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Optimized Latency and Energy Management in Fog-Based Agriculture 4.0

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Abstract: The implementation of IoT devices in agriculture has transformed smart farming, enabling precise real-time monitoring and management of agricultural activities. However, traditional smart farming applications that rely on centralized cloud servers face significant challenges, including increased latency and network congestion, which hinder the timely processing of critical data. To address these issues, this research proposes a fog computing-based solution tailored for smart farming, focusing on optimized latency and energy management. We introduce a clustering algorithm to enhance the communication and collaboration between fog nodes and their corresponding Fog Controller Nodes (FCNs), ensuring efficient data processing within the fog layer. Additionally, an energy-aware algorithm is presented to improve the FCN's awareness of each fog node's energy profile, allowing for adaptive power management strategies that optimize energy consumption. An optimal module placement algorithm is also proposed, prioritizing tasks based on their latency sensitivity and urgency, which ensures efficient resource utilization and timely responses to critical agricultural needs. The proposed approaches have been implemented and tested using the iFogSim simulator, demonstrating significant improvements in latency, network usage, and energy consumption compared to FCMSF and Agrifog models. This comprehensive evaluation underscores the potential of fog computing in revolutionizing smart farming by addressing key challenges and enhancing overall system efficiency.

Keywords: IoT, Cloud, Smart Farming, Fog computing , iFogSim

1. Introduction (Heading 1)

According to research findings, the adoption of IoT devices in the agriculture industry was projected to reach 75 million by 2020, with an annual growth rate of 20%. By 2025, the global smart agriculture market is anticipated to triple in size, reaching an estimated $15.3 billion [1]. Furthermore, estimates from the International Data Corporation (IDC) [2] predict that the volume of data produced by IoT devices will reach approximately 80 zettabytes by 2025, with a significant portion originating from the agricultural sector. Presently, most smart farming applications are developed by integrating IoT devices with remote cloud servers. These servers provide crucial resources on demand for processing, storage, and analysis of the extensive data generated by IoT-enabled smart farming [3]. However, the centralized nature of cloud architecture presents significant challenges for the large-scale implementation of smart farming applications due to increased response times as data volumes grow. Transmitting and processing vast amounts of data at remote cloud servers can lead to high latency and considerable network strain. In smart farming, timely responses are crucial for real-time data analysis, which encompasses applications such as agricultural robots, drones, and anti-hail systems [4]. These latency-sensitive applications require rapid data processing to effectively monitor soil moisture, weather conditions, crop health, and to operate machinery efficiently. This underscores the need for more localized data processing solutions.

As shown in TABLE I, there are stricter quality of service (QoS) requirements when dealing with IoT-based applications in smart farming, particularly those that are latency-sensitive, such as agricultural robots, drones, and anti-hail systems. These applications demand real-time data processing and quick response times to function effectively. For instance, agricultural robots need immediate feedback to navigate and perform tasks like planting and harvesting. Drones require rapid data processing to accurately monitor crop health and manage

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precision agriculture tasks. Anti-hail systems must react instantly to weather data to deploy protective measures. Therefore, the centralized nature of cloud architecture often fails to meet the stringent QoS requirements for these applications, necessitating the adoption of more localized processing solutions to ensure minimal latency and optimal performance.

TABLE I. LATENCY REQUIREMENTS OF SOME IOT APPLICATIONS IN SMART FARMING

Smart Farming Applications	Data Type	Maximum Delay
Agribots [5]	Control signals for robotics	<100 milliseconds round-trip time
Agricultural Drones [6]	Control and telemetry data	<150 milliseconds round-trip time
Livestock Monitoring [7]	Biosignals from sensors	<200 milliseconds one-way
Precision Irrigation [8]	Sensor data and control signals	<250 milliseconds one-way
Crop Monitoring [9]	Image and sensor data	<300 milliseconds one-way
Soil Monitoring [10]	Sensor data	<300 milliseconds one-way

Substantial delays, high network traffic, and excessive energy consumption are critical challenges hindering the widespread deployment of cloud-based IoT applications in smart farming. In traditional setups, cloud servers process the received data, enabling real-time decision-making and action-taking capabilities through a web application. However, this direct sensor-to-cloud configuration creates significant latencies, making it inadequate for operations requiring timely intervention, such as precision irrigation, pest management, and the operation of automated machinery. Furthermore, many works have proposed using fog computing in smart farming to decentralize processing and reduce response times. However, relying on the traditional hierarchical architecture of fog and cloud without establishing connections between fog nodes poses several challenges.
To address these issues, we propose adopting optimized latency and energy management algorithms for fog-based smart farming systems. This approach significantly reduces latency, enhances network efficiency, and optimizes energy consumption, which are crucial for effective real-time agricultural management.

