Comparative Analysis of Filtering Techniques for Efficient Data Aggregation in Smart Hydroponic Systems

Nurul Qomariyah[1,a)], Septafiansyah Dwi Putra[1,b)], Imam Asrowardi[1,c)]

[1]*Internet Engineering Technology, Politeknik Negeri Lampung, Indonesia*

[a)]Corresponding author: nqomariyah@polinela.ac.id
[b)]septa@polinela.ac.id
[c)]imam@polinela.ac.id

Abstract. The rapid evolution of digital technologies has transformed traditional agriculture into a more efficient and intelligent system. This study focuses on the development of a data aggregation strategy in Smart Hydroponic Systems to optimize network consumption without sacrificing data accuracy. By utilizing Threshold Filtering and Delta-Based Filtering techniques, significant reductions in data transmission were achieved while maintaining essential temperature monitoring capabilities. Experimental results demonstrated that both techniques effectively reduced data points and optimized bandwidth usage, particularly in temperature-stable environments. This research contributes to the advancement of sustainable digital agriculture by providing an efficient approach to managing network resources in IoT-based hydroponic systems.

Keywords: *data aggregation, threshold filtering, delta-based filtering*

INTRODUCTION

The integration of Internet of Things (IoT) technology in agriculture has led to the development of Smart Hydroponic Systems, where environmental conditions such as temperature, humidity, and nutrient levels are monitored in real time using sensors. These systems allow farmers to maintain optimal growing environments, making hydroponics more efficient and sustainable[1]. However, the continuous transmission of raw data from multiple sensors can lead to high network bandwidth consumption, particularly in large-scale applications[2].

To address the issue of excessive network loads, intelligent data aggregation strategies are crucial. By implementing techniques that filter and compress the collected data, it is possible to reduce network traffic without compromising the accuracy of the information needed for decision-making[3]. The challenge lies in finding a balance between reducing data volume and maintaining the quality of sensor readings to ensure precise control of the hydroponic environment.

The integration of IoT technology in agriculture has been widely researched in recent years, with a focus on its application to smart farming systems, including hydroponics. Smart Hydroponic Systems, in particular, leverage IoT sensors to continuously monitor critical environmental parameters such as temperature, humidity, pH, and nutrient availability. The real-time data collected by these sensors allow farmers to optimize growing conditions, reducing water and nutrient waste while increasing crop yields [4]. However, continuous data transmission from multiple sensors poses challenges related to network congestion and increased energy consumption, particularly in large-scale operations[5]. These challenges highlight the need for efficient data management strategies that reduce network traffic while maintaining data accuracy.

a. Data Aggregation Techniques

Several studies have explored various data aggregation techniques to address the challenges associated with high data volume in IoT systems. Data aggregation involves combining and processing data from multiple sensors to reduce redundancy and the overall amount of data transmitted over a network. No filtering, for instance, represents a baseline scenario where all data from sensors are transmitted without any reduction. While this approach ensures maximum data accuracy, it results in high bandwidth consumption and energy usage[6].

Threshold filtering, on the other hand, is a method where data is only transmitted if the sensor reading exceeds or falls below a certain predefined threshold. This technique has been shown to significantly reduce network traffic in resource-constrained IoT systems [3]. However, one limitation of threshold filtering is the potential loss of valuable data that falls within the threshold range, which could lead to less precise monitoring of environmental conditions in Smart Hydroponic Systems.

Delta-based filtering is a more adaptive technique that only transmits data if the change in sensor readings exceeds a certain delta value. This method ensures that only significant changes in environmental parameters are transmitted, which helps in reducing data transmission frequency while still capturing important fluctuations[7]. Studies have found that delta-based filtering strikes a good balance between reducing data volume and maintaining data integrity, making it a promising technique for smart agriculture applications [8].

b. Applications in Smart Hydroponic Systems

In the context of Smart Hydroponic Systems, the application of efficient data aggregation techniques is crucial for improving both network and energy efficiency. Kokilavani and Sathish Kumar (2022) emphasized the importance of these systems in modern agriculture, noting that sensor networks play a vital role in maintaining optimal growing conditions for plants [9]. Continuous sensor data is essential for effective decision-making in hydroponic management, but transmitting all raw data can overload communication networks, especially when scaled to commercial farming operations [9].

By applying aggregation techniques like threshold and delta-based filtering, network load can be significantly reduced, as demonstrated in studies focused on resource-constrained IoT environments[3]. These methods not only lower data traffic but also improve the sustainability of IoT-based agricultural systems by minimizing energy consumption [10]. Further research, such as the present study, is necessary to compare the effectiveness of these filtering techniques within the specific context of hydroponic systems to determine the most efficient strategy for optimizing both network resource usage and data integrity.

