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STOCHASTIC MODELING-BASED ADAPTIVE CONTROL FOR MARITIME DEFENSE IN SIMULATION COMPUTER GAMES

The object of the study is the modeling process of virtual adversary behavior and automated control systems for mine weapons in game-based naval combat scenarios, taking into account uncertainty and incomplete information, particularly in conditions of partial or erroneous functioning of the sensor system. One of the most problematic aspects is ensuring effective decision-making in situations where the sensor system exhibits Type I and Type II errors or its feedback is completely absent due to malfunctions or damage.

The study employs stochastic modeling methods, mathematical expectation estimation for all possible combat scenarios, and adaptive control algorithms that consider the accuracy of the sensor system and the a priori probability of enemy presence.

An adaptive control method for anti-ship defense and a corresponding implementation system have been developed, which includes an adaptive controller capable of performing the core computations in real time to determine optimal control actions for mine weapon deployment.

The results of numerical experiments were obtained for various scenarios: with fixed parameters, variable minefield density, sensor system accuracy changes, and different a priori probabilities of ship appearances. These experiments enabled a comprehensive evaluation of the method's effectiveness. The conducted experiments confirm that the proposed method enables effective control of mine weapons in the presence of Type I and Type II errors with probabilities ranging from 0 to 0.9 during the detection of enemy and neutral ships.

As a result, the proposed solution provides the capability for adaptive control of combat operations even under high uncertainty, enhances the realism of virtual adversary behavior in simulation games, and lays the groundwork for the development of intelligent automatic control systems in naval combat scenarios.

Keywords: *simulation games, maritime defense, mine weapons, automatic control, stochastic modeling, mathematical expectation.*

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1. Introduction

The past decade has witnessed a significant rise in the development and application of computer-based simulation games as tools for education, training, and professional development [1, 2]. High-fidelity simulation environments offer immersive, risk-free platforms where users can practice decision-making, problem-solving, and strategic thinking. Systematic reviews have shown that simulation games enhance cognitive, behavioral, and affective learning outcomes, bridging the gap between theoretical knowledge and real-world application [3, 4]. These virtual contexts also promote critical thinking and scenario analysis in safe, controlled settings. Consequently, simulation games have become indispensable tools across diverse fields such as medicine, business, defense, and engineering, yielding measurable improvements in skills acquisition and decision-making performance [5, 6].

Military-style simulation games encompass a broad spectrum of formats, from real-time strategies (RTS) and tactical shooters to operational-level wargames [7, 8]. In particular, such games as Steel Beasts, Close Combat, and ARMA 3 are designed to promote sophisticated decision-making, team coordination, and situational awareness among players and trainees. These environments simulate real-world constraints like limited visibility, resource management, and dynamic adversary behavior. Empirical studies have demonstrated that participants in such simulations enhance critical cognitive skills, including spatial reasoning, risk assessment, and command judgment, that are directly transferable to professional domains including defense planning and emergency response [9, 10]. Among wargames of simulation genres, naval and maritime warfare games have gained outstanding popularity and academic interest due to their unique combination of technical complexity and strategic depth. In naval simulation games, such as Command: Modern Operations, ARMA 3 (with naval modules), Dangerous Waters (including Sub Command and 688(I) Hunter/Killer), etc., players engage with models of sensor arrays, hydrodynamic behavior, and asset coordination. Moreover, such platforms can be used as research testbeds when equipped with sufficiently effective mathematical and algorithmic support. This enables the validation of control algorithms, sonar tracking methods, and multi-agent coordination strategies in environments where physical experimentation would be impractical or unsafe [11].

Despite significant progress in the visual fidelity of modern war simulations, including high-resolution rendering, dynamic environmental effects, and photorealistic modeling, the strategic and behavioral realism of these platforms often remains limited [12]. Many existing games excel in replicating visual and physical phenomena but fall short in reproducing the complex, multi-layered decision-making processes characteristic of real-world military operations [13–15]. This gap is especially evident in the modeling of adversarial behavior, where scripted

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actions and simplistic rule-based agents fail to capture the adaptive and often unpredictable nature of modern combat. As a result, there is a growing consensus in both the academic and game development communities regarding the need to enhance the algorithmic backbone of such simulations. Specifically, the integration of advanced control strategies, probabilistic models, and decision-making algorithms inspired by current naval doctrines and emerging maritime threats is essential for creating more authentic and instructive scenarios. This direction not only enhances the educational and analytical utility of war games but also positions them as viable testbeds for tactical innovation and operational research.

For instance, in [12], a verification-based method for improving the accuracy of artillery fire was proposed, enabling enhanced realism and refinement of the artillery mechanics within the ARMA 3 simulation environment. Similarly, the study presented in [16] developed a mathematical model for simulating the operations of a virtual artillery unit. This model accounts for tactical requirements such as the relocation of firing positions, aimed at increasing operational efficiency while reducing the likelihood of detection by hostile forces. Regarding naval battle scenarios in digital simulations, works [17, 18] introduce various methods and models designed to counter amphibious assault vessels in both deep and shallow-water terrains. These approaches are intended to simulate effective coastal defense during amphibious operations through the deployment of artillery systems. Notably, the methods employed in these studies are grounded in Markov chains and other stochastic modeling techniques, which offer robust solutions for managing combat units under resource-constrained conditions. However, the challenge of developing effective automatic control algorithms for realistically simulating adversary behavior in scenarios involving remotely operated naval mine systems for anti-ship defense of maritime areas remains unresolved. Current military practice underscores the continued relevance of naval mines as a cost-effective and impactful tool in maritime warfare for implementing maritime area denial operations designed to prevent amphibious assaults and disrupt the execution of hostile naval missions [19–21].

Moreover, enhancing the realism of simulated combat scenarios necessitates that the automatic control of naval mine weaponry, particularly when modeling adversarial behavior, be grounded in comprehensive a priori information. This control must dynamically respond to the detection of vessel movements, which may include hostile, allied, or neutral ships. Importantly, such a priori information is not static; it evolves significantly in accordance with the operational context within the maritime theater. Additionally, the detection mechanisms employed for ship passage recognition are inherently prone to classification errors, including both false positives (Type I errors) and false negatives (Type II errors). These uncertainties collectively underscore the imperative for the development of adaptive control strategies that can account for shifting operational conditions and imperfect sensor inputs.

Accordingly, *the aim of research* is to develop a method for adaptive automatic control of anti-ship defense in maritime domains using naval mine systems, underpinned by stochastic modeling techniques, for implementation in simulation-based computer wargames.

To achieve this aim, the following objectives are accomplished:

– the formulation of a stepwise method for adaptive control of mine-based water area defense;
– the design of a functional architecture for an adaptive automatic control system implementing the proposed approach;
– the execution of a series of computational experiments to validate and evaluate the effectiveness of the developed method.

2. Materials and Methods

The object of research is the process of virtual adversary behavior and automated control systems for mine weapons in game-based naval combat scenarios, taking into account uncertainty and incomplete information, particularly in conditions of partial or erroneous functioning of the sensor system.

The following scientific methods were employed in the study: stochastic modeling techniques to investigate all possible combat scenario states. Adaptive control algorithms were used to account for sensor accuracy and a priori enemy presence probabilities. The Bayesian approach was applied for decision-making under incomplete information. Simulation modeling was conducted to evaluate the effectiveness of various control scenarios.

Let's consider the fundamental aspects of automatic control for anti-ship defense using naval mines. This is especially relevant in simulating adversarial behavior in computer-based war games. For the preliminary detection of hostile vessels, a specialized sensor system can be employed. One suitable option is a system with a branched hierarchical architecture, such as the one proposed in [22]. In the course of identifying naval targets using such a sensor network, three primary operational scenarios may arise:

1) the passage of enemy warships;
2) the transit of non-hostile vessels, including own fleet units, allied or neutral ships, and civilian maritime traffic;
3) the complete absence of any vessels within the monitored area.

To determine the appropriate control actions following the reception of specific signals from the sensor system, it is also essential to incorporate information about the prior probabilities P_{prior1}, P_{prior2} and P_{prior3} associated with the possible states described above. These prior probabilities are established in advance based on acquired intelligence data and expert knowledge, taking into account the current operational environment and a range of other external factors (in this case, in the game these data are set in advance by the designer).

For example, the prior probabilities of establishing the above states in a particular case may have the following values: $P_{\text{prior1}} = 0.3$; $P_{\text{prior2}} = 0.2$; $P_{\text{prior3}} = 0.5$.

During the preliminary detection of hostile naval vessels, the sensor system is capable of identifying and correctly classifying the corresponding operational states with certain probabilities. Moreover, the detection process is inherently prone to statistical Type I and Type II errors. The reliability of event classification is influenced by the precision of the sensor system, as well as by a variety of external and operational factors.

