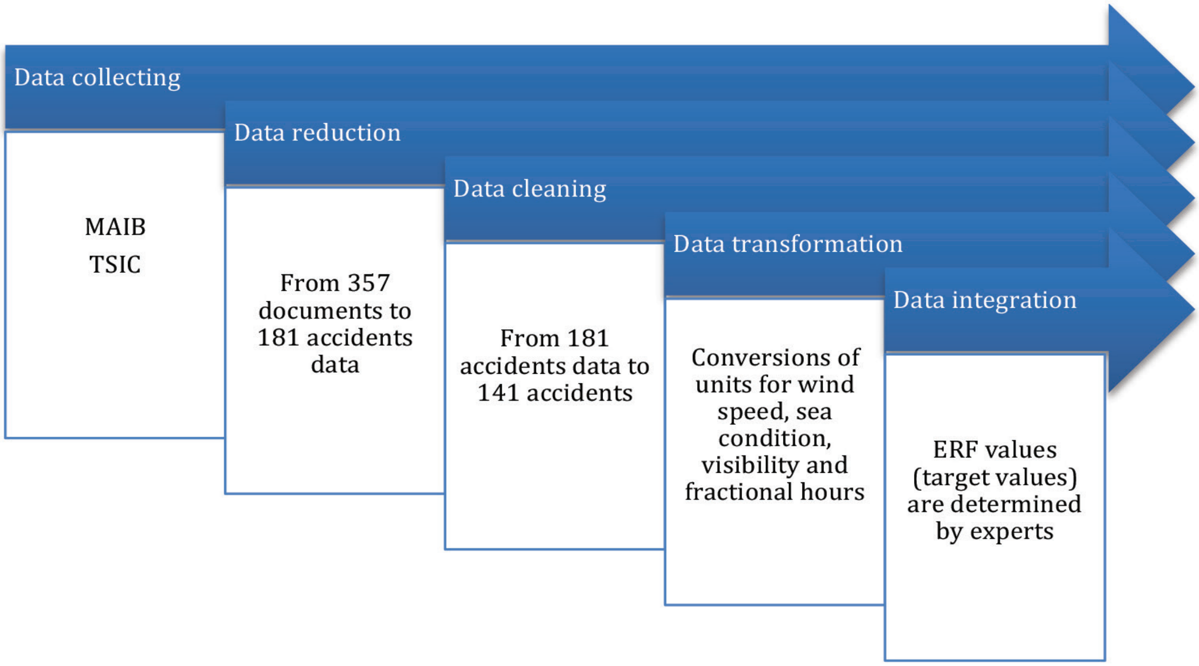

Figure 2. *Data pre-processing stages*

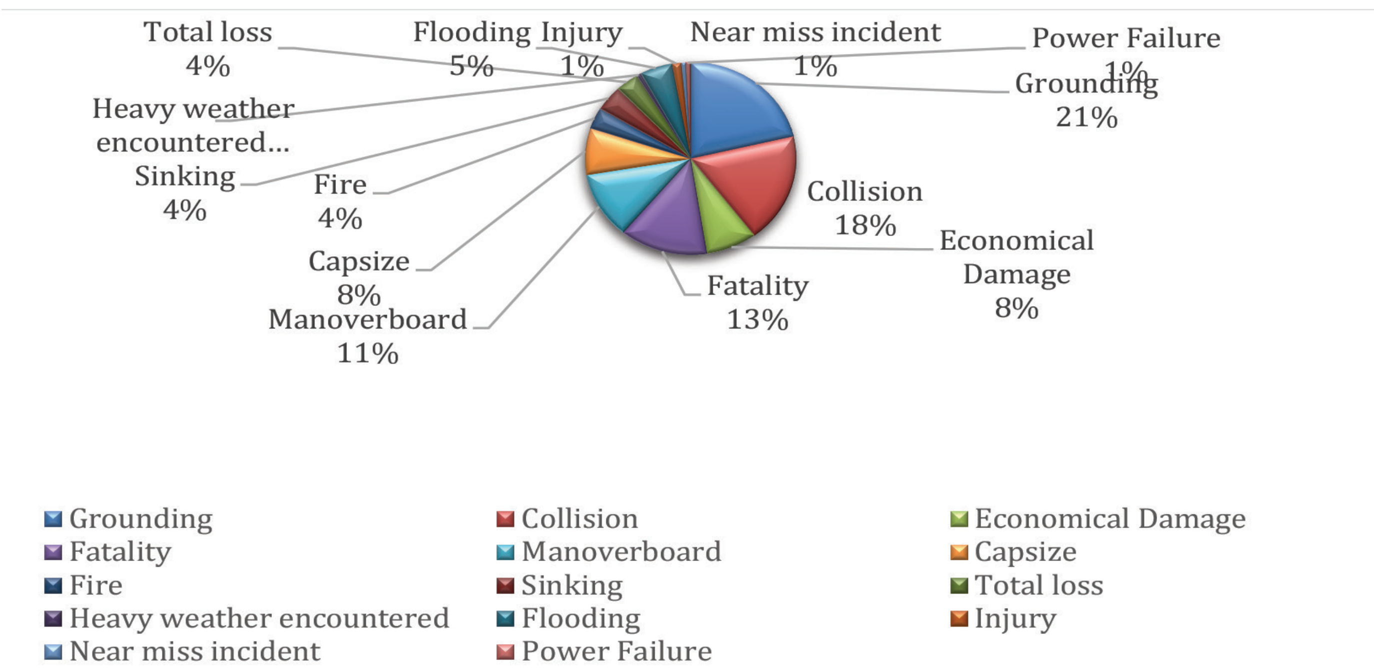

Figure 3. *Distribution of the dataset according to maritime accident types*

from 1 to 24. Therefore, units for all variables for accidents are transformed to a constant value in data transformation.

The dataset was arranged after the first four pre-processing stages, including values according to their constant conservation of four meteorological variables for 141 accidents.

2.2. Expert Assessment

In this study, the meteorological risk estimation is aimed at the ship. In maritime practice, no system determines this risk. Also, target values were needed to compare the accuracy of the proposed models. In other studies, no system calculated only meteorological risk values. For this reason, the dataset was needed for expert assessment to evaluate the proposed models in this study.

Based on the dataset mentioned in Chapter 2.1, the MERISA form is presented. MERISA form that explains the research content asked them to indicate their experience and contained only the meteorological variables for each accident. There are two parts to MERISA form. In the first part, there are two questions about the expert's professional experience. In the second part of the form, a Table has five columns and 142 lines. The first line has variable names, and other lines express 141 marine accidents information. Four of the columns include the variables entered in MERISA, and the last column remains blank. Experts anticipated determining meteorological risk as a percentage for 141 accidents to the blank columns. Thus, the MERISA form has been sent to the experts, and they have been expected to assess the dataset and determine the Expert Risk Factor (ERF) for each accident.

