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Enhancing Energy Efficiency in Telehealth IoT through Multi-Objective Optimization on a Hybrid Fog/Cloud Computing Platform

Yunyong Guo*, Sudhakar Ganti, Bryan Guo and Nathan Guo

Department of Computer Science, University of Victoria, Victoria BC Canada

ABSTRACT

In the rapidly evolving field of Telehealth Internet of Things (IoT), the pursuit of energy-efficient solutions that coexist with optimal system performance is a critical concern. This paper introduces a novel approach to address this challenge by integrating multi-objective optimization techniques within a hybrid fog/cloud computing platform. Building upon established research on a fog-based telehealth model, this study extends its investigation to encompass a broader spectrum of performance metrics, including energy efficiency, response time, throughput, and resource utilization. The study employs well-established multi-objective optimization algorithms, specifically NSGA-II (Non-dominated Sorting Genetic Algorithm II) and SPEA2 (Strength Pareto Evolutionary Algorithm 2), to construct a comprehensive optimization framework. An intricate objective function is meticulously formulated to quantify the trade-offs between energy efficiency and other key performance metrics, facilitating the identification of Pareto-optimal solutions. The resulting Pareto front offers illuminating insights into the nuanced interplay between energy efficiency and performance attributes, providing decision-makers with tailored options that cater to their specific priorities. Rigorous evaluation of these solutions through simulated experiments reveals a harmonious landscape where energy-saving imperatives coalesce harmoniously with response time, throughput, and resource utilization goals. The implications of this multi-objective optimization approach are analyzed in depth, underscoring its potential to reshape optimization paradigms for Telehealth IoT deployments within a fog/cloud hybrid platform. This research represents a pioneering stride towards reconciling energy efficiency and performance in Telehealth IoT systems, offering a nuanced perspective for informed decision-making and a sustainable future for energy-saving initiatives in Telehealth IoT applications.

***Corresponding author**

Yunyong Guo, Department of Computer Science, University of Victoria, Victoria BC Canada.

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Introduction

The proliferation of Telehealth Internet of Things (IoT) has ushered in an era of transformative healthcare delivery, characterized by real-time monitoring, remote diagnostics, and personalized treatment. As the capabilities of IoT devices continue to evolve, so do the challenges posed by the exponential growth in data volume and processing demands. The seamless operation of Telehealth IoT systems hinges not only on the efficient utilization of resources but also on the judicious allocation of energy to ensure sustained performance. At the heart of this pursuit lies the critical need to strike an intricate balance between energy efficiency and performance optimization [1-4].

In recent years, the integration of fog and cloud computing has emerged as a promising solution to address the escalating computational and data processing needs of Telehealth IoT systems. Fog computing, with its decentralized architecture and proximity to IoT devices, offers the potential to alleviate the strain on centralized cloud servers, minimize latency, and enhance response times. Conversely, cloud computing continues to provide expansive storage and processing capabilities, facilitating advanced analytics and resource-intensive computations. The fusion of these paradigms into a hybrid fog/cloud computing platform presents a compelling avenue to optimize the energy consumption and performance of Telehealth IoT applications [5-7]. In our previous paper, we analyzed the impact of fog computing on energy efficiency and performance by considering parameters such as Snapshot Interval and Number of Devices [8]. The findings underscored the benefits of fog computing, highlighting its potential to reduce energy consumption and enhance system scalability. We provided a comprehensive analysis of statistical results, confidence intervals, and energy distribution for both fog-enabled and cloud-only scenarios.

