

Intelligent Vessel Course Stabilization Control System

V. Mykhailenko, I. Hvozdeva, V. Shevchenko, G. Grama & V. Leshchenko

National University "Odessa Maritime Academy", Odessa, Ukraine

ABSTRACT: This article presents the development of an intelligent vessel course stabilization control system using an artificial neural network. The objective of the study was to improve vessel control efficiency under external disturbances. A neural network capable of adapting to changing navigational conditions and compensating for external disturbances was used to implement the controller in the vessel course stabilization control system. Simulation of the developed vessel's automatic course stabilization control system (ACS) was conducted in MATLAB/Simulink using mathematical models of vessel dynamics and wave disturbances. The simulation permit to analyze the effects of sea waves of varying intensity and interactions with oncoming vessels. A comparative analysis of the transient processes of the developed neural network-based system and a traditional adaptive course stabilization system with a PID controller was conducted. A combined method for controlling the vessel course stabilization system is proposed, including the use of a PID controller during stable navigation and automatic switching to a neural network controller when challenging operating conditions and intense external disturbances arise. The results of computer simulations conducted by the authors showed that the developed intelligent automatic control system ensures stable stabilization of the vessel's course when exposed to disturbances of varying intensity. The use of an intelligent approach reduced the transition time and minimized deviations from the set course. The trained neural controller demonstrated high adaptability and resilience to changing parameters of a complex navigational environment.

1 INTRODUCTION

The modern development of artificial intelligence technologies opens up new opportunities for improving vessel's automatic course stabilization control system. Traditional autosteering systems, which are built within the framework of the linear theory of automatic control using PID regulators, have limitations in cases where the ship operates under conditions of changing parameters (load) and disruptive influences (sea waves, currents and wind). In such conditions, the use of neural networks capable of learning, adaptation and self-organization becomes an effective solution [1].

Intelligent control systems are able to analyze the parameters of the vessel's motion in real time, assess deviations from the set course, predict state changes and make optimal decisions to reduce control errors. Such systems integrate self-adaptation and optimization algorithms, which allow to increase the efficiency of stabilization and to reduce energy consumption. The development of autonomous navigation and the use of intelligent systems increase the requirements for the accuracy and adaptability of ACS.

A number of difficulties may arise when developing, configuring, and operating intelligent

systems on ships. In particular, training a neural network controller (NNC) requires a large amount of measurement data (Dataset) of controlled parameters of ship equipment during operation under various load modes, sailing conditions, maneuvering, etc. However, experimental data are often incomplete or heterogeneous, contain measurement errors, and do not reflect rare but critical emergency situations well. Another important problem is the lack of sufficient international standards and regulations governing the use of neural network (NN) and other intelligent systems on autonomous and traditional ships [2].

To implement intelligent systems on ships, according to the authors, it may be necessary to:

- developing the methods for testing and validating mathematical models and control algorithms, created on the basis of machine learning methods;
- searching the methods to ensure the reliability of intelligent control systems in the face of cyberattacks and loss of Internet connection due to weather conditions;
- creating the generally accepted methods for developing, training and testing on ships neural networks (NN) and other intelligent ACS.

Testing the proposed approaches to collecting data on measurement parameters for training intelligent (neural network) control systems, modelling their operation under different external conditions and assessing the quality indicators of transient processes can be useful for further implementation in ACS of traditional and autonomous vessels and is a relevant scientific and applied problem.

The purpose of the research is the analysing, modelling and improving the processes in an intelligent (neural network) system for controlling the course of a vessel, taking into account external disturbances and nonlinear characteristics of the control object. The obtained results can be used in the development of modern ACS for sea and river vessels, which will contribute to increasing the safety and efficiency of navigation.

Many modern works are devoted to the improvement of PID controllers with adaptive adjustment of coefficients. ACS with such controllers take into account changes in the dynamics of the vessel and the influence of external disturbances, which increases the accuracy of keeping the vessel on course. However, with significant nonlinearities caused by external disturbances (waves, wind, currents, etc.), the efficiency of PID controllers decreases [3, 4].

Studies by Huang C. and Bertilsson T. show the effectiveness of adaptive methods with inverse linearization and real-time algorithms of parameters estimations. Such models allow compensating for uncertainty in the hydrodynamic coefficients of the vessel [5, 6].

Adaptive Dynamic Programming (ADP) and Reinforcement Learning (RL) methods are used in ACS to optimize energy consumption during course stabilization. According to Abudu R. (2024), ADP-based systems show a 10–15% improvement in fuel efficiency compared to classical controllers [7].

The application of fuzzy logic in ship autopilot systems was studied by Velagic J. (2003) and Sutton R.

(1996). Such systems are effective in the presence of uncertainty in external influences. Their development was neuro-fuzzy systems (ANFIS), which automatically adjust fuzzy logic rules using neural networks [8–11].

Current research integrates Deep Learning technologies for predicting disturbances and optimizing the vessel's trajectory. Describes systems that combine data from multiple sensors (Sensory fusion) and use deep neural networks to form control actions. However, such systems have problems with certification and decision justification [12–15].

Currently, highly efficient course control systems based on fuzzy logic are already being used on merchant ships, which are mass-produced [16, 17]. Among them, the Navipilot AD II autopilot from Sperry Marine and the NAVpilot 500 from Furuno can be mentioned [18].

Further research focuses on creating hybrid systems (combining classical adaptive controllers with artificial intelligence), reducing energy consumption, and increasing reliability during autonomous navigation [19, 20].

2 DEVELOPMENT OF THE CONTROL OBJECT MATHEMATICAL MODEL

Stabilization of the ship's course consists in maintaining the specified values of angular velocity and course by compensating the rudder for random influences (Fig. 1). The ACS with PID controller when solving this problem has:

- measure and maintain with the necessary accuracy the set course value at maneuvering speeds;
- produce the minimum possible number of steering gear (RM) engagements;
- ensure the minimum rudder deflection in amplitude;
- operate stably without self-oscillations.

When stabilizing the course, the principle of deviation control is used, which consists in forming the amount of rudder shift to keep the vessel on course depending on the control errors. The course meter in the system is a gyrocompass (GC).

