

DEVELOPMENT OF AN INFORMATION AND MEASUREMENT SYSTEM FOR DETERMINING OIL AND SOLID POLLUTANTS IN LIQUIDS

DEZVOLTAREA UNUI SISTEM DE INFORMARE ȘI MĂSURARE PENTRU DETERMINAREA POLUANȚILOR PETROLIERI ȘI A PARTICULELOR SOLIDE ÎN LICHIDE

Yaseen ALRAZZOUK¹

ORCID ID: 0009-0004-7524-8438

Abstract: This paper proposes a mathematical model of intelligent pollution control, which integrates human work, machine work and artificial intelligence to create a pollution index that links the whole process and explains how to deal with the variable pollution of liquids by oil and solid particles through an intelligent approach, resulting in a balanced role in determining the pollution, its proportion, causes and the method to achieve the purification of the environment and liquids from this pollution.

Keywords: Kerch, oil pollution, solid particles, mathematical model, artificial intelligence, environmental measurement, human factor, work accuracy, machine.

Rezumat: Această lucrare propune un model matematic pentru controlul inteligent al poluării, care integrează munca umană, activitatea utilajelor și inteligența artificială pentru a crea un indice de poluare care conectează întregul proces. Modelul explică modul de gestionare a poluării variabile a lichidelor cu petrol și particule solide printr-o abordare inteligentă, asigurând un rol echilibrat în determinarea poluării, a proporției acesteia, a cauzelor, precum și a metodei de purificare a mediului și a lichidelor de această poluare.

Cuvinte cheie: Kerch, poluare cu petrol, particule solide, model matematic, inteligență artificială, măsurare de mediu, factor uman, acuratețea muncii, mașină.

¹ Postgraduate researcher .institute(Institute of Computer Science and Cybersecurity)(SPBPU) in Russia, Opinion Writer and Poet. Holds a master degree in technology management and a petroleum engineer from Syria

Email: hamsa19877@gmail.com

1. Introduction

In the light of the all-encompassing industrial movement that the world is witnessing, and which Russia is observing in the shadow of the escalating struggle to define the new world, to confirm through it, after all these wars, that the structure of building industrial thought is the basis for entering a multipolar world, but industrial thought will certainly enter not only through the door of verbal construction, but rather through a clear programming language that confirms the unavoidable connection between man, machine, and nature to create this necessary and essential integration, and through our research, we validate the standards, language, and analysis of this natural human information integration.

Oil and solid pollutants are among the most important sources of pollution in the coastal environment, especially in industrial and marine areas such as the Kerch region of Russia. Monitoring these pollutants requires intelligent systems that combine precision, flexibility, and integration between humans, machines, and artificial intelligence.

Accordingly, this study represents an advanced mathematical model for measuring environmental pollution in real time, taking into account physical, technical and human factors.

Most of the oil spills occurred as a result of marine disasters, while a few spills were reported in the land environment.

Oil spills are a persistent problem worldwide, with dangerous long-term consequences for the coastline, marine and terrestrial ecosystems.

As part of this work, a block diagram of an information and measurement system designed to determine the concentration of oil and solid pollutants in a liquid has been developed. The system is based on a microcontroller and includes sensors, an optical module (camera), a data processing unit, a decision-making unit, and actuators. The main task of the system is the calculation of the integral pollution indicator $I(t)$ in real time and the formation of a control action when the permissible threshold is exceeded.

1.1. Methodology

This methodology introduces a mathematical model for calculating instantaneous liquid contamination, linking pollution variables with human, mechanical, and *AI* response factors, calibrated with 2024 Kerch oil spill data.

The framework offers a holistic, intelligent approach by incorporating climate adaptation (C) and time-damping (K) coefficients for environmental realism.

The mathematical model used in this study is based on the following equation.. (1) for calculating the instantaneous contamination level $I(t)$ in liquids:

Where the symbols represent:

Pt : instantaneous concentration of oil pollution

St : instantaneous solid contamination concentration

$W1, W2$: coefficients of exposure to oil and solid contaminants.