The key contributions of this work are outlined as follows:

- **Proposed Clustering Algorithm for Fog Nodes:** This paper introduces a clustering algorithm to establish connections between each fog node and its corresponding Fog Controller Node (FCN) in a fog-based smart farming architecture.

- **Energy-Aware Fog Controller Algorithm:** An algorithm is introduced to enhance the Fog Controller Node's awareness of each fog node's energy profile in the smart farming system.

- **To Optimal Module Placement Algorithm**: An algorithm is proposed for the optimal placement of application modules within the fog layer of a smart farming ecosystem. The algorithm prioritizes module placement based on latency sensitivity and urgency, ensuring that critical tasks are handled with minimal latency, moderate tasks balance latency and energy consumption, and normal tasks focus on energy efficiency.

- The Implementation and Testing: The proposed approaches have been implemented and rigorously tested using the iFogSim simulator. Extensive simulations demonstrate the effectiveness of the proposed algorithms in reducing execution cost, latency, energy consumption, and network usage compared to traditional cloud computing models.

The remainder of this document is structured as follows. Section 2 reviews related works in cloud and fog computing architectures. Section 3 introduces the proposed optimized latency and energy management system for smart farming Section 4 outlines the performance evaluation methodology and presents the findings of this study. Finally, the paper concludes with a summary of the research in the Conclusion section.

2. RELATED WORKS

The fog computing paradigm has garnered significant attention from researchers in recent years, particularly in the field of IoT-based smart farming. In their work [11], the authors introduced a cost-effective fog computing platform designed for soil moisture management. This platform leverages IoT and edge computing to monitor soil moisture through sensors and data communication. It features an Analytics-as-a-Service cloud component, which provides soil moisture density maps to facilitate better irrigation decisions. Small-scale evaluations conducted in a rural area demonstrated that this approach achieves accuracy comparable to conventional methods, all without necessitating human presence. Alharbi et al. [12] proposed a new integrated edge-fog-cloud architecture for smart agriculture to enhance energy efficiency and reduce carbon emissions. This approach processes real-time agricultural data at the edge and fog layers, reducing cloud load, overall energy consumption by 36%, carbon emissions by 43%, and network traffic by up to 86%, as demonstrated through mixed-integer linear programming (MILP) and heuristic algorithms. Artetxe et al. [13] proposed using AI and edge/fog/cloud paradigms to manage water in agriculture. They combined fuzzy logic and LoRa technology, achieving a 23.1% reduction in water loss, with an additional 4.07% reduction using weather forecasts. Fog and cloud computing concepts are included to better scale the control scheme for multiple plants. Kalyani et al. [14] highlighted the potential of digital twin (DT) technology in agriculture, emphasizing its role in improving management through real-time data and simulations. They noted that integrating DTs with fog computing enables effective, decentralized agricultural management and monitoring, offering significant benefits and addressing key challenges.

Ortiz-Garcés et al. [15] proposed using fog computing to improve IoT applications, specifically for emergency vehicles. Their prototype uses in-vehicle beacons to enable green traffic lights and fog nodes with a long-range wide area network protocol to reduce response times and limit data sent to the cloud. They also compared the response times of fog computing and cloud computing. Sajid et al. [16] proposed a fog computing-based smart farming framework to enhance precision agriculture using UAVs for data collection from IoT sensors. The framework offloads data to fog sites at the network edge and uses a charging token system for UAVs, which receive tokens from fog nodes to recharge. An intrusion detection system with machine learning at the fog nodes classifies UAV behavior and reduces tokens for malicious UAVs, effectively eliminating them. The system demonstrated 99.7% accuracy in detecting intrusions and efficiently conserved energy through token-based elimination, ensuring reliable data collection despite attacks. Alaty et al. [17] proposed a smart agricultural system integrating IoT, cloud, and fog computing technologies. The system consists of three interacting layers to manage, monitor, and control the agricultural environment. Deployed and tested on a small farm, it enables remote monitoring of soil humidity and timely alerts to users about potential hazards such as fire, demonstrating its practical application and effectiveness in enhancing agricultural management.

Sucharitha et al. [18] proposed an IoT-Fog based farm management system to enhance farming activities by reducing latency and improving real-time decision-making through proximity-based data processing. Their study showed that traditional cloud models are inadequate for handling the vast and diverse data from IoT devices, whereas fog-based models optimize bandwidth usage and offer lower latency. Their simulation using iFogSim demonstrated superior scalability, responsiveness, and efficiency compared to cloud-based systems.