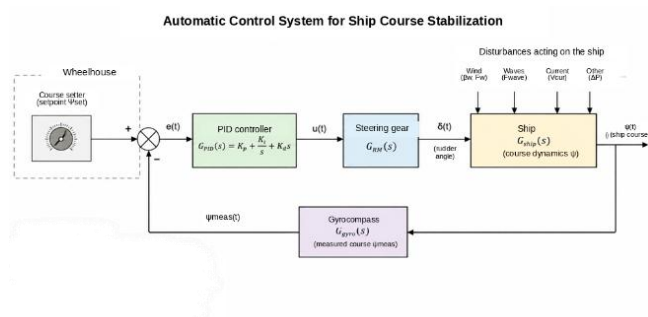


Figure 1. ACS for stabilizing the course of the vessel with PID – regulator

The following symbols are used in the figure 1: ψ_s – desired heading (setpoint), ψ_m – heading measured by gyrocompass, $e(t)$ – heading error, $u(t)$ – controller control action, $\delta(t)$ – rudder deflection angle, $\psi(t)$ – current ship heading

2.1 Mathematical models of components of the vessel's automatic course stabilization control system

One of the most common models for describing the movement of a ship along a course is the nonlinear Nomoto model, proposed in the publication "Nomoto, K., Taguchi, T., Honda, K., Hirano, S. "On the Steering Qualities of Ships" International Shipbuilding Progress, 1957". The Nomoto 1st Order Model is used to describe the dynamics of a vessel's course change under rudder control. Let us consider the first-order model (Nomoto 1st Order Model) [21].

Differential equation for angular velocity $r(t)$:

$$T \frac{dr(t)}{dt} + r(t) = K\delta(t - \tau) \quad (1)$$

Transfer functions at zero initial conditions:

$$W_{r\delta}(s) = \frac{r(s)}{\delta(s)} = \frac{K}{Ts + 1} \cdot e^{(-\tau s)}, \quad (2)$$

$$W_{\psi\delta}(s) = \frac{\psi(s)}{\delta(s)} = \frac{K}{s(Ts + 1)} \cdot e^{(-\tau s)}, \quad (3)$$

because $\psi = r(s)/s$.

Designations and units of measurement: $\delta(t)$ – rudder angle (degrees), $r(t) = d\psi/dt$ – angular velocity (degrees/s), $\psi(t)$ is heading (degrees). K is the gain (degrees/s per degree), T is time constant (sec), τ is delay (sec). Numerical values (example for a medium-sized cargo ship) according to studies [22]: $K = 0.08$ (°/s) / (°), $T = 80$ s, $\tau = 5$ s.

Eq. (1) – Eq. (3) taking into account numerical values have the following form:

$$80 \frac{dr(t)}{dt} + r(t) = 0.08\delta(t - 5), \quad (4)$$

$$W_{r\delta}(s) = \frac{r(s)}{\delta(s)} = \frac{0.08}{80s + 1} \cdot e^{(-5s)}, \quad (5)$$

$$W_{\psi\delta}(s) = \frac{\psi(s)}{\delta(s)} = \frac{0.08}{s(80s + 1)} \cdot e^{(-5s)}. \quad (6)$$

Based on the analysis [22], a Table 1 was obtained with typical values of the Nomoto mathematical model, which can be used in modeling the ACS for stabilizing the course of a vessel.

Table 1. Typical values of ship model parameters

Vessel type	K	T
Tanker	0,03 – 0,08	80–200 c
Container ship	0,05 – 0,15	40–120 c
Small vessel	0,1 – 0,3	10–40 c

2.2 Steering machine model

The mathematical model of the steering machine can be represented as the following relationship:

$$T_{rm} \frac{d\delta(t)}{dt} + \delta(t) = \delta_c(t), \quad (7)$$

where $\delta(t)$ is the actual steering angle; $\delta_c(t)$ is the specified angle; T_{rm} is the inertia of the drive.

The steering gear of a ship is in many cases described by an aperiodic link of the first order with a limitation on the speed of the rudder. The transfer function of the steering gear has the form:

$$W_{rm}(s) = \frac{\delta(s)}{\delta_c(s)} = \frac{1}{T_{rm}(s) + 1}. \quad (8)$$

The model is subject to rudder speed restrictions, namely: $|d\delta/dt| \leq \delta_{max}$, where δ_{max} is the maximum rudder speed: 3–6 °/s for large vessels; up to 10 °/s for small vessels. For modeling in the Simulink (MATLAB) application, the following blocks were used (Fig. 2): Saturation – rudder angle limitation ($\pm 35^\circ$); Rate Limiter – steering speed limitation ($\pm 3^\circ$); Inertial link – hydraulic drive dynamics.

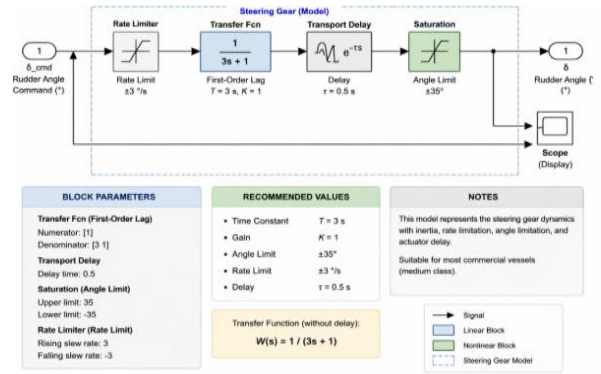


Figure 2. Steering machine model

2.3 Models of Influences

2.3.1 Models of environmental impact (disturbances)

The ship is affected to some extent by wind and wave disturbance caused by weather conditions and sea waves. Models of such disturbance can be represented as the sum of harmonic components (strong sea waves and weak sea waves superimposed on it) and a constant component (wind wear):

$$f(t) = \sum_{i=1}^n A_i \sin(\omega_i t + \varphi_i). \quad (9)$$

where A_i and ω_i are the amplitude and frequency of strong sea waves, respectively; φ_i is an initial phase.

To simulate this disturbance in Simulink, the authors use a Sine Wave block with the following parameters: A is the wave amplitude, f is the frequency (Hz), and φ_i is the initial phase of i component. A sum of several waves of different frequencies (Sine Wave blocks) was also used to simulate a severe storm. The values used to simulate the processes in vessel's automatic course stabilization control system and obtained from the analysis [23] are summarized in Table 2.