This research focuses on evaluating three data aggregation techniques—no filtering, threshold filtering, and delta-based filtering—to determine which method is most effective in minimizing network resource consumption while preserving data integrity. The findings aim to provide insights that will improve the overall efficiency of Smart Hydroponic Systems, contributing to their scalability and sustainability in modern agriculture.

METHODS

This study aims to analyze and compare data aggregation techniques to optimize network resource consumption while maintaining data accuracy. The methodology involves implementing and evaluating three data aggregation methods: no filtering, threshold filtering, and delta-based filtering. These techniques are applied to data collected from a single temperature sensor, simulating a real-time monitoring environment.

A. Data Aggregation Techniques

a) *No Filtering (Baseline)*: The no filtering technique serves as the baseline for comparison. In this approach, raw data from the sensor is transmitted to the server without any modifications [11]. This ensures that all data is captured and transmitted, preserving complete accuracy but resulting in high bandwidth consumption. This method will allow the comparison of the other two techniques in terms of efficiency and network load reduction [12].

b) *Threshold Filtering*: Threshold filtering reduces the amount of data transmitted by sending sensor readings only when they exceed or fall below a predefined threshold [13]. For instance, if the temperature changes by more than 2°C from the previous reading, the data is sent; otherwise, it is discarded. The key challenge with this method lies in determining an optimal threshold that reduces data transmission without sacrificing the relevance of important changes in the monitored environment.

c) *Delta-based Filtering*: Delta-based filtering transmits data only when the difference between consecutive sensor readings exceeds a specified delta value. For example, if the change between two readings exceeds 2°C, the data is sent; otherwise, it is ignored. This method dynamically adjusts to environmental changes, capturing significant variations while minimizing the transmission of irrelevant data.

B. Experimental Setup and Evaluation Criteria

Each of the three techniques will be implemented and tested using the same dataset of sensor readings. The evaluation will be based on the following criteria:

- Network Bandwidth Usage: The amount of data transmitted for each technique will be measured to assess the reduction in network load.
- Data Accuracy: The accuracy of the data after applying the aggregation techniques will be compared to the original raw data to determine any loss of critical information.
- Energy Consumption: The energy used by the communication module during data transmission will be analyzed, as less frequent transmissions are expected to save power.

C. Comparative Analysis

Once the data is collected and processed, a comparative analysis will be conducted to evaluate the performance of each aggregation method. The goal is to identify the technique that provides the best trade-off between reducing network usage and maintaining the accuracy of the sensor data. This analysis will provide insight into how data aggregation can be optimized for efficient data transmission in real-world IoT applications.

RESULTS AND DISCUSSION

The comparison between the three data aggregation strategies—No Filter, Threshold Filtering, and Delta-based Filtering—is presented in **FIGURE 1**. The figure displays the effectiveness of each technique over a two-hour period, from 08:00 to 10:00. The aggregation process aims to minimize the volume of data without losing critical information.

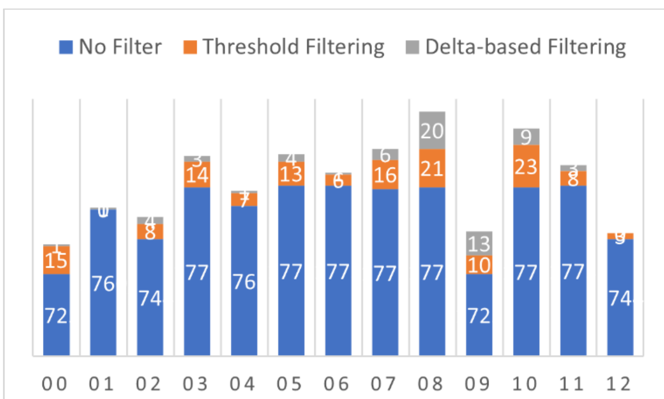

FIGURE 1 Effectiveness of Data Aggregation Techniques on the Number of Data Points Based on Time

From the first hour (08:00–09:00), we observe that the No Filter approach captures 1725 and 1772 data points across the different intervals, maintaining the raw influx of data with no reduction. In contrast, Threshold Filtering significantly reduces the data points to a range of 10 to 23 during the same period, and Delta-based Filtering cuts the number of data points further down, with values ranging between 1 to 20. This clearly indicates the efficiency of the Delta-based approach in data reduction.