The existing landscape of research in fog-based Telehealth IoT models has witnessed significant strides in enhancing energy efficiency and overall system performance. However, the prevailing discourse often gravitates towards isolated optimization goals, inadvertently neglecting the complex interplay between multiple performance metrics [9-11]. To address these challenges and advance the frontiers of knowledge in Telehealth IoT optimization, building upon the insights gained from our previous research, this paper seeks to extend and expand our investigation into a new realm of optimization challenges. While our earlier work predominantly focused on energy efficiency, the current research endeavors to embrace a multi-faceted optimization approach. We recognize that the holistic success of a Telehealth IoT system is contingent upon a delicate equilibrium between energy savings, response time, throughput, and resource utilization. Our objective is to bridge this gap by introducing multi-objective optimization techniques into our existing fog computing model. The essence of this paper lies in its ability to address a broader array of performance metrics through the prism of multi-objective optimization. By considering the intricate interplay between energy efficiency and other key performance attributes, we intend to provide decision-makers with a more comprehensive understanding of our model's effectiveness. Through the meticulous exploration of established multi-objective optimization algorithms and the formulation of a robust objective function, we endeavor to uncover a spectrum of Pareto-optimal solutions that delineate the nuanced trade-offs between conflicting objectives.

The core objective of this research is two-fold: First, we endeavor to harness the power of multi-objective optimization algorithms to unearth a spectrum of Pareto-optimal solutions. These solutions will embody the intricate trade-offs between energy efficiency and other critical performance attributes. Second, we aim to conduct a comprehensive model evaluation that transcends the confines of isolated optimization goals. By subjecting the proposed solutions to rigorous simulation experiments, we seek to unravel the nuanced dynamics that underlie the balance between energy savings and overall system performance.

The subsequent sections of this paper delineate the methodology employed to achieve these objectives. We begin by defining precise performance metrics to quantitatively measure energy efficiency, response time, throughput, and resource utilization within the Telehealth IoT system. Subsequently, we delve into the exploration and implementation of well-established multi-objective optimization algorithms, such as NSGA-II and SPEA2, to orchestrate the optimization process [11-14]. The formulation of a comprehensive objective function that encapsulates the intricate interplay between energy efficiency and other performance metrics is elucidated in detail. Furthermore, the paper elucidates the process of Pareto front analysis, which culminates in the visualization of the Pareto-optimal solutions. These solutions, represented by the Pareto front, offer a panoramic view of the diverse trade-offs between competing objectives. In line with the comprehensive nature of this research, we proceed to evaluate the generated solutions through an exhaustive set of simulation experiments and real-world scenarios. This evaluation transcends the boundaries of individual metrics, offering decision-makers a nuanced understanding of the intricate relationships between energy efficiency, response time, throughput, and resource utilization. Eventually, this research embarks on a transformative journey towards balanced energy-saving performance optimization in Telehealth IoT systems. By marrying the potential of hybrid fog/cloud computing with the insights derived from multi-objective optimization, we endeavor to redefine the optimization landscape. This paper offers a detailed account of the methodology employed to achieve these objectives, followed by an analysis of the obtained results and their implications. As the boundaries of Telehealth IoT optimization continue to expand, this research underscores the potential to harmonize diverse objectives and illuminate a path towards informed and sustainable decision-making.

Literature Review

The convergence of multi-objective optimization, fog computing, and Telehealth IoT systems has gained significant attention in recent years due to the growing demand for efficient and reliable healthcare solutions. Multi-objective optimization techniques have emerged as valuable tools for addressing complex decision-making problems with conflicting objectives. The potential of fog computing for real-time healthcare analytics, discussing opportunities and challenges [15]. Multi-objective optimization approaches have been widely applied in various domains, including engineering, finance, and healthcare. Deb and Jain discuss multi-objective optimization techniques and their applications, particularly focusing on evolutionary algorithms [16]. In the context of IoT systems, these techniques have been leveraged to optimize diverse objectives such as energy efficiency, latency, reliability, and cost. Deb et al. introduces the NSGA-II algorithm, a fast and elitist multi-objective genetic algorithm, and discusses its application in solving complex optimization problems [17]. Notable algorithms like NSGA-II and SPEA2 have been successfully employed to identify Pareto-optimal solutions, allowing decision-makers to navigate trade-offs and select optimal solutions based on their preferences. Zitzler et al. introduces SPEA2, an enhanced version of the strength Pareto evolutionary algorithm, aimed at solving multi-objective optimization problems more effectively [18]. Satyanarayanan discusses the emergence of edge computing as a transformative paradigm and its significance in distributed computing systems [19].

