An Energy-Efficient Model of Integrating Telehealth IoT Devices with Fog and Cloud Computing-Based Platform

Yunyong Guo, Sudhakar Ganti, Bryan Guo

Abstract**—**The rapid growth of telehealth Internet of Things (IoT) devices has raised concerns about energy consumption and efficient data processing. This paper presents an energy-efficient model that integrates telehealth IoT devices with a fog and cloud computing-based platform, offering a sustainable and robust solution to overcome these challenges. Our model employs fog computing as a localized data processing layer while leveraging cloud computing for resource-intensive tasks, significantly reducing energy consumption. We incorporate adaptive energy-saving strategies. Simulation analysis validates our approach's effectiveness in enhancing energy efficiency for telehealth IoT systems integrated with localized fog nodes and both private and public cloud infrastructures. Future research will focus on further optimization of the energy-saving model, exploring additional functional enhancements, and assessing its broader applicability in other healthcare and industry sectors.

Keywords**—**Energy-efficient, fog computing, IoT, telehealth.

I. Introduction

HEALTHCARE is a critical global industry, and the advent of the IoT and cloud computing has significantly transformed healthcare system management. The ever-increasing data volume generated by these systems demands efficient, energy-saving computing platforms. Telehealth IoT devices often need to communicate with a variety of other devices and platforms [[1]]. Despite the benefits, the large-scale deployment of telehealth IoT devices presents several challenges, including [2]: *a) Energy Consumption:* Telehealth IoT devices require a continuous power supply to operate and communicate with other devices and servers; *b) Data Management:* The vast amount of data generated by telehealth IoT devices demands efficient data management solutions; *c) Latency:* Real-time healthcare services require low-latency communication between IoT devices and servers. However, as the number of devices increases, network congestion, and longer transmission distances can result in higher latency, affecting the quality of healthcare services; *d) Security and Privacy:* The large-scale implementation of such devices exposes them to potential cyber-attacks and data breaches, requiring robust security measures and encryption techniques.

Our energy-efficient model integrates fog and cloud computing paradigms to optimize data processing for telehealth IoT devices without compromising real-time healthcare services. The model enables localized data processing by incorporating fog computing as an intermediary layer between IoT devices and public or private cloud servers, effectively reducing latency and data transfer overhead. Simultaneously, public and private cloud computing provides a robust infrastructure for handling large data volumes and performing resource-intensive computations. The primary goal of this model is to minimize energy consumption through intelligent task allocation between fog nodes and cloud servers, by considering their computational capacity and proximity to IoT devices. This task allocation process also considers various sensitivity and priority levels within the healthcare context, ensuring prompt responses to critical and high-sensitivity requests. Moreover, a simulation method is employed to evaluate the effectiveness and efficiency of the system, as examining complex IoT-Fog-Cloud systems within a simulation environment is a prevalent approach among researchers.

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II. Related Work

In recent years, several simulation methods have been developed to study the integration of fog nodes in IoT devices and cloud computing. Gupta et al. [3] introduced iFogSim, a toolkit for modeling and simulating resource management techniques in IoT, edge, and fog computing environments. Oueis et al. [4] presented a simulation study on load distribution in small-cell cloud computing using fog computing and proposed a fog balancing technique to optimize resource allocation and reduce latency. Barcelo et al. [5] explored IoT-cloud service optimization through simulation in smart environments, presenting a novel optimization framework that utilizes fog nodes to reduce latency and energy consumption. Zeng et al. [6] conducted a comparative study of IoT cloud and fog computing simulations using iFogSim and Cooja, discussing the advantages and limitations of both simulators and providing insights into selecting an appropriate tool for specific scenarios. Lastly, Byers and Wetterwald [7] discussed the concept of fog computing and its importance in distributing data and intelligence for IoT resiliency and scalability, presenting various simulation models and techniques used to evaluate the performance of fog computing in IoT environments.

Several studies have focused on the YAFS (Yet Another Fog Simulator) framework, a simulator designed for modeling and simulating fog computing environments in IoT scenarios. Bermejo et al. [8] introduced YAFS, presenting the architecture, components, and use cases of the simulator, demonstrating its effectiveness in modeling and simulating fog computing deployments. García et al. [9] showcased YAFS's ability to model and simulate fog computing scenarios and analyze the performance of different scheduling algorithms.