MERISA form was sent to seven experienced master mariners whose watchkeeping experience onboard ranges from 1 to 18 years. These experts have been asked to assess the meteorological data for each accident data separately. They were asked to assess the meteorological risk rather than the general risk on the bridge and determine a value range between 0-100 applicable in all conditions.

$$\mathrm{ERF} = \bar{x} = = \frac{1}{n}\sum_{k=1}^{k=n} x_k \tag{1}$$

$\bar{x}$ is the risk factor determined by the experts for each accident, and n is the number of experts. The average of the values given by the experts for each accident was calculated as shown in equation (1). ERF is thereby calculated for each accident.

Expert portraits who will best evaluate meteorological variables for ships were determined. While choosing experts, we paid attention to the experts' experience and their current activeness to have representatives from different positions. It was asked seven experts to assess meteorological risk carefully by explaining the content and scope within the research. Professional experience periods of experts are 18 (Master), 13 (Master), 10 (Master), 7 (Chief Officer), 5 (Chief Officer), 3 (Second Officer), 1 (Third Officer) years from highest to lowest. Experts have not been informed about other variables of the dataset outside the research scope because they were asked to make a general assessment.

Therefore, ERF values and target values for each accident have been determined for the modeling of this study. In this way, a pure and general assessment is conducted, and the necessary data are accessed for the final arrangement in the dataset. It was needed to add ERF values to the dataset. Data integration is the final stage of data pre-processing for this study. In this stage, ERF values are added being as variables. Finally, the dataset has been arranged by including values of four variables and ERF. Table 1 presents the sample dataset used in this study.

