Development of a Virtual Environment for Monitoring Underwater Electrical Cables by an Autonomous Underwater Vehicle Based on Fuzzy Cellular Automata

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Abstract. The object of the study is to enhance operational efficiency and reduce fuel consumption of autonomous underwater vehicles during the monitoring of underwater electrical and optical cables based on FCA under conditions of uncertainty. To achieve the goal of the research fuzzy cellular automata are used, combining the advantages inherent in traditional cellular automata and provided by the capabilities of fuzzy sets and fuzzy logic. The cable location uncertainty is caused by possible earthquakes, turbulent currents, random impacts of anchors or fishing gear, cable fouling by marine vegetation and terrorist attacks. The developed approach allows to synthesise a Pareto-optimal vehicle route along the estimated coordinates of the object of study, providing minimum fuel consumption for minimum cable inspection time and satisfying the given system of constraints. Formal models are based on the use of fuzzy cellular automata, which are used to describe the three-dimensional model of the operating environment, zones and objects that hinder or limit the movement, and the behaviour of the underwater vehicle. The most significant results are the formal description of the problem solution space, and the method of modelling the route of an autonomous underwater vehicle in space to improve the efficiency and quality of the solution of the problem of monitoring the state of the object of interest. The significance of the results obtained is the possibility of solving a complex multi-criteria optimisation problem of finding the route of an autonomous underwater vehicle to monitor the cable system in three-dimensional space.
Keywords: electric cable, autonomous underwater vehicle, fuzzy cellular automaton, Pareto-optimality, route, fuel consumption, minimum time.
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Dezvoltarea unui mediu virtual pentru controlul cablurilor electrice subacvatice de către un vehicul subacvatic autonom bazat pe automate celulare fuzzy

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Rezumat. Obiectul cercetării este planificarea timpului minim de monitorizare a cablurilor electrice și optice subacvatice pe o anumită zonă a fundului mării de către un vehicul subacvatic autonom la costuri operaționale minime. Scopul lucrării este de a crește eficiența și de a reduce consumul de combustibil al vehiculelor subacvatice autonome în procesul de monitorizare a cablurilor electrice și optice subacvatice pe baza automatelor celulare fuzzy în condiții de incertitudine. Aparatele celulare fuzzy au fost utilizate pentru a atinge scopul studiului. Incertitudinea localizării cablurilor este cauzată de posibile cutremure, curenți turbulenți, impacturi aleatorii ale ancorelor sau uneltelor de pescuit, murdărirea cablurilor de către vegetația marină și atacuri teroriste. Abordarea dezvoltată permite sintetizarea unui traseu Pareto-optimal al deplasării vehiculului de-a lungul coordonatelor estimate ale obiectului de studiu, care asigură un consum minim de combustibil pentru un timp minim de inspecție a cablurilor și satisface sistemul de constrângeri dat. Modelele formale se bazează pe utilizarea automatelor celulare fuzzy, care sunt utilizate pentru a descrie modelul tridimensional al mediului de operare, zonele și obiectele care împiedică sau limitează mişcarea, precum și comportamentul vehiculului subacvatic. Cele mai semnificative rezultate sunt descrierea formală a spațiului de soluționare a problemei și metoda de modelare a traseului unui vehicul subacvatic autonom în spațiu pentru a îmbunătăți eficiența și calitatea soluționării problemei de monitorizare a stării obiectului de interes. Semnificația rezultatelor obținute constă în posibilitatea de a rezolva

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o problemă complexă de optimizare multicriterială a găsirii traseului unui vehicul subacvatic autonom pentru monitorizarea sistemului de cabluri în spațiul tridimensional.

Cuvinte cheie: cablu electric, vehicul subacvatic autonom, automat celular fuzzy, Pareto-optimalitate, traseu, consum de combustibil, timp minim.

Разработка виртуальной среды контроля подводных электрических кабелей автономным подводным аппаратом на основе нечетких клеточных автоматов

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Аннотация. Объект исследования – планирование минимального времени мониторинга подводных электрических и оптических кабелей на заданном участке морского дна автономным подводным аппаратом при минимальных эксплуатационных расходах. Цель работы – повышение оперативности и снижение расхода топлива автономными подводными аппаратами в процессе мониторинга подводных электрических и оптических кабелей на основе нечетких клеточных автоматов в условиях неопределенности. Для достижения цели исследования использованы нечеткие клеточные аппараты, сочетающие преимущества, заложенные в традиционных клеточных автоматах и предоставляемые возможностями нечетких множеств и нечеткой логики. Неопределенность местоположении кабеля вызвана возможными землетрясениями, турбулентными течениями, случайными воздействиями якорей или орудий лова, обрастанием кабелей морской растительностью и террористическими атаками. Разработанный подход позволяет синтезировать Парето-оптимальный маршрут движения аппарата вдоль предполагаемых координат залегания объекта исследования, обеспечивающий минимальный расход топлива за минимальное время контроля кабеля и удовлетворяющий заданной системе ограничений. Формальные модели базируются на использовании нечетких клеточных автоматов, с помощью которых описываются трехмерная модель среды функционирования, зоны и объекты, затрудняющие или ограничивающие перемещение, поведение подводного аппарата. Наиболее существенными результатами является формальное описание пространства решения задачи, и метод моделирования маршрута автономного подводного аппарата в пространстве для повышения оперативности и качества решения задачи мониторинга состояния объекта интереса. Значимость полученных результатов состоит в возможности решения сложной задачи многокритериальной оптимизации по нахождению маршрута передвижения автономного подводного аппарата для мониторинга кабельной системы в трехмерном пространстве. Таким образом, исследование свидетельствует об эффективности использования нечетких клеточных автоматов для построения маршрутов в процессе мониторинга подводных электрических и оптических кабелей в различных условиях, что позволит создать эффективную систему мониторинга за состоянием объектов наблюдения.

Ключевые слова: электрический кабель, автономный подводный аппарат, нечеткий клеточный автомат, Парето-оптимальность, маршрут, расход топлива, минимальное время.

ВВЕДЕНИЕ

With the advent of underwater electrical and fiber-optic cables, the issue of their protection from intentional and unintentional impacts from nature and humans has become extremely pressing [1]. Usually, in shallow waters, cable systems are placed underground, while in deep waters, they are laid on the seabed, requiring timely information about the cable's location, the current condition of its sheath, and the seabed along the route.

Monitoring of underwater cables is typically carried out using visual and acoustic methods with the application of underwater cameras, side-scan sonars, bottom profilers, and magnetic sensors that employ passive and active methods of electromagnetic field probing [2, 3].

In the passive method, an alternating current is induced onto the power line to determine the parameters of the resulting electromagnetic field. In the active probing method, on the other hand, a source of magnetic excitation induces a current within the ferromagnetic materials of the cables.

The determination of the location and inspection of underwater cables can be performed by both humans and various types of underwater vehicles. However, there are time, physical, temperature, and other limitations to the use of divers. Often, this is compounded by subjective, human judgment-based assessments of the location and condition of underwater cables [4].

An alternative for using divers to detect underwater cables is the use of various types of underwater vehicles, such as those remotely operated. However, the constant use of mother ships alongside with them leads to high operational costs.

Autonomous underwater vehicles (AUVs) without support from mother ships are considered a promising means for detecting and tracking underwater electrical cables [5]. To control the AUV, a cable-tracking controller calculates the control actions and nullifies the relative direction and distance between the vehicle and the cable, causing the AUV to follow the desired geometric trajectory. In recent years, intelligent controllers have been actively implemented.