III. Model Overview

The model comprises three main components: IoT devices, fog nodes, and public/private cloud servers, interconnected through a communication network.

1. *IoT Devices:* Telehealth IoT devices, such as wearables, sensors, and remote monitoring systems, collect and transmit patient data in real-time.
2. *Fog Nodes*: Fog nodes, located near IoT devices, serve as intermediate processing units.
3. *Cloud Servers:* Cloud servers provide a robust infrastructure for large-scale data storage, processing, and advanced analytics.
4. *Communication Network:* A communication network connects IoT devices, fog nodes, and cloud servers, enabling seamless data transmission and task allocation.

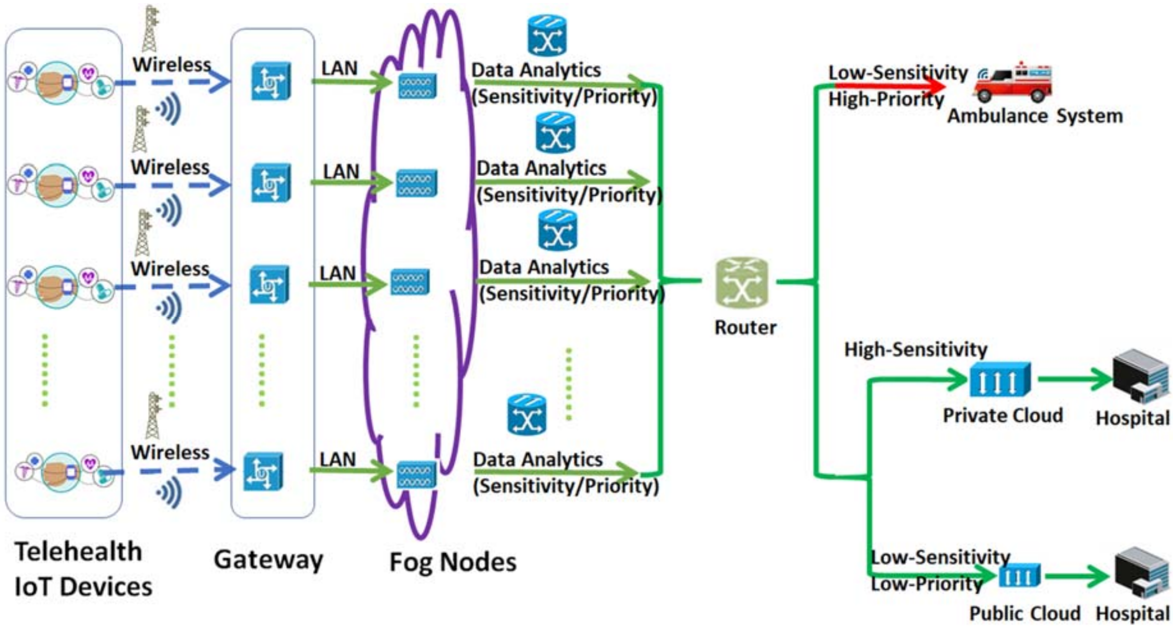

Fig. 1 Telehealth IoT devices integrated with Fog nodes and private/public cloud architecture model

To process the data requests, the fog nodes are equipped with data analytics functions that enable them to intelligently assign different types of requests to either fog nodes, private cloud, or public cloud. This intelligent decision-making process is more effective and efficient than the traditional "first-come, first-served" approach.

Here is a brief overview of the components in the network topology: IoT devices represent individual IoT devices in the network, each associated with a specific fog node. Gateways are used to connect IoT devices to fog nodes. Fog nodes are intermediate computing resources that process and store data from IoT devices. A router connects the fog nodes to the private cloud and public cloud. Private Cloud and Public Cloud are the two cloud resources in the network.