Table 1. *Sample of the dataset used in this study*

Number	Wind Speed	Sea Conditions	Visibility	Day/Night	ERF
1	2	2	7	00:00	22.14
2	4	3	1	07:00	73.57
3	3	2	2	08:00	62.86
4	2	1	7	03:00	22.57
5	4	4	7	23:00	40
6	9	5	7	18:00	57.86
7	2	1	7	12:00	15.71
8	2	1	7	05:00	22.86
9	9	7	7	05:00	67.86
10	2	2	7	18:00	21.43
⋮	⋮	⋮	⋮	⋮	⋮
141	9	6	0	16:00	93.57

3. Methodology

The dataset was designed following the data pre-processing stages in the previous chapter. The dataset has been arranged following this study about meteorological risk assessment. In this chapter, MERISA system is designed based on fuzzy logic with a fuzzy inference system (FIS) considering expert opinions. In this study, ANFIS is used to estimate meteorological risk factors. Therefore, in this chapter, fuzzy logic that is the basis of FIS and ANFIS methods is explained. After this explanation, information about evaluation methods in this study is presented. In the next chapter, the Implementation of MERISA is performed, and modeling is explained.

3.1. Fuzzy Logic and Systems

According to the fuzzy set theory, a proposition is either a member (1) or not (0) [24,25]. While this theory is used in many areas, it is impossible to accept it in areas such as risk assessment. Fuzzy logic and fuzzy clusters can be used in risk assessments because no event can be completely risky or completely risk-free [25,26]. A Meteorological Risk Factor (MRF) has been calculated in this study. While calculating MRF, a proposition underlying fuzzy logic must be expressed as membership values in the range 0-1 as true or false. Moreover, for MERISA, the Mamdani type FIS accepted in the literature is used [27]. Therefore, according to fuzzy logic theory, the MERISA system has been designed based on fuzzy logic by paying attention to membership functions and fuzzy relationships and rules. While determining these, opinions of experts on safe navigation were taken, and IMO codes and conventions such as COLREG, SOLAS, and MLC were examined. Literature on this subject and accident information has also been considered. Simultaneously, the conformity of the established rules and relationships is tested by scientists who are experts in fuzzy logic.

ANFIS is a widely used method for modeling non-linear or chaotic systems and was first described as suggested [28]. It requires previously collected data about the problem to be modeled. It uses fuzzy logic and artificial neural networks together while modeling. In the fuzzy logic and fuzzy inference part, Sugeno FIS (Sugeno FIS) is usually included. The training model in the artificial neural network combines least squares and the least squares and backpropagation algorithms. ANFIS has a single output in its structure and uses weighted average defuzzification. It supports various fuzzy membership functions. The fuzzy rules in its structure have equal priority. After the model is created with a specific data group, it can be tested with a different test data group. In this study, ANFIS was used to compare MERISA using meteorological variables and expert evaluation. The ERF values represent the risk assessment of experts. These values are target values for meteorological risk assessment.

3.2. Evaluation Methods

In this study, expert evaluation, in which meteorological variables turn into a risk factor, was used both in the formation of mean error (ME), mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE) and symmetric mean absolute percentage error (sMAPE) methods, which are the evaluation methods of the MERISA program created by FIS, and the ANFIS application, which we compared with MERISA.

Assessment of a machine learning application is a critical part of the process. Therefore, in this study, ERF values are target values after creating MRF. t is the number of marine accidents; m is a difference when MRF (for each accident) is subtracted, and then the ME was calculated according to the following equation,

$$\mathrm{ME} = \frac{1}{t}\sum_{k=0}^{k=t} m_k \tag{2}$$

ME was calculated according to equation (2);

$$\mathrm{MAE} = \frac{1}{t}\sum_{k=0}^{k=t} |m_k| \tag{3}$$

e is ERF (for each accident), MAE was calculated according to equation (3);

$$\mathrm{MAPE} = \frac{100}{t}\sum_{k=0}^{k=t} \frac{|m_k|}{|e_k|} \tag{4}$$

MAPE was calculated according to equation (4);

$$\mathrm{MSE} = \frac{1}{t}\sum_{k=0}^{k=t} m_k^2 \tag{5}$$

MSE was calculated according to equation (5);

$$\mathrm{RMSE} = \sqrt{MSE} \tag{6}$$

RMSE was calculated according to equation (6);

$$\mathrm{sMAPE} = \frac{100}{t}\sum_{k=0}^{k=t} \frac{2\,|m_k|}{|s_k| + |e_k|} \tag{7}$$

And s is MRF (for each accident), sMAPE values were calculated according to equation (7) to compare MRF and ERF values [28-30].

