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DEVELOPMENT OF AN INTEGRATED APPROACH TO THE ANALYSIS AND FORECAST OF HYDROGRAPHIC AND BATHYMETRIC DATA OF WATER BODIES AND TAILINGS PONDS

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There is a need for an effective monitoring solution for water quality control in tailings dumps and adjacent water bodies in order to prevent environmental pollution. This article highlights the importance of water quality monitoring and surveillance to prevent pollution. It is proposed to develop a mobile robotic complex equipped with sensors for monitoring water bodies and tailings, which is also capable of measuring underwater topographic data. The objects of study were a tailings pond and water bodies.

The authors analyzed existing technical monitoring solutions, designed and developed a robotic complex, echolocation device, tested them on specific sites (the tailings dump of the Zhayrem Mining and Processing Plant and the Ishim River), conducted laboratory analysis of water samples, classified the results. Additionally, they obtained 2D and 3D maps of the bottom, and entered all collected data into a developed database and software.

The developed complex demonstrated high accuracy of movement (an error of about 0.2 m on the x axis and 0.1 m on the y axis) and the ability to register environmental parameters such as temperature, humidity, PH. Data analysis for 2021–2023 showed a significant excess of recycled water discharged into the evaporator pond, which emphasizes the importance of monitoring and management of water resources.

The research applies ARIMA models, neural networks to predict water body parameters. The results obtained indicate the high efficiency of the developed robotic complex and methods for analyzing data on water resources. These methods can be used in industry, scientific research and environmental projects to regularly monitor water quality and take measures to protect it

Keywords: radio-controlled robotic complex, monitoring, tailings, echolocation device, forecasting, neural networks

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1. Introduction

It is important to note that the development of effective methods for monitoring and controlling tailings dumps is becoming necessary in the context of preserving natural resources and minimizing harmful effects on the environment [1]. Obtaining accurate data on the condition of water bodies [2] and the quality of water in them is the basis for the development and implementation of measures to prevent pollution and improve the environmental situation [3].

In addition, the problem of waste management of mining and processing plants is not only of ecological, but also of economic importance [4]. The possibility of reuse or disposal of materials contained in waste contributes to a more efficient use of natural resources and reduces the negative impact on the environment [5].

Assessing and monitoring the impacts of mining operations on water bodies have become critical issues in modern ecology and economics. In paper [6] examined the impact of mining operations on water resources, highlighting the importance of monitoring, assessing and managing the consequences of these operations. It is especially important especially the need to monitor hazardous substances [7]. In paper [8] proposed a modified classification procedure for assessing the quality of irrigation water, which is an important step in the development of methods for assessing suitable water resources for agriculture. The use of neural networks to predict water quality parameters, which emphasizes the importance of modern technologies in the field of monitoring and management of water resources [9].

In light of these considerations, the research on the development of monitoring and control systems for water bodies is not only timely but also critical for fostering a sustainable balance between industrial activities and environmental preservation.

2. Literature review and problem statement

A review of the literature showed that hardware solutions that are used for monitoring tailing dumps can be divided into several categories [10]:

– land-based mobile platforms;
– unmanned underwater vehicles;
– unmanned surface vehicles;
– unmanned aerial vehicles.

Developed mobile platforms and geotechnical equipment development, improving a gas-operated ground-based robot for controlled ground interaction research [11, 12]. This work does not, however, provide details on how exactly these improvements might be applied in the context of tailings management monitoring. The paper [13] provides an overview of underwater technology platforms, but does not discuss their applicability to specific monitoring tasks, including monitoring of tailings dumps. The paper [14] proposes an assessment of localization uncertainty for navigation of autonomous underwater vehicles, but the work does not consider an assessment of the quality of a water body. The paper [15] considers monitoring of water quality using image recognition, but it must be borne in mind that pollution in water is not always visually detectable. The paper [16] contains useful information about the methods of hydromechanization, but its applicability to modern technologies and methods of monitoring tailings is limited. The paper [17] describes the development of an unmanned aerial boat for mapping water quality, which is of interest in the context of alternative monitoring methods, but its applicability to monitoring tailings and rivers is not discussed. Due to its compact size and two hulls providing stability, the Unmanned Airboat [17] can successfully navigate in narrow channels, overgrown with aquatic plants or places with limited maneuver space. But it is equipped with two gasoline four-stroke engines, which can be a source of noise and environmental pollution due to gas emissions. The maximum rotation speed of the output motor is 7000 rpm, which may limit the efficiency of collecting water data at high travel speeds. This may reduce the accuracy or reliability of the collected data during high-speed operations.

Existing methods for monitoring water bodies, including tailings ponds, are not effective enough due to limited availability, technology and financial resources. A comprehensive approach is needed, covering all stages from the development of robots and equipment to data collection, analysis and forecasting of results, in order to improve the monitoring and management of water bodies.

3. The aim and objectives of the study

The aim of the study is to development of an integrated approach to monitoring water bodies.

To achieve this aim, the following objectives are accomplished:

– to design and create a mobile robotic complex for collecting data from water bodies;
– to develop a web server and software for managing, monitoring and storing data collected by a mobile robotic complex;
– process and predict data using ARIMA models and neural networks for further analysis and prediction based on real data.

4. Materials and Methods

The objects of research are the tailings dump of the Zhayrem mining and processing plant and the Ishim River of the Republic of Kazakhstan. At the initial stage, authors analyzed the available approaches, methods and generally accepted world practice of using mobile robotic systems based on materials from international scientific and technical literature.