Table 2. Sine Wave block parameter values

Component	A (rad)	ω (rad/s)	Phase φ (rad)	Physical meaning
Wave 1	0.06	0.4	0	Long ocean waves
Wave 2	0.04	0.8	0.5	Primary swells
Wave 3	0.03	1.5	1.0	Wind waves
Wave 4	0.02	2.2	1.8	Short waves
Wave 5	0.18	0.25	0.8	Storm waves

2.3.2 Disturbances from the action of an oncoming vessel on course

The disturbance from an oncoming vessel is modeled as a dynamic force dependent on the distance between the vessels. The model for changing the distance between the vessels can be represented as a first-order inertial link:

$$W(s) = \frac{K(d)}{T(d)s + 1}, \quad (10)$$

where $K(d)$ is the gain coefficient, reflecting the sensitivity of the distance change to the control action. $T(d)$ is the time constant, characterizing the inertia of the distance change process. The model determines the nature of the influence, for example, speed change, maneuvering, etc. The parameters of the model for changing the distance between vessels were selected based on a simplified representation of the dynamics of relative motion in the form of a first-order aperiodic link, similar to Nomoto models, widely used in problems of maneuvering and collision avoidance. The values of the gain factors and time constants were determined taking into account the intensity of maneuvering at different distances between vessels based on the analysis [24] and are presented in Table 3.

Table 3. Values of the parameters of the mathematical model "oncoming vessel"

Distance d (m)	$K(d)$	$T(d)$ (s)	Impact Type
0–100	0.8–1.2	5–10	Sharp maneuvering
100–500	0.5–0.8	10–30	Moderate speed changes
500–1000	0.3–0.5	30–60	Smooth control
>1000	0.1–0.3	60–120	Weak impact on the ACS

3 DEVELOPMENT OF NEURAL NETWORK (INTELLIGENT) AUTOMATIC COURSE STABILIZATION CONTROL SYSTEMS

Classic PID controllers are widely used in course stabilization systems due to their simplicity and stability in basic vessel motion modes. However, when the ACS operate in challenging navigation conditions, the effectiveness of PID controllers decreases sharply. This is due to the nonlinearity of the vessel's dynamics, changes in hydrodynamic characteristics, the influence of sea waves, wind gusts, and currents, as well as the need for frequent maneuvers in confined waters.

A promising approach to solving this applied scientific problem is to use a neural network controller in conjunction with a PID controller. In the design solution proposed by the authors (Fig. 3), the neural network analyzes signals from wave, wind, and oncoming vessel sensors and generates a corrective control signal even before a significant course deviation occurs. The PID controller ensures basic stability of the course stabilization system in favorable navigation conditions, and the neural network controller generates additional intelligent control in

complex motion modes and strong wave effects (storm conditions).

The main operating stages of the proposed intelligent ACS (Fig. 3) are as follows:

- Setting the vessel's heading;
- Measuring the vessel's current heading;
- Calculating the control error;
- Generating a control signal by the PID controller;
- Measuring external disturbance parameters using sensor data;
- Transmitting information to the neural network controller;
- Correcting the PID controller control signal using the signal from the neural network controller;
- Steering machine control;
- Correcting the control signal using negative feedback.

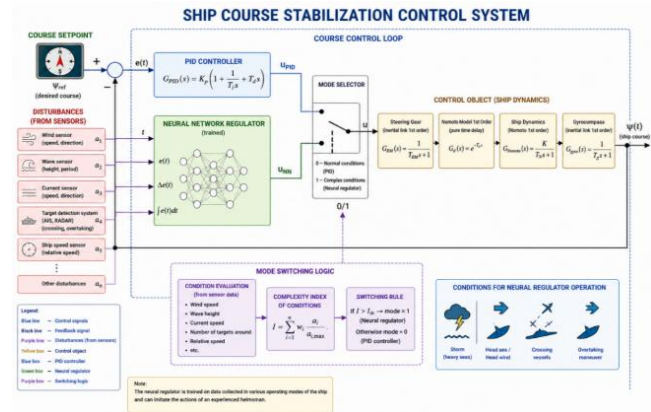


Figure 3. Neural network automatic course stabilization control system (the figure was designed by the authors using the ChatGPT graphical function)

The threshold value of the complex conditions parameter I is the condition for switching on the neural network controller (selector switching). This parameter is determined by the formula

$$I = \sum_{i=1}^n w_i \cdot \frac{a_i}{a_{i \max}}, \quad (11)$$

where a_i is the current value of the parameter (wind, waves, etc.); $a_{i \max}$ is the maximum permissible value of the parameter; w_i is the weighting coefficient (the sum of the weights is 1) that determines the degree of significance, from the perspective of an expert navigator, of the impact of disturbances on the vessel's course.

The parameter value I can vary within the range (0–1), where the value $I < 0.4$ corresponds to quiet operating conditions of the ACS (only the PID controller is active). Values of $0.4 \leq I < 0.8$ correspond to average ACS complexity (the PID controller is active and correction is performed using a filter and an adaptive algorithm (e.g., Ziegler-Nichols, etc.). The range of values $I \geq 0.8$ corresponds to complex navigation conditions (only the neural network controller is active under observation and control of the navigator).

The authors propose a table of controlled parameters and their threshold values with weighting factors from the expert's point of view (Table 4).

Table 4. Values of the parameter for assessing difficult vessel movement conditions

No	Parameter	a	a_{max}	Weight w_i
1	Wind speed (m/s)	a1	20	0,25
2	Wave height (m)	a2	5	0,25
3	Current speed (m/s)	a3	3	0,10
4	Number of targets (AIS)	a4	10	0,25
5	Relative speed (m/s)	a5	15 (passenger ship)	0,15

To simulate the proposed ACS, train the neural network controller, and test its performance, the MATLAB package with built-in tools was used: Simulink (for ACS synthesis and PID controller tuning), Neural Network Toolbox (for designing and training neural networks). The general scheme for testing the intelligent ACS is shown in Fig. 4.

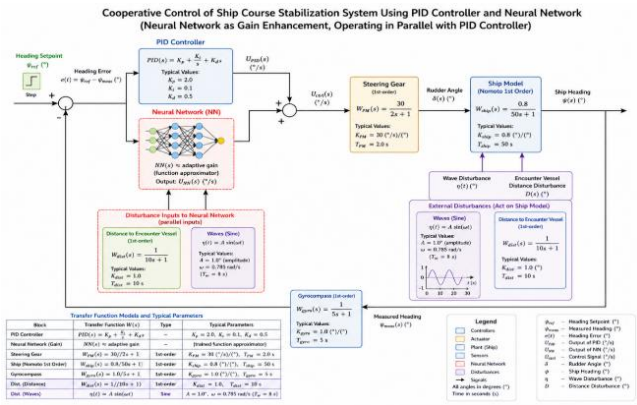


Figure 4. Parametric diagram of an intelligent automatic course stabilization control system (the figure was designed by the authors using the ChatGPT graphical function)

The simulation model of the ACS using a PID controller under the influence of external disturbances (waves: strong, moderate, storm (Table 2) and course distance (oncoming vessel, crossing course, overtaking vessel (Table 3)) is presented in Fig. 5.