The data collected from IoT devices have two parameters: a) sensitivity and b) priority. Sensitivity refers to the level of importance or criticality associated with the data generated by telehealth IoT devices. In the healthcare domain, different types of patient data have varying levels of sensitivity. For instance, vital signs like heart rate, blood pressure, or oxygen levels might be considered highly sensitive data, as they directly impact patient health and require immediate attention. The sensitivity level helps determine how urgently and through which route (fog node or cloud server) the data should be processed and analyzed to ensure timely and appropriate responses. Priority refers to the level of urgency or importance assigned to a particular data request or task generated by telehealth IoT devices. In a healthcare context, different data requests may have varying priority levels based on their potential impact on patient care. For example, a critical medical alert indicating a life-threatening condition may have the highest priority, requiring immediate attention and processing. The combination of sensitivity and priority is used to determine the appropriate processing location for the data generated by the IoT devices. The decision-making process considers the sensitivity and priority levels of the data along with other factors, such as energy consumption and latency, to intelligently allocate tasks to fog nodes or cloud servers. This approach ensures that critical data are processed promptly and efficiently, while less critical data are processed in a manner that optimizes energy consumption and resource utilization. The categorization of high and low sensitivity and high and low priority data sent from telehealth IoT monitor devices can depend on various factors, including the specific use case, regulatory requirements, and patient needs. One possible approach could be to use threshold values based on vital signs such as pulse and heartbeat to categorize the data.

IV. Simulation Study

The simulation process can be analyzed in the following steps:

1. *Initialization:* Create IoT devices $D = \{d_1, d_2, ..., d_n\}$, fog nodes $F = \{f_1, f_2, ..., f_m\}$; and cloud instances $C = \{c_1, c_2\}$ with their respective properties.
2. *Connection:* Connect IoT devices to fog nodes and then fog nodes determine which data are transferred to cloud instances (private and public). Each device is connected to a corresponding fog node.
3. *Data transmission simulation:* Simulate data transmission from IoT devices to their respective fog nodes, and then fog nodes assign the requests to private cloud or public cloud based on their priority and sensitivity. If the sensitivity of the device is 'high', data are sent to the private cloud. If the sensitivity is 'low' and the priority is 'high', there is a chance that data are sent to the fog node. If this condition is not met, the device does not send data. If the sensitivity is 'low' and the priority is 'low', data are sent to the public cloud.
4. *Energy consumption calculation at time t:* Calculate the energy consumed by each IoT device during data transmission considering the latency. Different energy costs are associated with sending data to different destinations (fog nodes, private cloud, or public cloud).

- Calculate the average processing time $P_{\_ti}$ and energy consumption $E_{\_ti}$ for each IoT device i in D and fog node j in F.
- Calculate average energy consumption $E_{\_ti}$, sensitivity $S_{\_ti}$, and priority $P_{\_rti}$ for each IoT device i in D and fog node j in F.
- Calculate the latency $L_{\_dti}$ for transmitting data from device d to each fog node i in F and cloud server j in C.
- Calculate the priority P_{r_dti}, sensitivity $S_{\_dti}$, energy consumption $E_{\_dti}$ for device d and each fog node i in F and cloud server j in C.
- Find the fog node j^* and cloud server l^* with the minimum latency for device i^*, considering P_{rti}, $S_{\_ti}$, and $E_{\_dti}$: $j^* = \text{argmin}\_j(L_{dt})$ for j in F, such that $L_{\_dti} <= L_t$, $P_{r\_dti} <= P_{rt}$ and $S_{\_dti} <= S_t$. $l^* = \text{argmin}\_l(L_{dt})$ for l in C, such that $L_{\_dti} <= L_t$, $P_{r\_dti} <= P_{rt}$ and $S_{\_dti} <= S_t$
- If $S_{dt}[j^*] <= S_t$, then allocate task could server l^* and add it to the queue: $Q_C[l^*]$. append $((d, t))$
- Else if $P_{r\_dt}[j^*] <= P_{\_rti}$, then allocate task t to fog node j^* and add it to the queue: $Q_F[j^*]$. append $((d, t))$
- Else if $P_{r\_dt}[l^*] <= P_{\_rti}$, then allocate task t to cloud server l^* and add it to the queue: $Q_C[l^*]$. append $((d, t))$
- Else, consider alternative energy-saving strategies or adjust the energy consumption threshold E_t.

Explanation of subscripts and ranges:

– i: individual IoT devices in the network.
– j: fog nodes in the network.
– l: cloud servers in the network.
– d: individual data transmission instances from IoT devices.
– D: Range of IoT devices (1 to n).
– F: Range of fog nodes (1 to m).
– C: Range of cloud servers (1 to 2, representing private and public cloud).
– $Q_F[j]$: Task allocation queue for fog node j.
– $Q_C[l]$: Task allocation queue for cloud server l.

5. *Comparison:* Compare the energy consumption of IoT devices when using fog nodes and when not using fog nodes.