Taking into account the duration of the existence of a water body, monitoring should be carried out for a long time in order to determine the consequences and influence of external factors (control of composition and properties), authors monitored objects from 2021–2023 in the pre-flood and post-flood periods. The laptop will be used as an onboard computer. As part of the computing system, a component - presented for testing algorithms and evaluating their effectiveness and time complexity, which will be evaluated according to several criteria: acceleration of the program, scaling algorithm, etc. The robotic complex will be equipped with various sensors, sensors and devices that process echolocation signals, determine the bottom relief (2d, 3d), hydrographic and bathymetric indicators of the reservoir, help collect water samples from hard-to-reach places. For this, authors collect data on *XY* coordinates from the echo sounder authors developed and *Z* from GPS.

The volume formula V for a water body based on a set of points x_t, y_t, z_t , where t is the point index, can be approximately expressed using surface approximation methods Let's assume that authors have an approximated function $z=f(x, y)$ representing the bottom surface. Then the volume can be expressed as (1):

$$V \approx \iint_D f(x,y)\,\mathrm{d}x\mathrm{d}y, \tag{1}$$

where D is the region in the plane XY bounded by your mesh or approximated surface. This is the double integral over domain D of the function $f(x, y)$ representing your approximated bottom surface.

After the sampling is carried out, a qualitative and quantitative analysis of the water will be performed, the identification of the object, i. e. the nature of the object is determined (authors check for the presence of certain key components, impurities); the acidity, alkalinity of the water, the alkalinity of the water is determined. The alkalinity of water is determined by the neutralization method, the amount of dissolved oxygen by the method of iodometry, and the oxidation of water by permanganometry. After that, all experimental data about the reservoir will be entered into database. The database structure, access organization, and data typing are carried out using IT technologies [17] in accordance with standard rules. Collecting sufficient data is necessary for further forecasting using Arima methods and neural networks [18].

Python programming languages will be used to implement a computer system for analyzing large amounts of data. The web platform was developed using Note.js, SQL.

It is expected that mobile robotic systems will be able to effectively collect data on water bodies and water quality. Simplification is based on the assumption of the availability and reliability of modern technologies for the implementation of this project [19]. The introduction of mobile robotic systems for monitoring water bodies and analyzing water quality will provide accurate data for assessing the state of aquatic ecosystems and making decisions in the field of environmental protection.

5. Results of development of an integrated approach to monitoring water bodies.

5. 1. Creation of a robotic complex

5. 1. 1. Development of the case

For the hull it was chosen the catamaran shape.

A review of various patents and techniques intended to improve ship designs and their functionality showed that they include innovations such as folding catamarans [20], inflatable sailing vessels [21, 22], multihulls [23], etc. Each offers unique benefits such as compactness, improved handling, increased stability and maneuverability. However, some of these innovations may also have disadvantages, such as limited applicability [24] in certain environments or potential issues with strength [25] and sustainability [26]. The disadvantages of the mentioned well-known catamarans are large size, high intensity of keel, vertical and side pitching, large shock loads on the ship's structure, high capacity, low comfort and economic efficiency. The hull has nose tips at an angle of 45 degrees, a trapezoidal flat bottom, two hulls, two sections along the entire length on both sides, located in the middle line of the hull bottom, designed to supply sensors that will facilitate the control of a mobile robotic complex. The material of manufacture is aluminum.

The hull has a profiled flat bottom, which will allow to control maneuvering while driving. Cross beams are used to prevent excessive bending of the catamaran. The invention has a small draft, which allows access to shallow reservoirs inaccessible to boats with other hull designs, this catamaran is less likely to catch on obstacles such as rocks or other debris at the bottom of a river or lake or other improper distribution of forces created during movement. The invention makes it possible to reduce the intensity of longitudinal pitching, the loads acting on the structure in conditions of unrest, the overall vibration of the structure and the material consumption of structures, increase comfort and reduce water resistance. The material for the manufacture of the proposed version of the catamaran for a mobile robotic complex is marine aluminum, since it is not subject to corrosion and does not require painting. The walls of the buoys are made of aluminum sheet AlMg5s, thick of 2 mm, the bottom of the buoys (2 mm), the deck is a corrugated aluminum sheet (quintet) thick of 3 mm. The connection of the buoys is realized by transverse beams (40*25). Fender aluminum e-shaped profile. If to fill the floats with foam, this will ensure unsinkability. If will fill the floats with foam, this will ensure unsinkability. The aluminum body helps to reduce weight, increase impact resistance and reduce development costs, it also greatly simplifies the creation of custom models (Fig. 1).

The payload compartment must be filled with foam to ensure unsinkability.

Chassis specifications are as follows:

– overall length 1570 mm;
– overall width 515 mm;
– buoy width 350 mm;
– buoy height 300 mm;
– case weight 50 kg;
– load capacity 55 kg;
– hull material AMg-5 (all-welded) (Fig. 2).

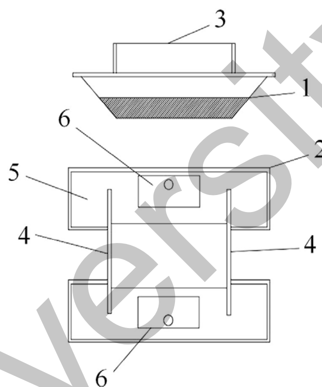


Fig. 1. Drawing of the catamaran: 1 – catamaran (Fig. 2), buoy walls made of aluminum sheet AMG5M thickness of 2 mm; 2 – bottom of buoys (2 mm); 3 – corrugated aluminum sheet (quintet) thickness of 3 mm; 4 – connection of buoys with cross beams made of aluminum corner (40*25); 5 – an aluminum e-shaped profile; 6 – a payload compartment

Fig. 2. Catamaran with an airboat installed

Authors decided to install an airboat on the catamaran for the following reasons: Airboats are able to overcome various types of surfaces, including water, snow-covered or swampy; Airboats, as a rule, use an air cushion to move over the water surface, which reduces drag and, therefore, minimizes damage to the bottom and shoreline; An airboat on a catamaran is able to provide a wider platform for the placement of various sensors and equipment necessary for monitoring the tail storage; This will increase the amount of information collected and allow for more comprehensive and detailed research; They also have relatively low operating costs, especially in comparison with the use of helicopters or other specialized air-crafts.

