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Research Article

The Neural-Fuzzy Approach as a Way of Preventing a Maritime Vessel Accident in a Heavy Traffic Zone

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The paper dwells on the methodology of neural-fuzzy approach to solving the problem of ship collision prevention in a heavy traffic zone. The authors present the technique of using maneuvering board to form the elements of learning sample. The authors prove that it is rational to use a neural-fuzzy system, where generation is carried out by the lattice method without clustering. The authors investigate the effect of optimization on the quality differences. The researchers define optimal membership functions that are used to generate the input linguistic variables of a neural-fuzzy system.

1. Introduction

Despite all significant positive outcomes, the issue of ship collision avoidance in a heavy traffic zone [1] is still urgent. So, in the paper [2] the authors report on the concept of expected dangerous patterns (areas) projected on the automatic identification system data. The integration of the Geographic Information System, the International Regulations for Preventing Collisions at Sea (COLREGs), and a thorough investigation of various navigation vessel cases gives the system an opportunity to generate a safe ship collision prevention route and maritime features. The authors [3] suggest a similar task of making up a system for preventing vessel collisions on the ECDIS (electronic chart display and information system) and AIS (automatic identification system). The authors of the paper [4] introduce a method for automatic trajectory planning and collision avoidance using the APF (artificial potential field) search method and speed vector. Another approach providing ship collision avoidance is Bayesian networks declared in the paper [5]. Fuzzy logic is also successfully applied [6] for this kind of problem. In particular, the papers [7, 8] are devoted to support systems of decision making that are undertaken on board vessels. Thus, the authors specify an approach for decision making on sea vessels collision avoidance in the research [8]. The authors are encouraged to use Microsoft Visual Studio to build up a list rule according to the International Regulations for Preventing Collisions at Sea (COLREGs, 1972). That list is able to offer an appropriate collision avoidance algorithm to the boat master after the assessment of maritime traffic according to the vessel traffic service (VTS).

In the papers [9, 10] authors present a model based on the fuzzy sets theory to rank a risk of sea vessel collision in a heavy traffic zone to agree on the navigational decision support because of safe ship control needed. In this model, a maneuvering board was used to draft a fuzzy production rules system [11–13]. In addition, a well-known Mamdani Algorithm was used as an algorithm for fuzzy logic conclusion.

These days, neural network technologies are widely used in navigation issues [14, 15]. For example, the paper [16] focuses on the neural network classification of marine targets on noise images in bad weather conditions and in case of sea waves. In the paper [17] the neural network succeeds in detecting icebergs by typical textural features from the image of satellite-based Synthetic Aperture Radar. Moreover, the neural network has been used successfully in issues of improving an accurate position of a vessel from radar data [18] and designing laser metering systems [19].

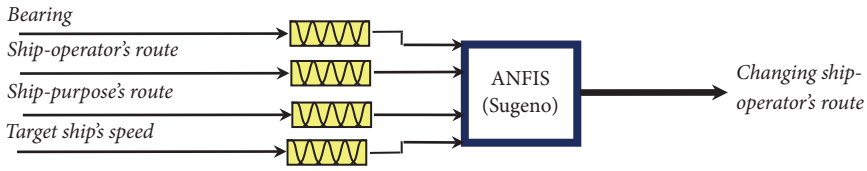

Figure 1: Neural-fuzzy ship collision prevention in a heavy traffic zone.

Neural networks are also proved to be successful in warning [20, 21]. A number of surveys are worth noting in the supplement to navigation practice. In particular, the methodology of a short-term forecast of the Caspian Sea level by means of a perceptron-type neural network [22] is developed in the paper [23]. The paper [24] deals with online forecast of the maneuvering vessel turn, a neural network model RBF having a mutating nature, and the ability to adjust network features by the sliding window method. The authors designed a predictive model which was marked by a leaner structure, fast processing, and a high degree of measurement accuracy.

As the use of neural nets has clear benefits [22], it is potentially capable of improving the projection of ship collision risks. In addition, significant headway had been made against it. For example, the paper [25] comments on the methodology and strategy of ship collision avoidance using artificial neural networks, optimal control theory methods [26, 27], and a game theory. The paper [28] also mentions an autonomous navigation system for a robotic submarine based on an adaptive neurocontroller.

