

Integrated Monitoring of Radioactive Fallout Based on Artificial Intelligence and the Internet of Things

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Abstract

The development of wireless systems for detecting radioactive fallout in Azerbaijan is a critically important task for ensuring public safety and protecting the environment. Azerbaijan, like many other countries, is at risk of radioactive contamination as a result of accidents at nuclear facilities, terrorist acts, or natural disasters. When developing wireless systems for detecting radioactive fallout, a number of factors must be considered, such as the type and sensitivity of detectors, the range and reliability of wireless communication, the energy efficiency of the system, and its resistance to environmental influences. It is also important to ensure the system's compatibility with existing infrastructure and the possibility of scaling it in the future. Investing in the development and implementation of wireless systems for detecting radioactive fallout is an important step in ensuring Azerbaijan's national security. Such systems allow for the timely detection of and response to radioactive threats, minimizing the consequences of radioactive contamination and protecting public health.

Keywords: Radioactive fallout, wireless systems, safety, environmental monitoring, risks, emergencies, safety, sensors.

Introduction

Environmental radiation monitoring is a crucial component of the system for protecting populations and natural ecosystems from exposure to ionizing radiation. Its primary objective is not only to record radiation levels but also to identify sources of contamination, assess the pathways of radionuclide migration, determine the spatial distribution of contamination, and provide information support for decision-making authorities. International practice involves the

use of environmental monitoring to assess existing radionuclide levels, environmental characteristics, and potential pathways of exposure to the population [1].

Particular complexity is associated with the monitoring of radioactive fallout, as the deposition of radionuclides onto the Earth's surface may occur unevenly in both time and space. The pattern of radioactive fallout is influenced by atmospheric circulation, wind speed and direction, precipitation, temperature, humidity, terrain, and the characteristics of the underlying surface. Subsequently, radionuclides may be redistributed among the atmosphere, soil, surface and groundwater, bottom sediments, and biological components of ecosystems [2, 3].

Traditional environmental radiation monitoring involves the collection of air, water, soil, sediment, and biota samples, followed by laboratory determination of radionuclide activity. These methods provide the required analytical accuracy; however, they do not always allow information to be obtained in near-real time. Recent studies of environmental radioactivity emphasize the need to combine highly accurate laboratory methods, field measurements, and spatiotemporal approaches to data interpretation [3, 4].

The development of distributed sensor networks has significantly expanded the capabilities of environmental monitoring. IoT technologies make it possible to integrate multiple sensor devices into a unified information infrastructure, enabling automated data collection, transmission, and storage. The use of distributed sensor networks, wireless data transmission, and LoRa technologies for continuous monitoring of radiation conditions has already been demonstrated in radiation monitoring applications [5].

At the same time, artificial intelligence provides tools for processing large volumes of heterogeneous data. Machine learning algorithms can be used for classification, time-series forecasting, anomaly detection, and the development of spatiotemporal models of environmental processes. Studies in related areas of environmental monitoring indicate that the combination of IoT and machine learning can enable continuous observation and forecasting systems; however, challenges remain regarding data quality, the spatial heterogeneity of observations, and the integration of information from multiple sources [6].

Thus, a scientific problem arises from the need to move from fragmented radiation monitoring systems toward an integrated intelligent platform capable of combining radiometric measurements, meteorological data, remote sensing, GIS, and mathematical modeling.

The aim of this study is to develop a conceptual architecture of an integrated radioactive fallout monitoring system based on artificial intelligence and the Internet of Things (IoT) to improve the effectiveness of environmental monitoring, forecast radioecological risks, and establish an early warning system.

To achieve this aim, the following objectives have been formulated:

1. to develop the architecture of a multilayer IoT-based radiation monitoring system;
2. to identify the main data sources;
3. to develop a mechanism for integrating radiometric, meteorological, satellite, and GIS data;
4. to determine the potential applications of machine learning methods;
5. to develop a framework for constructing an integrated radioecological risk index;
6. to formulate the concept of an intelligent early warning system.

Current State of Radiation Monitoring

Environmental radiation monitoring is a comprehensive system of measurements that includes the selection of monitoring sites, sampling, laboratory analysis, measurement of dose rates, and interpretation of the obtained results. The specific structure of a monitoring system should correspond to the nature of the radioactive source and the anticipated exposure pathways [4].

Gamma-ray spectrometric methods are of particular importance, as they enable the identification of radionuclides and the determination of their activity in various environmental components. Modern radioecology widely uses ^{137}Cs and other radionuclides as indicators of atmospheric transport, deposition, erosion, and material accumulation processes [7].