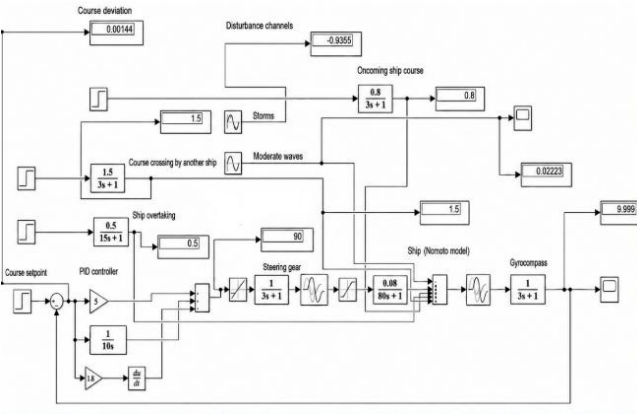


Figure 5. Simulation model of the vessel's automatic course stabilization control system in the Simulink program

Fig. 6 is illustrated the transient process in an ACS with a PID controller under moderate wave conditions and a significant distance from other vessels. The process is aperiodic and meets the required performance criteria. The axes indicate the vessel's target heading (measured in degrees) and time t (measured in seconds). All transient processes considered in the ACS with a PID controller and a neural network controller are also described by these parameters.

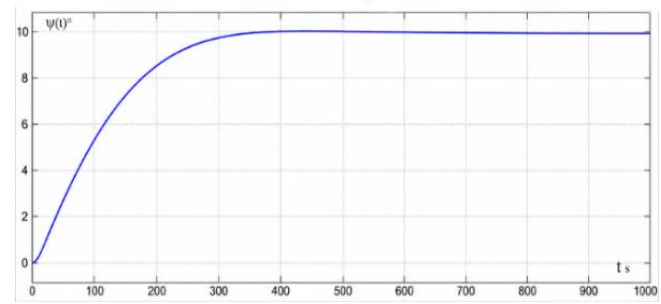


Figure 6. ACS for vessel course stabilization with a PID controller in favorable navigation conditions

The effectiveness of a traditional ACS, as well as an adaptive ACS, was tested using frequency response tuning (Frequency Response Based Tuning). This method analyzes the frequency characteristics of the control object under challenging navigation conditions (such as approaching vessels—changes in transfer function parameters and increasing sea state—changes in amplitude, frequency, and phase). The results of the simulation experiments are presented in Fig.7– Fig.10

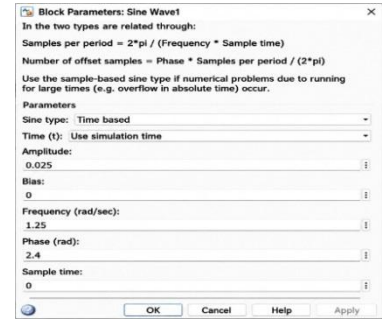


Figure 7. Modeling the influence of different types of waves (Sine Wave signals are summed up along the disturbance channel)

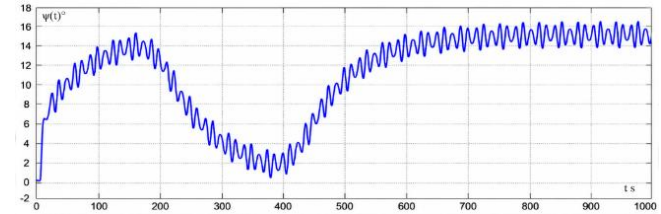


Figure 8 Transitional process of vessel course stabilization: the task is 10 degrees

An analysis of the ACS operation (Fig. 8) revealed significant vessel yaw and significant deviations from the set course of $\pm 10^\circ$. The PID controller is stable but ineffective, as a significant deviation from the set course in the ACS, especially by more than 10° , can create an extremely hazardous navigational situation in severe storm conditions and when vessels are approaching each other. Therefore, the PID controller must be adapted to the new navigational conditions. Fig. 9 illustrates the adaptation process in the interactive MATLAB environment using the built-in PID Autotuner program.

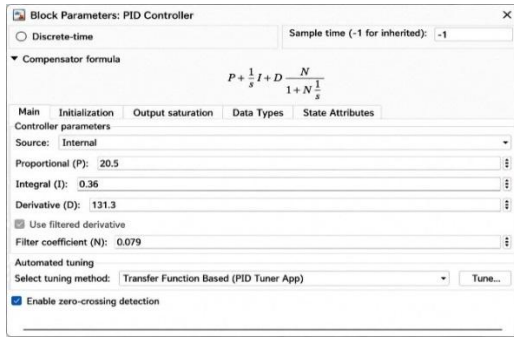


Figure 9. Calculation of adaptive settings in the PID Autotuner block

The online method for adaptive tuning of a PID controller is based on introducing a test signal into the system and calculating the optimal PID controller coefficients using frequency criteria [12]. Analysis of the transient process in the adaptive ACS (Fig. 10) revealed the following parameter values: overshoot, stability, and permissible deviation from course – up to $\pm 5^\circ$, the control time is more than 550 s, which is a limiting value.

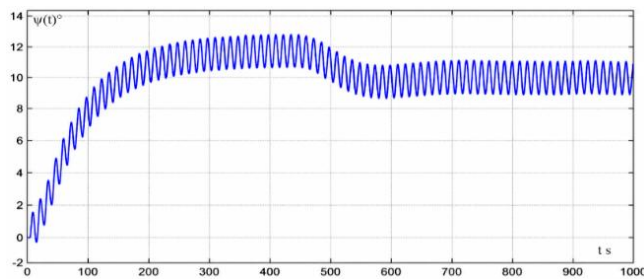


Figure 10. Transient process in the adaptive frequency control system

It should be noted that the introduction of an additional test signal into the course stabilization control system under the influence of significant disturbances, the time spent on calculating and installing new controller coefficients, etc., may lead to a loss of course stability of the vessel and the creation of a dangerous situation for navigation. Thus, training a neural network controller capable of predicting the impact of disturbance parameters and responding promptly to complex navigation conditions is a promising technical solution. Fig. 11 illustrates the process of collecting the training data from control and disturbance channels under the influence of disturbances of various types and adjusting PID controller signals.