Several papers [29–34] should also be noted in the connection with developing approaches to prevent ship collisions.

In order to improve the effects of a fuzzy system [35], the authors carried out hybridization involving the elements of artificial neural networks theory, which resulted in designing a neural-fuzzy network [36, 37]. In turn, a neural-fuzzy ship collision prevention system is based on it. This paper submits the results of simulating modelling.

2. Materials and Methods

The neural-fuzzy ship collision prevention system in a heavy traffic zone is an adaptive neural-fuzzy inference system (ANFIS) [22, 36, 37], consisting of 5 layers. This kind of system is defined as a multilayer feedforward neural network without any feedback. Its features are those of fuzzy logic inference. But an algorithm for making a decision of the neural network is a fuzzy logic inference algorithm. ANFIS model used for the neural-fuzzy ship collision prevention system in a heavy traffic zone development is based on Takagi–Sugeno fuzzy inference system, which is highly interpretable and efficient in connection with computing.

The first layer of ANFIS is a layer of membership functions. There is a fuzzification in the first layer; i.e., fuzzy sets are established corresponding to the terms of source (input) and target (output) linguistic variables.

The neural-fuzzy ship collision prevention system in a heavy traffic zone observed in the paper (Figure 1) includes four input linguistic variables:

(i) Electronic bearing on the target ship, i.e., on that one to which the operator vessel needs to prevent collision safely

(ii) The ship-operator course

(iii) The target-ship course, i.e., a vessel in a heavy traffic zone, to which, if necessary, it is required to prevent collision

(iv) The target-vessel speed [35], as well as the only output linguistic variable, which is the value of the operator-vessel course change calculated on the maneuvering board in advance with the output value corresponding to the interval [-60°; 360°], where the value of -60° corresponds to the term "much to the left," the value to -30° corresponds to the term "to the left," the value 0° corresponds to the term "keep it steady" (neither the course nor the speed of the operator-vessel changes); 60° stands for the term "much to the right," the value of 30° means the term "to the right," and the value of 360° implies the maneuver (AmE) or manoeuvre (BrE) of circulation (that is, the term "circulation")

The set of values for the inputs "bearing," "the ship-operator course," and "vessel-target course" is the set [0; 360]°. The range of values for the ship-target speed source is determined according to the information from the reviewing feedback of The Russian Maritime Register of Shipping (RS), [0; 34] knots.

The number of nodes performed in the first layer is equal to the sum of the term powers of the input linguistic variable sets. The output values focused in the first layer are the values of membership functions with specific values of the input variables. The features of membership functions in the first layer compose the first group of features that are to be set during the learning process.

The second layer of ANFIS is a layer of fuzzy production rules. The number of nodes is the same as the number of rules in the second layer. Moreover, each node is connected to those ones in the first layer that form the premises (antecedents) of the corresponding rule. In general, the distribution of the links between the first and second layers is performed in such a way that each input variable of the neural-fuzzy network is associated with each neuron of the rule layer.

The output values in the second layer correspond to the relative degrees (weights) of the rules, which are calculated as a logical product (intersection) of membership functions of the input variables.

The third layer of ANFIS is a layer of absolute value in which the output values of this layer are determined by adding the outputs of all nodes of the rule layer and dividing each of the output values in the second layer by this total value. This ensures scaling of the output values so that increases the neural-fuzzy network resilience.

The fourth layer of ANFIS is the output layer of the linear combination. Each node of the fourth layer is connected to

one node of the previous layer and, as a consequence, to all inputs of the neural-fuzzy network. In the fourth layer there is determination of coefficients of linear combinations, as a result, for example, of an algorithm for backpropagation (backpropa) or hybrid, which is a combination of the method of Ordinary Least Squares (OLS) and a backward propagation of errors (backpropa). Coefficients of linear combinations constitute the second group of features to be determined in the learning process.

Finally, the fifth layer of ANFIS is the output total layer. The fifth layer, corresponding to the adder of the legacy neural network, completes defuzzification.

Learning a neural-fuzzy network, which is a combination of two stages, is an iterative procedure that allows determining the features of membership functions that minimize the discrepancy between "real (or valid) and desired behavior of the model."

In the first stage, the learning sample goes to the inputs, and then the parameters of the fourth layer of the neural-fuzzy network are set up in such a way so as to minimize the discrepancy between the reference output values and the calculated output of the neural-fuzzy network.