Correspondingly, the output signal of the sensor system u_{SS}, in response to one of the three possible detection outcomes, can assume the following discrete values:

1) passage of enemy ships $u_{SS} = u_{ES}$;
2) passage of other vessels (including friendly, allied, neutral, or civilian) $u_{SS} = u_{NS}$;
3) absence of any vessels $u_{SS} = 0$.

For instance, the probabilities associated with accurate detection, as well as the likelihood of Type I and Type II errors for the classification of the aforementioned events under a given scenario, may be represented by the values provided in Table 1.

As illustrated in Table 1, various types of Type I and Type II errors may arise during the detection of environmental states. Specifically, in the first column, the Type II errors with probabilities P_{21} and P_{31} can lead to critical operational consequences. These scenarios correspond to the failure to identify hostile vessels, thereby allowing enemy ships to proceed unimpeded with their assigned missions, such as amphibious landings or delivering fire strikes on coastal infrastructure. Conversely, a Type II error in the second column, represented by the probability P_{32}, does not result in adverse outcomes. In this case, both the actual and erroneously interpreted states imply the absence of enemy forces, and no countermeasures are activated. As a result, non-hostile vessels, whether friendly, allied, neutral, or civilian, are safely allowed to transit the monitored maritime area without unnecessary intervention.

Table 1

Probabilities of correct detection and occurrence of Type I and Type II errors

A state determined by a sensory system	Real state		
	Passage of enemy ships	Passage of other vessels	Absence of any vessels
$u_{SS} = u_{ES}$ (passage of enemy ships)	$P_{11} = 0.9$ (correct detection)	$P_{12} = 0.09$ (Type I error)	$P_{13} = 0.01$ (Type I error)
$u_{SS} = u_{NS}$ (passage of other vessels)	$P_{21} = 0.09$ (Type II error)	$P_{22} = 0.9$ (correct detection)	$P_{23} = 0.01$ (Type I error)
$u_{SS} = 0$ (absence of any vessels)	$P_{31} = 0.01$ (Type II error)	$P_{32} = 0.01$ (Type II error)	$P_{33} = 0.98$ (correct detection)

In turn, a Type I error with probability P_{12}, as presented in the second column, may lead to substantial or even critical consequences. In this scenario, the deployment of countermeasures would erroneously target non-hostile vessels, such as allied, neutral, or civilian ships, resulting in their potential damage or destruction. Moreover, such misclassification would cause the unnecessary expenditure of valuable strike assets, particularly anti-ship naval mines, which otherwise could have been reserved for engaging actual enemy targets. In contrast, Type I errors associated with probabilities P_{13} and P_{23} in the third column do not entail severe operational repercussions. A misjudgment corresponding to P_{13} may merely result in the premature or ineffective activation of weapon systems, leading to the loss of a munition without inflicting collateral damage. Similarly, the occurrence of an error with probability P_{23} entails no tangible loss or unintended consequences, as no hostile or friendly vessels are present, and the response triggered has no real-world effect.

Subsequently, after the sensor system completes the detection process and identifies one of the possible environmental states, the identified state may not always reflect the actual situation. Due to possible classification errors, the true state may differ and occurs with a posterior probability denoted as P_{postji}. This posterior probability can be rigorously computed using Bayes' theorem, as expressed in equation [23, 24]

$$P_{postji} = \frac{P_{priori} P_{ji}}{\sum_{i=1}^{3} P_{priori} P_{ji}}, \tag{1}$$

where i – the real state number ($i = 1, ..., 3$); j – the state number determined by the sensor system during detection ($j = 1, ..., 3$); P_{ji} – the probability of correct detection or occurrence of errors from Table 1.

For example, when detecting the passage of enemy ships by a sensor system, the posterior probability P_{post11} of the actual passage of these ships will be calculated by formula

$$P_{post11} = \frac{P_{prior1} P_{11}}{P_{prior1} P_{11} + P_{prior2} P_{12} + P_{prior3} P_{13}}. \tag{2}$$

Thus, Table 2 presents the calculated values of the posterior probabilities P_{postji}, which represent the likelihood of the actual occurrence of specific environmental states. These values were derived using equation (1), based on the conditional probabilities P_{ji} provided in Table 1, along with the previously defined prior probabilities corresponding to the passage of enemy ships, other non-hostile vessels, or the absence of maritime activity, respectively: $P_{prior1} = 0.3$; $P_{prior2} = 0.2$; $P_{prior3} = 0.5$.

When naval mines deployed within a maritime area are used as the primary means of engagement in computer-based war games, the automatic control system responsible for anti-ship defense operations can generate a control signal u_{CS} to initiate mine activation upon the detection of enemy vessels. This control signal may assume one of two principal values:

1) $u_{CS} = u_{ASM}$, corresponding to the activated (armed) state of the mine system;

2) $u_{CS} = 0$, corresponding to a temporary transition to a non-active (standby) state.

Accordingly, at the target detection stage, based on the output signal u_{SS} from the sensor subsystem, indicating one of the detected environmental states ($u_{SS} = u_{ES}$; $u_{SS} = u_{NS}$; $u_{SS} = 0$), the automatic control system for anti-ship defense that simulates enemy behavior may generate one of the above control actions: either $u_{CS} = u_{ASM}$ or $u_{CS} = 0$.

Given that the accuracy of detecting the aforementioned environmental states through the sensor system is not absolute, there are non-negligible probabilities of both Type I and Type II errors. As a result, using a conventional direct control algorithm for mines activation (activation upon detection of enemy ships and deactivation in the absence of threats) is likely to demonstrate limited effectiveness. To significantly enhance the performance of anti-ship defense control and increase the realism of virtual adversary behavior, it is advisable to develop an adaptive automatic control method. This approach helps prevent the opposing force from accomplishing its operational objectives while also minimizing the risk of erroneously engaging neutral or non-hostile vessels. Such a method should account for available a priori information, the reliability of the sensor system, and the probabilistic nature of detection errors of both the first and second types.

To evaluate the efficiency of the automatic control process for maritime area defense, the potential operational scenarios and the associated probabilities of their occurrence were analyzed for each of the three detected environmental states ($u_{SS} = u_{ES}$; $u_{SS} = u_{NS}$; $u_{SS} = 0$), in conjunction with the formation of either of the two possible control actions ($u_{CS} = u_{ASM}$; $u_{CS} = 0$).

Table 3 presents the probabilities corresponding to all feasible scenarios resulting from the execution of each control action. Specifically, when sea mines are activated ($u_{CS} = u_{ASM}$) and enemy vessels are present ($u_{SS} = u_{ES}$), two principal outcomes may occur depending on mine deployment density. First, the enemy vessels may be successfully destroyed, preventing them from completing their mission (e. g., amphibious landing or offensive operation). Second, the enemy fleet may pass through undisturbed and later fulfill its operational objectives. Analogous outcomes may also arise in the case of non-hostile vessels traversing the area, with scenarios ranging from accidental destruction to safe passage, again contingent upon the intensity of the minefield. Moreover, when the control system initiates mine activation in the absence of any vessels ($u_{SS} = 0$), there remains a small but non-negligible probability of unintended detonation due to environmental influences such as adverse weather conditions or other stochastic external factors.

Table 2

A posteriori probabilities of the real occurrence of certain states in the event of preliminary detection of enemy ships

Sensory system response	Probabilities of actual occurrence of states and errors		
	Passage of enemy ships	Passage of other vessels	Absence of any vessels
$u_{SS} = u_{ES}$ (detecting the passage of enemy ships)	$P_{post11} = 0.922$ (correct detection)	$P_{post12} = 0.061$ (Type I error)	$P_{post13} = 0.017$ (Type I error)
$u_{SS} = u_{NS}$ (detecting the passage of other vessels)	$P_{post21} = 0.127$ (Type II error)	$P_{post22} = 0.849$ (correct detection)	$P_{post23} = 0.024$ (Type I error)
$u_{SS} = 0$ (detecting the absence of any vessels)	$P_{post31} = 0.006$ (Type II error)	$P_{post32} = 0.004$ (Type II error)	$P_{post33} = 0.99$ (correct detection)

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Table 3

Probabilities of occurrence of possible scenarios when detecting the passage of enemy ships

Control signal of the water area defense control system	A state determined by a sensory system					
	Passage of enemy ships		Passage of other vessels		Absence of any vessels	
	Possible scenarios					
$u_{CS} = u_{ASM}$ (mines activation)	Destruction of enemy ships and disruption of the operation	Safe passage of enemy ships and execution of the operation	Destruction of other vessels	Safe passage of other vessels	Accidental detonation of mines	No detonation of mines
	P_{AS1}	P_{AS2}	P_{AS3}	P_{AS4}	P_{AS5}	P_{AS6}
$u_{CS} = 0$ (transferring mines into a non-active state)	Safe passage of enemy ships and execution of the operation		Safe passage of other vessels		No detonation of mines	
	P_{NAS1}		P_{NAS2}		P_{NAS3}	

To calculate the probabilities of the occurrence of scenarios when mines P_{AS1}, P_{AS2}, P_{AS3}, P_{AS4}, P_{AS5}, P_{AS6} are activated and when they are turned into an non-active state P_{NAS1}, P_{NAS2}, P_{NAS3} for each of the three detected states (passage of enemy ships, passage of other vessels, absence of any vessels), it is advisable to use the formulas presented in Table 4.