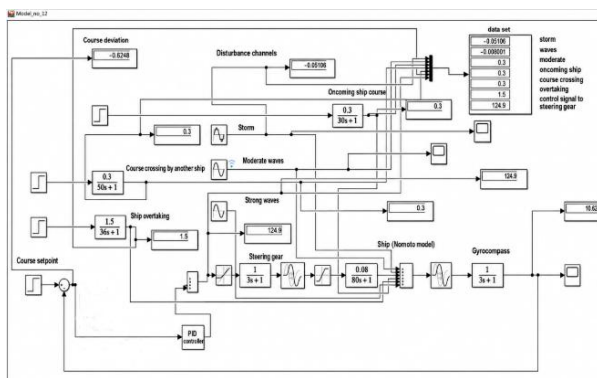


Figure 11. The process of collecting data (on seven channels) for training a neural network

The process of training a neural network on a data sample in the Neural Network Toolbox program is shown in Fig. 12 – Fig. 14.

TO Workspace blocks were used to collect data during simulation experiments. By varying the external disturbance values on the ACS, training samples were obtained in the form of input value arrays of 7×2108 values and output values (control signals) of 1×2108 sizes. This data volume represents a high-quality sample for training the neural network controller (Fig. 12).

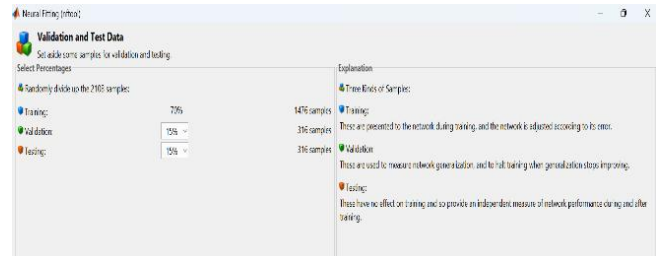


Figure 12 The process of distributing the training sample into training, validation, and test data

It should be noted that it is crucial to control neural network (NN) overfitting. For efficient training, a standard distribution was used:

1. Training: 70% (about 1475 points) - the network uses this data to select weights.
2. Validation: 15% (approximately 316 points) – MATLAB uses this data to check for overfitting. As soon as the validation error stops declining, training automatically stops.
3. Testing: 15% (approximately 316 points) is an "emergency reserve" of data that the network does not see during the training process. This reserve data is necessary for the final assessment of the neural network's training accuracy.

The Levenberg-Marquardt algorithm was used as the neural network training algorithm. This algorithm is a fairly fast and accurate algorithm in MATLAB for networks of moderate size and for conditions where experimental data was obtained from a Simulink simulation (Fig. 13).

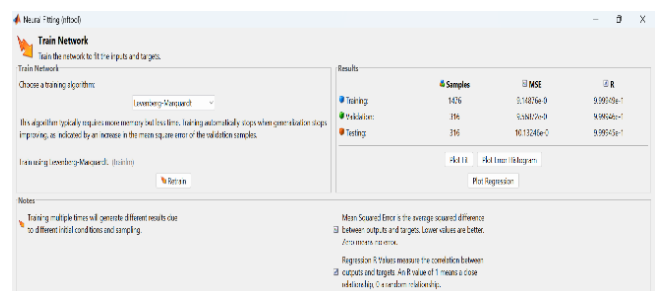


Figure 13. The process of training a neural network using the Levenberg-Marquardt algorithm

A two-layer feedforward network with a 7-15-1 architecture was used to synthesize the neural network controller. The hidden layer contains 15 neurons with a tangent sigmoid activation function (tansig), and the output layer contains one neuron with a linear activation function (purelin).

The histogram of the neural network errors is shown in Figure 14. The histogram shows the neural network error values, with the vast majority of values

having an error close to zero. The graph has a bell-shaped form, reflecting a normal distribution with a peak near zero, indicating high network training quality.

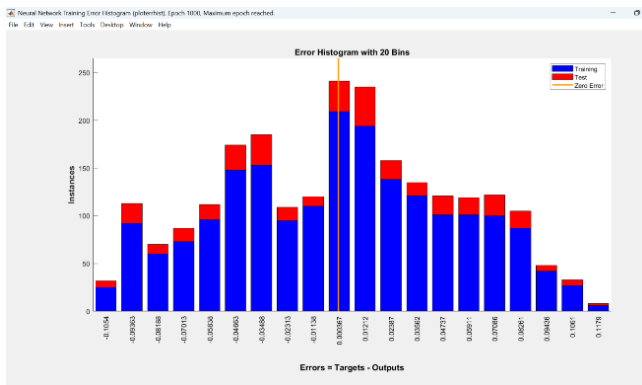


Figure 14. Histogram of neural network errors

Fig. 15 illustrates the testing of the trained neural network for possible software implementation in the controller.

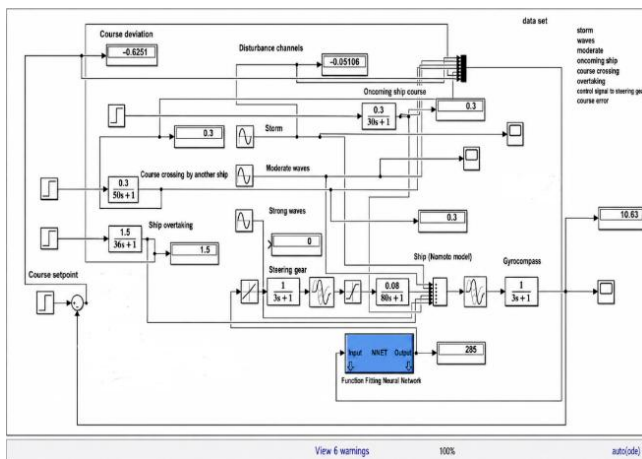


Figure 15. Simulation of a neural network (intelligent) vessel's automatic course stabilization control system under the influence of moderate waves and an average distance to other vessels

The analysis of the transient process in the neural network ACS (Fig. 16) demonstrates the acceptable values of the quality parameters of the transient process: the control time is 200 s and the deviation from the set course is no more than 1° , associated with the dead zone of the controller, necessary to avoid excessive influence on the steering machine.

