Automated Farmland Contamination Monitoring Using Internet of Things

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I. *Introduction*

Throughout history, farmland contamination has persistently been a significant threat to our society. It has not only negatively impacted crop quality but also endangered the health of consumers. A 2015 study's findings highlighted the profound impact of pollution, revealing its substantial contribution to a staggering 268 million disability-adjusted life years (DALYs) [1]. A majority of this can be directly attributed to farmland pollution, emphasizing the severity of this issue. Furthermore, in a 2021 study by the University of Sydney, scientists collected data on 92 chemicals commonly used in pesticides from over 160 countries. The results showed that 64% of global agricultural land (or about 24.5 million km^2) was in danger of pesticide pollution [2]. Therefore, it is imperative to monitor environmental contamination before implementing mitigation measures. This is especially necessary in agricultural lands, as they are at the frontline of human exposure to pollutants.

Sensors play a vital role in detecting and measuring contaminants in farmland. These devices utilize advanced technologies to capture real-time data on the presence and concentration of contaminants [3]. Recent advancements on Internet of Things (IoT) have enabled the seamless integration of sensors, drones, and wireless communications. Ranging from nitrate sensors gauging charged nitrate ions in soil [4] to metal sensors detecting heavy metal cations in farmland [5], these technologies offer a dynamic approach to environmental monitoring [6]. A deeper understanding of the environment empowers conscious decision-making and fosters a proactive approach to environmental sustainability.

This work applies recent advancements in IoT sensors and systems to tackle the issue of farmland contamination monitoring. It deploys IoT sensor networks that utilize drones, IoT gateways, IoT servers, and data storage for comprehensive data collection, transmission, and analysis. In addition, system models are proposed to determine the minimum number of sensors needed to monitor farmland efficiently. They depict the relationship between each sensor's detection capability and the number of sensors deployed or the total number of readouts, allowing users to minimize resource waste while ensuring adequate readouts.

II. *Background and Related Work*

Sensors are devices made on a small scale to perceive and respond to certain types of inputs, such as pressure, heat, moisture, illumination, locomotion, density, and more [3]. The sensors then transform these inputs into representations for further processing.

Soil contamination monitoring involves a process of long-term evaluation of large areas. Unmanned aerial vehicles (UAVs), commonly known as drones, are the ideal tools to facilitate this process. A drone is a flying aircraft that operates without a pilot on board and with different levels of autonomy, such as based on software flight plans.

In agricultural applications, drones have been used for plant health monitoring, livestock management, and aerial survey [7].

The exploration of IoT applications specifically in the environment and agriculture has attracted extensive research efforts. A framework based upon wireless sensor networks was proposed in [8], aimed at integrating sensors for detecting environmental parameters. The functions of the framework's components were thoroughly discussed, presenting a comprehensive overview of employing wireless sensors for environmental monitoring.

In [9], the authors conducted a review of recent technical advancements in greenhouse agriculture. IoT-based smart solutions were introduced to automate various farming parameters. Agricultural procedures, such as plant monitoring, internal atmosphere control, and irrigation control, were enhanced by the data collected from IoT sensors. The paper also highlighted typical use cases and successful stories from agricultural countries to underscore the advantages of IoT in automating farming processes.

Major challenges of smart farming were explored in [10]. Low operational efficiency and management difficulties were pointed out as key concerns for current farming methods. Using IoT and big data analysis was proposed to address the low efficiency. Specifically, the lack of a general model was identified as an obstacle to the wide adoption of IoT within the agriculture industry.

The guidelines of sensor deployment were discussed in [11]. It focused on controlling maintenance costs for low-power, long-range environmental sensors. Thermal degradation and battery depletion were the main reasons for needing maintenance. The absence of a system model was also recognized as a primary cause of operational and managerial inefficiencies.

III. Contributions of Our Work

Based on these previous research efforts, our work makes the following new contributions:

First, we integrate a generic IoT framework into the specialized context of farmland contamination monitoring. This includes exploring the framework’s key elements and explaining the major steps of the monitoring process.

Second, we propose system models to highlight the impact of various parameters within the IoT system. These parameters include sensor quantity, monitoring coverage, as well as readout amount. The models offer guidelines for the optimal number of sensors, which can be extended to their strategic placement.

Third, our research presents simulation results and quantitative analysis for practical IoT sensor deployment in real-world scenarios. By analyzing key threshold values and their contingent factors, our research provides information that is essential for decision-making in farmland contamination monitoring.