5. 1. 2. Design of a robotic complex

The unmanned swimming device is a complex system consisting of two main parts: the onboard part located on the device itself, and the ground part that controls the device and processes the received data (Fig. 3):

1. Onboard part: the main body of the device is made of aluminum to ensure lightness and strength.

The catamaran provides stability and buoyancy on the surface of the water.

The body of the device is sealed, which protects the electronic components from moisture and allows the device to work in various water conditions. Some internal cavities of the device are filled with foam, which improves its buoyancy and prevents possible dam-age in collisions [27].

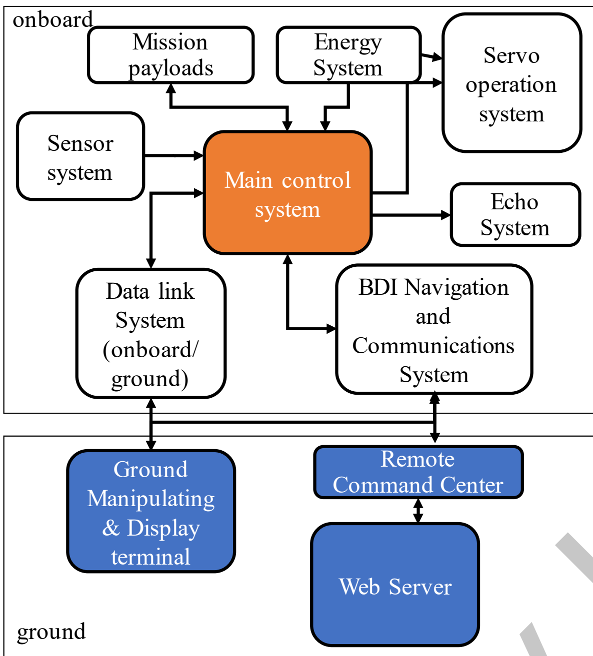


Fig. 3. Control unmanned scheme

Sensor system the on-board part houses various sensors designed to determine water quality parameters, such as temperature, salinity, pollution level and other chemical parameters.

Main measured parameters and sensor models:

– hydrogen index (pH) – HM Digital pH meter professional PH-200 in water-proof design;

– redox potential (ORP) – Thermo Orion 9189BNMD ORP Electrode;

– temperature sensor – S8000 Modular Temperature Sensor;

– absolute electrical conductivity – Oakton CON 6+ Conductivity Meter;

– solute content (total mineralization) – Thermo Orion Star A212 Conductivity Benchtop Meter;

– salinity – TDS Meter, HM Digital TDS-3.

Echolocation device: The device is equipped with an echolocation device that uses sound waves to determine the map of the bottom of the reservoir, which allows to build a three-dimensional model of the underwater terrain. In the next paragraph, the principle of development and operation are described in more de-tail.

Mission payload: the onboard system also includes various instruments and equipment specifically designed to perform a specific scientific or research mission, collecting water samples, and a pump.

Energy system: to provide power to all electronics on board, an energy system is used, which is based on rechargeable batteries TATTU 22000 mAh 44.4 V 25C batteries are replaceable batteries specially designed for use in radio-controlled drones.

Servo system: to control the movement of the device, a servo system is used (FEICHAO 40 kg 180-degree waterproof brushless servo with high torque), which controls the motors and steering devices for navigation and course changes.

Navigation and communication system: in the onboard part there is a navigation system that deter-mines the location of the device, as well as a communication system that provides data transmission between the onboard and ground parts, HEX Pixhawk 2.1 CUBE ORANGE+ is responsible for this.

Main Control System (MCS): the entire on-board part is controlled by the main control system, which processes data from sensors, controls the operation of systems and ensures the fulfillment of assigned tasks. All systems are connected to the MCS, which sends data via a radio module.

2. Ground part:

– display terminal: a display terminal is installed on the ground part, which allows operators to monitor in real time. data and information received from the UUV;

– ground manipulator: the ground manipulator allows operators to remotely monitor and adjust the operation of the UUV, as well as change its mission parameters;

– remote control center: the remote-control center is a centralized system for managing and monitoring the operation of the UUV. Operators can send commands to the onboard system and receive data from its UUV;

– web server and database: all selected data and water samples must be classified and all results entered into a DBMS. The UUV cannot determine all detailed data on site; additionally, samples will be analyzed in the laboratory. This approach will allow to fully observe the trend;

– trajectory construction: to build the trajectory, HEX Pixhawk 2.1 CUBE ORANGE+ is used. For this purpose, specialized software packages and algorithms are used to set the desired flight path.

To build a trajectory using HEX Pixhawk 2.1 CUBE ORANGE+, it is necessary to use specialized software packages and algorithms that allow to set the desired trajectory for flight. The construction of the route map is shown in Fig. 4.

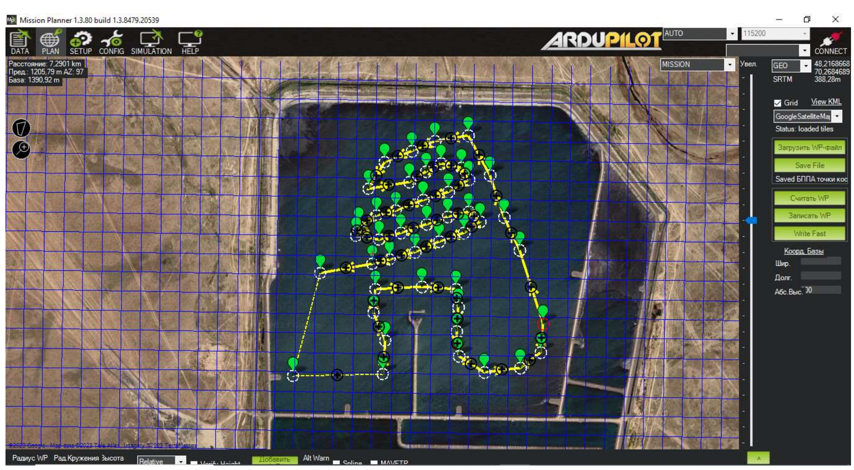


Fig. 4. Building a trajectory in Mission Planner

It was implemented through the Mission Planner software packages. When plotting a trajectory with HEX Pixhawk 2.1 CUBE ORANGE+, various flight parameters are taken into account, such as altitude, speed, course and destination points. This allows to control the UAV in accordance with the specified goals and to perform the required routes with high accuracy (Fig. 4).