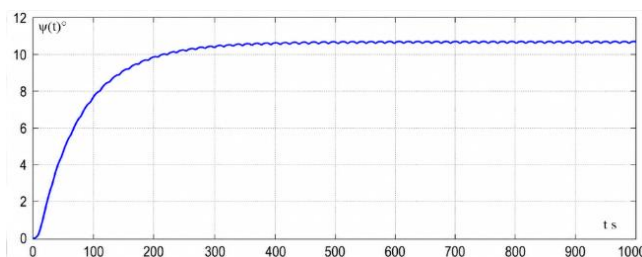


Figure 16. Transition process in the neural network (intelligent) vessel's automatic course stabilization control system under moderately complex navigation conditions

Testing the neural network (intelligent) vessel's automatic course stabilization control system proposed

by the authors for operationally changing the set course in the event of a dangerous approach to another vessel in order to analyse its effectiveness is an important task.

The following problem is posed: a vessel must alter its course to pass another vessel at a distance of two hull lengths, assuming the oncoming vessel takes no action. If the minimum time of closest approach at full speed is 3 minutes before collision, given a vessel 300 meters long and a speed of 20 knots, then after determining the point of collision (POC) on radar, the vessel must turn 20 degrees. Figure 17 illustrates the process of modelling a new task. The transient process in the neural network ACS with a new target course is shown in Figure 18. The quality of the transient process fully satisfies the specified operating conditions of the ACS in terms of deviation and response time.

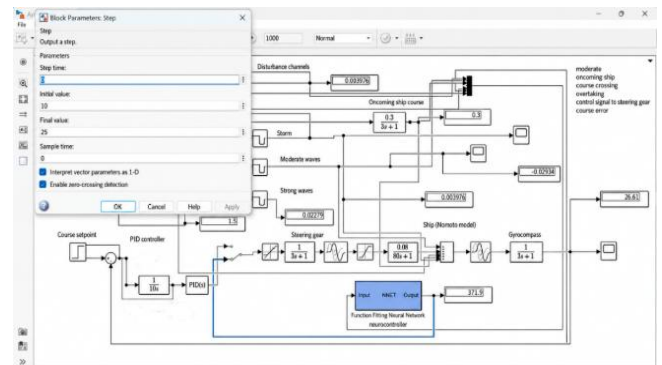


Figure 17. Setting a new course in the Step block - specifies the desired change in the course setting: Step time = 0, Initial value = 10 (initial course) and Final value = 25 (the required turning angle in degrees to avoid a collision)

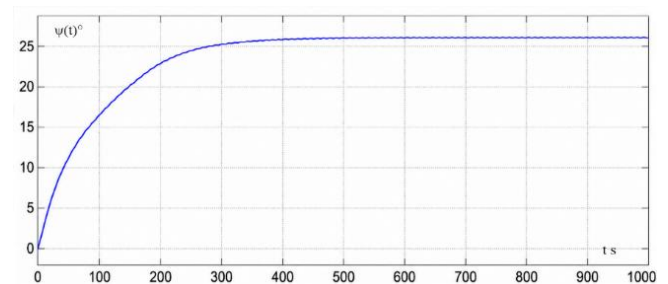


Figure 18. Transition process in the neural network automatic control system for stabilizing a vessel's new course when there is a threat of approaching an oncoming vessel

Existing ship ACS successfully utilize filters to reduce the impact of random disturbances and noise. However, their use in some situations is associated with delays in useful sensor signals, reduced system response time, and the difficulty of adjusting filter parameters. Signal filtering can result in the control system responding to course changes with a significant delay in complex navigational conditions. Therefore, when designing a course-holding system, a compromise is required between noise suppression, speed, and course-holding accuracy. The use of a predictive filter with a neural network, which receives information from a neural network controller for subsequent filtering of the control action, is a promising approach. Adaptive filtering can significantly reduce the load on the steering gear mechanisms and lead to fuel savings. Therefore, a simulation experiment using a low-pass filter and a

neural network controller in combination is relevant. The operation of a Butterworth filter in a neural network-based course-holding system is shown in Fig. 19. The filter parameters that were selected during simulation experiments under the influence of significant wave disturbances are shown in Fig. 20. Fig. 21 illustrates the transient process in the neural network (intelligent) ACS using signal filtering.

It can be concluded that, with the inclusion of an integrated filter (such as a low-pass filter), a neural network (intelligent) vessel's automatic course stabilization control system executes infrequent and smooth adjustments to the rudder position, thereby saving fuel and reducing wear on the steering gear. (Fig. 21). The filter successfully smooths out the transient response with a 100-second delay. Thus, it can be concluded that the synthesis of a neural network controller with a Butterworth filter allows for compensation of vessel yaw and the effects of strong wave oscillations. However, the authors intend to explore optimal methods for synthesizing neural network filters with a predictive function for ship heading stabilization systems in future studies.

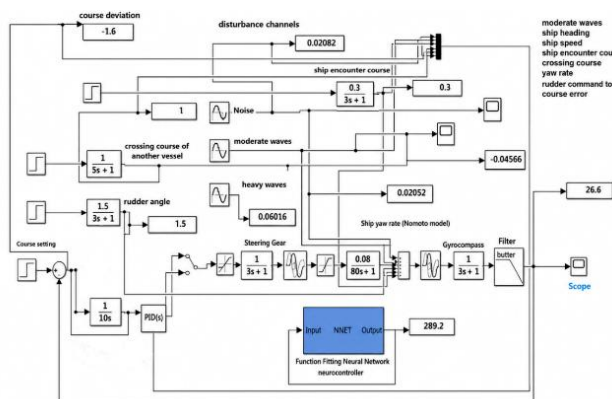


Figure 19. Testing the joint operation of the neural network controller and filter

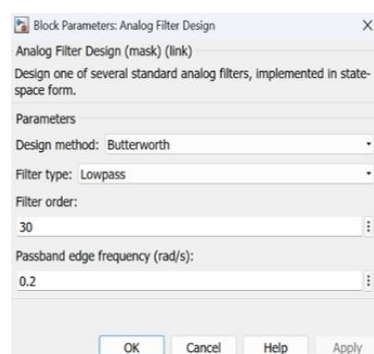


Figure 20. Configuring filter parameters

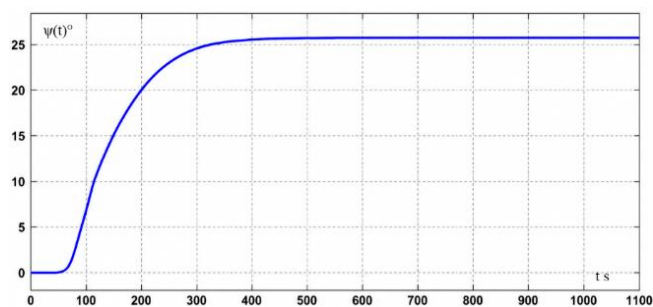


Figure 21. Transition process in a neural network (intelligent) vessel's automatic course stabilization control system using a filter in a navigational environment of medium complexity

Further simulation experiments demonstrated that the developed neural network successfully compensates for external disturbances over a wide range of variations (sea state up to 6 and a head-on course of a vessel traveling at speeds up to 20 knots). Thus, the neural network ACS meets the established requirements and satisfies IMO Resolution A.342(IX) for course-keeping accuracy and transient response quality (Table 5), and does not tolerate deviations greater than $\pm 5^\circ$, even in challenging navigational conditions.