In the second stage, residual discrepancy is transferred from the network output to the inputs, and backpropa modifies the parameters of the nodes in the first layer. Besides, the coefficients of the conclusion of the rules produced in the first stage do not change.

The iterative setup procedure continues until discrepancy exceeds a preestablished value.

Thus, the general methodology for constructing the neural-fuzzy network underlying the neural-fuzzy ship collision prevention system in a heavy traffic zone includes the following steps.

Step 1. Forming a sample for learning, which contains implicit knowledge, revealed as a result of learning the neural-fuzzy network.

Step 2. Selecting fuzzy inference parameters, i.e., selection of membership functions, fuzzy intersection, and defuzzification.

Step 3. Selecting an algorithm for learning and setting up the parameters of the neural-fuzzy network.

Step 4. Direct learning of the neural-fuzzy network to configure both groups of parameters.

Step 5. Optimizing and verifying learning outcomes of a neural-fuzzy network.

The implementation of the neural-fuzzy ship collision prevention system in a heavy traffic zone was carried out by the Fuzzy Logic Toolbox of MATLAB system [14, 15]. The model is shown in Figure 1.

Furthermore, a series of computer experiments was conducted to define the following.

(1) The best type of membership functions used to specify the terms of input linguistic variables

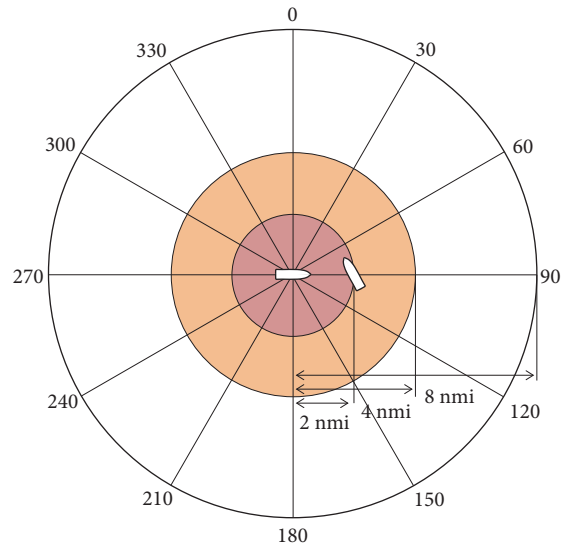

Figure 2: Resulting simulation model with ships in a heavy traffic zone.

(2) The best type of membership functions used to specify the terms of the output linguistic variable, i.e., a type of dependence that connects input and output linguistic variables (constant or linear coefficients)

(3) The best learning algorithm: the backpropagation algorithm (AOPO, backpropa) or the hybrid algorithm. They are a combination of AOPO and OLS [22]

(4) The optimal number of learning cycles for a neural-fuzzy network

A learning set is designed to carry out simulation modelling of the neural-fuzzy collision ship prevention system. At first, a list of different cases with ships in a heavy traffic zone was developed by means of a full search having stepped to broaden the input ranges. Then, the equation of each certain case and assessment of a changing value on the operator ship course were made on the maneuvering board. It should be noted that the equation on the maneuvering board was followed by the rules of the International Regulations for Preventing Collisions at Sea (COLREGS), commentaries to them, and recommendations on so-called "good seamanship." Finally, the values of the input vector and the value corresponding to that one made with the maneuvering board for changing the operator ship course were recorded in a learning sample.

The authors would like to present the way of designing one of the learning pairs. They also imagine the situation when ships are in a heavy traffic zone, as shown in Figure 2. The distance from the ship-operator to the target ship is 2 miles, the ship-operator course is 90 degrees, and the operator ship speed is 15 knots. The radar navigation determined that the target-ship course is 330 degrees, an object bearing is 90 degrees, and the target-ship speed is 8 knots.

In the circumstances described, the target ship is right ahead the ship-operator and at risk of colliding, since the ship-operator and the target ship are too close to each other.

As it is prescribed in Rule 16 of the International Regulations for Preventing Collisions of Ships at Sea, the ship-operator must give way not to run into the target ship. Having simulated this case on a maneuvering board and having calculated it, the scholars found out that the new ship-operator course was going to be 120 degrees. It requires turning a ship at 30 degrees to the right and the ship-operator will not collide with the ship-target at a safe distance behind the vessel stern. After considering this situation it was possible to set a learning pair number 91. The rest of the 525 training pairs were similarly set.