In this work [19], the authors proposed a fog computing model for smart farming to address high latency and data volume issues associated with traditional cloud-based systems. By processing data closer to its source, the model reduces latency and network usage. Simulated using iFogSim, the architecture demonstrated improved performance in bandwidth usage, computing resources, and latency. compared to cloud-only implementations.

The reviewed fog-based solutions aim to reduce latency, optimize network utilization, and enhance overall system performance. However, these approaches have several notable limitations.

Firstly, the reliance on the traditional hierarchical architecture of fog and cloud, without creating connections between fog nodes, presents a significant challenge. This approach can lead to less effective communication and collaboration among fog nodes.

Secondly, many studies have not addressed the critical issue of module placement within the fog computing framework. Proper distribution of application modules across fog nodes is essential for efficient resource utilization and latency reduction.

Thirdly, some prior works do not include Fog Controller Nodes (FCNs), which are vital for managing fog clusters. FCNs are crucial for coordinating modules and tasks, allocating resources, balancing loads, and optimizing energy within fog-based systems.

Lastly, previous research often lacks a focus on energy consumption optimization within the fog layer. Key aspects such as monitoring the energy profiles of individual fog nodes, incorporating energy-aware FCNs, and considering energy efficiency before task distribution are frequently overlooked.

3. PROPOSED OPTIMIZED LATENCY AND ENERGY MANAGEMENT SYSTEM

A. Clustering Fog Nodes

In the initial phase of this work, we propose enhancing the effectiveness of fog-based smart farming architecture by introducing a clustering approach for fog nodes within the fog layer. This strategy optimizes the distribution of computational resources, thereby increasing the overall efficiency of the smart farming system. By grouping fog nodes based on proximity and resource availability, we can achieve more efficient load balancing, reduced latency, and improved energy consumption across the network.

Each cluster is managed by a Fog Controller Node (FCN), which plays a crucial role in enhancing system efficiency. The primary objective is to improve the distribution of computational resources through this clustering approach. Our defined Algorithm 1 groups fog nodes (FNs) into clusters to enable efficient communication and collaboration. The FCN in each cluster is responsible for managing resource allocation, load balancing, and executing the module placement algorithm. By linking fog nodes to their respective FCNs using predefined delay thresholds, our clustering algorithm promotes effective communication and resource sharing within clusters. This strategy maximizes resource utilization and reduces delays between nodes and their FCNs.

Moreover, inter-cluster communication facilitated by the FCNs allows fog nodes to share critical information, such as workload status and available resources, further optimizing the performance of the fog layer. This interconnected approach ensures that resources are utilized effectively and that delays are minimized, leading to a more robust and efficient smart farming system. In addition to the primary components of the Fog Node, the Fog Controller Node (FCN) includes:

- The Resource Manager within the FCN is pivotal for the effective management and optimization of computational resources across the fog nodes. It oversees the allocation and utilization of essential resources such as CPU, memory, and storage. This dynamic allocation is crucial to ensure that resources are used efficiently, adapting to the varying demands of the smart farming system. By continuously monitoring resource usage, the Resource Manager can make real-time adjustments to optimize performance, prevent resource bottlenecks, and maintain a balanced load across all fog nodes. This ensures that the system remains responsive and capable of handling the complex tasks associated with smart farming, such as data processing from IoT sensors, real-time analytics, and decision-making processes.

- The Module Scheduler is a critical component of the Fog Controller Node (FCN), responsible for the efficient coordination of real-time smart farming application modules across distributed fog nodes (FNs). It dynamically assigns tasks based on factors such as urgency, resource requirements, and current workload. By closely collaborating with the Resource Manager, the Module Scheduler ensures the optimal use of computational resources, including CPU, memory, and storage. This coordination allows for efficient task execution and streamlined resource utilization within the fog layer. The Module Scheduler employs advanced algorithms to prioritize tasks according to their urgency and importance, ensuring that critical operations, such as immediate data processing or real-time decision-making, are handled promptly. For example, in a smart farming scenario where real-time monitoring of soil moisture levels is essential, the Module Scheduler can prioritize tasks related to data collection from IoT sensors and immediate analysis to determine irrigation needs. By dynamically adjusting task assignments in response to changing conditions, such as varying moisture levels or weather forecasts, the Module Scheduler enhances the overall efficiency and responsiveness of the smart farming system. This leads to improved performance, reduced latency, and optimized resource utilization, ultimately supporting the complex and dynamic needs of modern agriculture. This approach not only ensures that high-priority tasks receive immediate attention but also helps prevent resource overloading on any single node, promoting a balanced distribution of tasks throughout the fog layer.