5. 1. 4. The Echo Sounder system

Hydrographic surveys are the most accurate method of measuring the nature of sediment distribution and occupied volume. The depth with horizontal coordinates (X, Y) should be obtained during hydrographic studies. It is necessary to develop a radio-controlled [28] device equipped with various sensors [29] for environmental monitoring, determining the relief and hydrographic characteristics [30] of a tailings dump, studying the habitat for local fish species [31] and collecting samples in hard-to-reach areas of reservoirs, examining dams for various damages [32], and developing a database system for accounting.

The Echo Sounder system is designed to measure the depth of the water layer to the surface of the reservoir, the purpose is to measure the depth of the water layer at the measurement point and then calculate the actual volume of water in the reservoir. The echo sounder should work by means of ultrasonic waves, measuring depth up to 20 meters [33].

Given the goals and objectives of the project, the following factors were taken into account when choosing a ready-made ultrasonic module:

1. Work on the principle of piezoelectric effect.
2. Simple digital interface. UART with text commands/responses.
3. Supply voltage – up to 5 Volts.
4. Waterproof housing.

This microcontroller has the best combination of price, performance and dimensions, and also has an Arduino interface, a convenient connection interface, low power consumption. The operation of the module is based on the principle of echolocation. The module sends an ultrasonic signal and receives its reflection from the object. By measuring the time between sending and receiving the pulse, it is not difficult to calculate the distance to the obstacle. This module generates a signal for the transmitting unit, digitizes and processes the signal from the receiving unit. Provides user applications with access to config the system and measurement data in a convenient format. An analog-to-digital converter with a frequency of 8 MHz Arduino Uno was chosen as a platform for creating an echo sounder. For the purposes of generating an audio signal, an actuating device is selected – an ultrasonic waterproof sensor JSN-SR04T.

The characteristics of this sensor allow to work in environments while being completely immersed, that is, minimally reducing the measurement error in transient environments. With this sensor, it is possible to cover an area at an angle of 75 degrees and a depth of up to 600 cm.

The first measurements are displayed on the LCD display with backlight ST792 (Fig. 5).

The working model looks like this and requires further design and installation on an aerobot (Fig. 6).

To write code for this scheme, it was necessary to find out several key parameters. First, the speed of sound propagation in water. The speed at a temperature of 8 degrees is 1435 m/s and increases with increasing temperature. The speed is also affected by: salinity, density and atmospheric pressure. However, considering that authors are taking measurements from the surface of the water, in fresh water, with a temperature in the range of 5–12 degrees, authors calculate the normalizing coefficient in the program, which is equal to the value of 13.

Fig. 5. Instrument test results

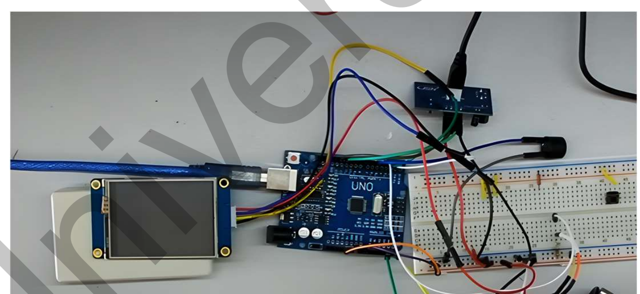


Fig. 6. The working model

5. 2. Web server and software development

The web server consists of three modules (Fig. 7):

– data collection module – database for saving bathymetric and hydrographic indicators;

– data processing module – software developed in Python for processing and visualizing data, a website for interacting with users and manual data entry;

– management and configuration module-provides a web interface for managing and configuring the software, including selecting data sources, setting analysis parameters, managing data access, user interactions, etc.

The received data from the board, in particular from the echolocation device (depth data) and HEX Pixhawk 2.1 CUBE ORANGE+ (GPS data, status data, trajectory data) are sent to a remote command center (computer) [34]. Data received from HEX Pixhawk 2.1 CUBE ORANGE+ is sent to Mission Planner to monitor real-time data such as GPS coordinates, altitude, speed, battery status and other parameters [35, 36]. This data can be saved to a text file and sent to a web server for later saving in a MySQL database [32]. Next, using the developed python program code and its libraries, data is processed and visualized in 2D and 3D graphics [37, 38]. To create 2D and 3D graphics [39], the express tool is used, which, receiving a previously created data array, creates a dynamic window with graphs (Fig. 8). Then python builds an html file with ready-made graphs. CSS classes are added to this window for a more convenient interface with which the user will interact (Fig. 9). The finished html file is sent to the application client, where the user can see and interact with them [40].

For fast processing, the Numpy library is used, which allows to convert data into an array convenient for analysis. The array created in this way is visualized using the plotly library.