4. Implementation

The first step of a good scientific study is to identify the problem correctly. The most appropriate method for solving this problem should be chosen to achieve success. However, despite all this, a study could fail if the application of a scientific method is not carried out correctly. In this chapter, the methods described so far have been applied, and this application has been explained in detail. MERISA is applied in Chapter 4.1, and then ANFIS is applied in Chapter 4.2.

4.1. Implementation of MERISA

In this chapter, MERISA modeling is explained in detail. MATLAB Fuzzy Toolbox is used for this study.

There are four inputs and one output in MERISA based fuzzy logic. There are three fuzzy sets for each input and five sets for the output. MERISA is designed with 81 rules considering all input sets. Rules, function members, and sets are determined for MERISA model based on experience and similar studies in the literature [6-8]. Wind speed, Sea Condition, Visibility, Day/Night variables of 29 marine accidents have been validated by three expert assessments in [16]. While determining the rules and membership functions, every possibility was made by considering literature and accidental information, and the best results were obtained. Thus, MERISA has been revised and improved. The minimum is used as “and method” and “implication”; maximum (max) is used as “or method” and “aggregation” for MERISA. The Mamdani inference system is used for MERISA as the defuzzification method is central to MERISA. Figure 4 presents a FIS.

The MERISA system has four inputs, and one output variable is shown in Figure 5. These four inputs are Wind Speed, Sea Conditions, Visibility, Day/Night, and the one output is the risk factor. Table 2 presents the information on these functions.

Wind speed, Sea Conditions, Visibility, Day/Night are inputs, and MRF is the output for MERISA system. Limits and membership function types have been made specifically for this study to obtain the most accurate result by doing trial and error, considering the previously mentioned literature and marine accident data.

Wind speed is another input function for the MERISA system. It has three fuzzy sets: Light Air, Breeze, and High Wind. Figure 5 depicts membership function plots for Wind Speed. The Meteorological Beaufort Scale has been used for these membership functions limits, where the range is 0-12.