Table 5. Tolerances (engineering standards) for deviation of a vessel from a given course, established by IMO Resolution A.342(IX)

Port / Maneuvering	$\pm 1^\circ \dots \pm 2^\circ$
Open Sea	$\pm 2^\circ \dots \pm 5^\circ$
Heavy Seas	$\pm 5^\circ \dots \pm 10^\circ$
Storm	$\pm 10^\circ \dots \pm 20^\circ$ (briefly)

A computer experiment was conducted to compare a typical adaptation algorithm for a PID controller in a vessel's course stabilization control system (ACS) based on frequency analysis (PID Autotuner program) and the neural network algorithm proposed by the authors. Under rough sea conditions and the presence of oncoming vessels, the controller's target was varied from 1 to 7 degrees. The typical PID controller required adaptation of its parameters, as the initial transient process was unstable. The neural network controller demonstrated superior transient performance and executed the control action without the need to adjust the learning algorithm (Fig. 22). A comparative analysis of the ACS performance indicators is presented in Table 6.

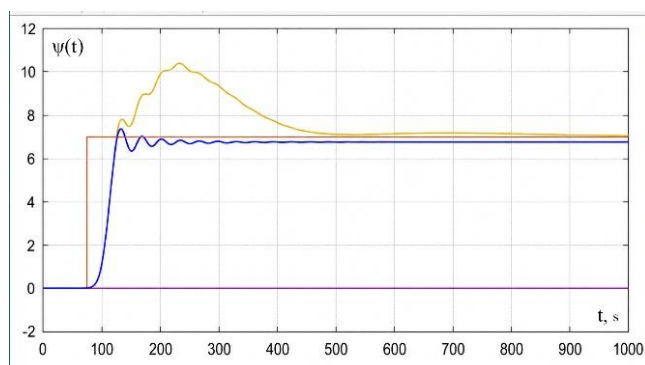


Figure 22. Transient processes of a neural network (blue) and a typical adaptive control system with a PID controller (yellow) for the task channel – orange line

Based on an analysis of Table 6, it can be concluded that under conditions of heavy seas and the need to

accurately maintain the vessel's course among other vessels, the neural network controller provides significantly higher control quality compared to an adaptive PID controller. It reduces overshoot by approximately 6-7 times, shortens settling time by 2-3 times, and ensures safer vessel navigation due to smaller deviations from the set course.

Table 6. Comparative analysis of quality indicators of neural network and typical adaptive control systems with PID controller

Indicator	Neural network controller	Adaptive PID controller
Set Course	7°	7°
Maximum Course Deviation	≈7.5°	≈10.3°
Overshoot	≈7 - 8 %	≈47 %
Rise Time	≈20 - 25 c	≈40 - 50 c
Regulation Time (±5%)	≈120 - 150 c	≈350 - 450 c
Oscillation	Small, quickly fading	Significant
Number of noticeable oscillations	4-6	2-3 large slow oscillations
Static error	Almost absent	Almost absent
Time to change course by 6°, taking into account the permissible deviation	20 c	100 c
Resilience to disturbances	High	Average
Maneuvering safety	High	Below due to large deviations
Time to calculate and set the adaptive parameters of the controller	30 c	45 c

It should be noted that the initial delay of the neural network ACS is due to the time required to calculate the optimal control action in the MATLAB programming environment. When implementing a neural network algorithm in an vessel's ACS, this drawback can be significantly reduced by using specialized hardware to accelerate neural network calculations. In particular, a promising solution is the use of graphics processing units (GPUs), such as the NVIDIA RTX 4060, which enable parallel processing of a large number of operations. Additionally, specialized neural processing units (NPU), such as the NVIDIA Jetson Orin NX, designed for running artificial intelligence algorithms in real time on autonomous systems, can be used. The use of the pointed hardware can significantly reduce the computation time for control actions and improve the performance of the automatic control system of the vessel's course.

4 CONCLUSIONS

Thus, the authors have developed an effective intelligent vessel's automatic course stabilization control system based on the combined use of a classic PID controller and a neural network controller (hybrid architecture). The proposed automated course stabilization control system provides adaptive control depending on the current navigation situation and the level of external disturbances. The developed system implements an algorithm for switching control modes between the PID controller and the neural network controller based on navigation situation assessment parameters varying from 0 to 1.

Under stable navigation conditions, moderate sea conditions, and no risk of collision, a classic PID

controller is used to ensure stable course control. When the navigation situation deteriorates, strong waves or storms occur, or there is a risk of crossing paths or collisions with other vessels, a trained neural network controller is activated, capable of adapting to changing external disturbances. Computer simulations conducted in the MATLAB programming environment confirmed the effectiveness intelligent control system structure, proposed by the authors. Transient analysis of the intelligent ACS confirmed its potential, demonstrating increased stability and adaptability, reduced transient response time, and reduced deviations in vessel heading from the setpoint compared to the frequency-adaptive PID controller used on ships.

The addition of a Butterworth filter to the neural network-based control loop reduced the impact of high-frequency wave disturbances and measurement noise. The filter in the hybrid control system smoothed the control signal and reduced vessel yaw, which could potentially lead to a subsequent reduction in the number of rudder corrections and, consequently, increased steering system reliability.

Computer simulation results showed that the proposed neural network (intelligent) vessel's automatic course stabilization control system provides higher accuracy in vessel heading stabilization in complex navigation conditions and can be further used for both manned and autonomous vessels.