- The Load Balancer in the Fog Controller Node (FCN) plays a pivotal role in managing computational workloads within smart farming applications. It ensures the efficient operation of the fog computing infrastructure by dynamically distributing tasks and modules across the network of fog nodes. By continuously monitoring resource utilization and processing capabilities, the Load Balancer aims to achieve a balanced distribution of workloads, preventing any single fog node from becoming overloaded or underutilized. This dynamic task distribution is critical in a smart farming environment, where diverse and resource-intensive processes, such as real-time sensor data analysis, predictive modeling for crop management, and automated control of irrigation systems, are constantly at play. For instance, if one fog node is processing data from soil moisture sensors while another is managing drone surveillance footage, the Load Balancer will ensure that neither node becomes a bottleneck. By redistributing tasks as needed, the Load Balancer maintains optimal performance across the entire fog layer, enhancing the reliability and efficiency of the smart farming system. This not only improves overall system responsiveness but also ensures that all fog nodes are utilized effectively, maximizing the computational resources available and supporting the seamless operation of various agricultural processes.

- The Energy Monitor within the Fog Controller Node (FCN) is dedicated to optimizing and managing the energy consumption of fog nodes (FNs) in the fog layer. It continuously monitors the energy profiles of individual FNs, considering factors such as power consumption, activity levels, and resource utilization. By comprehensively understanding the current state of each fog node, the Energy Monitor can make informed decisions about how to optimize energy usage without compromising operational efficiency. This is particularly important in smart farming environments, where energy efficiency is crucial for sustainability and cost-effectiveness. For example, if certain fog nodes are underutilized or consuming more power than necessary, the Energy Monitor can redistribute tasks or adjust processing loads to balance energy consumption across the network. This proactive management helps to reduce overall energy usage, extending the lifespan of fog nodes and reducing operational costs. By ensuring that energy consumption is aligned with the actual workload and operational demands, the Energy Monitor enhances the sustainability of the smart farming system, supporting continuous and efficient agricultural operations while minimizing environmental impact.

B. Proposed algorithms

In the proposed fog-based smart farming network designed for IoT applications in greenhouses, the set $F_{fi} = \{f_1, f_2, \ldots, f_n\}$ (1) represents fog nodes allocated for IoT sensors. Each fog node fi has finite resources including CPU, RAM, and bandwidth, denoted as $C_{fi} = \{CPU_i, RAM_i, Bandwidth_i\}$. (2)

Algorithm 1 Fog Node Clustering Algorithm

```
Input: Set of Fog nodes F, Set of Fog Controller Nodes FCN
Output: Clustered Fog nodes

function clusterFogNodes(F, FCN):
   clusteredFogNodes = List<Pair<FogNode, FCN>>
   for each fogNode in F:
      closestControllerNodes =
findClosestControllerNodes(fogNode, FCN)
      for each (controllerNode, delay) in closestControllerNodes:
         if delay < DelayThreshold:
            clusteredFogNodes.add(Pair(fogNode,
controllerNode))
         end if
      end for
   end for
   return clusteredFogNodes
end function
```

Smart farming applications (A) are composed of modules (M) essential for data processing, given by

$M = \{m_i\}$ (3)

The IoT application (A) can be comprehensively defined as

$A = \{M, Dep\}$ (4)

where Dep describes the data dependency relationships among these modules, with

$M = \{tuple_1, tuple_2 \ldots\}$ (5)

Each module m_i must meet specific resource requirements $R_{mi} = \{CPU_i, RAM_i, Bandwidth_i\}$ (6) and adhere to a deadline $D_{mi} \le T_{mi} \quad \forall m \in M$ (7) for timely processing on fog nodes within their capacity:

$R_{mi} \le C_{fi} \quad \forall f \in F, \forall m \in M$ (8)

Furthermore, consider E as the set of energy profiles within a fog cluster. For each fog node fi in F let $e_i \in E$ represent the specific energy profile associated with fi.
The energy efficiency EE_i of a fog node fi is determined by calculating the ratio of its computational output CO_i to its energy consumption EC_i:

$$EE_i = \frac{CO_i}{EC_i}$$

To optimize the energy usage of fog nodes in fog-based smart farming, we introduce a binary variable U_i. This variable indicates whether a fog node fi is underutilized ($U_i = 1$) or not ($U_i = 0$).
When $U_i = 1$, indicating that the fog node fi is underutilized, the FCN initiates adaptive power management strategies. These strategies involve adjusting the power state of the fog node by transitioning

it to a low-power mode or deactivating specific components. Consequently, the fog node fi reduces the allocation of computational resources, including CPU, memory, and other processing units. This approach aligns the fog node's resource utilization with the current workload, ensuring efficient allocation and minimizing unnecessary power consumption.