Improving the methods of AUV application, considering the characteristics of the vehicle, the features of the seabed relief, navigational hazards, and more, affects the quality of monitoring underwater electrical cables.

Tasks of this class are successfully solved using three-dimensional geographic information systems that describe the monitoring space. However, the question of planning the AUV's route along the cable's path in three-dimensional space remains relevant, as traditional methods do not allow for considering the full range of conditions affecting the trajectory formation.

Therefore, constructing an optimal (rational) route during the vehicle's monitoring mission, considering the design features, characteristics of the onboard equipment, and navigation conditions, is a relevant scientific task.

LITERATURE REVIEW

The application of AUVs with a nonlinear trajectory-following regulator based on the backstepping method is limited by singularity. To eliminate this, a virtual target is introduced, moving along the trajectory and providing an additional degree of freedom [6].

Backstepping methods, supplemented by prediction based on the guidance law within the line of sight, are considered in [7].

Fuzzy and neural network controllers for the AUV tracking control are studied in [8]. Their excessive sensitivity to control parameters and complex logical inference are somewhat reduced by simplifying the control methods.

For automatic cable tracking by an inspection AUV, the integration of cable localization algorithms and magnetic guidance is proposed in [9]. The cable's location is determined using the magnetic guidance law based on the line of sight, utilizing the relative geometric relationship between the AUV and the cable.

A thorough analysis of research on optimal route planning for ships considering weather forecasts is conducted in [10]. The study explores solutions for multi-objective optimization problems with various constraints. It is shown that, in most cases, the uncertainty of weather forecasts is not considered, which reduces the quality of problem-solving.

The ship route optimization method based on the w-MOEA/D algorithm, considering weather forecast uncertainty, is discussed in [11]. Using the w-dominance principle, the method models the actions of the decision maker (DM). However, the method does not consider quantitative characteristics of the human factor's influence on fuel consumption and does not support real-time operation.

Research results on simultaneous optimization of ship course and speed for the entire transit route within the calculated arrival time are presented in [12]. However, the modeling results are not entirely accurate due to the lack of data on currents, ice-covered waters, etc., and cannot be used by ship operators in the real-time mode.

In [13], a modified probabilistic algorithm for ship route planning to avoid hazardous areas due to adverse weather conditions is presented. A drawback of the algorithm is its insufficient route accuracy. Improving the quality of weather information can be attempted through the application of fuzzy set theory.

An enhanced ant colony method, considering navigation risks and fuel consumption in complex hydro-meteorological conditions, is presented in [14]. However, while allowing for a comprehensive solution to ship route strategy selection, the method lacks precision.

Multi-dynamic elements in objective functions as weight coefficients allow for obtaining an optimal ship route [15]. However, the complexity of calculating the weight coefficients prevents the algorithm from being used in real-time.

An improved classical A* algorithm for enhancing routing efficiency considering fuel consumption in various navigational conditions is implemented in [16]. However, the algorithm does not determine the minimum necessary meteorological information for calculations.

In [17], the authors calculate the optimal route as the estimated time of passing waypoints and arriving at the final point under unstable weather and sea conditions. The lack of an order for selecting route segments when hydro-meteorological conditions change complicates the application of the proposed approach.

In [18], a method for formulating optimal ship routes within the e-Navigation system, integrating weather forecasts, is presented using fuzzy cellular automata. However, this method is not tailored for addressing multi-parameter optimization challenges.

The algorithm for route planning with obstacle avoidance, based on a combination of depth-first search methods and reinforcement learning algorithm on an artificial neural network, requires significant time and computational resources for implementation [19].

A metaheuristic algorithm for goal-seeking strategy determination by maximizing/minimizing the objective function was discussed in [20].

The use of cellular automata for modeling group behavior strategies and the external environment is explored in [21].

In [22], the use of a cellular automaton for searching the moving objects within a defined space on a homogeneous cellular grid with established boundaries is described. The accuracy of the developed route search automaton within a specified timeframe is confirmed.

The application of cellular automata for implementing intelligent agent behaviors in tasks involving movement and adaptive strategy adjustment based on evolving conditions is presented in [23].

The article [24] presents the results of modeling human group behavior considering their mental characteristics based on cellular automata.

In [25], a cellular automaton approach is described for modeling transportation and pedestrian behavior.

The work [26] examines the movement of individual homogeneous objects in a two-dimensional space to search for optimal routes based on cellular automata. For the route planning in three-dimensional space, the model requires further development to account for the area-specific features of the search.

The feasibility of applying the cellular automaton approach to solving the traveling salesman problem is discussed in [27].

The [28] successfully addresses the search for optimal routes from suppliers to consumers based on the cellular automata. However, constructing an optimal route for the AUV in such a scenario cannot be achieved.

The research on behavior models of unmanned systems in various environments and their deployment planning based on cellular automata is ongoing. An important issue is the development and investigation of a mathematical model for planning routes of AUVs for monitoring electrical and optical cables, considering constraints in three-dimensional space based on cellular automata.

From the analysis of studies dedicated to synthesizing optimal ship routes according to specified parameters (criteria), the following conclusions can be drawn:

1) most of the methods and models reviewed are not sufficiently accurate and reliable because they incompletely account for certain hydro-meteorological factors;

2) uncertainty in weather forecasts impacts the accuracy of the results obtained;

3) the high computational complexity of a significant portion of the algorithms restricts their real-time application;

4) the difficulty in assigning weight coefficients to the importance of individual factors influencing the formation of optimal ship routes renders some models non-adaptive.

Traditional models based on hydrodynamic equations of ship motion and computational methods must be accurate, convergent, and stable. In contrast, a cellular automaton consists of a set of finite automata with integer coordinates (i, j), each capable of being in a specific state. At each computational step, the cellular automaton passes to another state. Using cellular automata requires describing the set of cell states and transition functions.

In situations with uncertain, incomplete, or fuzzy information, where the cell states and transition functions cannot be precisely described, fuzzy cellular automata (FCA) and fuzzy rules defined as membership functions are applied. Cellular automata also observe changes in the cell's neighborhood over time and/or space. In FCA, the new state of a cell can be influenced by the states of neighboring cells.

Therefore, the use of FCA enables the development of precise, reliable, easily implementable, and adaptive algorithms for calculating optimal ship routes, including AUVs.

Consequently, the development of fuzzy control cellular automaton models based on fuzzy mathematics elements represents a promising research direction.

OBJECTIVE AND RESEARCH TASKS

Objective: To enhance operational efficiency and reduce fuel consumption of autonomous underwater vehicles during the monitoring of underwater electrical and optical cables based on FCA under conditions of uncertainty.

To achieve the research objective, the following tasks need to be addressed:

– develop a monitoring route for electrical cables considering hydro-meteorological and navigational conditions, discretely represented in time and space;

– analyze the factors influencing the solution to the problem of planning AUV routes with minimal mission execution time and fuel consumption, and formalize its statement;

– develop a method for forming an optimal monitoring route for the object of interest based on FCA.

Cellular automata are a computational system that performs tasks in discrete spaces. The uncertainty of conditions under which the AUVs monitor cables has favored the use of a fuzzy system. Describing complex object behaviors with cellular automata considering local regularities and constraints ensures minimal operational costs for the mission execution.

Describing the domain with fuzzy mathematics and the ability to solve dynamic tasks with fuzzy input data allow overcoming traditional complexity associated with the inability to conduct precise mathematical calculations.

FCA, as a result of integrating automata and elements of fuzzy mathematics, function well in uncertain situations and enhance computational system performance by avoiding continuous data stream processing.