REFERENCES

- [1] Ma G., Li D., Wei Q., Song L. Neural Unilateral Nussbaum Gain Sliding Mode Control for Uncertain Ship Course Keeping with an Unknown Control Direction // Journal of Marine Science and Engineering, 2025. Vol. 13, No. 5. P. 846.
- [2] Wang Y., Johansen T.A., Fossen T.I. Artificial Intelligence Challenges for Autonomous Maritime Systems under Uncertain Environmental Conditions // Journal of Marine Science and Technology, 2026. Vol. 31, No. 1. P. 55-71.
- [3] Pham, D.-A., & Han, S.-H. (2023). Designing a Ship Autopilot System for Operation in a Disturbed Environment Using the Adaptive Neural Fuzzy Inference System. Journal of Marine Science and Engineering, 11(7), 1262, pp. 1-24.
- [4] Zheng, M.; Chen, Q.; Yan, D.; Zhang, Y. (2025). A Comprehensive Review of Ship Automatic Rudder Technology: Development, Challenges, and Prospects. Journal of Marine Science and Engineering, 13(5), 851. <https://doi.org/10.3390/jmse13050851>
- [5] Huang, C., Zhao, Y., Li, B., Zhang, G. (2024). Manual Steering and Robust Adaptive Constrained Control of Ships. Ocean Engineering, 312, Article 119248, pp. 1-19. <https://doi.org/10.1016/j.oceaneng.2024.119248>
- [6] Bertilsson, T. (2022). Adaptive Ship Stabilization: Control of Ship Stabilizing Actuators Using Modified Deep Model Reference Adaptive Control. Master's Thesis No. 2022:28, Chalmers University of Technology, Department of Mechanics and Maritime Sciences, Gothenburg, Sweden, pp. 1-88. <https://hdl.handle.net/20.500.12380/304953>
- [7] Abudu, R., Bridgelall, R. (2024). Autonomous Ships: A Thematic Review. World, 5(2), pp. 276-292. <https://doi.org/10.3390/world5020015>
- [8] Sutton, R.; Taylor, S. D. H.; Roberts, G. N. (1996). Neuro - Fuzzy Techniques Applied to a Ship Autopilot Design. Journal of Navigation, 49(3), pp. 410-430. <https://doi.org/10.1017/S037346330001362>

- [9] Velagic, J.; Vukic, Z.; Omerdic, E. (2003). Adaptive Fuzzy Ship Autopilot for Track-Keeping. *Control Engineering Practice*, 11(4), pp. 433–443. [https://doi.org/10.1016/S0967-0661\(02\)00009-6](https://doi.org/10.1016/S0967-0661(02)00009-6)
- [10] Namazi Rabati, H.; Perera, L.P.C. (2025). Adaptive Neuro - Fuzzy Inference for Predicting Control Inputs in Maritime Autonomous Surface Ships Maneuvers. In: *Innovations in Sustainable Maritime Technology (IMAM 2025)*, Springer, pp. 234–244.
- [11] Nayak, N.; Das, S.R.; Panigrahi, T.K.; et al. (2023). Overshoot Reduction Using Adaptive Neuro-Fuzzy Inference System for an Autonomous Underwater Vehicle. *Mathematics*, 11(8), 1868, pp. 1–18. <https://doi.org/10.3390/math11081868>
- [12] Wang, P.; Pan, M.; Liu, Z.; et al. (2024). Ship Trajectory Prediction in Complex Waterways Based on Transformer and Social Variational Autoencoder (SocialVAE). *Journal of Marine Science and Engineering*, 12(12), 2233. <https://doi.org/10.3390/jmse12122233>
- [13] Zhang, X.; Chen, Y.; Liu, H. (2024). A CNNGRU-MHA method for ship trajectory prediction based on marine fusion data. *Ocean Engineering*, 310, 118701. <https://doi.org/10.1016/j.oceaneng.2024.118701>
- [14] Wu, X.; Chen, J.; Xiong, C.; Liu, D.; et al. (2024). Vessel Trajectory Prediction Method Based on the Time Series Data Fusion Model. *Promet – Traffic & Transportation*, 36(6), 1160–1175. <https://doi.org/10.7307/ptt.v36i6.772>
- [15] Liu, W.; Cao, Y.; Guan, M.; Liu, L. (2024). Research on Ship Trajectory Prediction Method Based on CNN-RGRU-Attention Fusion Model. *IEEE Access*, 12, 63950–63957. <https://doi.org/10.1109/ACCESS.2024.3396475>
- [16] Spadon, G.; Matwin, S.; Pelot, R. (2023). Multi-Path Long-Term Vessel Trajectories Forecasting with Probabilistic Feature Fusion. *arXiv preprint*. <https://arxiv.org/abs/2310.18948>
- [17] Bi, J.; Cheng, H.; Zhang, W.; et al. (2024). Artificial Intelligence in Ship Trajectory Prediction. *Journal of Marine Science and Engineering*, 12(5), 769, pp. 1–26. <https://doi.org/10.3390/jmse12050769>
- [18] Omerdic, E.; Roberts, G. N.; Vukic, Z. (2003). A fuzzy track-keeping autopilot for ship steering. *Journal of Marine Engineering & Technology*, 2(1), pp. 23–35. <https://doi.org/10.1080/20464177.2003.11020163>
- [19] Li, H.; Xing, W.; Yang, Z.; et al. (2024). Deep Bi-Directional Information-Empowered Ship Trajectory Prediction for Maritime Autonomous Surface Ships. *Transportation Research Part E*, 181, 103770. <https://doi.org/10.1016/j.tre.2024.103770>
- [20] Guo, S.; Ma, W. (2026). A Systematic Review of Deep Learning-Based Methods for Ship Trajectory Prediction. *Journal of Marine Science and Engineering*, 14(9), 810, pp. 1–28. <https://doi.org/10.3390/jmse14090810>
- [21] Nomoto, K.; Taguchi, T.; Honda, K.; Hirano, S. (1957). On the Steering Qualities of Ships. *International Shipbuilding Progress*, 4(35), pp. 354–370. <https://doi.org/10.3233/ISP-1957-43504>
- [22] Lu, S.; Wang, B.; Dong, Z.; et al. (2025). Parameter Identification of an Unmanned Surface Vessel Nomoto Model Based on an Improved Extended Kalman Filter. *Applied Sciences*, 15(1), 161, pp. 1–18. <https://doi.org/10.3390/app15010161>
- [23] Bhattacharyya, R. (1978). *Dynamics of Marine Vehicles*. New York, NY: John Wiley & Sons, Inc., Ocean Engineering Series, pp. x–498. ISBN-13: 978-0-471-07206-5.
- [24] Fossen T. I. *Handbook of Marine Craft Hydrodynamics and Motion Control*. — 2nd ed. — Hoboken, NJ : Wiley, 2021. 710 p.