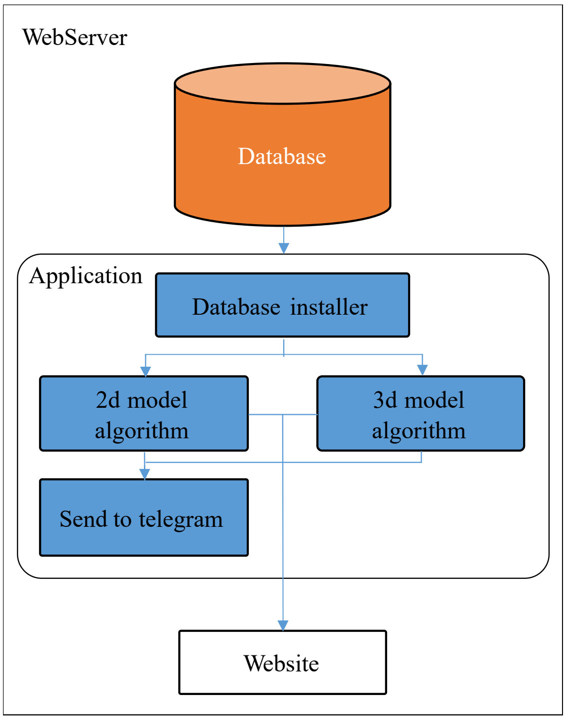


Fig. 7. Web server structure

5. 3. Data processing and forecasting using Arima models and neural networks

Indicators of the qualitative composition of wastewater at the Tailings Dump of the ZhMPP is shown in Fig. 10. The chemical composition of the samples was checked for compliance with the RMPC. Organoleptic characteristics of the sample water: colorless, odorless and sediment-free. Physical and chemical indicators were studied (Fig. 11, Table 1).

In addition to the data that was collected using sensors installed on the catamaran, water samples were collected during pre- and post-flood periods from 2021 to 2023 and analyzed in laboratory conditions and in legacy databases. The studied aqueous particles obtained from various water bodies were certified by analysis for 13 physicochemical parameters, including ion content (Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, total Fe, Cl- and others). Water samples of the Ishim River in Akmola region and the tailings of the Zhayrem mining and processing plant in the Karaganda region of Kazakhstan from surface water sources using the method of atomic emission spectroscopy (inductively coupled plasma) to determine the content of six stable metals (cadmium, copper, manganese, nickel, lead and mercury) [40]. Next, authors compared the accuracy of prediction results using the Arima model, neural network and regression analysis. For this article, authors analyzed at manganese health indicators as they have been overestimated. For calculations, the Google Colab environment and Python language were used. Authors graphically presented the prediction results using the Arima model, network neural and regression analysis (Fig. 12). Below is shown the data for predicting health indicators manganese in the Ishim river of the Akmola region of the Republic of Kazakhstan.

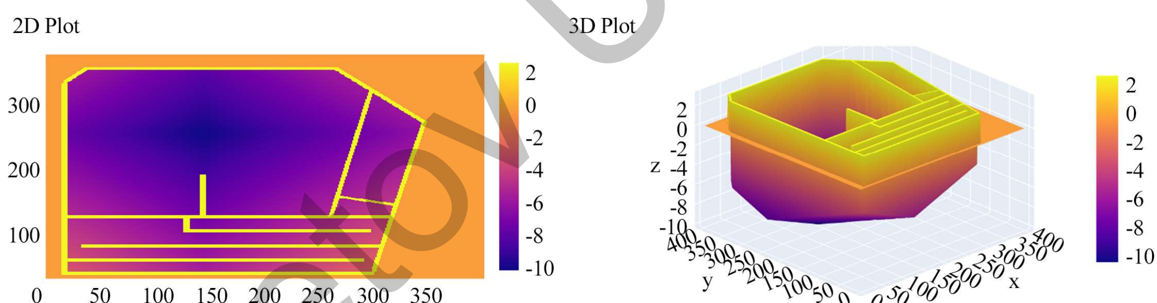


Fig. 8. The working model

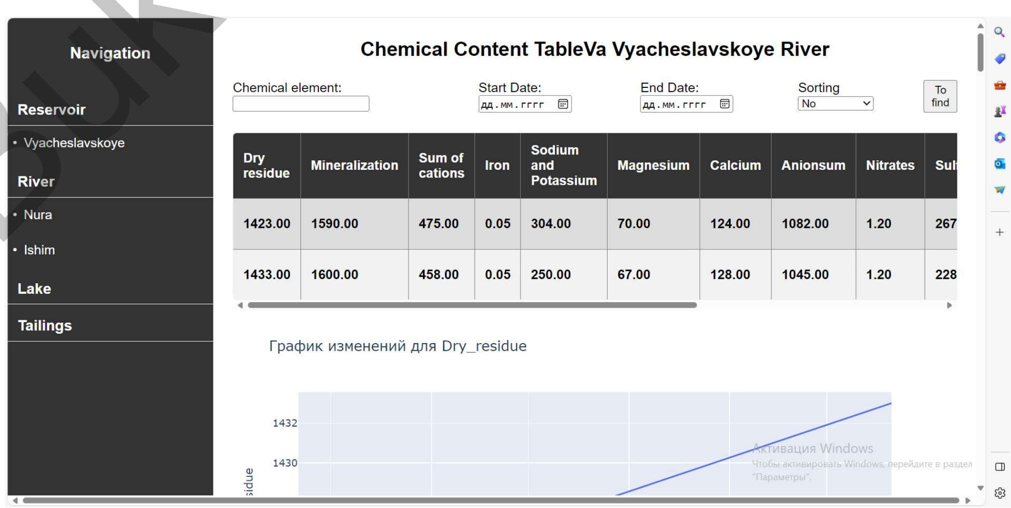


Fig. 9. Bathymetric and hydrographic database

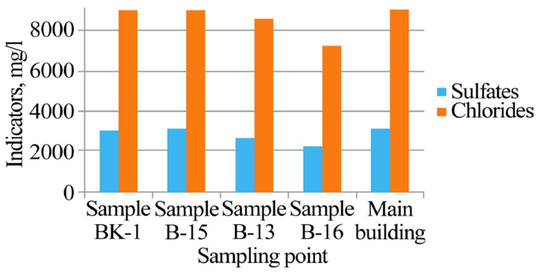


Fig. 10. Indicators of the qualitative composition of wastewater at the Tailings Dump of the ZhMPP, mg/l