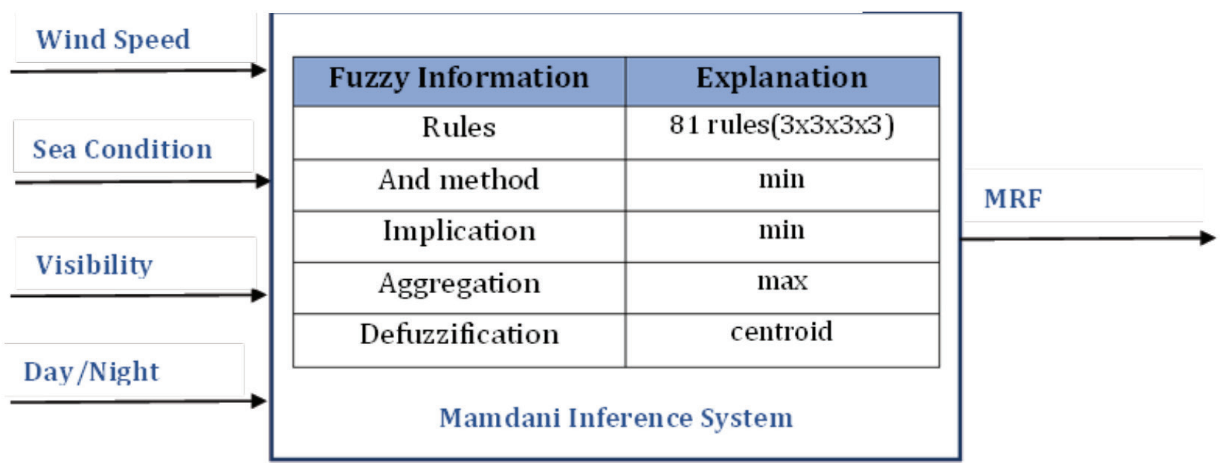

__Figure 4.__ Fuzzy box for MERISA system

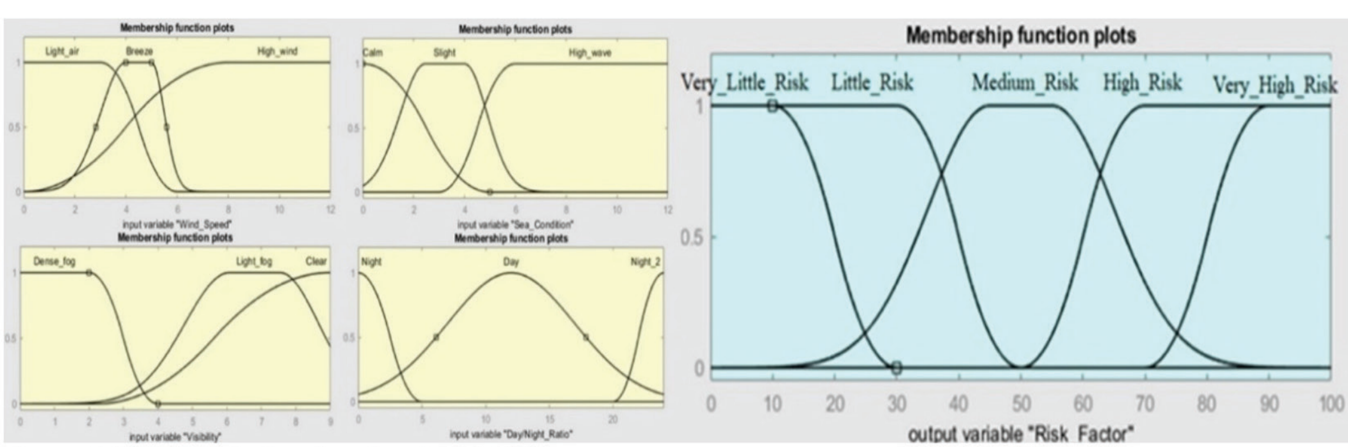

__Figure 5.__ Membership function plots for MERISA system

Table 2. *Fuzzy membership functions' details*

Function	Wind Speed	Sea Condition	Visibility	Day/Night	Risk Factor
Input/Output	Input	Input	Input	Input	Output
Range	0-12	0-12	0-9	0-24	0-100
Number of Fuzzy Sets	3	3	3	3	5
Fuzzy Sets	Light Air	Calm	Dense Fog	Night	Very Little Risk
					Little Risk
	Breeze	Slight	Light Fog	Day	Medium Risk
	High Wind	High Wave	Clear	Night 2	High Risk
					Very High Risk

Sea Conditions is the second input function for the MERISA system. It has three fuzzy sets: Calm, Slight, and High Wave. Figure 5 presents membership function plots for Sea Conditions. The Meteorological Beaufort Scale has been used for these membership functions, where the range is 0-12.

Visibility is the third input function for the MERISA system. It has three fuzzy sets: Dense Fog, Light Fog, and clear. Membership function plots for Visibility are shown in Figure 5. An optical range Table has been used for these membership functions, where the range is 0-9.

Day/Night Ratio is the fourth input function for the MERISA system. It has three fuzzy sets: Night, Day, and Night 2. Membership function plots for Day/Night Ratio are shown in Figure 5. Local time has been used for these membership functions, where the range is 0-24.

MRF is the output function for the MERISA system. It has five fuzzy sets: Very Little Risk, Little Risk, Medium Risk, High Risk, and Very High Risk. Membership function plots for MRF are shown in Figure 5. Percentage evaluation has been used for MRF's 5 membership functions, where the range is 0-100.

4.2. Implementation of ANFIS

In this study, the second system is designed for meteorological risk assessment based on ANFIS.

ANFIS models have a different structure that gives the best results sought by giving alternative values. Table 3 presents the parameter determined in this study. A 2-fold cross-validation method was chosen to evaluate ANFIS. For 2-fold cross-validation, the dataset is divided into two parts: training data and test data., The system is run twice. The dataset in this study contains 141 accidents, divided into two parts: 70 accidents and 71 accidents. Each part is used for both training data and test data.

Table 3. *Information about the ANFIS*

Fuzzy Information	Explanation
Generate FIS	Grid partition
Number of Membership Functions	3+3+3+3
Type of Input Membership Functions	Triangle
Optimal Method	Hybrid
Type of Output Membership Functions	Constant

5. Evaluation

In this chapter, there are evaluations for MERISA and ANFIS modeling.