In Table 4, the following notations are adopted: P_{ESD} is the probability of destruction of enemy ships and disruption of the operation; P_{NSD} is the probability of destruction of other vessels; P_{MRD} is the probability of accidental mines detonation. In turn, the probabilities P_{ESD} and P_{NSD} depend on the density of mines placement in the water area ρ_m. To simplify the calculations, the following exponential dependence can be adopted for calculating the values of P_{ESD} and P_{NSD}

$$P_{ESD} = P_{NSD} = 1 - e^{-\frac{k_e \rho_m}{\rho_{mmax}}}, \tag{3}$$

where ρ_{mmax} denotes the maximum attainable mines density within the maritime area, and k_e is the mining efficiency coefficient, which reflects the effectiveness of mines deployment depending on the spatial configuration and ordering of mines across the protected water zone.

Accordingly, the current mine density ρ_m may be computed from relationship

$$\rho_m = \frac{n}{S_{wa}}, \tag{4}$$

where n denotes the total number of mines deployed, and S_{wa} represents the surface area of the maritime zone.

Moreover, the probability of accidental mine detonation P_{MRD} is parameterized using empirical statistical data.

Moreover, one must consider the potential for sensor-system malfunctions, intermittent failures, or temporary loss of communication during operation, which may result in a complete absence of feedback. Under such conditions, it is appropriate to estimate the probabilities P_{AS1}, P_{AS2}, P_{AS3}, P_{AS4}, P_{AS5}, P_{AS6} and P_{NAS1}, P_{NAS2}, P_{NAS3} by relying on the prior probabilities of the respective environmental states, P_{prior1}, P_{prior2} and P_{prior3} as detailed in Table 5.

To evaluate the potential consequences of the scenarios outlined in Table 3 within the framework of automatic anti-ship defense control using naval mines, it is advisable to introduce a set of evaluative (cost or utility) functions that reflect the desirability or detriment of each outcome (Table 6). These functions enable a quantitative assessment of control decisions in terms of operational effectiveness and risk.

Table 4

Computation of scenario probabilities for mine activation ($u_{CS} = u_{ASM}$) and deactivation ($u_{CS} = 0$)

Control signal of the water area defense control system	Sensory system response		
	Detecting the passage of enemy ships ($u_{SS} = u_{ES}$)	Detecting the passage of other vessels ($u_{SS} = u_{NS}$)	Detecting the absence of any vessels ($u_{SS} = 0$)
$u_{CS} = u_{ASM}$ (mines activation)	$P_{AS1} = P_{post11}P_{ESD}$	$P_{AS1} = P_{post21}P_{ESD}$	$P_{AS1} = P_{post31}P_{ESD}$
	$P_{AS2} = P_{post11}(1 - P_{ESD})$	$P_{AS2} = P_{post21}(1 - P_{ESD})$	$P_{AS2} = P_{post31}(1 - P_{ESD})$
	$P_{AS3} = P_{post12}P_{NSD}$	$P_{AS3} = P_{post22}P_{NSD}$	$P_{AS3} = P_{post32}P_{NSD}$
	$P_{AS4} = P_{post12}(1 - P_{NSD})$	$P_{AS4} = P_{post22}(1 - P_{NSD})$	$P_{AS4} = P_{post32}(1 - P_{NSD})$
	$P_{AS5} = P_{post13}P_{MRD}$	$P_{AS5} = P_{post23}P_{MRD}$	$P_{AS5} = P_{post33}P_{MRD}$
	$P_{AS6} = P_{post13}(1 - P_{MRD})$	$P_{AS6} = P_{post23}(1 - P_{MRD})$	$P_{AS6} = P_{post33}(1 - P_{MRD})$
$u_{CS} = 0$ (transferring mines into a non-active state)	$P_{NAS1} = P_{post11}$	$P_{NAS1} = P_{post21}$	$P_{NAS1} = P_{post31}$
	$P_{NAS2} = P_{post12}$	$P_{NAS2} = P_{post22}$	$P_{NAS2} = P_{post32}$
	$P_{NAS3} = P_{post13}$	$P_{NAS3} = P_{post23}$	$P_{NAS3} = P_{post33}$

Table 5

Computation of scenario probabilities for mine activation ($u_{CS} = u_{ASM}$) and deactivation ($u_{CS} = 0$) in the absence of sensory system response

Control signal of the water area defense control system	Sensory system response is absent
$u_{CS} = u_{ASM}$ (mines activation)	$P_{AS1} = P_{prior1}P_{ESD}$
	$P_{AS2} = P_{prior1}(1 - P_{ESD})$
	$P_{AS3} = P_{prior2}P_{NSD}$
	$P_{AS4} = P_{prior2}(1 - P_{NSD})$
	$P_{AS5} = P_{prior3}P_{MRD}$
	$P_{AS6} = P_{prior3}(1 - P_{MRD})$
$u_{CS} = 0$ (transferring mines into a non-active state)	$P_{NAS1} = P_{prior1}$
	$P_{NAS2} = P_{prior2}$
	$P_{NAS3} = P_{prior3}$

Table 6

Evaluative functions of possible scenarios for mines activation ($u_{CS} = u_{ASM}$) and deactivation ($u_{CS} = 0$)

<table>
<tr><td rowspan="3">Control signal of the water area defense control system</td><td colspan="6">Real state</td></tr>
<tr><td colspan="2">Passage of enemy ships</td><td colspan="2">Passage of other vessels</td><td colspan="2">Absence of any vessels</td></tr>
<tr><td colspan="6">Possible scenarios</td></tr>
<tr><td rowspan="2">$u_{CS} = u_{ASM}$ (mines activation)</td><td>Destruction of enemy ships and disruption of the operation</td><td>Safe passage of enemy ships and execution of the operation</td><td>Destruction of other vessels</td><td>Safe passage of other vessels</td><td>Accidental detonation of mines</td><td>No detonation of mines</td></tr>
<tr><td>J_{AS1}</td><td>J_{AS2}</td><td>J_{AS3}</td><td>J_{AS4}</td><td>J_{AS5}</td><td>J_{AS6}</td></tr>
<tr><td rowspan="2">$u_{CS} = 0$ (transferring mines into a non-active state)</td><td colspan="2">Safe passage of enemy ships and execution of the operation</td><td colspan="2">Safe passage of other vessels</td><td colspan="2">No detonation of mines</td></tr>
<tr><td colspan="2">J_{NAS1}</td><td colspan="2">J_{NAS2}</td><td colspan="2">J_{NAS3}</td></tr>
</table>

Accordingly, the evaluative functions presented in Table 6, namely, J_{AS1}, J_{AS2}, J_{AS3}, J_{AS4}, J_{AS5}, J_{AS6} for mines activation, and J_{NAS1}, J_{NAS2}, J_{NAS3} for deactivation, should be calculated using the corresponding expressions defined by equations (5)–(13). These formulations provide a structured basis for quantifying the effectiveness and consequences of automated control decisions in naval mine deployment scenarios:

$$J_{AS1} = \sum_{i=1}^{m} \sigma_{spi} - \sum_{i=1}^{m} \sigma_{m} n_i,\ i = 1,...,m; \tag{5}$$

$$J_{AS2} = -\sum_{i=1}^{m} \sigma_{sdi},\ i = 1,...,m; \tag{6}$$

$$J_{AS3} = -\sum_{j=1}^{l} \sigma_{nsj} - \sum_{j=1}^{l} \sigma_{m} n_j,\ j = 1,...,l; \tag{7}$$

$$J_{AS4} = 0; \tag{8}$$

$$J_{AS5} = -n\sigma_{m}; \tag{9}$$

$$J_{AS6} = 0; \tag{10}$$

$$J_{NAS1} = -\sum_{i=1}^{m} \sigma_{sdi},\ i = 1,...,m; \tag{11}$$

$$J_{NAS2} = 0; \tag{12}$$

$$J_{NAS3} = 0, \tag{13}$$

where σ_{spi} – notional cost associated with the destruction of the i-th enemy vessel and the consequent disruption of its assigned mission; σ_{sdi} – conditional cost of damage incurred due to the successful execution of the i-th enemy vessel's mission in the event of its safe passage through the maritime area; m – total number of enemy ships involved in the operation; σ_{nsj} – notional damage cost associated with the destruction of the j-th non-hostile vessel; l – number of such neutral or friendly ships that may traverse the area in question; σ_m – notional unit cost of a single naval mine.