Algorithm 2 Energy Optimization for Fog Nodes

```
Input:
   F: Set of all fog nodes
   E: Energy profiles for each fog node
Output:
   OE: Optimized energy usage for each fog node

function optimizeEnergyEfficiency(F, E):
   for each fogNode in F:
      energyProfile = E[fogNode]
      currentEnergyEfficiency =
calculateEnergyEfficiency(energyProfile)
identifyEnergySavingOpportunities(fogNode)
   for each fogNode in F:
      if isUnderutilized(fogNode):
         activateLowPowerMode(fogNode)
       else if isNearingMaxCapacity(fogNode):
         redistributeModules(fogNode)
      continuouslyMonitorEnergyConsumption(fogNode)
   return getOptimizedEnergyUsage(F)

end function
```

When U_i =0, indicating that the fog node fi is not underutilized, the FCN enhances energy efficiency by activating a low-power mode. This involves measures such as temporarily putting certain components of the node into a sleep state. These strategies ensure that even when the fog node is operational, it consumes minimal energy, contributing to overall energy efficiency.

Our proposed Algorithm 2 effectively manages and optimizes the energy consumption of fog nodes. It dynamically adjusts power states and resource allocations based on real-time workloads and energy profiles, ensuring optimal energy usage in the fog layer of a smart farming ecosystem.

4. Performance Evaluation

In this section, we validate the proposed scheme by implementing it in an IoT-based smart greenhouse application. Additionally, the algorithm was simulated using iFogSim to evaluate its performance with real data.

A. Implementation of IoT-based Smart Greenhouse System

Our scenario involves a greenhouse equipped with harvesting robots and a network of distributed sensors and actuators. These sensors continuously monitor specific environmental conditions such as temperature, humidity, and soil pH, and report these measurements to the fog nodes. This setup ensures efficient management and timely response to varying conditions within the greenhouse. The collected data is classified based on latency sensitivity, allowing for prioritized processing and optimal resource utilization.

Algorithm 3 Module Placement with Clustering and Optimized Energy Efficiency for Fog-based smart farming

```
 Input:
  M: Set of application modules
  F: Set of fog nodes
  E: Energy profiles for each fog node
  FCN: Set of Fog Controlled Nodes

Output:
  Rsp: Selected fog node
  OE: Optimized energy usage

function enhancedModulePlacementWithClustering(M, F, E, FCN):
   clusteredFogNodes = clusterFogNodes(F, FCN)
   Rsp = null

   for each fogNode in F:
      if not isOverloaded(fogNode) and capacity(fogNode) >=
requirement(M):
         delay = calculateDelay(fogNode)
         arrangeDelaysInAscendingOrder()
         Rsp = fogNode
         updateCapacityAndEnergyUsage(fogNode)
         break

   if Rsp == null:
      if isUrgentSmartFarmingApplication(M):
         while true:
            fogNode = selectRandomFogNode(F)
            if hasNoUrgentTasks(fogNode):
               Rsp = fogNode
               break
      else:
         Rsp = Cloud

   OE = optimizeEnergyEfficiency(F, E)
   return Rsp, OE

end function
```

Case 1: Regular Monitoring of Soil Moisture Levels

If the analysis of soil moisture levels indicates optimal conditions for plant growth, the system can reduce the frequency of data collection and analysis. This adjustment conserves energy and processing resources. The aggregated soil moisture data is then transmitted to the fog layer's database for record-keeping and future reference, demonstrating the system's ability to adapt to changing conditions and optimize resource usage.

Case 2: Immediate Response to Critical Irrigation Needs

When soil moisture analysis reveals drought conditions in certain areas of the greenhouse, the system prioritizes this data and sends it immediately to the fog scheduler. The fog computing algorithm classifies this task as high priority, ensuring that the irrigation system is activated promptly to address the water deficiency. The response is executed at the fog node with the lowest possible latency, mitigating potential damage to the plants and showcasing the system's capability to handle critical tasks efficiently.