V. Results and Analysis

Algorithm: Energy Consumption Calculation for Telehealth IoT Devices

Inputs:
- List of IoT devices: D = $\{d_1, d_2, ..., d_n\}$
- List of fog nodes: F = $\{f_1, f_2, ..., f_m\}$
- List of cloud servers: C = $\{c_1, c_2\}$
- Latency threshold: L_t (max allowable latency)
- Priority threshold: P_{rt} (minimum priority level)
- Sensitivity threshold: S_t (maximum sensitivity level)
- Energy consumption threshold: E_t (maximum energy consumption)

Outputs:
- Task allocation queues: Q_F[f] and $QC[c]$ for fog nodes and cloud servers
- Energy consumption E_ti for each IoT device i

Initialization:
- For each IoT device i in D and fog node j in F:
  Set E_ti = 0, initialize energy consumption for each device.
- For each IoT device d in D:
  Calculate sensitivity S_dt and priority Pr_dt for device d.
- For each IoT device i in D:
  Calculate latency L_dti for transmitting data from device d to each fog node j and cloud server l.
- For each IoT device d in D:
  Find fog node j* and cloud server l* with the minimum latency, considering P_{r_dt} and S_dt:
  $j^* = argmin\_j(L\_dti)$ for j in F, such that $L\_d_{ti} <= L_t$, $P_{r\_dt} <= P_{rt}$, and $S_{\_dt} <= S_t$
  $l^* = argmin\_l(L\_dti)$ for l in C, such that $L_{\_dti} <= L_t$, $P_{r\_dt} <= P_{rt}$, and $S_{\_dt} <= S_t$
  If $S\_dt[j^*] <= S_t$, then allocate task to cloud server l^* and add it to queue $QC[l^*]$
   Else if $Pr\_dt[j^*] <= P_{rt}$, then allocate task to fog node j^* and add it to queue $QF[j^*]$
   Else if Pr_dt[l*] <= P_{rt}, then allocate task to cloud server l^* and add it to queue $QC[l^*]$
   Else
    consider alternative energy-saving strategies or adjust the energy consumption threshold E_t
  - For each fog node j in F:
    Process tasks in queue $QF[j]$:
- Update E_ti for each IoT device i in the queue based on processing time and energy cost.
- For each cloud server l in C:
  Process tasks in queue $QC[l]$:
  Update E_ti for each IoT device i in the queue based on processing time and energy cost.

Based on the simulation results, we can analyze the impact of different parameters on the energy efficiency and performance of the proposed telehealth model with and without fog computing. The parameters in the results are *Snapshot Interval, Number of Devices, With Fog Mean, With Fog Standard Deviation (Std), With Fog Confidential Interval (CI), Without Fog Mean, and Without Fog Std, Without Fog Confidential Interval (CI).*

- *Snapshot Interval:* This parameter represents the frequency at which the IoT devices send their data to the fog nodes or cloud servers. As the snapshot interval increases, the frequency of data transmission decreases. With a snapshot interval of 1, the IoT devices are sending data continuously. As the number of devices increases, the energy consumption of both With Fog and Without Fog scenarios increases slightly, but the with-fog mean remains consistently higher than the without-fog mean. With a snapshot interval of 5, the IoT devices are sending data less frequently, which results in reduced energy consumption. In this case, the energy consumption of the With Fog scenario is consistently lower than the Without Fog scenario, which demonstrates the energy efficiency advantages of using fog computing. With a snapshot interval of 10, the IoT devices send data even less frequently, and the difference in energy consumption between the With Fog and Without Fog scenarios becomes more pronounced. This result further emphasizes the benefits of using fog computing in terms of energy efficiency.
- *Number of Devices:* This parameter refers to the number of telehealth IoT devices in the network. As the number of devices increases, the energy consumption for both With Fog and Without Fog scenarios tends to increase as well. This is expected, as more devices lead to higher data transmission and processing loads. However, the increase in energy consumption is consistently smaller in the With Fog scenario compared to the Without Fog scenario across all snapshot intervals. This shows that the proposed fog-based model is more scalable and can better handle the energy requirements of a growing number of devices.
- *With Fog Mean and Without Fog Mean:* These parameters represent the average energy consumption in the scenarios with and without fog computing, respectively. Across all snapshot intervals and number of devices, the With Fog Mean is generally lower than the Without Fog Mean, indicating that the fog-based model is more energy-efficient than the cloud-only model.
- *With Fog Std and Without Fog Std:* These parameters represent the standard deviation of the energy consumption in the scenarios with and without fog computing, respectively. In general, the standard deviation values are lower in the With Fog scenario compared to the Without Fog scenario. This suggests that the energy consumption is more consistent and less variable in the fog-based model, which could lead to more predictable and stable system performance.
- *With Fog Std and Without Fog CI:* The confidence interval (CI) in the simulation code is a range within which a certain percentage of the population parameter is expected to lie, with a specified level of confidence. In the context of the provided simulation results, the CIs represent the range within which the true mean performance of the system (either with or without fog computing) is likely to fall, with a certain level of confidence, typically 95%. A narrower CI indicates a more precise estimate, while a wider interval suggests more uncertainty.