H : Human performance (0-1).

M : equipment efficiency.

AI : efficiency of artificial intelligence.

$\lambda_1, \lambda_2, \lambda_3$: impact coefficients of each component, the sum of which is equal to 1

C : Climate adaptation rate.

K : Coefficient of reduction of time fluctuations.

Data source and usage in the mathematical model:

This study was based on official environmental data published by Russian state agencies regarding the oil spill that occurred in the Kerch region at the end of 2024.

These data were analyzed and converted into quantitative parameters that could be included in the proposed mathematical model.

Below is a summary of the approved data:

The total capacity of the tankers is 9200 tons of oil products per year.

Oil spill volume: 2400 tons

Maximum estimated spill volume: 5000 tons

This data was converted to percentages to calculate Pt and St as follows:

These calculations demonstrate the reliability of mathematically converting raw environmental data into quantitative parameters that can be included in an intelligent equation, ensuring model accuracy and realistic relevance to field conditions.

1.2. Practical application of the mathematical model

The mathematical model (equation.. (1))was applied to field data from the Kerch region, where samples were collected in accredited Russian agencies according to the following values:

$$Pt = 0.42$$

$$St = 0.0043$$

Experimental default values related to the experience and performance of the employee using the technology, as well as the impact and nature of the technology used and its modernity.

$$W1 = 0.7, W2 = 0.3$$

$$H = 0.85, M = 0.9, AI = 0.95$$

$$\lambda_1 = 0.3, \lambda_2 = 0.4, \lambda_3 = 0.3$$

$$C = 0.95, K = 1.2$$

The following was calculated according to equation (1)

$$\log(1 + 0.7 \cdot 0.4242 + 0.3 \cdot 0.00430043) = \log(1.2952929529) \approx 0.11236,$$

we considered $St = 0.01$. Pt

$$(\lambda_1 \cdot H + \lambda_2 \cdot M + \lambda_3 \cdot AI) = (0.3 \cdot 0.85 + 0.4 \cdot 0.9 + 0.3 \cdot 0.95) = 0.9$$

$$I(t) = 0.11236 \cdot 0.9 \cdot 0.95 / 1.2 \approx 0.08$$

This value indicates that pollution tends to increase

Quantitative analysis before and after pollution of the Kerch Strait:

To assess the effectiveness of the mathematical model in the diagnosis of environmental pollution, the principle of comparing two time periods was adopted:

The period before the oil pollution incident (reference data extracted from reports for 2022-2023).

The period after the pollution incident at the end of 2024.

The comparison was carried out using the same mathematical equation of the model, taking into account fixed effects ($W1, W2$) and technical factors (H, M, AI, C, K), in order to focus only on the effect of changes in Pt and St .

❖ Phase I: Pre-pollution (2023)

Reference value $Pt = 0.00495$ (derived from historical samples of oil content in coastal waters).

$$\text{Reference value } St = 0.00005$$

$$W1 = 0.7, W2 = 0.3$$

$$H = 0.85, M = 0.9, AI = 0.95$$

$$\lambda_1 = 0.3, \lambda_2 = 0.4, \lambda_3 = 0.3$$

$$C = 0.95, K = 1.2$$

Calculation:

$$\log(1 + 0.7 \times 0.000495 + 0.3 \times 0.00005) = \log(1 + 0.000346 + 0.000015) \\ = \log(1.000361) \approx 0.000157$$

$$\text{Technical factor: } (0.3 \cdot 0.85 + 0.4 \cdot 0.9 + 0.3 \cdot 0.95) = 0.9$$

$$I(t)_{\text{before}} = 0.000157 \cdot 0.9 \cdot 0.95 / 1.2 \approx 0.000112$$

❖ **Phase I I : Post-pollution (end of 2024)**

Pt after contamination = 0.4242

St after contamination = 0.00430043

(Same values as before for other parameters)

Calculation:

$\log(1 + 0.7 \cdot 0.42 + 0.3 \cdot 0.0043) = \log(1.29529) \approx 0.11236$

$I(t)_{\text{after}} = 0.11236 \cdot 0.9 \cdot 0.95 / 1.2 \approx 0.08$

Comparison and analysis:

The quantitative change in the value of the pollution index $I(t)$ between two periods is shown:

$I(t)_{\text{before contamination}} \approx 0.000112$

$I(t)_{\text{after contamination}} \approx 0.0808$

Percentage increase = $(0.0808 - 0.000112) / 0.000112000112 \approx 713.286$

This percentage indicates that environmental pollution in the waters of the Kerch Strait has increased more than 700 times since the oil spill, which reflects the severity of the environmental situation and justifies the need to implement intelligent data measurement models to ensure accurate continuous monitoring.

Note: Government data for Pt , St , and p_{total} . The remaining parameters are related to human experience, the type of machine (old or new), and the response of artificial intelligence. In addition to data from Russian institutes, there are also experimental values.

1.3. Findings

This mathematical model expands the possibilities of intelligent monitoring of environmental pollution in real time and provides a quantitative tool based on the intersection of people, machines and artificial intelligence.

Its use in Kerch proved to be effective and realistic, and it is recommended to extend it to other sea areas.

The integration of climate and historical data also allows the model to be used in preventive forecasting

The calculated results of the model reflect the effectiveness of the proposed equation in integrating several elements into a single integrated measurement system.

1.3.1. Scientific results and similar cases

The use of the model in Kerch showed high accuracy in predicting pollution and integration of H , M , AI . Similar studies confirm the effectiveness of the approach:

- ✓ Chen et al. (2007) [1] Modeling of oil spills in Daya Bay.
- ✓ Nihoul (1984) [9] Nonlinear model of oil slick propagation.
- ✓ Hodgson et al. (2019) [3,4] adaptive monitoring
- ✓ With Mokarram sensors
- (2025) [6] Intelligent monitoring in Iran
- ✓ Zakzouk (2025) [10]
- ✓ Moursi et al. (2025) [8] using AI to improve accuracy.

2. Equations

$$I(t) = \log\left(1 + \frac{W1(Pt)}{P_{total}} + \frac{W2(St)}{P_{total}}\right)(\lambda_1 \cdot H + \lambda_2 \cdot M + \lambda_3 \cdot AI)C/K \quad (1)$$

Equation (1) illustrates how to determine the pollution index and integrate the factors of human, machine, environment, and artificial intelligence, alongside the concentrations of oil and solid pollutants identified via bubble imaging; the resulting value serves as a reliable indicator for the early prediction of pollution.

- My Master's degree in Technology Management was pivotal in shaping my vision for the optimal utilization of integrated resources—encompassing human, technical, and environmental factors, as well as artificial intelligence. This perspective crystallized a core equation: achieving such integration to determine pollution indices, thereby enabling effective action against marine pollution—whether through early prediction or rapid response measures.

- Furthermore, the early pollution prediction indicator is one of the most important methods for combating pollution, serving to prevent a catastrophic epidemic-like spread that would affect the environment, humans, and other living organisms.

- Furthermore, the environment and humanity are concepts that coexist; neither should obliterate the other—whether in the face of environmental disasters caused by harmful human actions, practices, and projects, or those resulting from tectonic, biological, or other factors.