Case 3: Monitoring and Response to Agricultural Robot Alerts

When an agricultural robot detects signs of pest infestation or plant disease, such as Bayoud disease, the data is classified as latency-sensitive. If the robot identifies a critical issue that could spread quickly, the information is processed with high priority at the nearest fog node to ensure rapid intervention. For less critical issues, the data is still processed promptly but with medium priority, allowing the management system to schedule appropriate interventions without delay. This demonstrates the system's flexibility and responsiveness to varying levels of urgency in smart farming applications.

Figure 1. IoT-based monitoring system prototype

B. *Result*

The evaluation was conducted using the iFogSim simulator to assess the effectiveness of our proposed module placement algorithm. iFogSim is designed to simulate IoT, edge, fog, and cloud computing environments.

The evaluation of this implementation was carried out on a Dell computer featuring an Intel Core i5 processor and 8 GB of memory, running Windows 10 64-bit. During the simulation, specific parameters, including CPU length, RAM, and bandwidth for each node in the fog layer, were configured as detailed in TABLE II.

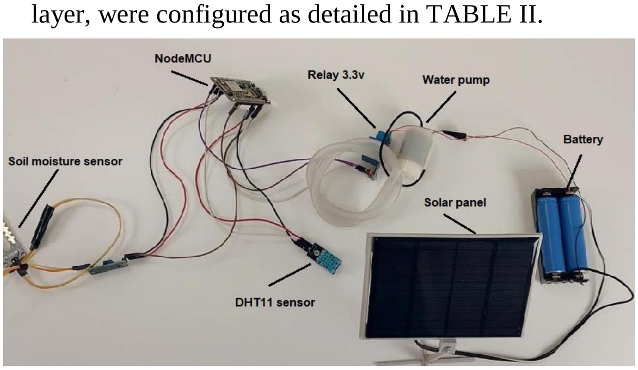

Figure 2. Main components of IoT-based monitoring system

TABLE II. CONFIGURATION DETAILS OF IFOGSIM SETUP

Parameter	Cloud	Proxy	FCN	Fog node	Senso r
CPU length (MIPS)	44800	23,800	23800	18500	500
RAM (MB)	40000	6000	6000	4000	1000
Uplink bandwidth (MB)	100	10000	10000	10000	10000
Download bandwidth (MB)	10000	10000	10000	10000	-
Level	0	1	2	3	4
Rate/MIPS	0.01	0	0	0	0
Busy power (Watt)	16*103	107.33	107.33	107.33	87.53
Idle power (watt)	16*83.25	83.43	83.43	83.43	83.43

The computational capabilities of the devices were categorized into five distinct levels. The first level includes various sensors and actuators used in smart greenhouse. The second level consists of Fog Nodes (FNs), followed by the third level, which comprises Fog Controller Nodes (FCNs). The fourth level includes the proxy that connects the cloud to the FCNs, and the fifth level is dedicated to the cloud server.

In the first step of this experimental test, we configured the simulator with one Fog Controller Node, three fog nodes, and nine IoT sensors. The results were averaged over 400 iterations. Figures 3-5 illustrate the outcomes for key performance metrics, including average latency, average network usage, and energy consumption.

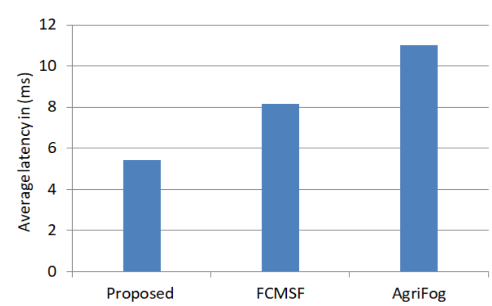

Figure 3. Average latency

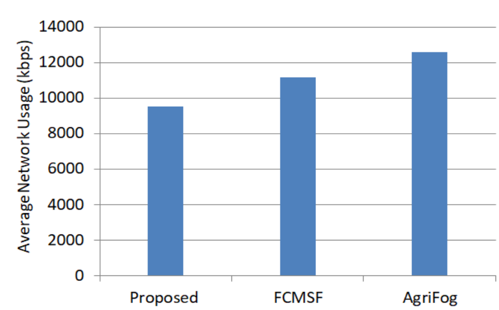

Figure 4. Average network usage

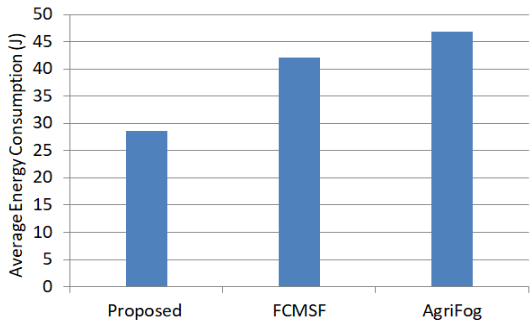

Figure 5. Average energy consumption

The simulation results demonstrate that our proposed module placement algorithm for fog-based smart farming applications significantly outperforms the Agrifog [18] and FCMSF [19] models across key performance metrics, including latency, network usage, and energy consumption. This improvement is largely due to the intelligent placement of modules within appropriate fog nodes, as coordinated by fog controller nodes (FCNs).