A set of consistent production rules to describe the FCA operation algorithms can facilitate the construction of a Pareto-optimal AUV route in sufficiently uncertain environments during the monitoring of underwater cables.

METHODS, RESULTS, AND DISCUSSION

Problem formulation for optimizing the monitoring of underwater electrical cables on extended sets by a vector criterion.

The problem of vector optimization arises in the development of an AUV route for assessing the condition of the electrical (optical) cables in two cases. Firstly, the route is evaluated based on a set of local quality indicators (criteria) that are typically inconsistent and cannot be unified. Secondly, it arises when constructing a trajectory to diverge in conflict situations under conditions of incomplete initial information. Essentially, improving one criterion leads to deterioration in another, impacting the effectiveness of decisions made regarding the AUV movement management.

Therefore, it is necessary to introduce a range of indicators and seek a compromise solution. To achieve this, complexity factors are typically considered, and the global problem is reduced to simpler scalar optimization tasks. That is, to collapse the vector criterion, relatively simple rules are introduced:

1) Construction of the Pareto zone and selection of a DM from the Pareto-optimal solutions: i.e., for the problem involving $E^{(q)}(x) \to \max$, $x \in X^{(f)}$, $q = \overline{1, L}$ a solution $x^{\text{п}} \in X^{f}$, is chosen such that among the set of solutions $x^{\text{п}}$ there is no variation $\delta(x)$, such that for $\forall$ $q = \overline{1, L}$ the following conditions are met:

$$E^{(q)}(x^{\text{п}} + \delta x) \geq E^{(q)}(x^{\text{п}}), \quad q = \overline{1, L}, \tag{1}$$

Expression (1) asserts that a Pareto solution cannot be simultaneously improved across all scalar criteria. Therefore, to select a single solution from sets of Pareto-optimal solutions, it is necessary to use additional information;

2) Application of scalarization methods. In practice, this means that initially priorities $E^{(1)} > E^{(2)} > E^{(3)} > \ldots > E^{(q)} > \ldots > \quad > E^{(L)}$ are introduced with or without concessions to scalar criteria, and then the vector optimization problem is stepwise resolved for each component of the vector criterion:

$$E^{(q)}(x) \geq \overline{E}^{(q)}, \tag{2}$$

where $\overline{E}^{(q)}$ is the minimum permissible value of $E^{(q)}$.

Next, criterion $E^{(1)}$ is maximized, the optimal solution $E^{(1)*}$ is found, and a concession $\Delta E^{(1)}$ is assigned, permissible for maximizing other components of the vector criterion $E^{(2)}(x) \to \max$, $E^{(1)}(x) \geq E^{(1)*} - \Delta E^{(1)}$.

Similarly, a concession $\Delta E^{(2)}$ is then assigned, criterion $E^{(3)}$ is maximized with constraints on criteria $E^{(1)}$ and $E^{(2)}$, and so on.

However, due to the large number of possible solutions, the method of sequential concessions is not suitable for making timely decisions. This could be due to an unsuccessful choice of priorities or concessions, and the strong influence even of small concession values $\Delta E^{(q)}$ on the final decision;

3) Optimization based on introduced compromise relations, i.e., weighting coefficients between local criteria or permissible values of all local criteria except the primary one. The formation of a unified criterion as a complete sum represents scalarization:

$$E(x) = \sum_{q=1}^{L} \lambda_q E^{(q)}(x) \to \max, \quad \sum_{q=1}^{L} \lambda_q = 1, \qquad (3)$$

where: λ_q are weighting coefficients of criterion significance, determined by expert methods.

The solution obtained using criterion (3) is Pareto-optimal.

When managing AUVs, it is relatively easy to determine permissible values for all scalar criteria, allowing us to find a solution that satisfies the constraints

$$E^{(q)}(x) \geq E^{(q)}, \quad q = \overline{1, L}, \qquad (4)$$

If the solution obtained according to rule 3 is not Pareto-optimal, then we select the most important or arbitrarily chosen criterion, while the others are constrained to a system

$$E^{(1)}(x) \to \max, \quad E^{(q)}(x) \geq E^{(q)}, \quad q = \overline{2, L}, \qquad (5)$$

whose solution belongs to the Pareto region;

4) Optimization when making operational decisions on expanded sets by introducing an ideal solution into the space L of maximized criteria, with an ideal point having coordinates $E^{(1)*}, E^{(2)*}, ..., E^{(q)*}, ..., \quad E^{(L)*}, \quad q = \overline{1, L},$ and approaching this ideal solution normatively

$$\left\{ \sum_{q=1}^{L} \left| \left[\frac{E^{(q)}(x)}{E^{(q)*}} \right] - 1 \right|^{p} \right\}^{\frac{1}{p}}, \qquad (6)$$

where: $E^{(q)*}$ is the maximum value of the q -th criterion without considering other criteria, and p is determined by the complexity of the specific task.

The introduction of such an ideal point implies solving a two-step optimization problem: first, determining the optimal values of each scalar criterion independently of other criteria (a linear programming problem), and then minimizing the deviation from the ideal point thus formed according to criterion (4) (a quadratic programming problem).

The only optimal solution is the point optimization. Vector efficiency indicators provide acceptable solutions, which is optimization in the region. The use of the decision-making concept on expanded sets and complexity assessment allows obtaining a Pareto-optimal solution.

When there is a set of optimal solutions to the threshold optimization problem

$$E^{(1)}(x) \to \max, \quad E^{(q)}(x) \geq \overline{E}^{(q)}, \quad q = \overline{2, L}, \qquad (7)$$

among these solutions, there is at least one Pareto-optimal solution.

The process of forming a vector criterion to enhance the efficiency of AUVs in searching for underwater electrical cables depends on the choice of weighting coefficients and is subjective in nature. It is equal to the maximum number of scalar criteria describing the control and output parameters of the process. Adding a new criterion to the chosen system usually means making changes to the weighting coefficients or thresholds, rather than to previously found solutions.

When formulating a bi-criteria optimization problem (Fig. 1):

$$\begin{aligned} &E^{(1)} \to \max, \quad E^{(2)}(x) \geq \overline{E}^{(2)}, \\ &E^{(2)} \to \max, \quad E^{(1)}(x) \geq \overline{E}^{(1)} \end{aligned} \qquad (8)$$

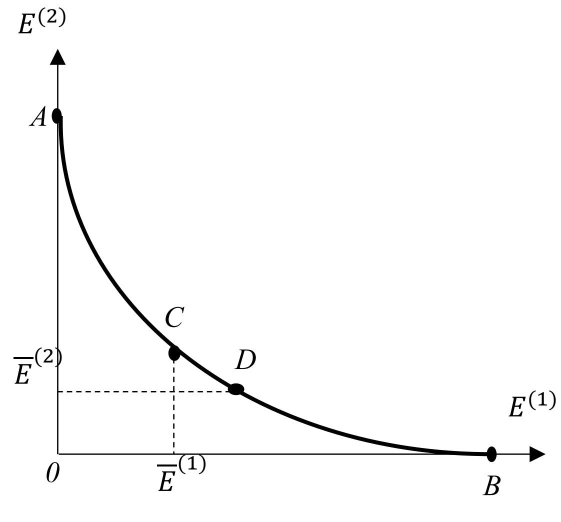

Fig. 1. Graphic interpretation of the solution of related problems.

$$E^{(1)} \to \max, \quad E^{(2)}(x) \geq \overline{E}^{(2)},$$
$$E^{(2)} \to \max, \quad E^{(1)}(x) \geq \overline{E}^{(1)} \qquad (8)$$

we have two solutions (points D and C for the first and second problems, respectively). In general, the principle of minimal complexity is used to select Pareto-optimal solutions. Thus, if the second problem is simpler to solve, then:

$$E^{(2)}(x) \to \max, \quad E^{(1)}(x) \geq E^0 + k\Delta E^{(1)},$$
$$k = 0, 1, 2, ..., \qquad (9)$$

where: E^0 – начальное значение порога по $E^{(1)}$;
k is the current multiplier;
$\Delta E^{(1)}$ is the increment for the first criterion.