Simulation modelling of neural-fuzzy ship collision prevention system was carried out in two modes. First, neural-fuzzy networks were generated using the lattice method without clustering, and, second, it was performed by the subclustering method. 192 different neural-fuzzy networks were trained for the first mode. Each of them had five terms in each of the four input linguistic variables. Although the backpropagation and hybrid algorithms were used [22], backpropagation has been widely applied in solving various problems, but the algorithm has a number of drawbacks, in particular, "a long time learning," as well as determining local or relative instead of global or absolute minima. The authors used eight different membership functions (MF) to determine the input linguistic variables. They are trimf (triangular MF), trapmf (trapezoidal MF), gbellmf (generalized bell-shaped MF), gaussmf (Gauss's MF), gauss2mf (two-sided Gauss's MF), pimf (P- shaped MF), dsigmf (MF as a difference between two sigmoid functions), psigmf (the product of two sigmoid MF), and constant or linear coefficients for the output variable. The learning intervals numbered from 100 to 600.

3. Results and Discussion

As a result of the simulation modelling of the neural-fuzzy ship collision prevention system in the mode of grating generation without clustering, it was revealed that the best were the hybrid method as a learning algorithm, constant factors as a type of the output linguistic variable, the product of two sigmoid MF, the difference between two sigmoid functions, and the U-shaped membership function to derive input linguistic variables.

The authors chose six out of learned neural-fuzzy networks with the least learning errors. They gave a test for each one and had quality evaluation.

3.1. Mean Absolute Error. MAE is given by the formula [38]

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| CCOS_i - \overline{CCOS_i} \right|, \tag{1}$$

where N is number of model-based testing instances, $CCOS_i$ is a standard value of the change in the ship-operator course for the i-model test counted with a maneuvering board, and $\overline{CCOS_i}$ is the value of changing the ship-operator course for the i-model test, counted using a neural-fuzzy network.

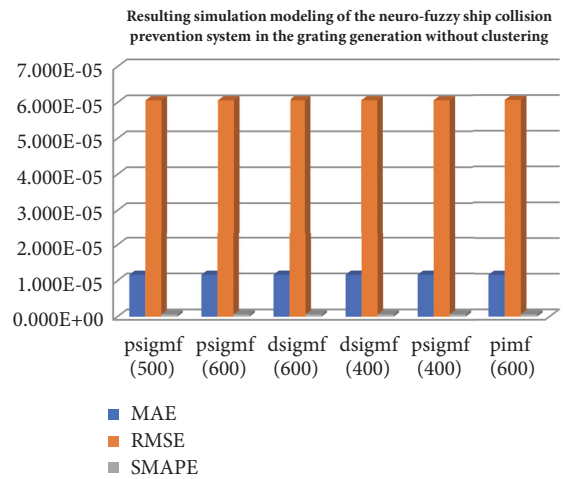

Figure 3: Resulting qualitative evaluation in the neural-fuzzy ship collision prevention system training in the generation by the lattice method without clustering.

3.2. Root Mean Square Error. RMSE is given by the formula [38]

$$RMSE = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(CCOS_i - \overline{CCOS_i} \right)^2}. \tag{2}$$

3.3. Symmetric Mean Absolute Percentage Error. SMAPE is given by the formula [38]

$$SMAPE = \frac{\sum_{i=1}^{N} \left(\left| CCOS_i - \overline{CCOS_i} \right| \right)}{\sum_{i=1}^{N} \left(\left| CCOS_i + \overline{CCOS_i} \right| \right)}. \tag{3}$$

The values of qualitative measures are summarized in Table 1, and a resulting diagram is in Figure 3.

For the second mode, 288 different neural-fuzzy networks were trained (144/144 by the backpropa and hybrid optimization method). Parameters of the subclustering method varied as follows: the parameter "Range of Influence" is from 0.2 to 0.5; step size is 0.1, the parameter 'Squash Factor' is from 1 to 1.375; step size is 0.125; the parameter "Accept Ratio" is from 0 to 0.4; step size is 0.2; and the parameter "Reject Ratio" is from 0 to 0.3; step size is 0.15. In all 288 neural-fuzzy nets 100 learning intervals were being selected.