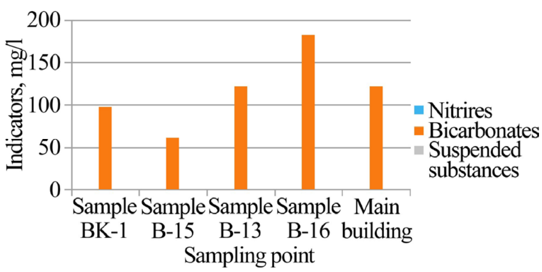


Fig. 11. Indicators of the qualitative composition of wastewater at the Tailings Dump of the ZhMPP, mg/l

Let's define a neural network architecture for prediction. The input layer consists of 1D dense 28 neurons, ReLU (rectified linear unit) is used as the activation function, as this layer processes 1D input data and introduces non-linearity with the ReLU activation function. As a result, 1D Dense used Linear Activation, a layer designed for task regression, so no activation function is used and the model produces continuous values. Adam (Adaptive Moment Estimation) was used as an optimizer, and Mean Squared Error was used as a loss function, since this model minimizes the MSE error between predicted and actual values. The model has been trained on data for 50 epochs.

Table 1

Physico-chemical indicators of water

Water hardness	pH	Sample locations
150	7	BK-1
145	6.12	B-15
133	6.96	B-13
110	7.2	B-16
169	7.3	Main building

Thus, the neural network uses a ReLU activation function to provide nonlinearity, an Adam optimizer to train and minimize losses, and metrics to evaluate its performance.

For the Arima model, the indicators were chosen Order (p, d, q): (1, 0, 0), where:

– p (AR) – autoregression order – 1. p determines the dependence of the current value on the previous one;

– d (I) – integration order – 0. d means the absence of differentiation of the series (stationary time series);

– q (MA): Moving average order – 0. q determines the dependence of the current value on previous forecast errors.

Previously, it was the parameters (1, 0, 0) that showed a good evaluation coefficient for AIC (Akaike information criterion) and BIC (Bayesian information criterion). They are informative criteria used to select the best model in statistical modeling, including time series.

Below are data for predicting Mg concentration indicators in the tailings of the Zhayrem mining and processing plant in the Karaganda region of the Republic of Kazakhstan (Fig. 13). Due to the specifics of the object, authors see that the indicators of heavy metal are relatively higher.

Quantitative indicators for predicting the concentration of heavy metals manganese in the Ishim river and Zhayrem mining and processing plant using ARIMA models, neural networks and regression are shown in the Table 2.

Graphs of losses, accuracy and completeness during training and testing of this neural network are presented in the Fig. 14.

The best verification accuracy is achieved at the 16th iteration. The error rate is minimized and reaches zero at the 16th iteration during the validation check as it can be a loss function for model training. The loss decreases as the number of iterations increases, which means the model learns very well from the data. It minimizes the distance between the predicted and actual sample value. From the entire error analysis, authors can conclude that the model requires only 16 iterations to train and set the optimal weight value.

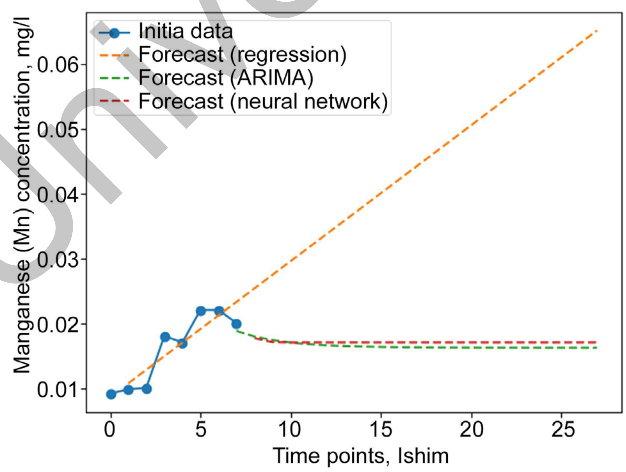


Fig. 12. Forecasting of indicators Mg in the Ishim river of the Akmola region of the Republic of Kazakhstan

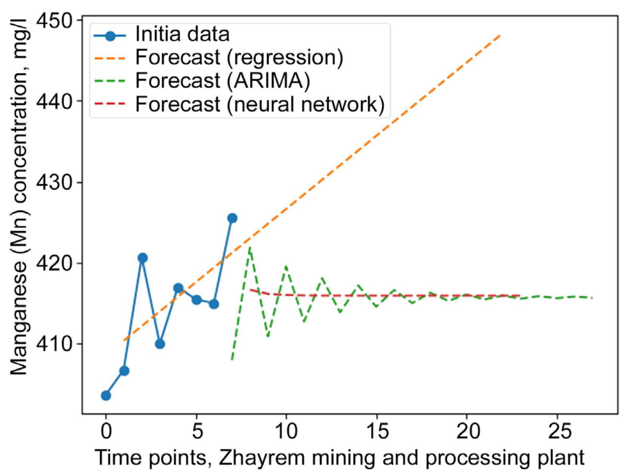
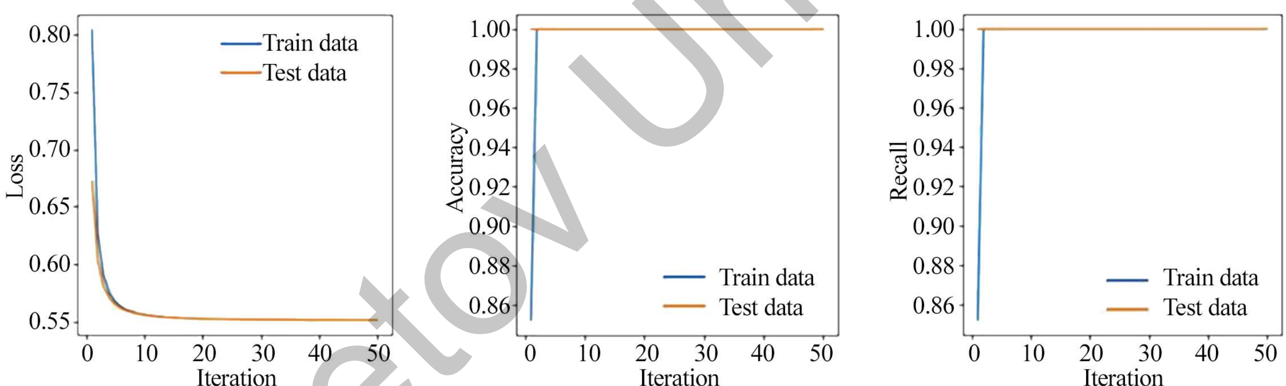