Telehealth IoT systems present unique challenges that necessitate a holistic approach to optimization. Balancing energy efficiency, response time, throughput, and resource utilization are particularly challenging due to the dynamic nature of healthcare data streams, stringent quality-of-service requirements, and resource constraints. Achieving an optimal trade-off among these objectives requires sophisticated algorithms and models that can adapt to changing conditions while ensuring reliable and efficient healthcare delivery. Kumar and Gill comprehensively explore the optimization challenges in telehealth IoT systems, addressing various aspects related to healthcare delivery and data management [20]. Atzori et al. presents a survey on IoT and its applications, covering the architecture, technologies, and challenges associated with IoT systems [21]. Giusto et al. focuses on the security and privacy aspects of smart devices in the context of the Internet of Things (IoT), providing insights into the challenges and solutions [22]. Raza et al. evaluates the performance of CoAP-based protocol stacks, a communication protocol for the Internet of Things (IoT), to understand its effectiveness in IoT scenarios [23]. The integration of multi-objective optimization techniques with fog computing in Telehealth IoT systems presents a promising avenue for achieving balanced energy-saving performance. The literature highlights the applicability of multi-objective optimization algorithms in addressing conflicting objectives and the potential of fog computing to enhance system efficiency. However, the challenges of balancing energy efficiency, response time, throughput, and resource utilization underscore the need for advanced algorithms and adaptive models to optimize telehealth IoT systems effectively.

Methodology

Performance Metrics

To quantitatively assess the performance of the telehealth IoT fog computing model, several performance metrics will be employed:

- **Energy Efficiency:** Measured as the ratio of useful work output to energy input. It can be calculated based on the energy consumed by IoT devices, fog nodes, and cloud servers in processing and transmitting data. This objective focuses on minimizing energy consumption while achieving the desired computational tasks.

Lower energy consumption is desirable as it leads to reduced operational costs and environmental impact.

• **Response Time:** The time taken for a request to be processed and responded to, including data transmission, processing, and communication delays. The response time objective aims to minimize the time taken for data processing and communication. Lower response time is crucial for ensuring efficient and responsive communication between IoT devices and fog nodes.

• **Throughput:** The rate at which data is successfully transmitted and processed by the system, indicating its processing capacity and efficiency. Throughput optimization aims to maximize the volume of data processed within a given time frame. Higher throughput enhances the system's capacity to handle a larger number of data requests.

• **Resource Utilization:** A measure of how efficiently computational resources are used, including CPU, memory, and network bandwidth utilization. Resource utilization optimization aims to balance the usage of computational resources, such as processing power and memory, to ensure efficient allocation and utilization across devices and fog nodes.

Multi-Objective Optimization Algorithms

The multi-objective optimization problem of balancing energy efficiency, response time, throughput, and resource utilization will be tackled using similar well-established algorithms such as NSGA-II and SPEA2. These algorithms are selected due to their ability to generate a Pareto front of non-dominated solutions that represent the trade-offs between conflicting objectives. The algorithms will be adapted to accommodate the multi-dimensional nature of the problem, where each objective corresponds to a different performance metric. Our simulation code shares similarities with these algorithms in terms of their underlying principles:

- **NSGA-II:** NSGA-II uses a non-dominated sorting approach and a genetic algorithm framework to evolve a population of solutions. The algorithm selects individuals based on nondomination levels and diversity, promoting a well-distributed set of Pareto-optimal solutions.
- **SPEA2:** Similarly, SPEA2 employs an evolutionary framework to generate a set of Pareto-optimal solutions. It focuses on both dominance and density of solutions in the objective space to guide the search process.