The authors came to the following conclusion after simulating the neural-fuzzy ship collision prevention system in the subclustering generation mode. The best method is the hybrid optimization method for neural-fuzzy networks as a learning algorithm, as well as for the grid-free generation mode, while "Range of Influence" constantly equals 0.3, the best ratio for "Squash Factor" is the parameter that equaled 1, and the parameter that equaled 0.4 is for "Accept Ratio."

Six best neural-fuzzy networks were chosen for testing. Furthermore, the authors made qualitative evaluation for each of them. The resulting Table 2 is presented in Figures 4 and 5.

Let the authors compare the results presented in this paper with the results of the neural-fuzzy ship collision

Table 1: Resulting simulation modelling of the neural-fuzzy ship collision prevention system in the grating generation without clustering.

Type of MF for input LVs	Number of Training intervals	Learning error	MAE	RMSE	SMAPE
psigmf	500	$5.4532 \cdot 10^{-5}$	$1.165 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.2555 \cdot 10^{-7}$
psigmf	600	$5.4532 \cdot 10^{-5}$	$1.165 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.2555 \cdot 10^{-7}$
dsigmf	600	$5.4553 \cdot 10^{-5}$	$1.166 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.257 \cdot 10^{-7}$
dsigmf	400	$5.4556 \cdot 10^{-5}$	$1.166 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.257 \cdot 10^{-7}$
psigmf	400	$5.456 \cdot 10^{-5}$	$1.1656 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.257 \cdot 10^{-7}$
pimf	600	$5.5002 \cdot 10^{-5}$	$1.171 \cdot 10^{-5}$	$6.064 \cdot 10^{-5}$	$6.2836 \cdot 10^{-7}$

Table 2: Resulting simulation modelling of the neural-fuzzy ship collision prevention system through subclustering generation method.

Range of influence	Squash factor	Accept ratio	Reject Ratio	Optim. Methods	Learning error	RMSE	MAE	SMAPE
0.3	1	0	0	backpropa	$1.26 \cdot 10^{-1}$	$3.865 \cdot 10^{-1}$	$5.05 \cdot 10^{-2}$	$2.7 \cdot 10^{-3}$
0.3	1.125	0	0	backpropa	$1.26 \cdot 10^{-1}$	$1.365 \cdot 10^{-1}$	$3.54 \cdot 10^{-2}$	$1.9 \cdot 10^{-3}$
0.3	1	0	0.15	backpropa	$1.26 \cdot 10^{-1}$	$3.865 \cdot 10^{-1}$	$5.05 \cdot 10^{-2}$	$2.7 \cdot 10^{-3}$
0.3	1	0.4	0	hibrid	$1.363 \cdot 10^{-3}$	$1.36 \cdot 10^{-3}$	$5.5 \cdot 10^{-4}$	$2.94 \cdot 10^{-5}$
0.3	1	0.4	0.15	hibrid	$1.363 \cdot 10^{-3}$	$1.36 \cdot 10^{-3}$	$5.5 \cdot 10^{-4}$	$2.94 \cdot 10^{-5}$
0.3	1	0.4	0.3	hibrid	$1.363 \cdot 10^{-3}$	$1.36 \cdot 10^{-3}$	$5.5 \cdot 10^{-4}$	$2.94 \cdot 10^{-5}$

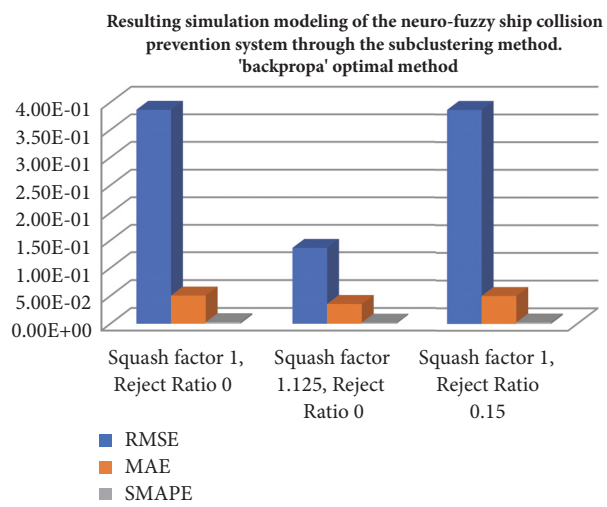

Figure 4: Resulting qualitative evaluation in the neural-fuzzy ship collision prevention system training when generating by the subclustering method through backpropagation error algorithm.