In all cases, the "With Fog Mean" is higher than the "Without Fog Mean," indicating that, on average, the remaining energy is higher when using fog computing. Looking at the CIs for both "With Fog" and "Without Fog" scenarios, if the CIs do not overlap, it suggests that the difference in energy remaining between the two scenarios is statistically significant. For example, in Fig. 2 (Snapshot Interval: 1, Number of Devices: 10), the "With Fog CI" is (87.98, 89.45), and the "Without Fog CI" is (84.90, 87.47). Since these intervals do not overlap, there's strong evidence that using fog computing leads to significantly higher energy remaining for this specific combination of parameters. Comparing the width of the CIs for each scenario: A narrower CI indicates a more precise estimate of the true population means. For most CI values, the "With Fog CI" is narrower than the "Without Fog CI" suggesting that the "With Fog" scenario has a more precise estimate. Analyzing the trends as the number of devices increases within each snapshot interval: In general, the energy remaining in both scenarios decreases as the number of devices increases. However, the rate of decrease seems to be lower when using fog computing. Observing the trends as the snapshot interval increases for each group of devices: As the snapshot interval increases, the energy remaining for both scenarios decrease, suggesting that less frequent snapshots may lead to less energy conservation. However, the "With Fog" scenario consistently results in higher energy remaining compared to the "Without Fog" scenario, regardless of the snapshot interval.

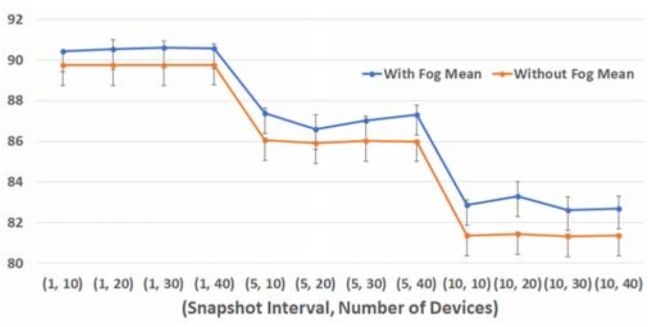

Fig. 2 Energy Remaining of IoT Devices with Standard Deviation

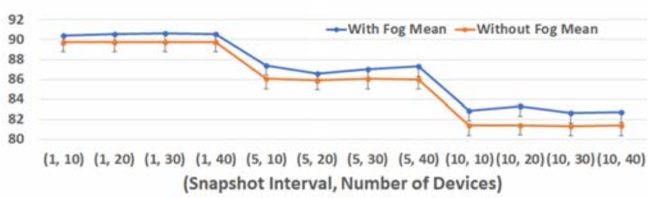

Fig. 3 Energy Remaining of IoT Devices with Confidential Interval

VI. Conclusion

This paper provides a compelling model for the use of fog and cloud computing-based platforms in telehealth IoT deployments to reduce energy consumption, improve data processing efficiency, and maintain high-quality healthcare services. The model leverages the strengths of both fog and cloud computing paradigms to address the challenges associated with large-scale telehealth IoT deployments. The simulation results show that the proposed fog-based model significantly reduces energy consumption compared to the cloud-only model while maintaining high-quality data processing and transmission. Moreover, the methodology described in this paper provides a comprehensive approach to analyzing network performance and energy consumption, which includes examining the impact of various parameters, such as the number of devices, fog node deployment, task allocation algorithm, energy consumption metrics, and performance metrics. The simulation results and methodology demonstrate the effectiveness of the proposed model and provide a roadmap for future research in this area. The proposed model can help healthcare providers and stakeholders improve patient care and outcomes while reducing costs and energy consumption.

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