A detailed evaluation of MERISA suggested in this study is given in Table 4, which contains the results obtained from the six statistical evaluation methods given in Chapter 3.2. The use of these various statistical evaluation methods reveals the performance of the MERISA system from different perspectives.

The RMSE value should be essential in evaluating the MERISA program since it increases the error rate in the larger values. Because the MERISA program is a risk assessment program, it is expected to be error-free in risky situations. Conversely, the MAPE value is also important because it gives MERISA's percentage error.

Because MERISA is a decision support program for meteorological risk assessment, it is required to know which value ranges MERISA works better according to the variables. Thus, a more accurate decision in risky situations is desired. Also, it is necessary to examine RMSE and MAPE values of MERISA according to variables ranges. Table 5 presents these values. Also, RMSE and MAPE values for variables have informed the performance of MERISA. Apart from these, Table 5 provides the range distribution of the dataset according to the variables.

Table 5 shows the values of RMSE and MAPE for Wind Speed. When these values were analyzed, it was found that our MAPE value is lower in the range of 7-11 bft, where the meteorological risk should be higher. This shows that MERISA provides more accurate results at increased risk for Wind Speed. Values of RMSE and MAPE for Sea Conditions are shown in Table 4.

Table 5 depicts the values of RMSE and MAPE for Sea Conditions. When the values in Table 5 are analyzed, it is clear that our MAPE value is lower in the range of 7-9 bft, where the meteorological risk should be higher. This demonstrates that MERISA provides more accurate results in high risk Sea Conditions.

Table 5 also presents the values of RMSE and MAPE for Visibility. When these values were analyzed, it was found that our MAPE value is lower in the range of 3-0, where the meteorological risk should be higher, implying that MERISA gives more accurate results at increased risk for Visibility.

Table 4. *Evaluation results for MERISA*

Evaluation method	Result
ME	-4.94
MAE	6.63
MSE	64.70
RMSE	8.04
MAPE	21.15
sMAPE	18.43

Values of RMSE and MAPE for the Day/Night Ratio are shown in Table 5. When these values were analyzed, it was found that our MAPE value is lower in the range of 20-23 and 8-13, where the meteorological risk should be higher, implying that MERISA gives more accurate results at higher risk for Day/Night Ratio. MAPE value lies between 0–3 in the range of 0–4, which is expected to be high due to the effect of all variables in the MERISA system.

Values of RMSE and MAPE for MRF are shown in Table 5. Analyzing these values shows that our MAPE value is lower in the ranges 50.1-75 and 75.1-100, where the meteorological risk is higher.

It has been observed that MERISA gives values closer to the target value in risky ranges for all variables. This means that MERISA meets the target. Subsequently, modeling that will be introduced in this topic can improve MERISA. For this, it is necessary to give better results than the values given in Tables 4 and 5.

A detailed evaluation of ANFIS mentioned in Chapter 4.2, RMSE value, 9,131, is obtained. RMSE value of MERISA is 8,043. MERISA, which is designed in this study, is better than ANFIS for RMSE value. Consequently, two fuzzy logic

Table 5. *Values of RMSE and MAPE for variables*

Variable	Range	Number of Accident	RMSE	MAPE
Wind Speed	**0-2 Beaufort (bft)**	35	5.97	22.46
	3-5 bft	75	8.32	23.47
	6-7 bft	13	12.22	23.10
	7-11 bft	18	6.41	7.50
Sea Condition	**0-2 bft**	61	8.04	26.49
	3-4 bft	55	7.57	18.65
	5-6 bft	17	9.88	14.67
	7-9 bft	8	8.56	11.43
Visibility (Optical Range Table)	**8-7**	107	8.29	24.62
	6-4	16	7.37	13.84
	3-0	18	7.07	4.86
Day/Night Ratio	**0-3**	24	9.17	26.81
	4-7	21	8.67	19.79
	8-11	16	5.69	17.25
	12-15	31	7.66	21.97
	16-19	32	8.54	23.26
	20-23	17	7.07	18.24
MRF	**0-25**	11	3.52	15.70
	25.1-37.5	54	6.49	24.51
	37.5-50	35	9.93	27.86
	50.1-75	36	8.93	12.88
	75.1-100	5	8.80	9.58

models are designed and evaluated in this study. For future studies, this study will be an incentive.