FIGURE 2 illustrates the total number of data points recorded by each method per hour. As seen, the No Filter method accumulates the largest dataset across all time intervals, peaking at 1773 data points during hour 06:00–07:00. Meanwhile, the Threshold Filtering technique consistently reduces the data to less than 25 points per hour, and Delta-based Filtering delivers an even more aggressive reduction, reaching as low as 1 data point in some intervals (e.g., at 00:00).

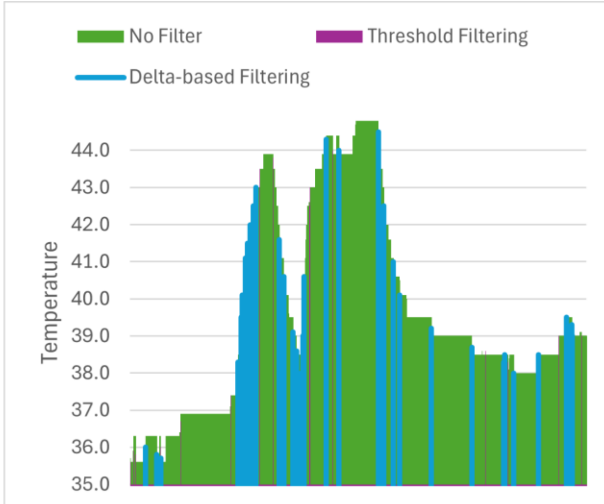

FIGURE 2 Comparative Analysis of Data Without Filtering, Threshold Filtering, and Delta-based Filtering

The quantitative results of the data aggregation techniques are summarized in **TABLE *1***, showing the bandwidth utilization over a 12-hour period for each method.

TABLE 1. Bandwidth utilization comparison of data aggregation techniques over 12 hours

Data Aggregation Technique	Data Transmitted
No Filtering	2.137 MB
Threshold Filtering	0.013 MB
Delta-based Filtering	0.006 MB

As demonstrated in **TABLE *1***, the No Filtering method results in the transmission of 2.137 MB of raw data, representing the baseline scenario where all sensor data is transmitted without any reduction. This method preserves full data accuracy but at the cost of significantly high bandwidth consumption, making it inefficient for large-scale IoT applications.

In contrast, Threshold Filtering effectively reduces the amount of data transmitted by only sending sensor readings when they exceed or fall below a predefined threshold. This method transmits just 0.013 MB of data, representing a dramatic reduction in bandwidth usage compared to the baseline. However, this approach may miss smaller variations in sensor readings that fall within the threshold, potentially leading to a loss of important data for certain applications.

The Delta-based Filtering technique offers the most significant bandwidth savings, transmitting only 0.006 MB of data over the same period. This method transmits data only when the change between consecutive sensor readings exceeds a specified delta value. By dynamically responding to significant fluctuations while ignoring minor variations, Delta-based Filtering achieves the best balance between reducing data transmission and preserving the integrity of critical environmental information. This makes it the most suitable technique for applications requiring efficient data management without sacrificing essential data accuracy, particularly in IoT-based smart hydroponic systems.

These results highlight the potential of Delta-based Filtering to optimize network bandwidth usage in IoT systems, making it a more sustainable solution for real-time monitoring and decision-making in agriculture.

On a qualitative level, Delta-based Filtering appears to offer the most balanced approach between minimizing data transmission and preserving the variability in temperature readings. Although both filtering techniques reduce the amount of data, Threshold Filtering might eliminate smaller, yet potentially significant changes in the sensor data. Delta-based Filtering, however, responds only to noticeable shifts in data, maintaining critical variations that may influence system performance or decision-making processes.

Overall, the results show that Delta-based Filtering offers the best compromise between reducing bandwidth usage and preserving meaningful data changes. This method allows the system to operate more efficiently, making it particularly suitable for smart hydroponic systems where minimizing data transmission without sacrificing important environmental metrics is essential.

CONCLUSIONS

This research successfully demonstrated that applying data aggregation techniques such as Threshold Filtering and Delta-Based Filtering can significantly reduce the amount of data transmitted in temperature monitoring for Smart Hydroponic Systems. Threshold Filtering proved to be effective in situations where temperature changes were sporadic and substantial, while Delta-Based Filtering was more sensitive to small, continuous changes in temperature. Both techniques contribute to optimizing bandwidth usage and reducing data consumption without compromising the accuracy of temperature monitoring. These methods have the potential to enhance the operational efficiency of IoT-based hydroponic systems, supporting the development of more advanced and sustainable digital agriculture technologies. Future research is recommended to explore adaptive algorithms and implementation in larger-scale environments for further optimization.