The complexity of solving each adjacent problem allows constructing a discrete complexity scale:

$$W_t = \left\{ W_t^{(q)} : W_t^{(q)} \leq W_t^{(q+1)}; \ q = \overline{1, L} \right\} \qquad (10)$$

and solving optimization problems of type (2) and threshold optimization problems (8) by setting the initial threshold value of the optimized criterion E^0, its increment $\Delta E^{(1)}$, and obtaining the expected estimate for the maximum number of iterations k.

If there is a time constraint for constructing the complexity scale, time estimates for scale construction are introduced:

$$W_t = \left\{ W_t^C, W_{t(a)} \right\}, \qquad (11)$$

where: W_t^C is the time for constructing the scale and solving the least complex problem;
$W_{t(a)}$ is the time for obtaining a satisfactory solution using some basic algorithm.

Vector optimization procedures based on the principle of complexity on expanded sets of alternatives become particularly significant given the specified error margins of the problems.

Let us consider the formulation of a decision-making problem on expanded sets according to a vector criterion.

Let the tuple $< P, G, D, y^0, U^f, H >$ define the problem of finding satisfactory solutions, where P is the initial function defining the structure and content of the decision-making problem; G is the evaluation function reflecting the decisions made based on a set of evaluations; D is the admissibility function determining the limit values of solution quality; y^0 is a specific element $y^0 \in Y$ from the set Y, subsequently leading to a solution with specific numerical parameters; U^f is a subset of permissible controls that can lead to solving the problem; H is the set of uncertainties, where each element $h \in H$ characterizes the degree of ignorance of the problem parameters or the nature of actual random disturbances.

Let there be a set of input parameters Y and a set of output parameters X, with a certain set of evaluation functions

$$G^{(q)} : Y \times H \times U \times X \to E^{(q)}, \quad q = \overline{1, L}, \ (12)$$

and an admissibility (tolerance) function and an admissibility (tolerance) function:

$$D^{(q)} : Y \times H \to E^{(q)}, \quad q = 1, 2, ...; \quad q \leq L \quad (13)$$

Thus, the tuple $< P, G, D, y^0, U^f, H >$ has transformed into the set:

$$< P, G^{(q)}, D^{(q)}, y^0, U^f, H >. \qquad (14)$$

The decision-making problem on expanded sets, when introducing additional criteria (10), becomes a multi-criteria optimization problem. In this case, it is necessary to solve the problem of scalarizing the vector criterion depending on the ratio of the number of tolerance and evaluation functions.

Case 1. If the number of functions (13) equals the number of functions (12), the problem of minimizing complexity based on evaluations is solved:

$$Z\left(P', G', D', Y', U^{f'}, H'\right) \ R \ \ Z\left(P, G, D, Y, U^f, H\right)$$

(where: Z is an indicator characterizing the complexity of the decision-making procedure; R is the order relation on evaluations Z) and L related tasks are formed for selecting the minimally complex one.

Case 2. If the number of evaluation functions (12) exceeds the number of admissibility functions (13) by unity, the problem can be set as one of minimal or constrained complexity depending on the chosen primary criterion.

Case 3. If the number of evaluation functions (12) exceeds the number of tolerance functions (13), then all previously considered approaches are permissible when solving the problem of scalarizing the vector criterion.

Case 4. If admissibility functions are not specified, then after introducing primary quality indicators, such as $q_V \in Q_V$, where Q_V are the tolerance areas, we proceed to Case 3.

Let the decision-making problem on expanded sets according to a vector criterion have primary quality indicators $q_V \in Q_V$ and a tuple in which all sets are expanded:

$$< P, G^{(q)}, D^{(q)}, Y, U, H >. \tag{17}$$

Let's pose the problem: find subsets $Y' \in Y$, $U^{f'} \in U$, $H' \in H$, $G^{(q)'} \in G$, $D^{(q)'} \in D$, and an element $P' \in P$, such that for any elements $y' \in Y'$ and $h' \in H'$, there exists an element $u' \in U'$ and a corresponding u' element x', under which the triplet $\langle y', u', x' \rangle \in S$ holds, meaning that primary quality indicators and condition

$$Z\left(P', G^{(q)'}, D^{(q)'}, Y', U^{f'}, H'\right) R$$
$$R\, Z\left(P, G^{(q)}, D^{(q)}, Y, U^{f}, H\right) \tag{18}$$

The problem generalizes the decision-making task for AUV motion control under fuzzy initial conditions together with the evaluation criterion $Z\left(G', D'\right) R_{g,D} Z\left(G, D\right)$, where $Z\left(G', D'\right)$ is the indicator of decision-making efficiency and its permissible values, considering the complexity of the decision-making procedure.

This problem is more complex to solve, but in this formulation, more efficient solutions can be obtained by expanding the set of considered alternatives and minimizing complexity using vector optimization procedures.

Solution to the problem.

The research object is the planning of the minimum monitoring time for underwater electrical and optical cables over a specified section of the seabed by an autonomous underwater vehicle (AUV) with minimal operational costs.

The operation of the "AUV-electrical (optical) cable-external environment" system occurs under conditions of non-stochastic uncertainty.

The fuzzy cellular automaton has the following advantages:

– the concept of "state," the ability to apply it to current, intermediate, and final positions, as well as the automaton's ability to perform a sequence of discrete constant steps (movement) in space and time;

– updating the state of each cell as a result of movement over time;

– synchronous updating of variables in each cell depending on their values at the previous step;

– the new state of a cell is determined only by its local values from a certain neighborhood of this cell.

Research hypotheses:

1. When forming the monitoring route for the object of interest, a reduction in the speed of the AUV is allowed.
2. The vessel's route is represented by a trajectory of movement and changes in linear speed over a finite number of segments with constant course values.
3. To determine the states of the cells in the fuzzy cellular automaton (FCA) and the transition function between them, a system of production rules and membership functions is applied.
4. The discrete operation space is due to the discrete representation in time and space of the initial data – the forecast of hydrometeorological conditions and the navigational situation.

Various obstacles and navigation safety requirements influenced the choice of routes during the modeling.

The research constraints include adopting a constant, identical track length in discrete time steps, which is due to the uniform size of the cells forming the discrete metric grid of the automaton. Each cell is described by the linguistic variable "fuel consumption" and is characterized by a transition function to model changes in fuel consumption during monitoring as environmental factors change.

To formalize the uncertainty of navigational and hydrometeorological conditions and AUV parameters, we describe them with triangular membership functions, which sufficiently accurately represent the subject area.