Fig. 13. Forecasting of indicators Mg in the tailings of the Zhayrem mining and processing plant in the Karaganda region of the Republic of Kazakhstan

Table 2

Predictions of Manganese (Mn) concentration

Date	Predictions of Manganese (Mn) concentration					
	Ishim River			Zhayrem Mining and Processing Plant		
	ARIMA	Regression	Neural networks	ARIMA	Regression	Neural networks
15.04.23	0.018761	0.01749186	0.01069286	407.9761423	410.3892857	416.20544
15.10.23	0.01792563	0.017001545	0.01278571	421.8608323	412.1928571	415.96234
15.04.24	0.01736239	0.01697051	0.01487857	410.9219891	413.9964286	415.93436
15.10.24	0.01698265	0.0169777	0.01697143	419.5399914	415.8	415.93106
15.04.25	0.01672661	0.016976034	0.01906429	412.7504285	417.6035714	415.93085
15.10.25	0.01655398	0.01697642	0.02115714	418.099483	419.4071429	415.93085
15.04.26	0.01643759	0.01697633	0.02325	413.8853113	421.2107143	415.93085
15.10.26	0.01635911	0.01697635	0.02534286	417.2053828	423.0142857	415.93085
15.04.27	0.0163062	0.016976345	0.02743571	414.5897146	424.8178571	415.93085
15.10.27	0.01627053	0.016976347	0.02952857	416.6504293	426.6214286	415.93085
15.04.28	0.01624648	0.016976347	0.03162143	415.0269264	428.425	415.93085
15.10.28	0.01623026	0.016976347	0.03371429	416.3059786	430.2285714	415.93085
15.04.29	0.01621933	0.016976347	0.03580714	415.2982966	432.0321429	415.93085
15.10.29	0.01621195	0.016976347	0.0379	416.0921836	433.8357143	415.93085
15.04.30	0.01620698	0.016976347	0.03999286	415.4667318	435.6392857	415.93085
15.10.30	0.01620363	0.016976347	0.04208571	415.9594846	437.4428571	415.9308
15.04.31	0.01620137	0.016976347	0.04627143	415.5712767	439.2464286	415.9308
15.10.31	0.01619985	0.016976347	0.04836429	415.8771204	441.05	415.93078
15.04.32	0.01619882	0.016976347	0.05045714	415.6361661	442.8535714	415.93083
15.10.32	0.01619813	0.016976347	0.05255	415.8259983	444.6571429	415.93084



a *b* *c*

Fig. 14. Graphs: *a* — losses; *b* — accuracy; *c* — completeness during training and testing of this neural network

6. Discussion of experimental results of analysis and forecasting of data obtained using a mobile robotic complex

During the research, data on XY coordinates was collected using the echo sounder authors developed and data on Z coordinates from GPS. When calculating the volume of a water body, authors used a formula based on a set of data points, where each point represents a unique time (t) and spatial coordinates (X, Y, Z) (1). Authors assume that these points can be approximately represented using surface approximation methods. According to the results of testing of the robotic complex, data on the error of the robot's movement in the coordinate system were obtained. This error is approximately 0.2 meters on the x axis and 0.1 meters on the y axis (1), (Fig. 4). Temperature, humidity, oxygen level (O_2) and particle concentration were almost constant during testing. It is also known that the average depth of the tailings dump is 4.56 meters.

Based on these data, calculations of the volume of water were made. To do this, the catchment areas of various sections were measured: the catchment area of the barite tailings section is 2.5 km^2, and the catchment area of the barite tailings section together with the filtration section is 0.38 km^2. It was also found that 1.85 million m^3 of water was accumulated in the oxidizer pond, which corresponds to the water level at 392.55 meters (Fig. 8).

The results of the calculations allowed to establish the following facts.

In the first half of 2021, there was a "zero" balance without dumping surpluses into the evaporation pond. This was achieved by soaking the base and filling the sections of the tailings dump, which prevented the discharge of water.

For the subsequent period until the end of 2023, an excess of recycled water was recorded in the range from 6700 to 24600 million m^3, which was discharged into the evaporator pond. This made it possible to control the water level in the system and avoid overflow [40].

It was also found out that the area and volume of the settling ponds of the tailings pond and oxidizer pond sections provide sufficient illumination of the recycled water returned to the factory in the technological process, which allows the reuse of this water.

The possibility of storing the volume of tailings entering the settling ponds during the year, which contributes to effective waste management.