The proposed algorithm for module placement optimization in fog-based smart farming applications ensures that fog nodes are selected based on the priority and latency sensitivity of each module. For example, when soil moisture analysis reveals optimal conditions for plant growth, the data collection and analysis frequency is reduced to conserve energy and processing resources. This normal module is strategically placed to minimize power consumption while adhering to deadline constraints. In contrast, if the soil moisture analysis detects drought conditions, the system prioritizes this data for immediate processing to activate the irrigation system promptly. This critical module, requiring immediate action, is allocated to the fog node with the lowest possible latency to minimize potential damage to the plants. Similarly, when an agricultural robot detects signs of pest infestation or plant disease, the data is classified as latency-sensitive. For critical issues that could spread quickly, the information is processed with high priority at the nearest fog node to ensure rapid intervention, such as activating pesticide systems. This priority-driven approach ensures that each module is assigned to the most suitable fog node, thereby enhancing overall system efficiency and performance.

C. Changing the number of the IoT devices

In this step of the test, we configured the simulator with one Fog Controller Node, three fog nodes, and nine IoT sensors. We systematically expanded the topology configuration by incorporating additional connected sensors, aiming to evaluate their impact on latency, energy consumption, and network usage. The number of connected sensors was increased to 12, 16, 20, 24, 28, 32, and 36. Figures 4-7 illustrate the outcomes for key performance metrics, including average latency, average network usage, and energy consumption.

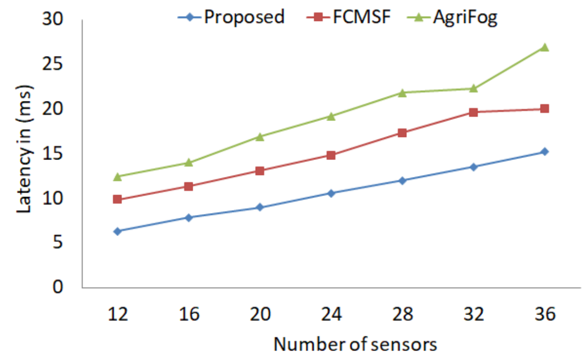

Figure 6. Latency

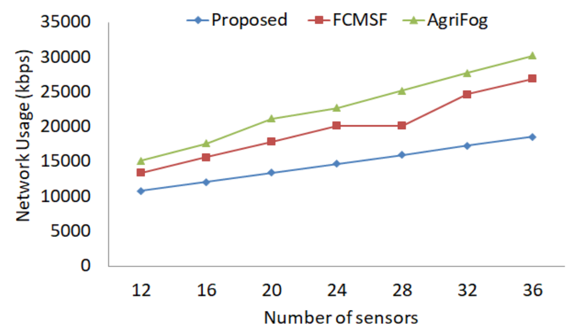

Figure 7. Network usage

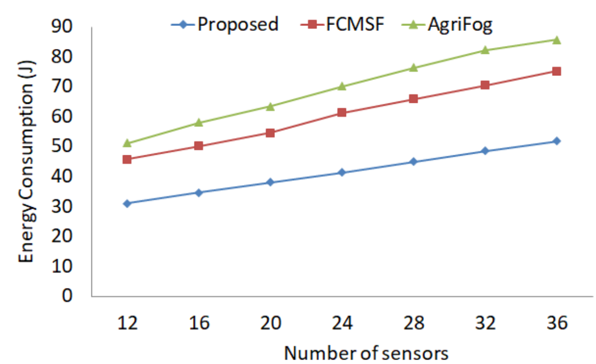

Figure 8. Energy consumption

Figures 6-8 provide a comprehensive comparison of latency, network usage, and energy consumption among the cloud, fog, and our proposed approach. With an increase in the number of connected sensors in smart farms, latency significantly rises in the cloud due to the considerable distance data must traverse for processing. In fog-only architectures like CMFC and Agrifog, the absence of Fog Controller Nodes (FCNs) leads to overloaded Fog Nodes and increased delay, negatively impacting latency-sensitive applications. Our proposed approach mitigates this by distributing the computational load effectively.