Results of the study on the impact of hydrometeorological conditions on the formation of the Pareto-optimal route for the AUV

Discrete representation in time and space for planning the monitoring route of electrical cables by an autonomous underwater vehicle, considering hydrometeorological conditions

The recommended monitoring route $\left(W_i^{rec}\right)$ includes the starting, ending, and intermediate points. Additionally, it is characterized by its width $\left(wid^{W^{rec}}\right)$ and height $\left(h^{W^{rec}}\right)$. The route should not include segments that pass through obstacles or do not meet safety requirements [28]. The choice of the recommended route is largely influenced by the type, technical characteristics, and equipment composition of the AUV, as well as hydrometeorological conditions, the navigational situation, and the choice of speed and course along the route:

$$W^{rec} = \left\{Cord_{st}^{W^{rec}}, Cord_{fin}^{W^{rec}}, Cord_i^{W^{rec}}, wid^{W^{rec}}, h^{W^{rec}}\right\}. \quad (19)$$

The optimal route for monitoring the electrical cables is a safe route with high quality criteria, specifically simultaneous fuel savings and minimal mission execution time. Clearly, this problem falls into the Pareto-optimal category and requires finding some economical speed V_e^{sh}.

On the one hand, fuel savings are utilized in constructing the optimal monitoring route under the condition that the mission allows for a reduction in AUV speed. In other words, it is possible to switch the vehicle's motion parameters to an economical speed mode, where it moves at an economical speed V_e^{sh} that achieves maximum fuel efficiency. At the same time, the vehicle must timely execute the mission and prevent any decrease in the reliability of its power system.

The primary indicator of efficiency in choosing V_e^{sh} is the specific fuel consumption g_{wr}^{sh} (при $V_e^{sh} > 0$):

$$g_{wr}^{sh} = \frac{G_{wr}^{sh}}{V^{sh} \cdot t_{wr}^{sh}}, \quad (20)$$

where: G_{wr}^{sh} is the standard fuel consumption for the passage of the autonomous underwater vehicle through the route segment, typically taken from pre-calculated tables;

V^{sh} is the speed of the AUV during the monitoring segment;

t_{wr}^{sh} is the time taken by the vehicle on this monitoring segment.

On the other hand, a safe optimal route for AUV monitoring is constructed considering hydro-meteorological conditions, navigation environment in the marine environment, and unconditional compliance with time constraints and mission safety. Routes are called optimal if they ensure high-quality cable monitoring with a safety level for the AUV and equipment not lower than specified, with minimal mission completion time. The task of route formation considering hydro-meteorological and navigation conditions is typically modeled as achieving the minimum mission completion time. However, the shortest route is not always completed in the shortest time. The mission completion time T_{route}^{sh} is defined as:

$$T_{route}^{sh} = \frac{D^{W_{route}^{sh}}}{V^{sh}}, \quad (21)$$

where: $D^{W_{route}^{sh}}$ is route length W_{route}^{sh};

V^{sh} is specified AUV speed.

Since the underwater vehicle moves at a constant speed and course from the starting point to the endpoint via intermediate points, the time of passage along the monitoring route is equal to the sum of times on individual segments:

$$T_{route}^{sh} = \sum_{i=1}^{N-1} \frac{d_i^{W_{route}^{sh}}}{v_i^{sh}}, \quad (22)$$

where: N is number of route points W_{route}^{sh};

$d_i^{W_{route}^{sh}}$ is distance between $(i-1)$-th and i-th route points W_{route}^{sh};

v_i^{sh} is AUV speed distance between $(i-1)$-th and i-th route points W_{route}^{sh}.

Thus, according to expression (22), to determine the time spent by the AUV on the route, it is necessary to define it as a collection of points forming the trajectory of the AUV (Fig. 2).

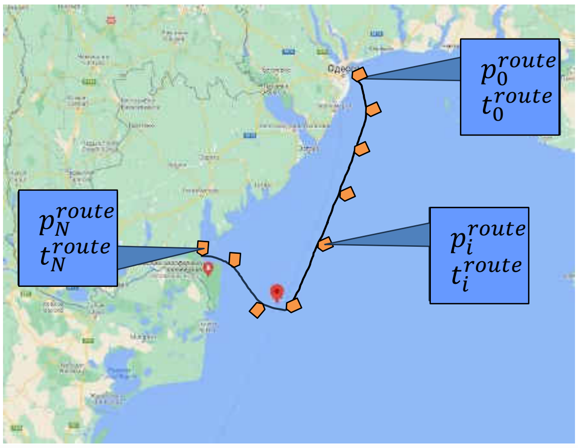

Fig. 2. A set of points forming the AUV underwater route.

Analysis of factors influencing the optimization of route.

Fuel efficiency is influenced by operational and external factors and the conditions of AUV movement. The impact of operational factors can be minimized through continuous monitoring of the technical condition of the vehicle and responding to deviations from permissible values. However, external factors directly affect the choice of rational, economical speed $V_e^{s\square}$, which is reflected in algorithms for calculating the optimal AUV route.

The impossibility of conducting experiments under identical conditions determines the uniqueness of the obtained routes. Hydro-meteorological conditions during monitoring also vary. Most indicators from ship systems sensors or support services also contain elements of non-stochastic uncertainty, expressed in parameter variability.

These circumstances, along with the representation of certain factors in qualitative form, confirm the feasibility of using fuzzy sets with triangular membership functions to describe factors in optimization problem formulation. Such an approach will ensure the required engine modes at different depths according to the calculated AUV movement modes.

External conditions in the form of forecasted parameter values come from underwater vehicle sensors and are represented for nodes of a grid with a fixed step in coordinates and time, projected onto the water area.

Let the AUV route be represented by its trajectory of movement and changes in linear velocity V_i^{sh}, $i \in \overline{1,n}$ over a finite number of segments with a constant course h_i. This allows describing the AUV route by the following vector

$$W_{route}^{sh} = \left\{ \left(h_1, S_1, V_1^{sh}\right), \left(h_2, S_2, V_2^{sh}\right), \ldots, \left(h_i, S_i, V_i^{sh}\right) \right\},$$
$$W_{route}^{sh} \in W^{rec}, \tag{23}$$

where S_i is the length of the i-th segment of the route.

The vector W_{route}^{sh} uniquely defines the ship's route. When determining V_e^{sh}, the specified V^{eng} and actual V^{sh} speed of the AUV are considered. The specified speed is directly related to fuel consumption. The specified speed, considering external conditions and the direction of the AUV's movement, becomes the actual speed. That is, in the absence of external influences, the actual and specified speeds are equal. Thus, the vector W_{route}^{sh} is formulated as follows:

$$W_{route}^{sh} = \left\{ \begin{matrix} \left(h_1, S_1, V_1^{eng}, INF_1\right), \left(h_2, S_2, V_2^{eng}, INF_2\right), \\ \ldots, \left(h_i, S_i, V_i^{eng}, INF_i\right) \end{matrix} \right\}, \tag{24}$$

where INF_i – is the vector of external influences – waves (inf_i^{wave}) and currents (inf_i^{curr}):

$$INF_i = \left\{ inf_i^{wave}, inf_i^{curr} \right\}. \tag{25}$$

Then, to design a route that ensures fuel economy, it is necessary to solve the problem:

$$G_F\left(W_{route}^{sh}\right) \to \min_{W_{route}^{sh} \in W^{rec}}, \tag{26}$$

where $G_F\left(W_{route}^{sh}\right)$ is the objective function for fuel consumption of route W_{route}^{sh}, calculated based on the path fuel consumption g_{wr}^{sh} at the specified speed V^{eng}.

The solution of problem (26) using numerical methods is challenging due to:

– categorizing this problem under nonlinear programming tasks;

– a wide range of values that the " AUV-cable-environment" system can reach, regardless of the degree of influence of factors;

– low probability of accurate forecasting, limited by a small amount of data;

– insufficient speed of obtaining results during the modeling process of the " AUV-cable-environment" system using differential equations.

Therefore, discrete models are necessary, where the formalization of a set of possible states and rules of their changes over time under conditions of uncertainty is implemented.