However, even highly accurate laboratory measurements have a fundamental limitation: they characterize the state of the environment at specific locations and during specific time intervals. Therefore, increasing the number of monitoring sites and moving toward continuous monitoring are important directions for further development.

The International Atomic Energy Agency (IAEA) International Radiation Monitoring Information System (IRMIS) demonstrates the need for centralized collection and visualization of large volumes of environmental radiation monitoring data during radiological and nuclear emergencies [8]. At the same time, IRMIS is primarily intended for data presentation and exchange rather than functioning as an automated early warning system. This highlights the potential of the

next technological stage-complementing monitoring infrastructure with algorithms for automatic anomaly detection and forecasting.

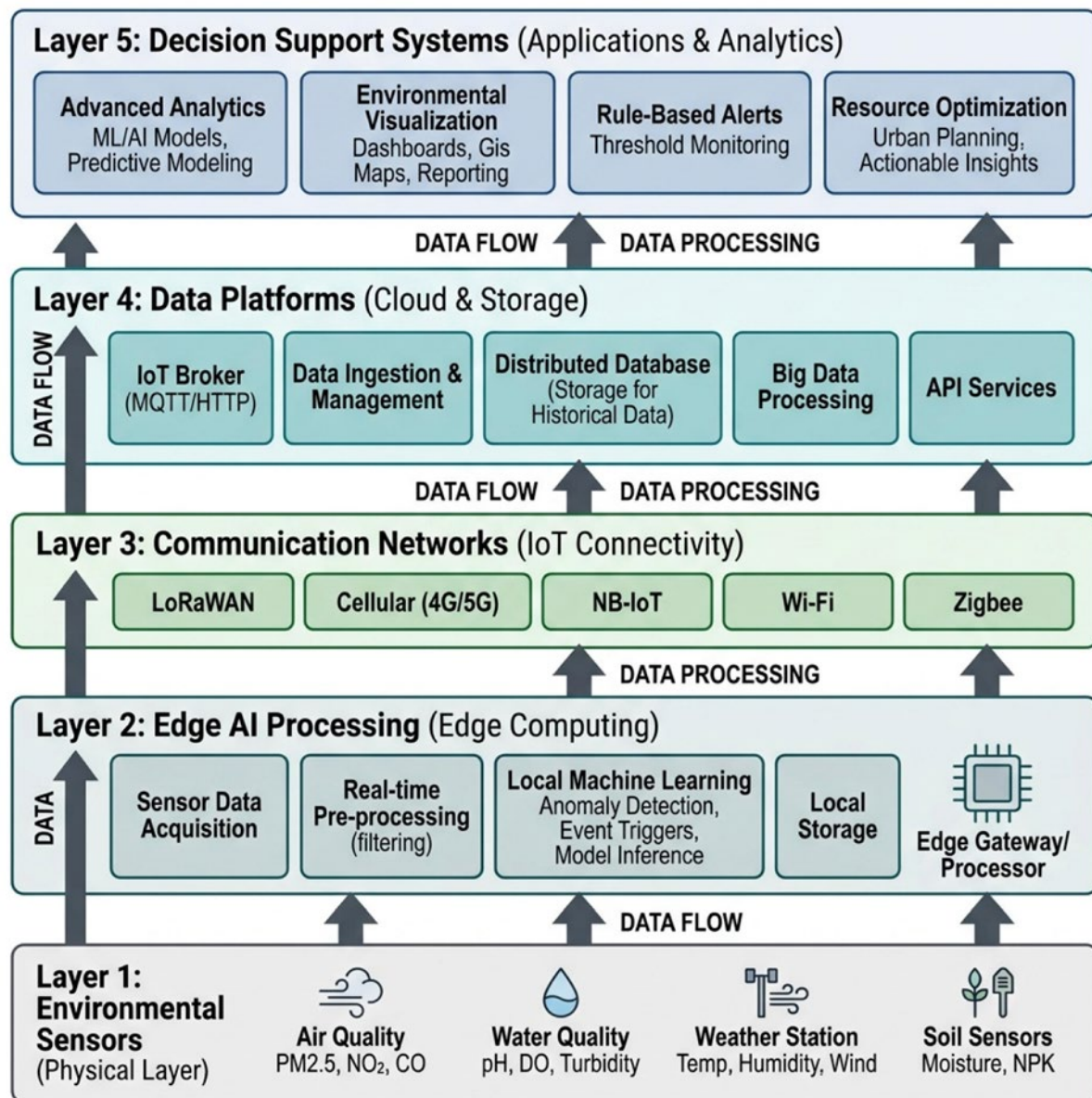


Figure 1. Five-layer architecture of an integrated intelligent environmental and radiation monitoring system

Multilevel Integrated Monitoring System

The proposed radioactive contamination monitoring system is based on the principle of multilevel data integration and comprises five interconnected levels.