Field experiments conducted using a mobile robotic complex allowed to conclude that the MRC provides stable and reliable data transmission. Overcoming the interference found at sensor outputs was achieved through the introduction of decoupling circuits, which significantly improved signal quality and provided more accurate measurements. Software designed to monitor and monitor system operation functions effectively when used on a personal laptop. This provides the full range of functionality of the proposed system and ensures its high practicality in real-life operating conditions. It should be noted that the implementation of a water sensor in a UAV provides water managers with a unique opportunity to continuously monitor and control water quality parameters in vulnerable and strategically important areas of tailings ponds and reservoirs. This approach significantly improves the efficiency and effectiveness of water management, facilitating more rational and informed decision-making in this area.

The results of samples taken from water bodies indicate that the MPC are exceeded. Wastewater from the processing plant is transported to the Tailings Dump at a distance of 3.5 km. Indicators of sulfates in water indicate an excess of MPC by 12 times, and indicators of chlorides by 7 times (Fig. 11, 12). As a rule, such water requires purification or settling. Constant monitoring of the chloride level is necessary for all water used by a person in order to track the excess in time and eliminate undesirable consequences. During the study, the water indicator is within the normal range. Water hardness is also within the normal range.

A comparative analysis of the methods of the forecasting models authors selected showed that in regression analysis the values increase monotonically and too quickly. This may be a sign that the regression model is fitting the training data too aggressively and is not accounting for enough structure in the data. ARIMA forecasts were more robust and followed the general trend in the data. However, they may also remain somewhat high in amplitude compared to a neural network. Neural network predictions are probably more realistic since they maintain a more moderate trend. However, they can also remain fairly static.

Analyzing the Forecast of indicators Mg in the tailings of the Zhayrem mining and processing plant in the Karaganda region of the Republic of Kazakhstan, authors can conclude that the regression forecasts in this case increase too quickly, and the growth amplitude is much higher than in the original data (Fig. 12). This supports the assumption that the regression model may be overfitting and fitting the data too aggressively. ARIMA forecasts are more stable and closer to real values. This may be an indication that ARIMA takes better account of the temporal structure of the data. And using the Ishim River data as an example, neural network predictions seem to be more stable than in the previous example, but they remain relatively static. The neural network may remain less flexible compared to ARMA (Fig. 13).

This research has the following limitations. The applicability of the proposed solutions is limited to controlled test conditions; if the network fails, the data may be transmitted with error or not reach the workstation. There may be difficulties in reproducing results under real operating conditions due to changes in external factors.

Thus, the results of the study allow to conclude that a robotic complex has been developed and successfully used for monitoring and analyzing water bodies, which contributes to more efficient water resource management and environmental safety. Further development of the study may include a more in-depth analysis and identification of factors influencing the robot's movement error, expanding the scope of application of forecasting models to other types of reservoirs and water systems, and repeating the study to complement the dataset.

7. Conclusions

1. A mobile robotic complex was developed to monitor the condition of water bodies. Authors have designed and developed a mobile robotic complex, an echolocation device. The MRC and echolocation device has been tested in testing facilities. The 2D and 3D map of the bottom of the tailings dump of the Zhairem mining and processing plant was also obtained. Testing of the robotic complex showed that the movement error is approximately 0.2 m along the x-axis and 0.1 m along the y-axis. Temperature, humidity, oxygen and particle concentrations were also recorded to remain constant throughout the tests. The average depth of the tailings pond was 4.56 m. Based on the collected data, the water volume and water balance were calculated. The results showed that in the first half of 2021, a "zero" balance was achieved with no excess discharged into the evaporation pond, and then there was an excess of recycled water that was discharged into the evaporation pond. It was found that the area and volume of settling ponds provide sufficient illumination of recycled water and storage of volumes of tailings entering the settling ponds throughout the year.

2. Authors developed a database, a web server and software for monitoring bathymetric and hydrographic indicators of water bodies, and obtained 2D and 3D maps of the bottom of the tailing dump. For the subsequent period until the end of 2023, an excess of recycled water was recorded in the range from 6700 to 24600 million m^3, which was discharged into the evaporator pond. In addition to the data collected from the sensors of the robotic complex (Hydrogen index (pH), Redox Potential (ORP), Temperature, Absolute electrical conductivity, Salinity), data were obtained from the physicochemical analysis of water samples (Ca^{2+}, Mg^{2+}, Na^+, K^+, total Fe, Cl^- and others), which were collected during 2021–2023. A value of $6.3<pH<7.3$ is not too high. On the pH scale, which measures the acidity or alkalinity of aqueous solutions, a value of 7 indicates neutral. This means that the concentration of hydrogen ions (H+) and hydroxide ions (OH–) in such an environment is balanced, making it neutral. Water analysis showed that the maximum permissible concentrations of Mg^{2+}, sulfates and chlorides in wastewater were exceeded, requiring additional treatment or sedimentation. The development of a database, web server and software for monitoring the bathymetric and hydrographic indicators of water bodies has made it possible to obtain valuable data on the condition of water bodies. The

analysis showed that during the period under review, the excess of recycled water was significant, which emphasizes the relevance of control and monitoring of water resources. Data obtained from sensors of the robotic complex and physical and chemical analysis of water samples revealed that the maximum permissible concentrations of certain substances in wastewater were exceeded, which emphasizes the need for additional treatment or sedimentation.

3. Authors collected a total of more than 1,500 data on the condition of the research objects and carried out forecasting.

However, during the study, the level of chlorides remained within normal limits, and water hardness also did not exceed the standards. ARIMA models and neural networks were used to predict the data. For forecasting, data on Mg concentration were selected, since their quantitative indicator was convenient for calculation. As a result of the comparative analysis, ARIMA turned out to be more effective for predicting data related to the Zhayrem mining and processing plant, while the neural network proved to be less flexible and accurate due to insufficient data. and using the example of the Ishim River, on the contrary, neural networks showed more accurate results. Forecast accuracy using a neural network exceeded 95 %.

Conflict of interest

Authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has associated data in a data repository: git@github.com:makkenskii/Ishim-and-Zhayrem.git [41].

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

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