Formation of an optimal route for an AUV based on a fuzzy cellular automaton

The fuzzy cellular automaton is a set of objects:

$$\left\{ W, S, N, R^{FCA} \right\}, \tag{27}$$

where: W – discrete metric grid of the fuzzy automaton;

S – finite set of possible states;

N – finite set determining the state of a cell influencing the new state of the current cell;

R^{FCA} – production rules FCA.

As a discrete metric grid for the automaton, a homogeneous three-dimensional grid is used.

Model FCA for forming a fuel-efficient optimal monitoring route for AUVs, considering hydrometeorological conditions, involves dividing the area

$$MR = \sum_{i=1}^{n} W_i^{rec}, \qquad (28)$$

into separate cells.

The cell sizes correspond to segments of the route of uniform length with discrete steps in time. These cells form the discrete metric grid of the automaton.

The linguistic variable "fuel consumption rate" takes values of "low," "medium," "high," quantitatively defined by fuzzy subsets g_{wr}^{low}, g_{wr}^{mid}, g_{wr}^{high} from the universe S using vector membership functions. This variable describes the state of any cell $s_i \in S$ at any arbitrary time t. Each cell is also characterized by environmental variables at the point associated with the cell. The transition function of the cellular automaton is used to model changes in fuel consumption rate at various values of external factors, such as current direction and speed. The AUV is described by its state and speed, which can be expressed as fuzzy sets.

Fuzzy production rules R^{FCA} define the operation algorithm of the fuzzy automaton.

Each cell $s_i \in S$, starting from an initial state with a specified initial membership function value at the initial time t_0, passes to step $t_0 + \Delta t$, where new membership function values of neighboring cells are computed

$$s_i : [S \times N] R^{FCA} \xrightarrow{t_0+\Delta t} \mu_{g_{wr}}(s_{i+1}). \qquad (29)$$

In the developed demonstrative version of the program, which models the optimal safe route for monitoring underwater cables by AUV with minimal time and fuel consumption based on fuzzy cellular automata, the technical condition of the AUV and certain hydrometeorological factors influencing its actual speed V^{sh} are taken into account.

The proposed route for monitoring underwater cables by an autonomous underwater vehicle is safe and optimal in terms of fuel consumption while completing the mission in minimal time.

If information about an obstacle along the route is received during the cable monitoring process by the AUV, navigational hazards near the endpoint of the route will be overcome.

Based on incoming hydrometeorological information at the cable's location and, accordingly, the AUV's route, a zone of hydrometeorological hazard is forecasted, which increases the temporal and operational costs of the vehicle. The AUV's route is not reconfigured in response to this.

Let's represent a cellular automaton as a set of finite cellular automata in a three-dimensional space with coordinates (i, j, n), which can be in one of the possible states S [19, 21]:

$$\theta_{i,j,n} \in S \equiv \{0, 1, 2, 3, ..., k\}. \qquad (30)$$

At each step of operation, the automaton changes its states according to specific rules:

$$\theta_{i,j,n}(t+1) = \phi(\theta_{k,l,m}(t)) \mid (k,l,m) \in N(i,j,n). \qquad (31)$$

where $N(i,j,n)$ is the space around the automaton (i,j,n), represented as the Moore neighborhood [29].

In the extension to the three-dimensional case:

$$N_U(i,j,n) = \begin{Bmatrix} (k,l,m) \mid |i-k| \\ \leq 1, |j-l| \\ \leq 1, |n-m| \leq 1 \end{Bmatrix}. \qquad (32)$$

Expressions (30) and (31) uniquely define a homogeneous three-dimensional grid [30].

A more precise description of the real operating environment for autonomous underwater vehicles is facilitated by a bounded grid (Fig. 3).

In the process of solving the search problem, two types of automata are used: search objects and search groups (Fig. 4).

For a three-dimensional cellular automaton, theoretically, there exist 26 possible movement patterns that can be applied to autonomous underwater vehicles. However, due to physical constraints and the specific motion characteristics of these vehicles, fewer movement patterns are implemented.

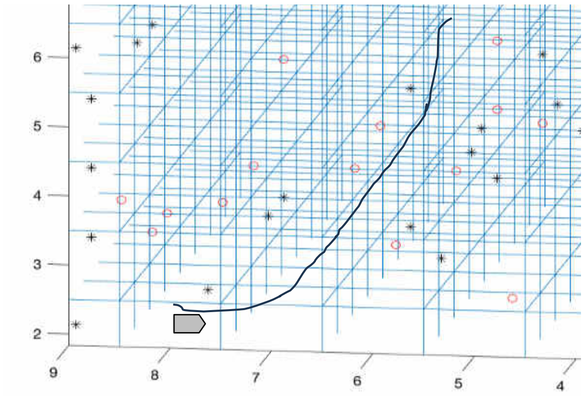

Fig. 3. Types of cellular automata (– objects of interest: electrical or optical cable; o and * – autonomous underwater vehicle AUV; – autonomous underwater vehicle AUV

The grid structure of the model is stable and homogeneous, where each grid node represents either an autonomous underwater vehicle, an insurmountable obstacle, a zone with different ways to overcome it, or an object of interest [29]. Such a representation allows for describing real objects in space by defining their spatial characteristics.

The previous state of the cell at time t_0 does not influence the choice of one of the 26 possible movement directions at time t_1, which is random and calculated based on corresponding probabilities or membership function values (Fig. 4) [30]:

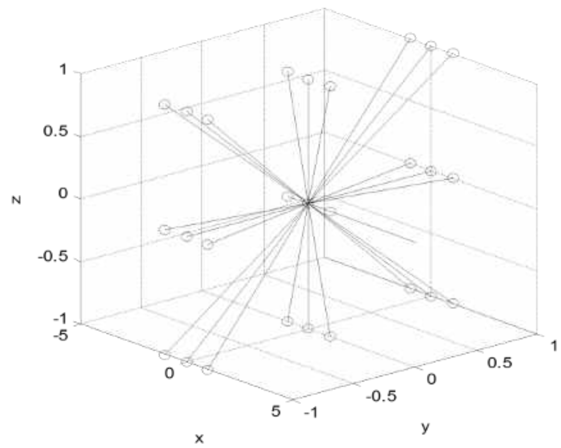

Fig. 4. Graphic representation of possible directions of movement of cellular automata.

$$P_i(x,y,z) = 1 - \frac{1}{N}\sum_{k=1}^{N} D(x,y,z+k),\ \ i = \overline{1,26}; \qquad (33)$$

where: (x,y,z) – current AUV's coordinates;

N – depth of the cell's environment analysis;

k – depth coefficient of analysis;

$D(x,y,z)$ – cell state:

$$D(x,y,z) = \begin{cases} 1, & \text{cell is occupied;} \\ 0, & \text{cell is free.} \end{cases}$$

To regulate the direction of a cell movement from the current position to a specified target, we will use vector theory.

Let's construct a vector from the current position of the cell along the target object $\overrightarrow{AB}$ (Fig. 5). Next, we will construct vectors from the current cell to all 26 possible neighboring cells:

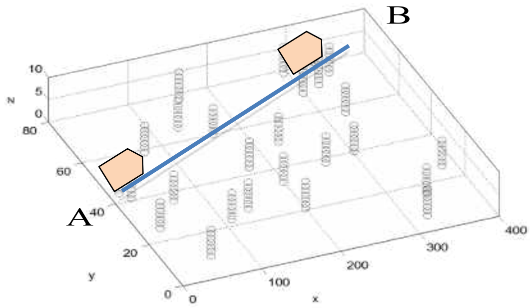

Fig. 5. Movement of the AUA along the object of interest.

$$\vec{f}_i(x,y,z) = x \in \{1,0,1\},\ y \in \{-1,0,1\},\ z \in \{-1,0,1\},$$
$$i = \overline{1,26}. \qquad (34)$$

The corresponding directions are determined by the combinations of component values (Fig. 6).