In turn, in equation (5), the required number of naval mines n_i for the neutralization of the i-th enemy ship can be estimated based on the data presented in [25], by converting the number of missiles typically engaged into an equivalent quantity of mines. This conversion is performed by equating the total explosive energy output, taking into account both the aggregate warhead mass and the specific type of explosive used. Similarly, the number of mines n_j required to destroy the j-th neutral vessel can be determined by adjusting for its displacement tonnage using an analogous equivalence approach.

To evaluate the overall effectiveness of the automatic control process for maritime anti-ship defense involving the deployment of naval mines at the stage of enemy ship detection, it is necessary to determine appropriate control actions. These actions should respond to the detection of one of the previously defined environmental states (enemy ship passage, passage of non-hostile vessels, or absence of any vessels) or account for cases of missing sensor feedback. To achieve this, it is advisable to compute the mathematical expectation based on the data presented in Tables 3 and 6 [26, 27]. Accordingly, the mathematical expectation associated with each of the two possible control actions ($u_{CS} = u_{ASM}$; $u_{CS} = 0$) is calculated as the sum of the products of the corresponding scenario probabilities and their associated evaluation functions. Specifically, the values of mathematical expectation μ_{ASM} and μ_0 for the control actions $u_{CS} = u_{ASM}$ and $u_{CS} = 0$ respectively, are determined using expressions:

$$\mu_{ASM} = \sum_{i=1}^{6} P_{ASi} J_{ASi}; \tag{14}$$

$$\mu_0 = \sum_{i=1}^{3} P_{NASi} J_{NASi}. \tag{15}$$

Accordingly, for each of the three previously identified environmental states, or in the absence of any response from the sensory system, the most effective control action u_{CSbest} is the one that yields the highest computed value of the mathematical expectation μ

$$u_{CSbest} = \arg\max \mu(u_{CS}). \tag{16}$$

This selection criterion ensures optimal performance of the autonomous anti-ship defense system based on probabilistic assessments of the expected outcomes.

3. Results and Discussion

Based on the aforementioned considerations, the key steps of the proposed adaptive automatic control method for anti-ship defense of a maritime area using naval mines was outlined.

Step 1. Obtaining of initial data. At this stage, the system acquires input parameters including the a priori probabilities P_{prior1}, P_{prior2} and P_{prior3} corresponding to the possible environmental states – enemy ship passage, neutral vessel passage, or absence of any vessels. Additionally, the conditional probabilities P_j (Table 1) reflecting the accuracy of state detection and the likelihood of Type I and Type II errors are obtained. The system also collects data necessary for the subsequent computation of scenario probabilities P_{ESD}, P_{NSD}, P_{MRD} as well as the evaluative functions J_{AS1}, J_{AS2}, J_{AS3}, J_{AS4}, J_{AS5}, J_{AS6} and J_{NAS1}, J_{NAS2}, J_{NAS3}. Specifically, this includes: the current mine deployment density ρ_m; the expected number m of enemy ships involved in an operation; the number l of neutral ships potentially traversing the area; the conditional cost values σ_{spi}, σ_{sdi}, σ_{nsj} and σ_m, ($i = 1, ..., m$; $j = 1, ..., l$). The minefield density ρ_m, in turn, can be computed using expression (4).

Step 2. Acquisition of sensor system response. At this stage, the system retrieves response from the sensor subsystem regarding the detection of one of the possible environmental states: passage of enemy ships, passage of other non-hostile vessels, or absence of any maritime activity. If a specific state is successfully detected, the procedure proceeds to *Step 3.*

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In the event that the sensor system fails to respond (due to damage, malfunction, or temporary communication loss) the method proceeds directly to *Step 4*.

Step 3. Computation of posterior probabilities. In this step, for the environmental state detected by the sensor system, the corresponding posterior probabilities P_{postji} are calculated using Bayes' theorem, in accordance with expression (1). These posterior estimates allow for probabilistic refinement of the system's situational awareness based on prior knowledge and newly received sensor data.

Step 4. Estimation of scenarios occurrence probabilities. At this stage, the probabilities of potential scenarios developments are calculated for both mines activation and deactivation. Specifically, the probabilities P_{AS1}, P_{AS2}, P_{AS3}, P_{AS4}, P_{AS5}, P_{AS6} (for mines activation) and P_{NAS1}, P_{NAS2}, P_{NAS3} (for deactivated state of mines) are evaluated based on the environmental state identified in *Step 2*, namely, the passage of enemy ships, the transit of other non-hostile vessels, or the absence of maritime traffic, as presented in Table 3. If one of the three possible states was successfully detected at *Step 2*, the scenarios probabilities are computed using the corresponding formulas outlined in Table 4. In contrast, if the sensor system provided no response, the estimation is performed according to the relations specified in Table 5. In both cases, the probabilities P_{ESD} and P_{NSD} are determined in accordance with equation (3), while the probability of random mines detonation P_{MRD} is set based on empirical statistical data.

Step 5. Computation of evaluation functions values. At this stage, the values of the evaluation functions associated with mine activation J_{AS1}, J_{AS2}, J_{AS3}, J_{AS4}, J_{AS5}, J_{AS6} and transferring mines to a temporarily inactive state J_{NAS1}, J_{NAS2}, J_{NAS3} (Table 6) are computed. These evaluations are based on the initial data obtained at *Step 1* and are determined using the corresponding formulas (5)–(13).

Step 6. Computation of mathematical expectations values. In this step, the mathematical expectations μ_{ASM} and μ_0 are calculated for the two possible control actions $u_{CS} = u_{ASM}$ and $u_{CS} = 0$, using the equations (14) and (15), respectively.

Step 7. Determination of the most effective control action. The most effective control action u_{CSbest} for the currently detected state is determined based on expression (16), by selecting the option associated with the greater value of the mathematical expectation μ, among the two values μ_{ASM} and μ_0 calculated in *Step 6*.

Step 8. Formation of the most effective control action. At this stage, the control action ($u_{CS} = u_{ASM}$ or $u_{CS} = 0$) that was determined in the previous step is formed.

To implement the above method, the adaptive automatic control system for maritime anti-ship defense must have the structure shown in Fig. 1. In turn, the following notations are adopted in Fig. 1:

SD – setting device;

PPCU – posterior probability calculation unit;

UPCSO – unit for probability calculation of scenarios occurrence;

EFCU – evaluation functions calculation unit;

MECU – mathematical expectation calculation unit;

CSCU – control signal calculation unit;

CSFU – control signal forming unit;

MW – remote-controlled mine weapon;

u_A – activation signal of the anti-ship defense control system, coming from the system operator;

u_{SD} – output signal of the setting device corresponding to the activated state of the system;

u_{SS} – sensor system output signal;

u_{CS} – mine weapon control signal;

u_{CSbest} – most effective control signal determined by the CSCU;

$\mathbf{Y}_{NB}$ – vector of parameters (initial data) that are previously entered by the operator into the knowledge base;

$\mathbf{Y}_{PP}$ – vector of parameters transmitted from the knowledge base to the PPCU to calculate the current values of posterior probabilities;

$\mathbf{Y}_{EF}$ – vector of parameters transferred from the knowledge base to the EFCU to calculate the current values of the evaluation functions;

$\mathbf{Y}_{PS}$ – vector of parameters transferred from the knowledge base to the UPCSO to calculate the current values of the probabilities of occurrence of possible scenarios;

$\mathbf{P}_{post}$ – vector of current values of posterior probabilities;

$\mathbf{J}_S$ – vector of current values of the evaluation functions;

$\mathbf{P}_S$ – vector of current values of probabilities of occurrence of possible scenarios;

μ – vector of current values of mathematical expectation;

$\mathbf{F}_{MW}$ – destructive effect of mine weapon on ships in the water area;

$\mathbf{F}_D$ – vector of disturbing effects.