In terms of network usage, our algorithm places modules near sensors on fog nodes, reducing network congestion. The fog-only approach without FCNs pushes modules to use cloud resources, further congesting the network and impacting response times. The proposed FCNs manage load distribution within the fog layer, significantly reducing network usage and intelligently routing data to the cloud only when necessary.

Regarding energy consumption, our model outperforms the FCMSF and Agrifog models by optimizing module placement based on urgency and energy needs. Critical modules are processed with minimal latency, moderate modules balance energy consumption and latency, and normal modules focus on minimizing energy consumption while meeting deadlines. This prioritization reduces overall energy consumption, enhancing the efficiency and sustainability of the smart farming system.

D. Changing the number of the fog

In this phase of the experimental test, the number of agricultural IoT devices was set to 18, and the number of fog nodes was varied between 8, 10, 12, and 14. This variation allowed for an assessment of how different numbers of fog nodes impact the system's performance metrics, such as latency, energy consumption, and network usage.

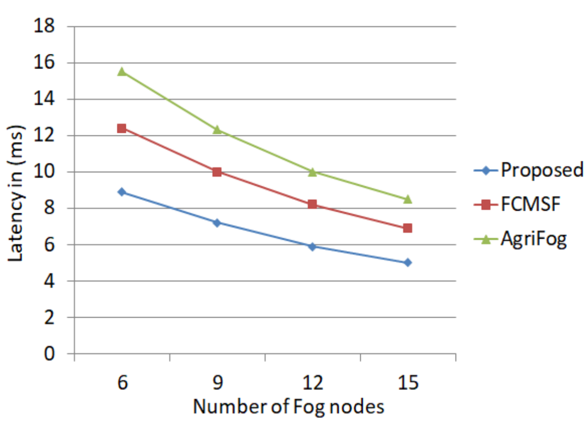

Figure 9. Latency

as shown in Figures 7-9, the simulation results indicate that as the number of fog nodes increases, there is a significant reduction in latency, energy consumption, and network usage across all models. This improvement is due to the enhanced ability to select the most suitable fog nodes for module placement, which minimizes the need to offload tasks to the cloud. Consequently, this leads to lower latency and decreased energy consumption and network bandwidth. Moreover, the increased number of fog nodes allows for better distribution of computational load, ensuring more efficient resource utilization in fog-based smart farming ecosystem.

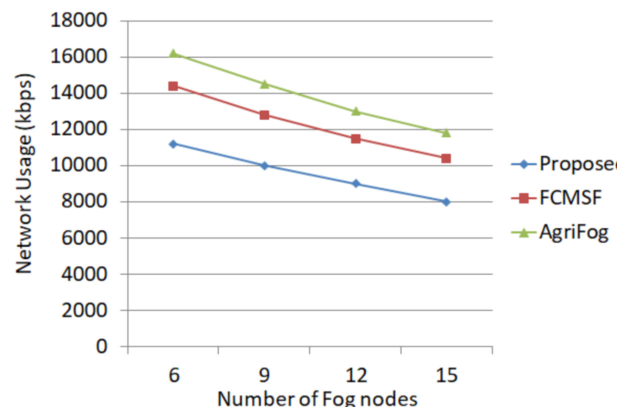

Figure 10. Network usage

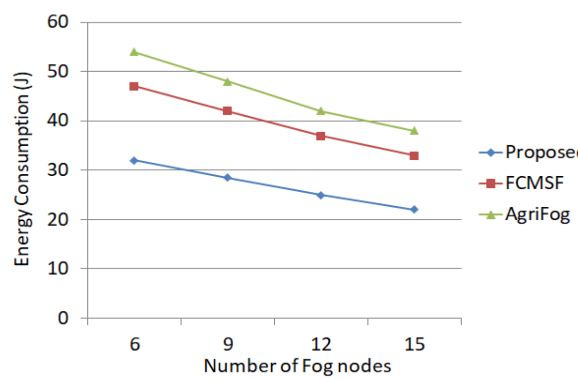

Figure 11. Energy consumption

5. CONCLUSION

This paper presents and evaluates three distinct approaches: FCMSF, Agrifog, and our proposed scheme, using simulations conducted with iFogSim. The performance evaluation focuses on overall latency, network usage, and energy consumption. Our proposed algorithm improves latency and optimizes network utilization by executing modules close to the data source while accounting for resource limitations within the fog layer. This enhancement is achieved through the creation of clusters, each containing multiple fog nodes led by a Fog Control Node. Future work will explore adaptive algorithms for dynamic module placement, utilizing machine learning techniques to enhance decision-making based on real-time changes in the smart farming environment.

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