The first level is formed by a ground-based measurement network comprising gamma sensors, dosimetric and aerosol radiometers, meteorological sensors, as well as sampling sites for water, soil, and bottom sediments.

The second level ensures the transmission of the collected information using LoRa/LoRaWAN, NB-IoT, LTE/5G, Wi-Fi, and satellite communication channels.

The use of a distributed sensor network makes it possible to move from periodic observations to continuous monitoring of the radioecological conditions. A similar approach using IoT and wireless data transmission based on LoRa technology has been examined in studies of distributed radiation sensor networks [5].

The third level is based on the use of Earth observation data, including Sentinel-1, Sentinel-2, Sentinel-3, Landsat, MODIS, VIIRS, and meteorological satellite observations. These data do not replace direct radiometric measurements but are used to characterize the Earth's surface, meteorological and hydrological conditions spatially, and to generate additional predictors for modeling the spread of radioactive contamination.

The fourth level represents the intelligent processing and analysis of data using machine learning methods, including Random Forest, Support Vector Machine, Artificial Neural Networks, and Gradient Boosting, as well as clustering, anomaly detection, and spatiotemporal modeling techniques. This enables the identification of patterns in radionuclide dispersion, forecasting changes in radioecological conditions, and detecting anomalous values.

The fifth level integrates the results within a Geographic Information System (GIS) and a decision support system. The final product is an interactive map of the radioecological conditions, showing observed and predicted radionuclide concentrations, areas of elevated risk, directions of contamination spread, changes in background radiation levels, and detected anomalies.

Thus, the proposed architecture provides comprehensive integration of ground-based observations, IoT communications, remote sensing, intelligent data analysis, and GIS technologies into a unified system for continuous radioecological monitoring.

Mathematical Model for Data Integration

For the quantitative assessment of the radioecological situation, the following integrated risk index is proposed:

$$R = \sum_{i=1}^n w_i X_i \quad (1)$$

where R - integrated radioecological risk index; X_i - normalized indicators; w_i - weighting coefficients.

The following structure may be used for the proposed system:

$$R = 0.25X_1 + 0.15X_2 + 0.10X_3 + 0.08X_4 + 0.05X_5 + 0.06X_6 + 0.04X_7 + 0.15X_8 + 0.10X_9 + 0.02X_{10} \quad (2)$$

where:

- X_1 - concentration ^{137}Cs and ^{90}Sr in water;
- X_2 - radionuclide concentration in bottom sediments;
- X_3 - anthropogenic pressure;
- X_4 - water surface area;
- X_5 - surface temperature;
- X_6 - vegetation cover condition;
- X_7 - precipitation;
- X_8 - terrain slope;
- X_9 - flood hazard index;
- X_{10} - additional indicator of anthropogenic pressure.

The obtained index can be classified into five levels:

After calculating the integrated risk indicator (R), the territory is assigned to one of five categories of environmental and radiation risk. If the calculated index value is very low, the territory is characterized by a very low risk. A somewhat higher value corresponds to a low risk. Medium values of the integrated index indicate a moderate risk. High values indicate a high risk, while the highest values correspond to a very high risk.

Thus, the integrated index makes it possible to transform a large number of individual indicators—including radionuclide concentrations, the condition of water bodies, terrain, vegetation, precipitation, anthropogenic pressure, and other factors—into a single composite

indicator that can be conveniently used for spatial mapping and comparative assessment of territories.

At the same time, each indicator is assigned a specific weight. The weight reflects the extent to which a given factor influences the overall risk assessment. For example, a higher weight indicates a more significant contribution of the indicator to the final index value.

In the final version of the scientific article, it is necessary to provide an additional explanation of why each factor was assigned its specific weight. This justification may be based on expert assessment by specialists, statistical analysis of the available data, or a combination of expert and statistical approaches. Such justification will make the proposed methodology more scientifically sound and reduce the likelihood of comments from reviewers.

Role of Artificial Intelligence

The application of artificial intelligence is proposed in three main areas.

Anomaly Detection

The first task is to identify deviations in the radiation background:

$$A_t = |C_t - \hat{C}_t| \quad (3)$$

where C_t – measured concentration or dose rate, and $\hat{C}_t$ - expected model value.

When the established threshold is exceeded:

$$A_t > T \quad (4)$$

an automatic warning is generated

This approach is particularly important for detecting short-term spikes that may be missed during infrequent periodic monitoring.