IV. Process

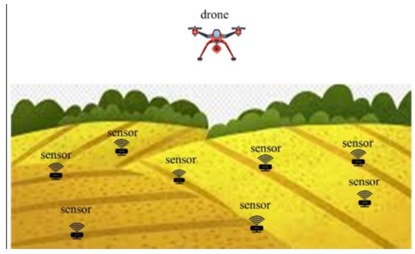

Fig. 1. A farmland network with drones and sensors for soil contamination monitoring.

As shown in Fig. 1, a farmland monitoring network is formed using two components: drones and sensors. These sensors are compact devices designed to detect and react to specific environmental inputs. In this case, they detect factors such as moisture levels, chemical compositions, contaminant levels, and more. Sensors will then convert these environmental stimuli into readable and processable representations for further analysis.

Drones serve as agile data collectors, efficiently gathering data using the wireless communication interfaces they are equipped with [7]. They eliminate the need for manual collection while also reducing the risk of human exposure to hazardous contaminants. Finally, drones facilitate data fusion, which makes real-time data analysis and interpretation from numerous sources possible.

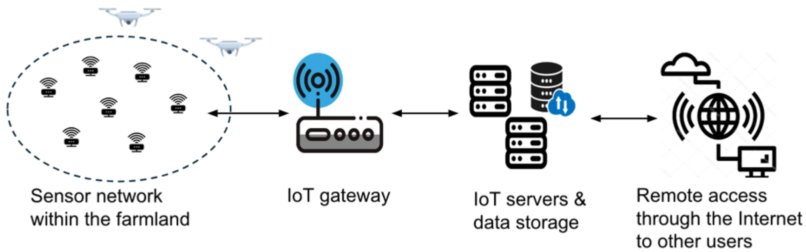

Fig. 2. IoT elements for farmland contamination monitoring.

The key elements in IoT-based farmland contamination monitoring are illustrated in Fig. 2, jointly forming an interconnected system [12, 13]. This system encompasses a range of technologies, including sensors, drones, IoT gateways, IoT servers, data storage, and remote access devices.

IoT gateways facilitate the safe and instantaneous transmission of data between sensors, drones, and eventually to the central IoT servers. The IoT servers then process and store this data, creating a centralized repository that manages the vast volumes of information generated by sensors. Data storage is a valuable resource that allows for the maintenance of records documenting the long-term changes in farmland over time.

Eventually, this data is transferred to the broader IoT network. Remote access users, such as farmers and environmental scientists, can access the stored data to analyze it and make timely decisions. The integration of these IoT elements creates a more time-efficient system for farmland contamination monitoring. The IoT system shown in Fig. 2 fosters sustainable agriculture and environmental awareness.

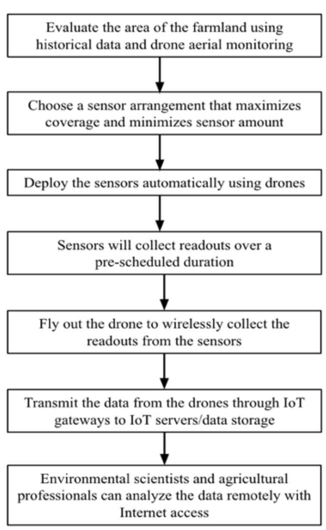

Fig. 3. Major steps of farmland contamination monitoring.

Farmland contamination monitoring involves a series of steps to ensure effective data collection and analysis. The major steps involved include the following:

(1) **Evaluating Land Size:** The first step is assessing the area of the land, a task accomplished through a combination of historical data analysis and drone aerial monitoring. This provides an understanding of the farmland's dimensions and helps to plan the next steps in this process.

(2) **Optimizing Sensor Placement:** To maximize coverage and minimize the number of sensors required, a strategic arrangement is essential. This step involves consideration of the farmland's topography, land soil composition, and potential contamination sources. Efficient sensor placement is important for obtaining accurate and representative data.

(3) **Drone-aided Sensor Deployment:** Utilizing drones, sensors are deployed throughout the farmland according to the optimized placement strategy. Drones offer a dynamic means of reaching different locations without having to worry about terrain challenges. Furthermore, they reduce the time and resources needed as compared to manual deployment.

(4) **Scheduled Sensor Data Collection:** Sensors are programmed to continuously operate over pre-scheduled durations to regularly collect data on specified environmental factors. This automated process ensures consistent, reliable, and timely data collection.

(5) **Drone Data Retrieval:** Following the completion of the sensor's data collection phase, drones are deployed once again to retrieve the data. This aerial approach facilitates swift data retrieval and allows for a quick turnaround in the monitoring process.