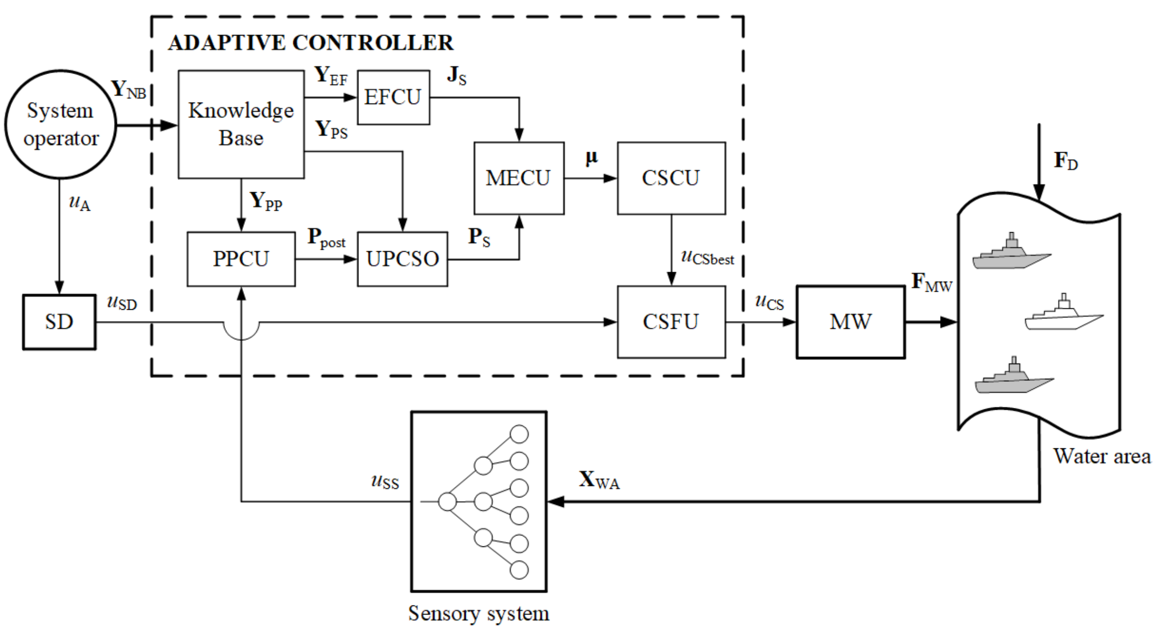

Fig. 1. Structure of the adaptive automatic control system for maritime anti-ship defense using mine weapons in simulation-based computer wargames

The proposed adaptive automatic control system operates as follows. When it becomes necessary to activate the system to manage anti-ship defense within a maritime area using naval mines in continuous mode, the operator (a participant in the game, or an opponent's program) initiates the activation by sending a signal u_A to the setting device. Upon receiving this signal, the setting device generates a system activation signal u_{SD} and transmits it to the input of the adaptive controller. The adaptive controller comprises the following functional modules: PPCU, UPCSO, EFCU, MECU, CSCU, CSFU, as well as an integrated knowledge base. At the initial stage (*Step 1* of the proposed method), the operator (a game participant or developer) inputs all necessary baseline data into the knowledge base as a vector of initial parameters $\mathbf{Y}_{NB}$. The adaptive controller receives, at specified discrete time intervals, the output signal u_{SS} from the sensor system. This sensor system performs real-time detection of enemy ships, neutral vessels, or the absence of any maritime objects in the operational area – thus implementing *Step 2* of the method. Based on the sensor signal u_{SS} and knowledge base data $\mathbf{Y}_{PP}$, the PPCU performs the computation of posterior probabilities $\mathbf{P}_{post}$ (*Step 3*). Subsequently, in *Step 4*, the UPCSO uses the values of $\mathbf{P}_{post}$ and $\mathbf{Y}_{PS}$ to compute the current probabilities of various operational scenarios. In turn, the EFCU and MECU carry out the necessary computations in *Steps* 5 and *6* – calculating the values of the evaluation functions $\mathbf{J}_S$ and the mathematical expectations μ. Then, in *Step 7*, the CSCU module determines the most effective control action u_{CSbest} for the current state, based on the maximum value of the mathematical expectation. If the system is in an activated state (indicated by the presence of signal u_{SD} sent to the CSFU), then in *Step 8*, the CSFU generates the corresponding control signal u_{CS}, which was computed by the CSCU in the previous step, and transmits it to the naval mines actuators.

To evaluate the effectiveness of the proposed method of adaptive automatic control for maritime anti-ship defense, as well as the system designed for its implementation (Fig. 1), a series of computational experiments was conducted in this study using various configurations of controllable parameters.

To validate the proposed method and assess the correctness of the system's operational behavior, the first computational experiment focused on determining the current values of the control input u_{CS} for all possible responses from the sensor system under a set of fixed baseline conditions. Specifically, the following parameter values were used (which can be specified by the game designer). Prior probabilities of the possible situational states: $P_{prior1} = 0.3$, $P_{prior2} = 0.2$, $P_{prior3} = 0.5$; probabilities of correct detection and first-second-type errors: $P_{11} = 0.9$, $P_{12} = 0.09$, $P_{13} = 0.01$, $P_{21} = 0.09$, $P_{22} = 0.9$, $P_{23} = 0.01$, $P_{31} = 0.01$, $P_{32} = 0.01$, $P_{33} = 0.98$; current minefield density: $\rho_m = 0.9\rho_{mmax}$; number of potentially involved ships: $m = 1$ (enemy ships), $l = 1$ (other vessels); conditional cost coefficients: $\sigma_{sp} = 100$, $\sigma_{sd} = 100$, $\sigma_{ns} = 1000$, $\sigma_m = 1$; displacement of either enemy or other vessels: 5000 tons; number of mines required to destroy or significantly disable a vessel: $n = 2$.

Based on these input data, the mathematical expectation values μ_{ASM} and μ_0 were calculated, and the resulting values of the control signal u_{CS} were obtained for each possible sensor system response. The results of these computations are summarized in Table 7.

Table 7

Calculated values of the mathematical expectation μ_{ASM}, μ_0 and control action u_{CS}

Sensory system response	μ_{ASM}	μ_0	u_{CS}
$u_{SS} = u_{ES}$ (detecting the passage of enemy ships)	26.64	–92.15	u_{ASM}
$u_{SS} = u_{NS}$ (detecting the passage of other vessels)	–823.9	–12.74	0
$u_{SS} = 0$ (detecting the absence of any vessels)	–3.407	–0.606	0
Sensory system response is absent	–168.5	–30	0

The results obtained from this computational experiment confirm the correct operation of the adaptive automatic control system with the developed structural architecture. They demonstrate that the proposed method effectively determines the most optimal control action u_{CSbest} based on the actual response of the sensor system and the prior parameters entered into the knowledge base.

Subsequently, the next computational experiment was conducted to investigate the influence of minefield density on the processes of automatic control in maritime anti-ship defense. Fig. 2–5 illustrate the variation in the mathematical expectation values μ_{ASM} and μ_0 as a function of the relative minefield density ρ_m/ρ_{mmax} for various sensor system responses.

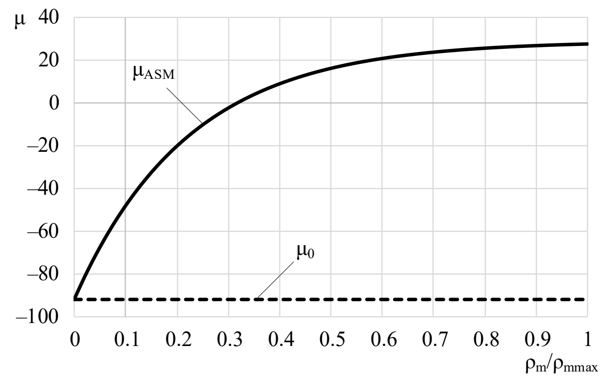

Fig. 2. Graphs of changes in the values of the mathematical expectation μ_{ASM} and μ_0 from the relative mining density ρ_m/ρ_{mmax} when detecting the passage of enemy ships ($u_{SS} = u_{ES}$)

At the same time, all other parameters are fixed and have the same values as in the first experiment.

As evident from the graphs presented in Fig. 2–5, variations in the relative minefield density from 0 to 1 affect solely the mathematical expectation value μ_{ASM} associated with the control action $u_{CS} = u_{ASM}$, which corresponds to the activation of the mine-based weaponry. This change follows an exponential trend. Specifically, when hostile ships are detected, the expected value μ_{ASM} increases, whereas its value decreases in the case of other detected states or when the sensor system fails to respond. In contrast, the expected value μ_0 corresponding to the control action $u_{CS} = 0$, representing the deactivation of the mines, remains unchanged regardless of variations in the minefield density. Hence, a change in the current mine density ρ_m, under a constant sensor system response and fixed values of all other control system parameters, does not lead to any alteration in the resulting control action u_{CS}.