3. Figures

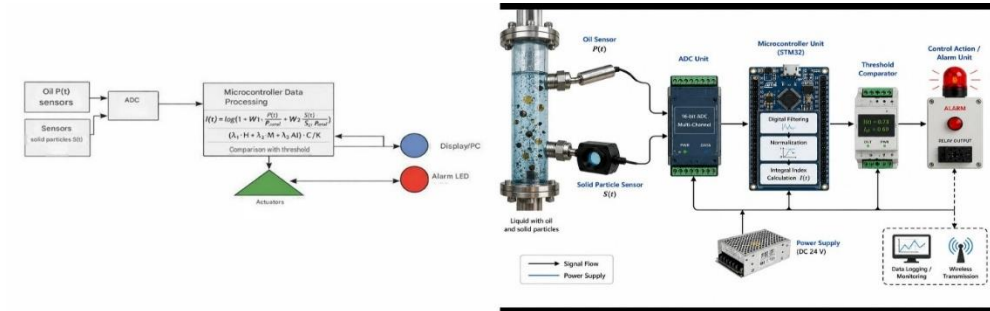


Fig. 1. Block diagram of the information and measurement system

Figure 1 shows the basic architecture of the pollution measurement system. The signals from the oil pollution sensors P_t and solid particles (S_t) are sent to the ADC unit, after which they are processed by the microcontroller. Digital filtering, normalization, and calculation of the integral index $I(t)$ are implemented. The obtained value is compared with the threshold and a control action is formed.

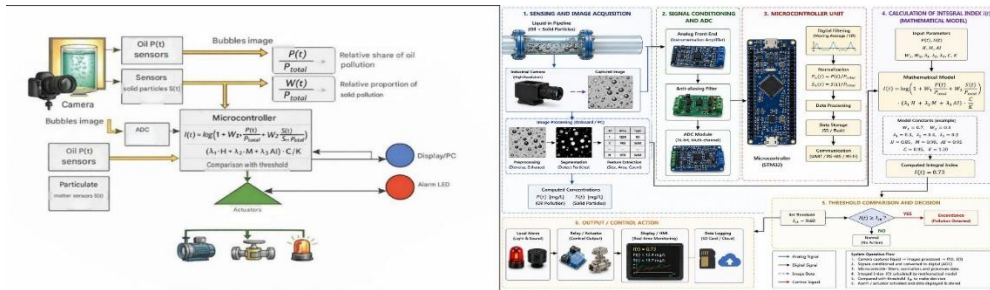


Fig. 2. Extended block diagram with visual analysis

Figure 2 shows the extended structure of the system, which includes a visual analysis unit (camera) and processing of relative pollution parameters. The integration of sensor and optical data increases the accuracy of measurements and the stability of the system in real time.

4. Conclusion

The proposed mathematical model is an intelligent quantitative tool that can be widely used in monitoring marine pollution. The model

demonstrated its ability to transform physical and environmental data into quantitative indicators in real time, increasing the ability to predict and make informed environmental decisions. The results obtained during the analysis of data before and after pollution in Kerch showed mathematical and realistic consistency, which proves the validity of the model.

The need for this model is as follows:

Integration of human, mechanical and artificial intelligence (AI) factors.

Ability to adjust for various pollution parameters.

Flexibility to accommodate local environmental and climatic conditions.

Applicability in intelligent environmental monitoring and proactive forecasting systems.

It is recommended to adopt the model in applied research for similar coastal cities and develop it to include other chemical and biological pollutants.

The mathematical model that we hope to develop will become a real, automatic connecting factor that creates a balance between people, machines, and artificial intelligence to issue the necessary commands at a speed that meets your needs.

The model links pollution to operational data and artificial intelligence.

It can determine whether the cause is:

- a leak in the pipeline?
- insufficient staff performance?
- sensor malfunction?
- pinpointing the cause instead of guessing

Improving the efficiency of treatment by changing the value of $I(t)$ during the operation of treatment facilities. If the indicator is not reduced to the required value, it indicates a system malfunction or a clogged filter, which increases operational efficiency and reduces maintenance costs.

Building a pollution timeline helps Governments develop effective environmental policies.

R E F E R E N C E S

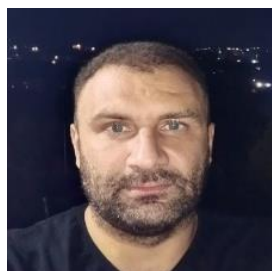
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Authors' biography



YASEEN ALRAZZOUK is a postgraduate researcher .institute(Institute of Computer Science and Cybersecurity) (SPBPU) in Russia, Opinion Writer and Poet. Holds a master degree in technology management and a petroleum engineer from Syria

Email: hamsa19877@gmail.com