6. Conclusion

It is a well-known fact that meteorological and Sea Conditions are unstable, which can have a significant impact on the safe navigation of ships. In this unique working environment, the risks and hazards associated with work on the sea are specific. At this point, continuous risk assessment is required to create and maintain a safe working condition and/or environment. Continuous risk assessment is a form of evaluation that should be integrated with existing safety management systems. Navigational safety, however, remains one of the shipping industry's top priorities, despite advanced navigation systems and the deployment of safety management systems onboard ships. Furthermore, numerous deaths have been linked to a lack of safe ship navigation in recent years. Thus, the present study provides continuous meteorological risk assessment for ships to improve marine navigational safety. The suggested model is a proactive modeling approach that uses fuzzy logic and ANFIS. The dataset, consisting of 181 accidents and 15 variables, has been presented in this study. To develop the MERISA system, fuzzy sets, fuzzy relationships, and fuzzy functions have been established. It clearly shows that fuzzy logic and ANFIS can prove robust modeling that could be used in meteorological risk assessments and other risk assessments in shipping operations. Based on the findings, the proposed risk assessment model, MERISA, can provide reasonably competitive results when assessing risky situations in terms of meteorological variables. It is a key factor influencing decision-making regarding accident prevention onboard ships. However, further studies are required to speed up the launch of smart ships and help to improve the technology associated with them. Especially, data analytics approaches are demanded to improve ship navigation safety.

Authorship Contributions

Concept design: İ. Karaca, Ö. Soner, R. Saraçoğlu, Data Collection or Processing: İ. Karaca, Ö. Soner, R. Saraçoğlu, Analysis or Interpretation İ. Karaca, Ö. Soner, R. Saraçoğlu, Literature Review: İ. Karaca, Ö. Soner, R. Saraçoğlu, Writing, Reviewing and Editing: İ. Karaca, Ö. Soner, R. Saraçoğlu.

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References

[1] K. Malde, N. O. Handegard, L. Eikvil, and A. B. Salberg, "Machine intelligence and the data-driven future of marine science," *Ices Journal of Marine Science*, vol. 77, pp. 1274-1285 July-August 2020.

[2] W. Tann, and H. J. Shaw, "Constructing web-based object-oriented design support system for collaborative ship modeling," *Marine Technology and Sname News*, vol. 44, pp. 139-150, 2007.

[3] K. Wrobel, J. Montewka, and P. Kujala, "Towards the assessment of potential impact of unmanned vessels on maritime transportation safety," *Reliability Engineering & System Safety*, vol. 165, pp. 155-169, Sep 2017.

[4] Wang, S.B., Y.J. Zhang, and L.B. Li, A collision avoidance decision-making system for autonomous ship based on modified velocity obstacle method. *Ocean Engineering,* vol. 215, pp. 107910, Nov 2020.

[5] S. Hu, Q. Fang, H. Xia, and Y. Xi, "Formal safety assessment based on relative risks model in ship navigation," *Reliability Engineering & System Safety,* vol. 92, pp. 369-377, Mar 2007.

[6] Y. Huang, and P. van Gelder, "Collision risk measure for triggering evasive actions of maritime autonomous surface ships," *Safety Science,* vol. 127, pp. 104708, July 2020.

[7] J.-F. Balmat, F. Lafont, R. Maifret, and N. Pessel, "Maritime risk assessment (MARISA), a fuzzy approach to define an individual ship risk factor," *Ocean Engineering*, vol. 36, pp. 1278-1286, Nov 2009.

[8] Balmat, J.-F., et al., A decision-making system to maritime risk assessment. *Ocean Engineering,* vol. 38, pp. 171-176, Jan 2011.

[9] G. K. Silber et al., "The role of the International Maritime Organization in reducing vessel threat to whales: Process, options, action and effectiveness," *Marine Policy,* vol. 36, pp. 1221-1233, Nov 2012.

[10] U. Ozturk, and K. Cicek, "Individual collision risk assessment in ship navigation: A systematic literature review," *Ocean Engineering,* vol. 180, pp. 130-143, May 2019.

[11] A. Toffoli, J. M. Lefèvre, E. Bitner-Gregersen, and J. Monbaliu, "Towards the identification of warning criteria: Analysis of a ship accident database," *Applied Ocean Research,* vol. 27, pp. 281-291, Dec 2005.