Spatial Forecasting

Machine learning can be used to estimate radionuclide concentrations at locations where direct measurements are unavailable.

$$C(x, y, t) = f(M, R, S, H, G) \quad (5)$$

where

- M - meteorological parameters;
- R - radiometric observations;
- S - satellite data;
- H - hydrological parameters;
- G - geomorphological parameters;

Thus, a continuous spatiotemporal surface of the probable distribution of contamination is generated.

Forecasting

A neural network can be used for temporal forecasting:

$$\hat{C}_{t+1} = F(C_t, C_{t-1}, P_t, W_t, T_t, H_t) \quad (6)$$

where P - precipitation, W – wind speed and direction, T – temperature, H – humidity.

In a more advanced version of the model, LSTM or Transformer architectures can be used to analyze time-series data.

Integration of IoT and Artificial Intelligence

The fundamental difference between the proposed system and traditional monitoring lies in the transition from the following scheme:

measurement → laboratory → report

to the scheme:

**measurement → IoT → cloud platform → AI (Artificial Intelligence) → GIS → forecast
→ warning → management decision.**

This approach is consistent with the current trend toward the development of intelligent environmental monitoring. Studies of IoT systems show that distributed sensor networks enable the collection of environmental data in near-real-time mode, while machine learning methods provide the capability for forecasting and automatic classification of environmental conditions [6, 9].

For radiation monitoring, the combination of IoT and LoRa is particularly promising, as this architecture enables the deployment of distributed sensor networks with low power consumption and long-range data transmission [5].

Early Warning System

The most important practical outcome of the proposed architecture is the development of an intelligent environmental early warning system.

Four warning levels are proposed:

Table 1. Radiation Monitoring, Status, and Response Levels

Level	Status	Action
I	Normal	Continuous monitoring
II	Potential anomaly	Additional data verification
III	Confirmed anomaly	Intensified monitoring
IV	High risk	Notification of the responsible authorities

When an anomaly is detected, the system should perform not only automatic classification but also data quality control. This is particularly important because a sudden increase in measurements may be caused not by a radioactive event, but by sensor failure, loss of communication, or a calibration error.

Thus, the system architecture should include the sequential chain **Sensor** → **Quality Control** → **AI Detection** → **Validation** → **GIS** → **Alert**, ensuring automated data collection and quality control, detection of potential anomalies using artificial intelligence methods, their subsequent validation, spatial analysis in GIS, and the generation of appropriate alerts. Such an integrated architecture enhances the reliability of the monitoring system and reduces the likelihood of false alarms.

Discussion

The proposed architecture integrates several technological areas that have traditionally been considered separately: radiometric measurements, IoT, remote sensing, GIS, and machine learning.

The main advantage is the possibility of creating a unified information environment. The IAEA emphasizes the importance of national and regional radiation monitoring networks, data exchange, and the use of radioactive material dispersion modeling to support decision-making [1, 8].

At the same time, a number of limitations should be taken into account.

First, IoT sensors require regular calibration and quality control. Second, machine learning is sensitive to the quality and representativeness of the training dataset. Third, satellite data provide predominantly indirect information about radioactive contamination processes and should therefore be used in conjunction with ground-based measurements. Fourth, the system must ensure data security and the resilience of the communication infrastructure.

Therefore, the most rational approach is a hybrid architecture in which high-precision radiometric measurements are used as the baseline information, IoT provides operational efficiency, GIS enables spatial integration, remote sensing provides additional spatial coverage, and artificial intelligence performs automated analysis and forecasting.

Conclusion

The paper proposes a concept of an integrated radioactive fallout monitoring system based on the combined use of artificial intelligence, the Internet of Things, Earth remote sensing, GIS, and mathematical modeling.

The main scientific advantage of the proposed approach is the transition from fragmented periodic observations to a continuous spatiotemporal monitoring system. IoT enables the rapid acquisition of data from distributed sensor stations, while artificial intelligence algorithms make it possible to detect anomalous changes, predict the dynamics of contamination, and generate spatial maps of radioecological risk.

The proposed system can be considered as a basis for the development of an intelligent environmental early warning system. Its practical application is particularly promising for areas

exposed to radioactive fallout, transboundary transport of pollutants, extreme meteorological processes, and hydrological phenomena.

Further development of the research should focus on the experimental validation of the proposed architecture, the establishment of a real dataset of radiometric and meteorological observations, the comparison of different machine learning algorithms, and the statistical validation of predictive models. Of particular importance is the development of a digital twin of the radioecological system, integrating real-world observations, mathematical modeling, and intelligent forecasting.

Thus, the integration of AI and IoT into radiation monitoring provides a technological foundation for shifting from monitoring the consequences of radioactive contamination to its intelligent prediction and early warning, in accordance with modern principles of environmental safety and sustainable development.

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