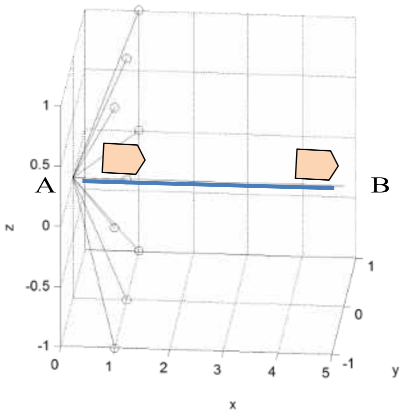

Fig. 6. Representation of vector $\overrightarrow{AB}$ and ortho-vectors

After finding the angles between vector $\overrightarrow{AB}$ and all ortho-vectors,

$$a_j = \arccos\left(\frac{\overrightarrow{AB} \cdot \vec{f_J}}{\left|\overrightarrow{AB}\right| \left|\vec{f_J}\right|}\right) \qquad (35)$$

an optimization problem is solved:

$$D_j(x,y,z) = D_0(x,y,z) + f_j^{*} \qquad (36)$$

under conditions of:

$$\max(P_i), \qquad (37)$$

$$\min(\alpha_j). \qquad (38)$$

If P or α values are equal, the choice is made randomly.

However, insufficient distinguishability of the probabilities of choosing a direction, the stalling of the automaton, significant deviations from the main direction of movement, etc., complicate the model's operation. Therefore, to calculate the probability, a sensitivity adjustment coefficient δ can be used:

$$P_i = e^{-\frac{\sum_{k=1}^{N} D(x+k,y,z)}{\delta}}. \qquad (39)$$

Set the movement of the AUV from the starting point along the object of interest as the goal of an irresistible force. That is, the AUV always aims toward the object under any conditions, turning obstacles and finding the "shortest" path to the electric cable [21].

Let the UAV be at the starting point with given coordinates. It should move along the electric cable, descending to a certain depth, and then move towards the monitoring object, whose coordinates are known.

Consider the movement of the AUV in a given direction from the "start" point along the object, which follows the rules of the cellular automaton's operation:

1. Find the vector from the AUV to the target.
2. Determine the step of changing the AUV's coordinates.
3. Recalculate the AUV's coordinates.
4. Check the depth of the route and adjust.
5. Recalculate the AUV's coordinates.
6. Upon reaching the AUV above the target, end the algorithm.

Consider the stages of the cellular automaton's operation.

Intermediate results in the form of a 3D model are shown in Fig. 7. The cellular automaton reaches the specified depth in n steps and accurately maintains its position over the object of interest. This type of behavior of the cellular automaton is characteristic in the absence of external factors affecting its trajectory.

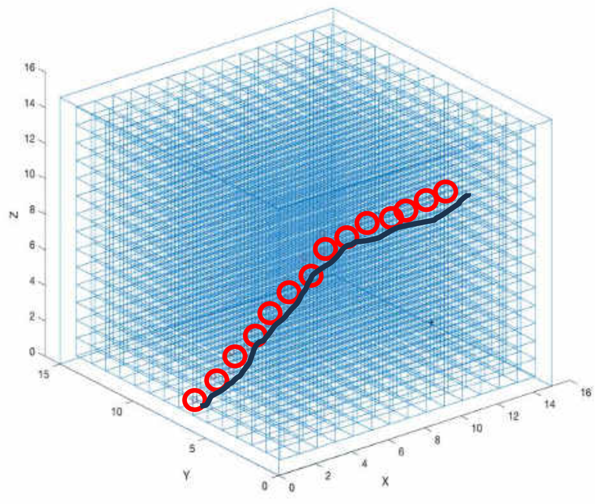

Fig. 7. Behavior of the cellular automaton when reaching the goal and loitering over it

Let's consider the behavior of the automaton in the presence of natural (relief, plants) and artificial obstacles (sunken ships, underwater networks, underwater oil and gas pipelines, etc.).

Under changed conditions, the rules of the cellular automaton's operation change:

1. Finding the vector from the AUV to the target.
2. Determining the step for changing the AUV's coordinates.
3. Recalculating coordinates if movement is possible.
4. Finding a bypass option if movement is not possible.
5. Checking and adjusting the depth.
6. Recalculating coordinates.
7. When the AUV is above the target (within the field of view), it moves along it.
8. Moving the AUV for a specified time and stopping the cellular automaton.

When changing the rules of the cellular automaton's behavior, it is possible to navigate around an obstacle and then return to the cable's location and move along it.

The efficiency of the work can be evaluated using the corresponding coefficient K:

$$K = \frac{N_{av}}{N_o}, \qquad (40)$$

where: N_{av} is the number of steps the automaton takes (effectively the number of cells visited);

N_o is the total number of cells in the model.

The efficiency of the cellular automaton's operation is minimally affected by the number of obstacles N_p (see Fig. 8) and is mainly determined by the area sizes of the obstacles and their mutual arrangement.

The results obtained demonstrated the high efficiency of the developed model compared to those obtained in [30] and its ability to construct an AUV route in complex conditions in minimal time.

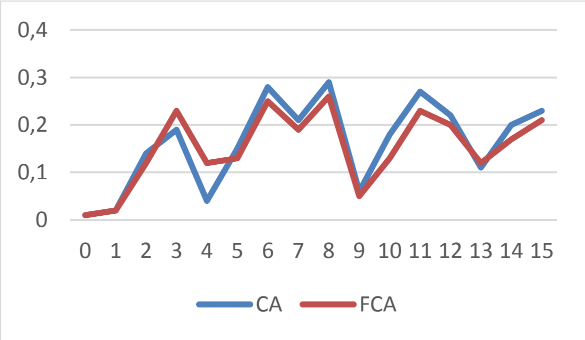

Fig. 8. Results of evaluation of the efficiency of cellular automaton with a different number of obstacles N_p

CONCLUSIONS

The proposed fuzzy cellular automata and fuzzy rules allow describing the behavior of the "AUV-cable-environment" system. To formalize the uncertainty of the parameter values of the autonomous underwater vehicle and environmental factors, membership functions were used. The introduction of fuzzy operations into the model update procedure allows for the description of the uncertainty of the AUV state.

The direction for further research is the development and study of a program that simulates a safe AUV route, optimal in terms of fuel consumption and mission time, based on fuzzy cellular automata, considering the influence of the environment on determining the coordinates of the cable. Plans include developing a program for more accurate modeling of the Pareto-optimal AUV route with given constraints. This will allow for assessing the accuracy and time of modeling when constructing the required monitoring route using different methods.

References

[1] Ortiz A., Antich J., Oliver G. A particle filter-based approach for tracking undersea narrow telecommunication cables. Mach. Vis. Appl. 2011;22:283–302. doi: 10.1007/s00138-009-0199-6.

[2] Szyrowski T., Sharma S.K., Sutton R., Kennedy G.A. Subsea cable tracking in an uncertain environment using particle filters. J. Mar. Eng. Technol. 2015;14:1–13. doi: 10.1080/20464177.2015.1022381.