[12] B. Wu, T. L. Yip, X. Yan, C. G. Soares, "Fuzzy logic based approach for ship-bridge collision alert system," *Ocean Engineering,* vol. 187, pp. 106152, Sep 2019.

[13] Y. Hu, and G.-K. Park, "Collision risk assessment based on the vulnerability of marine accidents using fuzzy logic," *International Journal of Naval Architecture and Ocean Engineering,* vol. 12, pp. 541-551, 2020.

[14] S.-L. Kao, K.-T. Lee, K.-Y. Chang, and M.-D. Ko, "A fuzzy logic method for collision avoidance in vessel traffic service," *The Journal of Navigation,* vol. 60, pp. 17-31 Jan 2007.

[15] R. Fiskin, E. Nasiboglu, and M. O. Yardimci, "A knowledge-based framework for two-dimensional (2D) asymmetrical polygonal ship domain," *Ocean Engineering,* vol. 202, pp. 107187, Apr 2020.

[16] İ. Karaca, R. Saraçoğlu, and O. Soner, "Meteorological risk assessment for ships with fuzzy logic designer," *International Journal Of Fuzzy Systems And Advanced Applications*, vol. 7, pp. 12-15, 2020.

[17] J. Chen, W. Bian, Z. Wan, Z. Yang, P. Wang and H. Zheng, "Identifying factors influencing total-loss marine accidents in the world: Analysis and evaluation based on ship types and sea regions," *Ocean Engineering,* vol. 191, pp. 106495, Nov 2019.

[18] R. J. Bye, and A. L. Aalberg, "Maritime navigation accidents and risk indicators: An exploratory statistical analysis using AIS data and accident reports," *Reliability Engineering & System Safety,* vol. 176, pp. 174-186, Aug 2018.

[19] B. Navas de Maya, and R. E. Kurt, "Marine accident learning with fuzzy cognitive maps (MALFCMs): A case study on bulk carrier's accident contributors," *Ocean Engineering,* vol. 208, pp. 107197, May 2020.

[20] X. Zhou, L. Cheng, and M. Li, "Assessing and mapping maritime transportation risk based on spatial fuzzy multi-criteria decision making: A case study in the South China sea," *Ocean Engineering,* vol. 208, pp. 107403, 2020.

[21] B. Wu, T. Cheng, T. L. Yip, Y. Wang, "Fuzzy logic based dynamic decision-making system for intelligent navigation strategy within inland traffic separation schemes," *Ocean Engineering,* vol. 197, pp. 106909, Feb 2020.

[22] J. M. Sur, and D. J. Kim, "Comprehensive risk estimation of maritime accident using fuzzy evaluation method – Focusing on fishing vessel accident in Korean waters," *The Asian Journal of Shipping and Logistics,* vol. 36, pp. 127-135, Sep 2020.

[23] D. Pyle, Data preparation for data mining. morgan kaufmann. 1999.

[24] CHAPTER 1 - Introduction to Fuzzy Systems, in Applied Fuzzy Systems, T. Terano, K. Asai, and M. Sugeno, Editors. 1989, Academic Press. p. 1-7.

[25] G. J. Klir, U. St. Clair, and B. Yuan, "Fuzzy set theory: foundations and applications," Upper Saddle River, NJ: Prentice Hall, 1997.

[26] L. A. Zadeh, "Fuzzy logic," *Computer,* vol. 21, pp. 83-93, Apr 1988.

[27] E. H. Mamdani, and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *International Journal of Man-Machine Studies,* vol. 7, pp. 1-13, Jan 1975.

[28] J. S. R. Jang, C. T. Sun, and E. Mizutani, "Neuro-fuzzy and soft computing, A computational approach to learning and machine intelligence," Prentice Hall. 1997.

[29] L.A. Bacci, L. G. Mello, T. Incerti, A. Paulo de Paiva, and P. P. Balestrassi, "Optimization of combined time series methods to forecast the demand for coffee in Brazil: A new approach using Normal Boundary Intersection coupled with mixture designs of experiments and rotated factor scores," *International Journal of Production Economics,* vol. 212, pp. 186-211, 2019.

[30] O. Ustun, and R. Kasimbeyli, "Combined forecasts in portfolio optimization: A generalized approach," *Computers & Operations Research,* vol. 39, pp. 805-819, 2012.