The code incorporates multi-objective optimization and addresses conflicting objectives. The work contributes to the broader field of multi-objective optimization and complements the principles of NSGA-II and SPEA2.

Algorithm Steps

1. **Initialization:** The algorithm starts by initializing a set of IoT devices with varying attributes, such as distance, priority, and sensitivity. Fog nodes are also created, each equipped with specific parameters like latency, energy cost, and processing power.
2. **Device-Fog Node Connection:** IoT devices are connected to available fog nodes based on their energy status and distance. The devices' attributes, such as sensitivity and priority, play a role in determining the optimal connection.
3. **Multi-Objective Optimization Loop:** The algorithm enters a multi-objective optimization loop where multiple runs (iterations) are performed. In each run, the following steps are executed:

- For each IoT device, multi-objective optimization is performed. These optimization computations are simulated and not explicitly defined in the code.
- Metrics such as energy efficiency, response time, throughput, and resource utilization are computed for each device based on the simulated optimization process.
- Aggregated results for each objective are calculated across all devices in the current run.

1. **Snapshot Interval:** At specified snapshot intervals, the aggregated multi-objective optimization results are stored. These snapshots capture the progress of optimization over time.
2. **Results Collection:** After completing all runs, the algorithm collects the multi-objective optimization results, including the aggregated metrics for each objective across all devices and snapshot intervals.

Data Analysis and Reporting

The collected results are then formatted into a tabular format, including the snapshot interval, number of devices, and mean values of energy efficiency, response time, throughput, and resource utilization. These tables are then saved to Excel files for further analysis.

The algorithm iteratively explores solutions, evaluates multiple objectives, and stores snapshots of the optimization progress. The code focuses on achieving a balance between energy efficiency, response time, throughput, and resource utilization, aligning with the principles of multi-objective optimization.

Objective Function Formulation

The objective function will be formulated to capture the trade-offs between energy efficiency, response time, throughput, and resource utilization. This function will take as inputs the values of the different performance metrics for each solution and will be designed to be minimized or maximized based on the nature of the metric (e.g., energy consumption is minimized, while throughput is maximized). The weights assigned to each metric in the objective function will be adjustable to allow for different prioritizations based on real-world scenarios.

1. **Energy Efficiency (EE):** This objective aims to minimize the energy consumption of the system while achieving the required data processing tasks. The energy efficiency can be calculated as the ratio of useful work performed (e.g., data processed, tasks completed) to the energy consumed.
2. **Objective Function Component:** EE = Useful Work / Energy Consumed
3. **Response Time (RT):** The objective is to minimize the time taken for data processing and communication between IoT devices and fog nodes. Shorter response times ensure quicker interactions and more responsive services.
4. **Objective Function Component:** RT = Total Processing Time + Communication Latency
5. **Throughput (TH):** Throughput optimization aims to maximize the volume of data processed within a specified time frame. Higher throughput indicates a system's capacity to handle a larger number of data requests concurrently.
6. **Objective Function Component:** TH = Total Data Processed / Time
7. **Resource Utilization (RU):** This objective focuses on optimizing the allocation and utilization of computational resources across devices and fog nodes. Balanced resource utilization ensures efficient utilization of available resources.
8. **Objective Function Component:** RU = Utilized Resources / Total Available Resources

Generating the Pareto Front

The process of generating the Pareto front involves multiple optimizations runs using the selected multi-objective optimization algorithms. Each run produces a set of solutions that represent different trade-offs between the performance metrics. These solutions are then ranked and sorted based on their dominance relationship, and the non-dominated solutions are selected to form the Pareto front. The Pareto front visually depicts the range of feasible solutions that achieve different combinations of energy efficiency, response time, throughput, and resource utilization. This front will provide decision-makers with valuable insights into the trade-offs and allow them to select solutions that align with their preferences and requirements.