(6) **Data Transmission to IoT Infrastructure:** When the drones return to their charging station, the collected data is then forwarded through IoT gateways to reach IoT servers. This transmission ensures that the data is securely and efficiently transferred to central repositories for further processing.

(7) **Data Analysis by Experts:** Environmental scientists and agricultural professionals can now interpret and analyze the collected data. They identify patterns and draw meaningful conclusions to assess the health of the farmland over time. This is highly valuable in suggesting future steps necessary to protect both crop quality and consumer health.

V. Mathematical Model

Sensor placement is a crucial aspect of designing an IoT system for farmland contamination monitoring. The following mathematical model considers various parameters and constraints to establish a framework for addressing this challenge.

Given that sensors are a valuable resource and are limited in number, a strategic sensor arrangement is essential to achieve adequate coverage and monitoring performance. Their usage should be limited to the extent of necessity. This requires a balance between maximizing the monitoring area and minimizing the number of sensors employed, reducing unnecessary resource waste.

The parameters involved in the model include the land perimeter (i.e., P), sensor detection area (i.e., S_i), the minimum number of readouts required for contamination analysis (i.e., K), farmland monitoring time (i.e., T), and the time of a sensor in producing a measurement (i.e., M). The primary goal is to determine the minimum number of sensors (i.e., N) needed to fully cover the land area, ensuring that the total readouts during the monitoring time are no less than K.

TABLE I. Parameters and their definitions

Parameter	Definition
P	Farmland perimeter
S_i	Detection area of Sensor i
A	Farmland area
R	Total number of readouts
K	Minimum number of readouts required for contamination analysis
T	Farmland monitoring time
M	Time for a sensor to produce a measurement
N	Minimum number of sensors needed to cover the land and produce no less than K readouts

To account for potential irregularities in the shape of the farmland, we can assume that the land area is a generic irregular polygon with a given perimeter P. The land size A is then represented within the bounds of the isoperimetric inequality [14]:

$$4\pi A \leq P^2 \ . \tag{1}$$

This inequality implies that the land area A cannot exceed the maximum area of a circle with the same perimeter P, as the circle is the shape with the largest area within a given perimeter. The maximum value of A, denoted as A_{max}, is calculated as:

$$A_{\max} = P^2/4\pi \ . \tag{2}$$

This value represents the upper limit of the land area based on the given perimeter. It provides a theoretical boundary for the monitored area.

To ensure effective coverage, the minimum required number of deployed sensors N is determined by the ratio of the land area A to the sensor detection area S_i:

$$\sum_{i=1}^{N} S_i \geq A \quad . \tag{3}$$

This relationship highlights the importance of strategically deploying sensors to cover the land adequately while optimizing resource utilization. It considers the efficiency of each sensor in detecting relevant environmental factors within its designated area.

The total amount of readouts R during the monitoring time is another key parameter. It is derived as:

$$R = \frac{NT}{M} \quad . \tag{4}$$

The model ensures that this quantity meets or exceeds the minimum required readouts K:

$$K \leq R \quad . \tag{5}$$

The above inequality details how the collected data over time must be greater than or equal to the minimum number of readouts required for contamination analysis to be sufficient for meaningful analysis. It accounts for the time M it takes for each sensor to produce a measurement. The goal is to find a balance between data granularity and monitoring efficiency.

The mathematical model provides a systematic approach to address farmland contamination monitoring through strategic sensor placement. By considering key parameters and constraints, it establishes guidelines for determining the minimum number of sensors needed. These sensors provide adequate coverage as well as enough data readouts for in-depth analysis. This model serves as a design tool in the development of farmland monitoring systems, contributing to sustainable and informed agricultural practices.

VI. Simulation Evaluation

The derived equations above provided a structured framework for addressing key aspects such as land size, sensor coverage, and readout requirements. Simulations were then conducted to evaluate the relationships between the various parameters outlined in the mathematical model. The simulations were carried out under certain assumptions to create realistic scenarios for testing the performance of the proposed deployment strategy.

Major assumptions were set as follows: the land perimeter was set at 100 meters, the minimum number of readouts needed to analyze the land was determined to be 20,000, the monitoring time for the farmland was 1 week or 168 hours, the time needed for each sensor to produce a measurement was 2, and finally, the detection area of each sensor varied from 0.5 to 4.1 m^2. The chosen values for these parameters were based on historical research and realistic agricultural situations. By holding these specific factors constant, we could properly assess the sensitivity of certain other key factors.