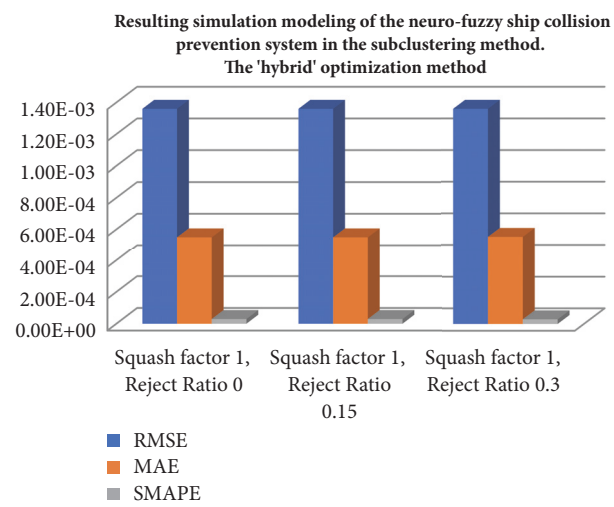

Figure 5: Resulting qualitative evaluation in the neural-fuzzy ship collision prevention system training in the generation of the hybrid algorithm through the subclustering method.

prevention system in a heavy traffic zone [35], in which only the fuzzy logic apparatus is used.

In the paper [35], a fuzzy system is offered. The first linguistic variable called *Peleng* included the following five terms of the basic term set: eastern bearing, western bearing, northern left bearing, northern right bearing, and southern bearing.

The second and third input linguistic variables *operator-vessel course* and *target-vessel course* had a basic term set consisting of the following elements [35]: the left course to the north, the right course to the north, easterly course, heading south, and westerly course.

The fourth input linguistic variable *ship-target speed* had the following terms of the basic term set [35]: fixed target, low speed, average speed, high speed, and a very high speed.

According to the point from Rule 8 in International Rules of Preventing Collision at Sea, COLREGS, "if there are enough waters, only a course change may be the most effective mode of action to prevent collisions." Boatmasters state that most of the ways to prevent collision at sea are due to the course maneuvers. So, the change of the operator-vessel course is chosen for the output linguistic variable.

In the description of terms for the output linguistic variable, the values of fuzzy set cores corresponding to the terms [35] are given in brackets: much to the left (-60°), to the left (-30°), keeping it steady (the course and speed do not change) (0°), to the right (30°), much to the right (60°), and circulation (360°).

In the paper [35] the author presents the results of fuzzification of the indicated input and output linguistic

Table 3: Results of imitating simulation of a fuzzy ship collision prevention system in a heavy traffic zone proposed in [35].

Defuzzification Method	MAE	RMSE	SMAPE
Centroid	$2.2460 \cdot 10^{-1}$	$2.3120 \cdot 10^{-1}$	$1.19 \cdot 10^{-2}$
Bisector	$1.2379 \cdot 10^{0}$	$1.2568 \cdot 10^{0}$	$7.12 \cdot 10^{-2}$
MOM	$1.2379 \cdot 10^{0}$	$1.2568 \cdot 10^{0}$	$7.12 \cdot 10^{-2}$
SOM	$1.2379 \cdot 10^{0}$	$1.2568 \cdot 10^{0}$	$7.12 \cdot 10^{-2}$

variables, as well as the characteristics of the fuzzy system product base with a description of the fuzzy logic inference algorithm designed by *Mamdani Algorithm*.

The author [35] did the testing for fuzzy ship collision prevention system in a heavy traffic zone. It should be noted that the same measures (MAE, RMSE, and SMAPE) were also used to evaluate the quality. Four defuzzification methods were used as a defuzzy: centroid, bisector, and the mean of maximums and the smallest of maximums. The results are summarized in Table 3.

As a result of testing the fuzzy ship collision prevention system in a heavy traffic zone offered in [35], it was found out that the best defuzzification method is centroid, but the discrepancy quality values are insufficient to decide on sea vessels collision prevention in a heavy traffic zone.