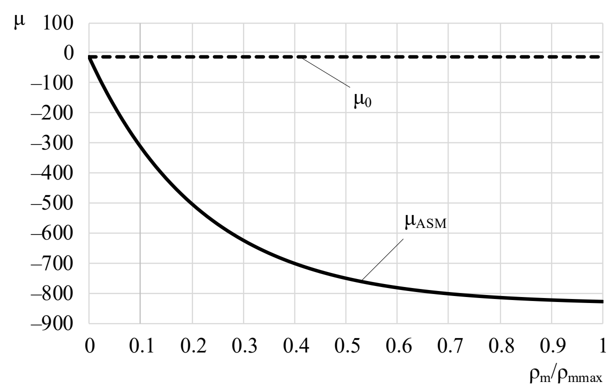

Fig. 3. Graphs of changes in the values of the mathematical expectation μ_{ASM} and μ_0 from the relative mining density ρ_m/ρ_{mmax} when detecting the passage of other vessels ($u_{SS} = u_{NS}$)

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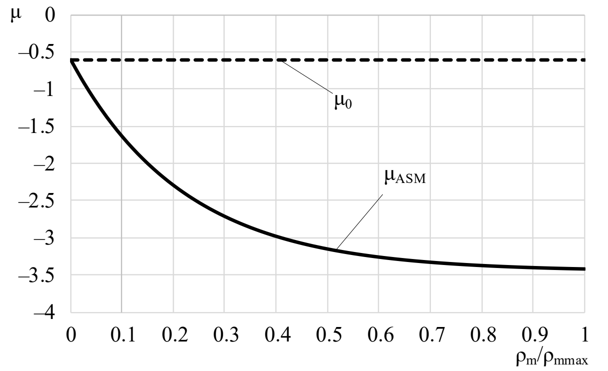

Fig. 4. Graphs of changes in the values of the mathematical expectation μ_{ASM} and μ_0 from the relative mining density $\rho_{\mathrm{m}}/\rho_{\mathrm{mmax}}$ when detecting the absence of any vessels ($u_{\mathrm{SS}} = 0$)

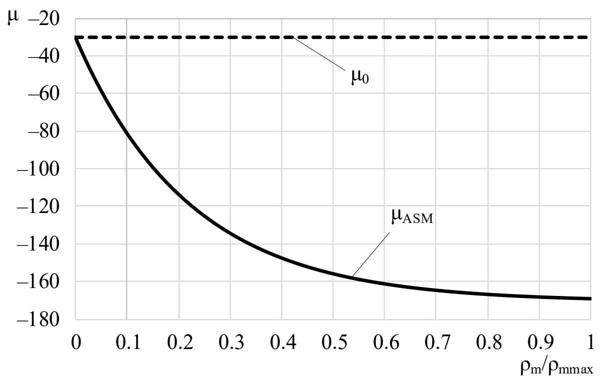

Fig. 5. Graphs of changes in the values of the mathematical expectation μ_{ASM} and μ_0 from the relative mining density $\rho_{\mathrm{m}}/\rho_{\mathrm{mmax}}$ in the absence of a response from the sensory system

In the subsequent computational experiment, the influence of sensor system performance accuracy on the processes of automatic control for maritime anti-ship defense was thoroughly examined. Specifically, the focus was placed on varying the values of the probabilities P_{ji} associated with correct detection of primary operational states or the occurrence of specific errors. Fig. 6–8 illustrate the changes of the mathematical expectation values μ_{ASM} and μ_0, as well as the corresponding control action u_{CS}, as functions of the probabilities P_{ji} under different sensor system responses. All other system parameters were held constant and retained the same values as those used in the initial experiment.

According to the setup of the computational experiment, Fig. 6 presents the scenario where the probability P_{11}, representing the correct detection by the sensor system in the case of enemy ship passage, was varied within the range from 0.1 to 0.9. The probability P_{12} of a Type I error under actual passage of non-hostile ships was computed as $0.99 - P_{11}$, while the probability P_{13} of a Type I error in the event of no ship presence was held constant at 0.01.

In Fig. 7, the probability P_{22}, denoting accurate detection of non-hostile ship passage, was similarly varied between 0.1 and 0.9. The probability P_{21} of a Type II error under real passage of enemy ships was computed as $0.99 - P_{22}$, while the probability P_{23} of a Type I error in the absence of any vessels remained fixed at 0.01.

Conversely, in Fig. 8, the probability P_{33}, representing correct detection of the absence of ships, was varied from 0.1 to 0.98. The probability P_{31} of a Type II error under actual enemy ship passage was determined as $0.99 - P_{33}$, and the probability P_{32} of a Type II error in the event of actual passage of non-hostile ships remained constant at 0.01.

As illustrated by the graphs in Fig. 6–8, variations in the probability values P_{ji}, which represent the accuracy of detecting specific operational states, lead to significant changes in both mathematical expectation values μ_{ASM} and μ_0. These changes directly influence the selection and formation of the required control action u_{CS}. Specifically, when detecting the passage of enemy ships (Fig. 6), the mathematical expectation value μ_{ASM} surpasses μ_0 only when the correct detection probability P_{11} reaches a threshold of 0.772. This triggers the control action $u_{\mathrm{CS}} = u_{\mathrm{ASM}}$, corresponding to the activation of the mine-based weapon system. Conversely, in the case of detecting the passage of non-hostile vessels (Fig. 7), μ_{ASM} becomes lower than μ_0 once the correct detection probability P_{22} reaches 0.228. This leads to the selection of the control action $u_{\mathrm{CS}} = 0$, which translates to the deactivation of mines. For scenarios where no vessels are detected (Fig. 8), μ_{ASM} only falls below μ_0 when the correct detection probability P_{33} reaches 0.962. As a result, the system again opts for $u_{\mathrm{CS}} = 0$, ensuring the mines remain inactive. Thus, through dynamic adjustment of the control signal u_{CS}, enabling the transition between mine activation and deactivation, the proposed adaptive control system ensured the most effective execution of defensive operations within the maritime area. This adaptability was maintained even under varying sensor feedback conditions and different probabilities of correct detection, as well as the presence of Type I and Type II errors.

In the final computational experiment, the influence of a priori information regarding the potential passage of enemy or non-hostile vessels through the maritime area was examined in the context of automatic control processes for anti-ship defense. Specifically, the values of the prior probabilities P_{prior1} and P_{prior2} were varied. Fig. 9–12 present the graphs illustrating the variation of the mathematical expectation values μ_{ASM} and μ_0, as well as the corresponding control action u_{CS}, as functions of the prior probability P_{prior1}, under different sensor system responses. Throughout this experiment, all other parameters remained fixed and identical to those used in the first experiment.

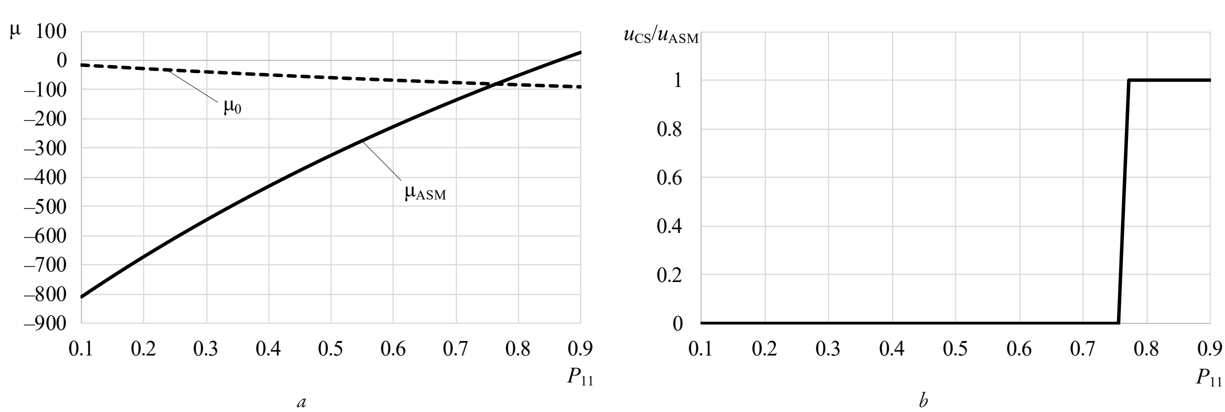

Fig. 6. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the probability P_{11} of correct detection of the sensor system when detecting the passage of enemy ships ($u_{\mathrm{SS}} = u_{\mathrm{ES}}$)