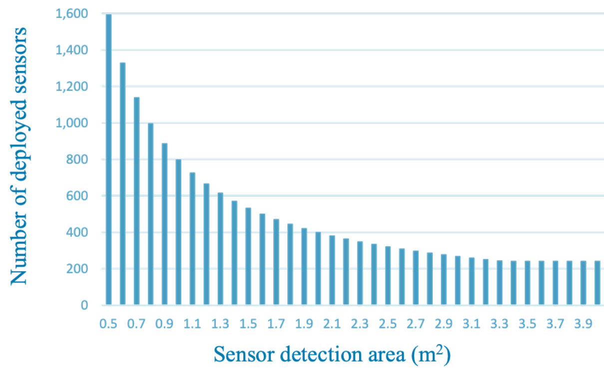

Fig. 4. Effect of each sensor's detection area on the number of deployed sensors.

The first set of simulations evaluated the impact of each sensor's detection area on the total amount of deployed sensors. The results are shown in Fig. 4. As the detection area of each sensor increased, the required number of sensors to cover the land decreased. When a sensor's detection area was 0.5 m^2, 1,592 sensors were required to monitor the land and satisfy all requirements. If the sensor's detection area increased to 3.4 m^2, 239 sensors were enough to monitor this land.

Beyond a detection area of 3.4 m^2, further increasing the sensor detection area did not contribute to a significant reduction in the required sensor amount. This phenomenon can be attributed to the time it takes for each sensor to produce a measurement. To obtain more than 20,000 readouts within the designated monitoring time of one week, a certain number of sensors became necessary, irrespective of the increased detection area. These observations show the intricacies of optimizing sensor deployment for farmland contamination monitoring. Both detection capabilities and time-related constraints should be considered and balanced.

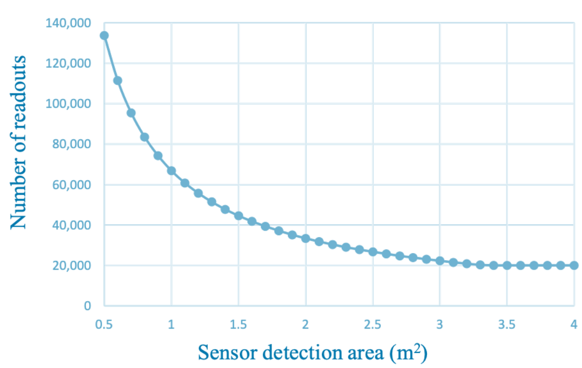

Fig. 5. Effect of sensor detection area on number of readouts.

The second set of simulations investigated the relationship between each sensor's detection area and the total amount of readouts. As shown in Fig. 5, when each sensor's detection area was 0.5 m^2, 1,592 sensors were required to monitor this land. In this case, the readout amount was 133,728, far more than the required amount of 20,000. To conserve resources, the detection area can be increased to use fewer sensors. Specifically, when each sensor's detection area was increased to 3.4 m^2, 20,076 readouts were generated by 239 sensors, which still fulfills all requirements.

Simulations demonstrate that the sensor deployment strategy is intricately influenced by multiple factors. When the key inputs, including land perimeter, monitoring time, and sensor measurement interval, are established, the minimum required sensor count becomes contingent on both each sensor's detection area and the specified readout target. Although at first seemingly exponential, this relationship is actually a piecewise function constructed by Equations (1)-(5). Due to the function's dynamic nature, adjustments in the detection area might yield unfavorable results of reducing the required sensor count beyond certain thresholds. The interplay of these variables necessitates an in-depth understanding to tailor sensor deployment strategies for farmland contamination monitoring.

VII. Conclusions

In this project, we have investigated the application of IoT technologies in farmland contamination monitoring, with a generic IoT framework being extended to this context. Key elements, their functions, and the major steps within the monitoring process have been explored.

Based upon the framework's extension, we have further proposed new system models to formulate different parameters of the IoT system. The models integrate resource factors alongside performance metrics to optimize the IoT sensor deployment in farmland contamination monitoring. Our simulation results have demonstrated quantitative guidelines on threshold value selection and contingent factor balancing. This research's proposed IoT system helps determine how to implement a drone-aided sensor network into farmland that will increase efficiency, reduce the risk of contamination, and automate the entire monitoring process. The comprehensive plan automates soil monitoring, which ultimately helps mitigate the issue of farmland contamination and its adverse effects on human health, crop quality, and the delicate balance of the ecosystem.

VIII. References

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