4. Conclusions

Having verified the results of simulating the neural-fuzzy ship collision prevention system for both modes (both for grid-generated without clustering and for subclustering generated) the authors draw the following conclusions.

First, it is advisable to use the neural-fuzzy ship collision prevention system to avoid ship collision in a heavy traffic zone, where generation is held through the lattice method without clustering. The comparison of the results of Tables 1 and 2 proves much better quality of discrepancies using the neural-fuzzy ship collision prevention system in a heavy traffic zone with generation by the lattice method without clustering than when generated by subclustering method, which produces the best MAE result comparable to 10^{-4}.

Second, the hybrid method of optimization gives much better results than the algorithm for backpropagation when using both the lattice method without clustering and the subclustering one. In particular, AOPO produces the best MAE result equal to $3.54 \bullet 10^{-2}$, while the hybrid algorithm produces MAE result equal to $5.5 \bullet 10^{-4}$ when generating by subclustering method.

Third, the authors believe that best results to develop input linguistic variables are given by such membership functions as the product of two sigmoid MF as a difference between two sigmoid functions and a U-shaped membership function. That is proved by the results in Table 1.

Fourth, it is necessary to refer to constant coefficients for the neural-fuzzy ship collision prevention system in the mode of grating generation without clustering, as a type of the output linguistic variable.

To sum up, 192 different simulating models of neural-fuzzy ship collision prevention systems were generated through the lattice-free clustering method, as well as 288 neural-fuzzy ship collision prevention systems, where the network was generated through the subclustering method. After finishing the simulation, the hybrid optimization method turned out to be the best (allows to get MAE value about 10^{-5}). The best neural-fuzzy ship collision prevention systems testing has proved that they can determine very accurately the value of changing the ship-operator course to avoid ship collision in a heavy traffic zone, which is dangerous for the ship-operator. The authors compared the results reflected in this paper, for example, with those of the fuzzy ship collision prevention system in a heavy traffic zone proposed in the paper [35]. They came to the conclusion that the defuzzification method *Centroid* with MAE and RMSE values about 10^{-1} and SMAPE about 10^{-2} produces the best result. Thus, it is correct to say that using neural network technologies in solving the problem significantly improves the quality of safe navigation of sea-going vessels in a heavy traffic zone. The neural-fuzzy collision avoidance system investigated in this research is one of the modules of the intelligent navigation safety system. The authors are definitely going to keep developing them in the future.

Data Availability

Data were obtained by the authors independently. The data used to support the findings of this study are included within the supplementary information files.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Supplementary Materials

Supplementary 1. Table 1_1.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 500 training intervals, using the membership function as a product of two sigmoid membership functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 2. Table 1_2.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 600 training intervals, using the membership function as a product of two sigmoid membership functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 3. Table 1_3.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 600 training intervals, using the membership function difference of functions (as a result of subtraction) between two sigmoid functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 4. Table 1_4.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 400 training intervals, using the membership function difference of functions (as a result of subtraction) between two sigmoid functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 5. Table 1_5.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 400 training intervals, using the membership function as a product between two sigmoid functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 6. Table 1_6.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 600 training intervals, using the U-shaped membership function for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 7. Table 2_1.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using backpropagation with parameters Range of Influence, Squash Factor, Accept Ratio, and Reject Ratio equal to 0.3, 1, 0, and 0, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 8. Table 2_2.xlsx: data for testing the neural-fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using backpropagation with parameters Range of Influence, Squash Factor, Accept Ratio, and Reject Ratio equal to 0.3, 1.125, 0, and 0 respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 9. Table 2_3.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using backpropagation with parameters Range of Influence, Squash Factor, Accept Ratio, and Reject Ratio equal to 0.3, 1, 0, and 0.15, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 10. Table 2_4.xlsx: data for testing the neural-fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using the hybrid optimization method with parameters Range of Influence, Squash Factor, Accept Ratio and Reject Ratio equal to 0.3, 1, 0.4, and 0, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 11. Table 2_5.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using the hybrid optimization method with parameters Range of Influence, Squash Factor, Accept Ratio and Reject Ratio equal to 0.3, 1, 0.4, and 0.15, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 12. Table 2_6.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using the hybrid optimization method with parameters Range of Influence, Squash Factor, Accept Ratio and Reject Ratio equal to 0.3, 1, 0.4, and 0.3, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

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