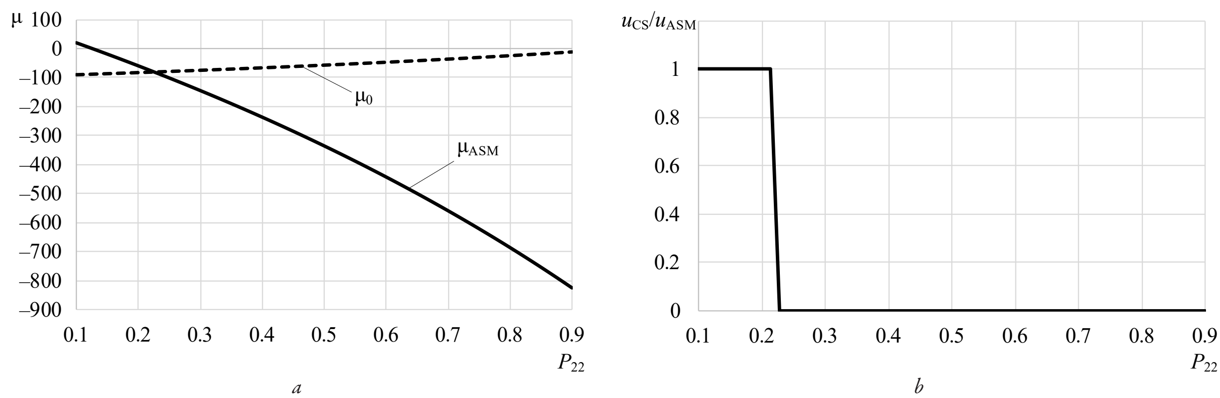

Fig. 7. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the probability P_{22} of correct detection of the sensor system when detecting the passage of other vessels ($u_{SS} = u_{NS}$)

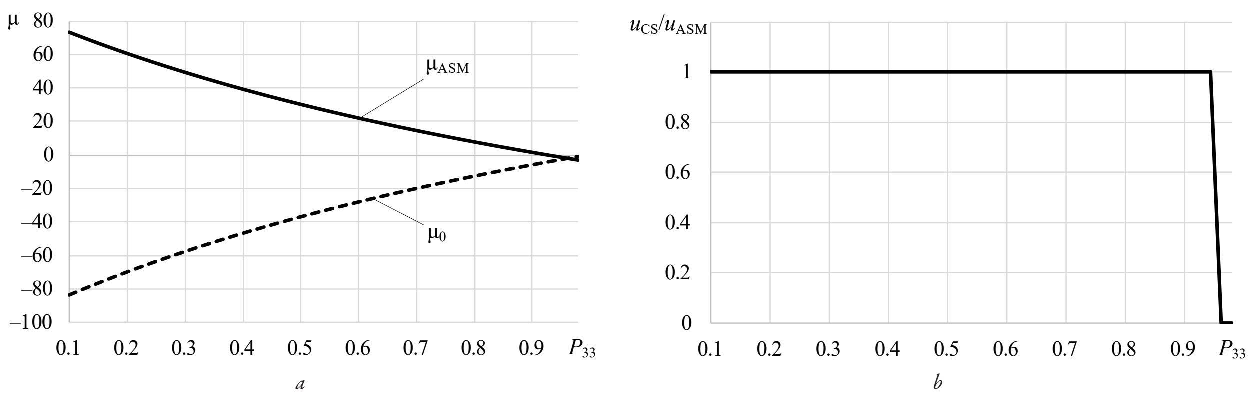

Fig. 8. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the probability P_{33} of correct detection of the sensor system when detecting the absence of any vessels ($u_{SS} = 0$)

In Fig. 9–12, the a priori probability P_{prior1}, representing the likelihood of the state corresponding to the passage of enemy vessels, at detected by the sensor system, was varied within the range of 0.1 to 0.8. Simultaneously, the a priori probability P_{prior2}, associated with the passage of other (non-enemy) vessels, was computed as $0.9 - P_{prior1}$. The a priori probability P_{prior3}, corresponding to the absence of any vessels within the area, remained constant at 0.1.

As illustrated by the graphs in Fig. 9–12, variations in the a priori probability P_{prior1}, which characterizes the likelihood of the enemy vessels' presence, significantly affect both mathematical expectation values μ_{ASM} and μ_0, thereby influencing the determination and generation of the appropriate control action u_{CS}. Specifically, when the sensor system detected the passage of enemy ships (Fig. 9), the mathematical expectation value μ_{ASM} surpassed μ_0 as early as $P_{prior1} = 0.31$, directly resulting in the formation of the control action $u_{CS} = u_{ASM}$, which corresponded to the activation of the mine-based defense. Conversely, in the case of detecting the passage of non-hostile vessels (Fig. 10), both μ_{ASM} and μ_0 also varied significantly, but even at the maximum tested a priori probability $P_{prior1} = 0.8$, μ_{ASM} never exceeded μ_0. As a result, the control action remained inactive ($u_{CS} = 0$), and the mine weaponry was not deployed. In the scenario of detecting no vessels in the area (Fig. 11), μ_{ASM} surpassed μ_0 only when P_{prior1} reached 0.758, that prompted the activation of the mines ($u_{CS} = u_{ASM}$). A similar trend was observed in the absence of any sensor feedback (Fig. 12), where the expected value μ_{ASM} again became greater than μ_0 only at $P_{prior1} = 0.758$, that led to the same control decision to activate the mines. Hence, by adaptively modifying the control output u_{CS}, to either trigger or deactivate the mine system, the proposed method ensured optimal performance of defensive operations strategies in the maritime domain, even under varying sensor responses and fluctuating a priori probabilities embedded in the system's knowledge base.

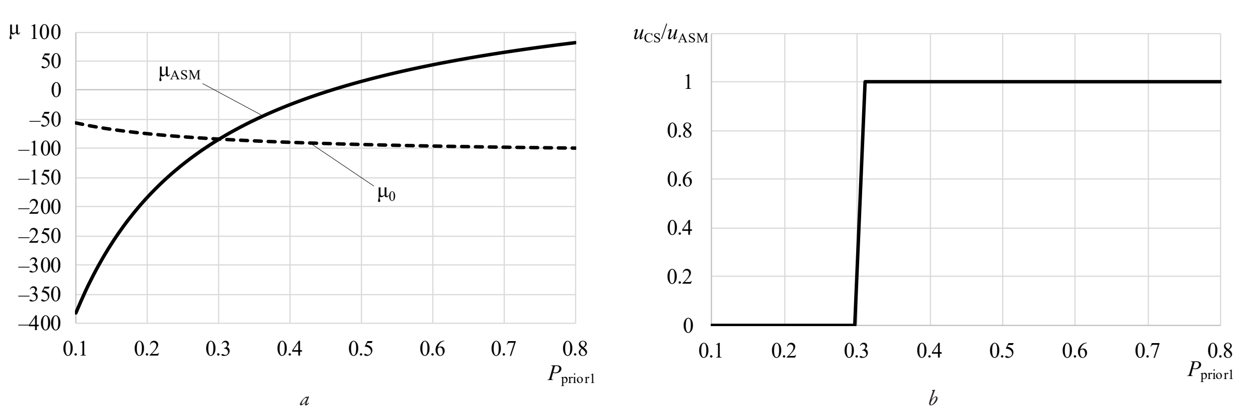

Fig. 9. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the prior probability P_{prior1} when detecting the passage of enemy ships ($u_{SS} = u_{ES}$)

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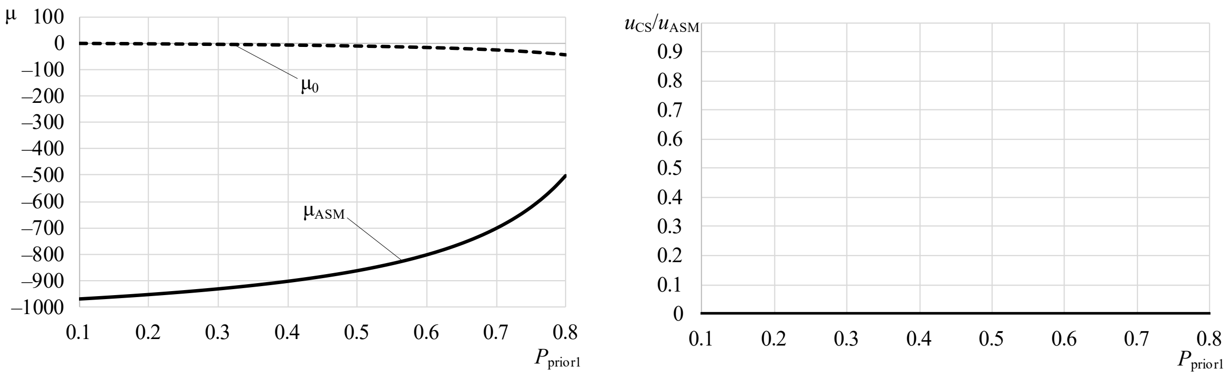
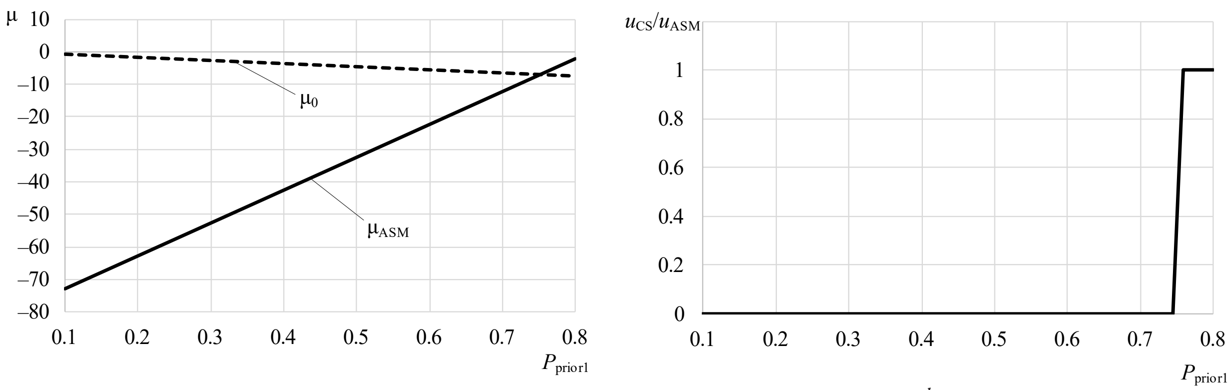