ACKNOWLEDGMENTS

This research was funded by the DIPA Research Grant 2024. We would like to express our gratitude for the financial support provided, which made this study possible.

REFERENCES

[1] S. D. Putra, A. Ambarwari, I. Asrowardi, and Moh. H. I. S. Jaya, "Vision-Based Object Detection for Efficient Monitoring in Smart Hydroponic Systems," in *Proceedings of the International Conference on Applied Science and Technology on Engineering Science 2023 (iCAST-ES 2023)*, vol. 230, M. U. H. Al Rasyid and M. R. Mufid, Eds., in Advances in Engineering Research, vol. 230. , Dordrecht: Atlantis Press International BV, 2024, pp. 421–434. doi: 10.2991/978-94-6463-364-1_40.

[2] H. Liazid, M. Lehsaini, and A. Liazid, "Data transmission reduction using prediction and aggregation techniques in IoT-based wireless sensor networks," *Journal of Network and Computer Applications*, vol. 211, p. 103556, Feb. 2023, doi: 10.1016/j.jnca.2022.103556.

[3] H. Zhang, J. Na, and B. Zhang, "Autonomous Internet of Things (IoT) Data Reduction Based on Adaptive Threshold," *Sensors*, vol. 23, no. 23, p. 9427, Nov. 2023, doi: 10.3390/s23239427.

[4] P. Rajak, A. Ganguly, S. Adhikary, and S. Bhattacharya, "Internet of Things and smart sensors in agriculture: Scopes and challenges," *Journal of Agriculture and Food Research*, vol. 14, p. 100776, Dec. 2023, doi: 10.1016/j.jafr.2023.100776.

[5] R. A. Desai and R. B. Kulkarni, "Energy efficient reliable data transmission for optimizing IoT data transmission in smart city," *IJEECS*, vol. 34, no. 3, p. 1978, Jun. 2024, doi: 10.11591/ijeecs.v34.i3.pp1978-1988.

[6] A. M. Raivi and S. Moh, "A comprehensive survey on data aggregation techniques in UAV-enabled Internet of things," *Computer Science Review*, vol. 50, p. 100599, Nov. 2023, doi: 10.1016/j.cosrev.2023.100599.

[7] R. Jindal, N. Kumar, and S. Patidar, "IoT streamed data handling model using delta encoding," *Int J Communication*, vol. 35, no. 13, p. e5243, Sep. 2022, doi: 10.1002/dac.5243.

[8] B. R. Stojkoska and Z. Nikolovski, "Data compression for energy efficient IoT solutions," in *2017 25th Telecommunication Forum (TELFOR)*, Belgrade: IEEE, Nov. 2017, pp. 1–4. doi: 10.1109/TELFOR.2017.8249368.

[9] S. Kokilavani, N. Sathish Kumar, and A. S. Narmadha, “Study and Analysis of Energy Efficient Data Aggregation Techniques for Wireless Sensor Networks,” in *2022 IEEE International Conference on Data Science and Information System (ICDSIS)*, Hassan, India: IEEE, Jul. 2022, pp. 1–5. doi: 10.1109/ICDSIS55133.2022.9915854.

[10] T. Kiruthiga and N. Shanmugasundaram, “In-network Data Aggregation Techniques for Wireless Sensor Networks: A Survey,” in *Computer Networks, Big Data and IoT*, vol. 66, A. P. Pandian, X. Fernando, and S. M. S. Islam, Eds., in Lecture Notes on Data Engineering and Communications Technologies, vol. 66. , Singapore: Springer Singapore, 2021, pp. 887–905. doi: 10.1007/978-981-16-0965-7_68.

[11] S. Li, L. D. Xu, and S. Zhao, “The internet of things: a survey,” *Inf Syst Front*, vol. 17, no. 2, pp. 243–259, Apr. 2015, doi: 10.1007/s10796-014-9492-7.

[12] C. Perera, A. Zaslavsky, P. Christen, and D. Georgakopoulos, “Context Aware Computing for The Internet of Things: A Survey,” *IEEE Commun. Surv. Tutorials*, vol. 16, no. 1, pp. 414–454, 2014, doi: 10.1109/SURV.2013.042313.00197.

[13] Z. Ning, P. Dong, X. Wang, J. J. P. C. Rodrigues, and F. Xia, “Deep Reinforcement Learning for Vehicular Edge Computing: An Intelligent Offloading System,” *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 6, pp. 1–24, Nov. 2019, doi: 10.1145/3317572.