[3] Szyrowski T., Sharma S.K., Sutton R., Kennedy G.A. Developments in subsea power and telecommunication cables detection: Part 2—Electromagnetic detection. Underw. Technol. 2013;31:133–143. doi: 10.3723/ut.31.133.

[4] Ortiz A., Simo M., Oliver G. Image sequence analysis for real-time underwater cable tracking; Proceedings of the Fifth IEEE Workshop on Applications of Computer Vision; Palm Springs, CA, USA. 4–6 December 2000; pp. 230–236.

[5] Campos R., Gracias N., Ridao P. Underwater multi-vehicle trajectory alignment and mapping using acoustic and optical constraints. Sensors. 2016;16:387. doi: 10.3390/s16030387.

[6] Xiang X., Lapierre L., Jouvencel B. Smooth transition of AUV motion control: From fully-actuated to under-actuated configuration. Robot. Auton. Syst. 2015;67:14–22. doi: 10.1016/j.robot.2014.09.024.

[7] Zheng Z., Yan K., Yu S., Zhu B., Zhu M. Path following control for a stratospheric airship with actuator saturation. Trans. Inst. Meas. Control. 2016 doi: 10.1177/0142331215625770.

[8] Sun B., Zhu D., Yang S.X. Real-time hybrid design of tracking control and obstacle avoidance for underactuated underwater vehicles. J. Intell. Fuzzy Syst. 2016;30:2541–2553. doi: 10.3233/IFS-151799.

[9] Tang, K.H.D.; Md Dawal, S.Z.; Olugu, E.U. A review of the offshore oil and gas safety indices. Saf. Sci. 2018, 109, 344–352. doi: 10.1016/j.ssci.2018.06.018.

[10] Zis, Thalis & Psaraftis, Harilaos & Ding, Li. (2020). Ship weather routing: A taxonomy and survey. Ocean Engineering. 213. DOI: 10.1016/j.oceaneng.2020.107697.

[11] R. Szlapczynski, J. Szlapczynska, R. Vettor (2023). Ship weather routing featuring w-MOEA/D and uncertainty handling. Applied Soft Computing. Volume 138, 123-140pp.

DOI: 10.1016/j.asoc.2023.110142.

[12] Y. Li, J.Cui, X. Zhang & X. Yang (2023). A Ship Route Planning Method under the sailing time constraint. Journal of marine science and engineering. Volume 11, 1-25pp. DOI: 10.3390/jmse11061242.

[13] N. Charalambopoulos, E. Xidias, A. Nearchou (2023). Efficient ship weather routing using probabilistic roadmaps. Ocean Engineering. Volume 273, 11-40pp. DOI: 10.1016/j.oceaneng.2023.114031.

[14] J. Yang, L. Wu & J. Zheng (2022) Multi-objective weather routing algorithm for ships: the perspective of shipping company's navigation strategy. Journal of marine science and engineering. Volume 10, 1-14pp. DOI: https://doi.org/10.3390/jmse10091212.

[15] Y. Lina, M.-C. Fanga, R.W. Yeung (2022) The optimization of ship weather-routing algorithm based on the composite influence of multi-dynamic elements. Journal of marine science and engineering. Volume 10, 16-30 pp. DOI: https://doi.org/10.1016/j.apor.2013.07.010.

[16] W. Sun, S. Tang, X. Liu, S. Zhou & Jinfang Wei (2022) An Improved Ship Weather Routing Framework for CII Reduction Accounting for Wind-Assisted Rotors. Journal of marine science and engineering. Volume 10, 16-30 pp. DOI: https://doi.org/10.3390/jmse10121979.

[17] Christiansen M., Fagerholt K., Nygreen B., and Ronen D. (2007) Hand. in Oper. Res. & Man. Sci. 189–284. DOI: https://doi.org/10.1016/S0927-0507(06)14004-9.

[18] Dudchenko, S., Tymochko, O., Makarchuk, D. & Golovan, A., 30 Apr 2024, Application of fuzzy cellular automata to optimize a vessel route considering the forecasted hydrometeorological conditionsIn: Eastern-European Journal of Enterprise Technologies. 2, 3 (128), p. 28-37 10 p.

[19] Abualigah L. Group Search Optimizer: a Nature-Inspired Meta-Heuristic Optimization Algorithm with its Results, Variants, and Applications. NeuralComput&Applic 2021. No 33, pp. 2949–2972.

[20] Wolfram S. Cellular automaton fluids 1: Basic Theory. Journal of Statistical Physics, 1986, Vol. 45(3), pp. 471-526.

[21] Semwal V. B., Gaud N., Nandi G. C. (2019). Human Gait State Prediction Using Cellular Automata and Classification Using ELM. In Machine Intelligence andSignal Analysis, 2019. pp. 135-145.

[22] Li, Yang, et al. A Review of Cellular Automata Models for Crowd Evacuation. Physica A: Statistical Mechanics and its Applications 526 (2019): 120752.

[23] Codd, Edgar F. Cellular Automata. Academic Press, 2014.

[24] Wu, Xinxin, et al. Simulating Mixed Land-Use Change under Multi-Label Concept by Integrating a Convolutional Neural Network and Cellular Automata: A Case Study of Huizhou, China. GIScience & Remote Sensing 59.1 (2022): 609-632.

[25] Freedman, Michael, Jeongwan Haah, and Matthew B. Hastings. The group structure of Quantum Cellular Automata. Communications in Mathematical Physics 389.3 (2022): 1277-1302.

[26] Khare, Ishaan, Harikumar Kandath, and K. Madhava Krishna. Predictive Optimal Collision Avoidance for a Swarm of Fixed-Wing Aircraft in 3D Space." 2022 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE, 2022.

[27] Wu, Xinxin, et al. Simulating Mixed Land-Use Change under Multi-Label Concept by Integrating a Convolutional Neural Network and Cellular Automata: A Case Study of Huizhou, China." GIScience& Remote Sensing 59.1 (2022): 609-632.

[28] Ji, Yanping, et al. Real Time Building Evacuation Modeling with an Improved Cellular Automata Method and Corresponding IoT System Implementation. Buildings 12.6 (2022): 718.

[29] Toffoli, Tommaso, and Norman H. Margolus. Invertible Cellular Automata: a Review." Physica D: NonlinearPhenomena 45.1-3 (1990): 229-253.

[30] Chistov V., Zakharchenko I., Pavlenko V. et al. Using the Mathematical Apparatus of Cellular Automata to Solve the Problem of Monitoring Critical Infrastructure Objects by Unmanned Aerial Vehicles. [In Russian]: *Problemele Energeticii Regionale*, 2022, nr. 3(55), pp. 156-167. ISSN 1857-0070. DOI: https://doi.org/10.52254/1857-0070.2022.3-55.12.

[31] K. Spyrou-Sioula, I. Kontopoulos, D. Kaklis, A. Makris, K. Tserpes, P. Eirinakis & F. Oikonomou (2022) AIS-Enabled Weather Routing for Cargo Loss Prevention. Journal of marine science and engineering. Volume 10, 16-30 pp. DOI: https://doi.org/10.3390/jmse10111755.

[32] Haiying Jia, Roar Adland, Vishnu Prakash, Tristan Smith, Energy efficiency with the application of Virtual Arrival policy, Transportation Research Part D: Transport and Environment, Volume 54, 2017, Pages 50-60, ISSN 1361-9209, https://doi.org/10.1016/j.trd.2017.04.037.

[33] Dhiman G., Kaur A. Spotted Hyena Optimizer for Solving Engineering Design Problems 2017 International Conference on Machine Learning and Data Science (MLDS), 2017, pp. 114-119.

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