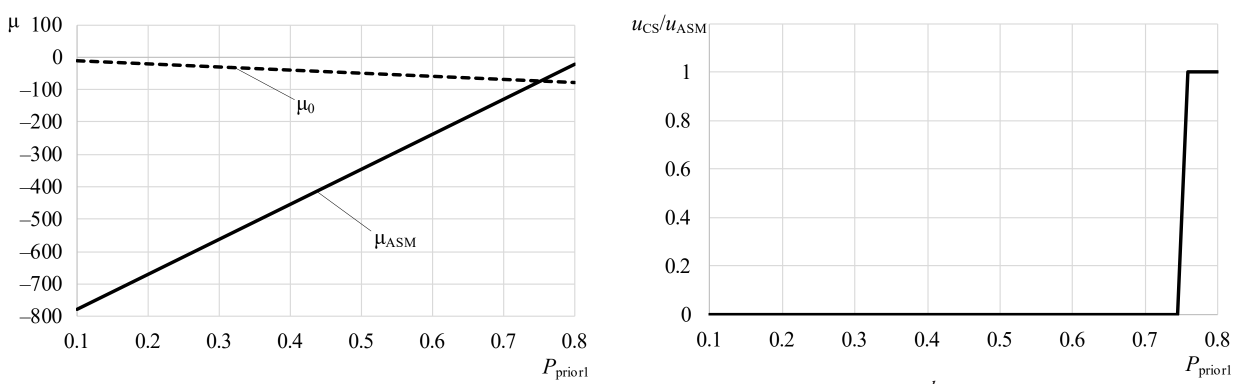
a *b*

Fig. 10. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the prior probability P_{prior1} when detecting the passage of other vessels ($u_{\mathrm{SS}} = u_{\mathrm{NS}}$)



a *b*

Fig. 11. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the prior probability P_{prior1} when detecting the absence of any vessels ($u_{\mathrm{SS}} = 0$)



a *b*

Fig. 12. Graphs of changes in the values of (*a*) the mathematical expectation μ_{ASM}, μ_0 and (*b*) the control action u_{CS} from the prior probability P_{prior1} in the absence of a response from the sensory system

The conducted computational experiments comprehensively validated the high effectiveness of the proposed method for automatic control of anti-ship defense within a maritime area, as well as the developed system designed for its implementation. This method, grounded in stochastic modeling under conditions of incomplete information and the presence of various sensor-related errors, enabled the accurate identification and generation of the most effective control actions. Crucially, it achieved this through adaptive adjustment to the reliability of sensor performance and to changing environmental factors. Moreover, the method demonstrated robust performance across a wide spectrum of sensor accuracy levels, including scenarios involving the presence of Type I and Type II detection errors. Remarkably, it remained functional even in cases of complete sensor silence, such as during damage, malfunction, or temporary communication loss, by leveraging the underlying probabilistic framework and knowledge base.

By modifying the values of a priori probabilities, the probabilities of correct detection, and the likelihood of Type I and Type II errors within the sensor system, a game developer can achieve a high degree of flexibility in shaping the behavior of a virtual adversary. These probabilistic parameters allow for the dynamic tuning of decision-making logic, enabling the simulation of opponents with varying levels of situational awareness, tactical reasoning, and operational reliability. Additionally, by adjusting the values of evaluation functions that affect the formation of control actions, developers can further refine the strategic complexity and responsiveness of the virtual entity adjusting to the specifics of each specific mission. This facilitates the creation of realistic, adaptable, and challenging scenarios in which the virtual opponent can exhibit both aggressive and cautious behavior, depending on the perceived threat level and environmental uncertainty, thereby significantly enhancing the depth and variability of the gameplay experience.

In summary, the application of the proposed adaptive control method and system in simulation-based computer wargames enables highly reliable and efficient management of anti-ship defense operations utilizing mine-based weaponry, ensuring high realism of virtual adversary behavior and mastery of decision-making in the uncertain combat conditions of naval battles.

Limitations of the study include its focus on game simulations, which may not account for all factors of real combat conditions, such as unpredictable changes, modern technologies, weather effects, specific water areas, etc. Also, this work does not consider different types of enemy ships and their specific missions, as well as different types of naval mines used in the defense system. In addition, limitations may include the inability of the sensor system to classify different types of enemy ships at the initial stage of their detection. Future studies are planned to consider these additional features, as well as to develop adaptive algorithms for managing anti-ship defense, taking into account different types of ships and their missions.

Moreover, future research directions may focus on enhancing the proposed adaptive control strategy through the integration with various artificial intelligence techniques [28–30]. Particularly, implementation of fuzzy logic models [31–33] can significantly improve decision-making under conditions of uncertainty and incomplete information, as well as bio-inspired algorithms [34, 35] can be used to fine-tune control parameters and decision thresholds in real time, adapting to evolving enemy strategies. Another promising avenue lies in the application of advanced identification methods [36] aimed at constructing dynamic models of enemy behavior. Such models would enable the system to anticipate and respond to evolving threats more effectively. These approaches can further increase the robustness and adaptability of the control system, making it more suitable for complex and unpredictable operational environments.

4. Conclusions

1. This study presents the development of an adaptive automatic control method for anti-ship defense in maritime domains using mine weapon, built upon stochastic modeling principles for application in computer simulation games. The formulated method is suitable both for simulating realistic behavior of a virtual adversary and for implementing automatic control systems for the player. The method enables the determination of the most effective control actions for mine deployment under various operational conditions, including scenarios characterized by incomplete information and diverse types of sensor detection errors during the defense of a water area. The task of selecting the optimal control action is solved through the computation of mathematical expectation values based on the probabilities of all possible state scenarios and their associated evaluation functions. Additionally, it involves adaptive adjustment of the control system to the sensory system's accuracy and the available a priori data.

2. For the proposed method implementation the functional architecture of the adaptive automatic control system for anti-ship maritime defense was developed. The given system incorporated the adaptive controller that executes the core computational steps of the formulated approach necessary for determining control actions related to mine activation. Moreover, the system with the proposed structure made it possible to study the performance and efficiency of the adaptive control method for anti-ship protection of the water area.

3. The effectiveness of the method was evaluated through a series of computational experiments. These experiments included scenarios with fixed values of controllable parameters. They also involved varying levels of minefield density. In addition, variations in the probabilities of correct detection and the incidence of Type I and Type II errors were tested to analyze the influence of sensor system accuracy on the control process. Furthermore, the experiments considered modifications in the a priori probabilities of enemy and non-hostile vessel presence in the area to assess the impact of prior knowledge on control outcomes. The comprehensive results demonstrate the effectiveness of the developed adaptive control method based on stochastic modeling. This approach reliably determines optimal control actions even under uncertain conditions. In particular, the proposed method enables effective control of mine weapons in the presence of Type I and Type II errors with probabilities ranging from 0 to 0.9 during the detection of enemy and neutral ships. The method also performs under total loss of sensor feedback due to system damage, malfunctions, or communication outages. In this case, the system switches the mines to an activated state only when the a priori probability of enemy ships appearing is equal to 0.758, which allows to significantly reduce the risk of neutral vessels being hit.

These findings confirm the high effectiveness of the proposed approach and substantiate its applicability in computer simulation games to enhance the realism of virtual adversary behavior and improve decision-making proficiency in uncertain naval combat scenarios.

Conflict of interest

The authors declare that they have no conflicts of interest in relation to this research, including financial, personal, authorship, or other, that could affect the paper and its results presented in this article.

Financing

The results was conducted without financial support.

Data availability

Data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in the creation of the presented work.

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