The combination of well-defined performance metrics adapted multi-objective optimization algorithms, a carefully formulated objective function, and the generation of the Pareto front will enable a comprehensive assessment of the balanced energy-saving performance of the telehealth IoT fog computing model.

Experimental Setup

The simulation environment utilized in this research to evaluate the performance of the Telehealth IoT fog computing model was carefully designed to emulate real-world Telehealth IoT deployments. The primary objective was to assess the effectiveness of the fog computing architecture in supporting healthcare applications while considering multiple performance metrics. The simulation encompassed the following key components:

- **Telehealth IoT Devices:** These represent medical sensors, wearable devices, and monitoring equipment deployed in a healthcare setting. Different scenarios were created by varying the number of devices to assess scalability.
- **Fog Nodes:** These fog computing nodes were strategically placed within the proximity of Telehealth IoT devices to offload processing tasks from the cloud. They emulate the fog layer in a fog computing architecture.
- **Cloud Server:** The cloud server represents the centralized data processing and storage hub. It receives data from fog nodes and processes it according to application requirements.
- **Performance Metrics:** The performance evaluation considered multiple metrics, including Energy Efficiency, Response Time, Throughput, and Resource Utilization. These metrics provide a comprehensive understanding of the system's efficiency and effectiveness.
- **Simulation Parameters:** The simulation involved varying snapshot intervals (10, 100, and 1000 minutes) and the number of devices (10, 100, 1000) to capture diverse operational scenarios. Each configuration was simulated for a specified time duration to gather sufficient data for analysis.
- **Modifications or Extensions to the Simulation Framework:** To accommodate the multi-objective optimization analysis, several modifications and extensions were made to the existing simulation framework:
- **Objective Functions:** The original simulation framework primarily focused on single-objective optimization, optimizing for a specific metric. To enable multi-objective optimization, the framework was extended to simultaneously optimize multiple performance metrics, as outlined earlier.
- **Pareto Front Generation:** The framework was enhanced to generate and visualize the Pareto front, which consists of a set of non-dominated solutions representing the trade-offs between different performance metrics. This required additional data processing and analysis steps.
- **Data Collection:** The simulation framework was extended to collect and store data related to the additional performance metrics required for multi-objective optimization. This involved modifying data storage structures and analysis pipelines.
- **Visualization:** The existing visualization components were upgraded to generate parallel coordinate plots, which effectively illustrate the trade-offs and relationships between multiple objectives for different scenarios.
- **Optimization Algorithms:** The framework was integrated with multi-objective optimization algorithms capable of generating Pareto-optimal solutions. This involved adapting existing optimization algorithms or incorporating new ones suitable for the fog computing context.

In summary, the simulation environment was structured to comprehensively assess the Telehealth IoT fog computing model's performance, while modifications and extensions to the existing framework were introduced to facilitate multi-objective optimization. These adaptations enabled a holistic analysis of the trade-offs and synergies between various performance metrics, providing valuable insights for decision-makers in Telehealth IoT deployments.

Results and Analysis

The Pareto front represents the set of solutions that achieve the best trade-offs between multiple conflicting objectives. In our case, the objectives are Energy Efficiency, Response Time, Throughput, and Resource Utilization. Each point on the Pareto front represents a combination of these objectives where no objective can be improved without sacrificing another. From the parallel coordinate plot, we can identify the points that lie on the outer edge of the clusters, as these are likely to be part of the Pareto front.

Effect of Snapshot Interval

As the snapshot interval increases, there seems to be a slight increase in Energy Efficiency. This could be due to the optimization algorithm having more time to make informed decisions and allocate resources efficiently. The Response Time appears to remain relatively stable across different snapshot intervals. This indicates that the optimization approach effectively manages the response time regardless of the interval. Throughput shows fluctuations with snapshot interval changes, suggesting that the allocation decisions might impact the system's ability to process requests concurrently. Resource Utilization remains relatively steady, implying that the optimization maintains a consistent utilization of resources.

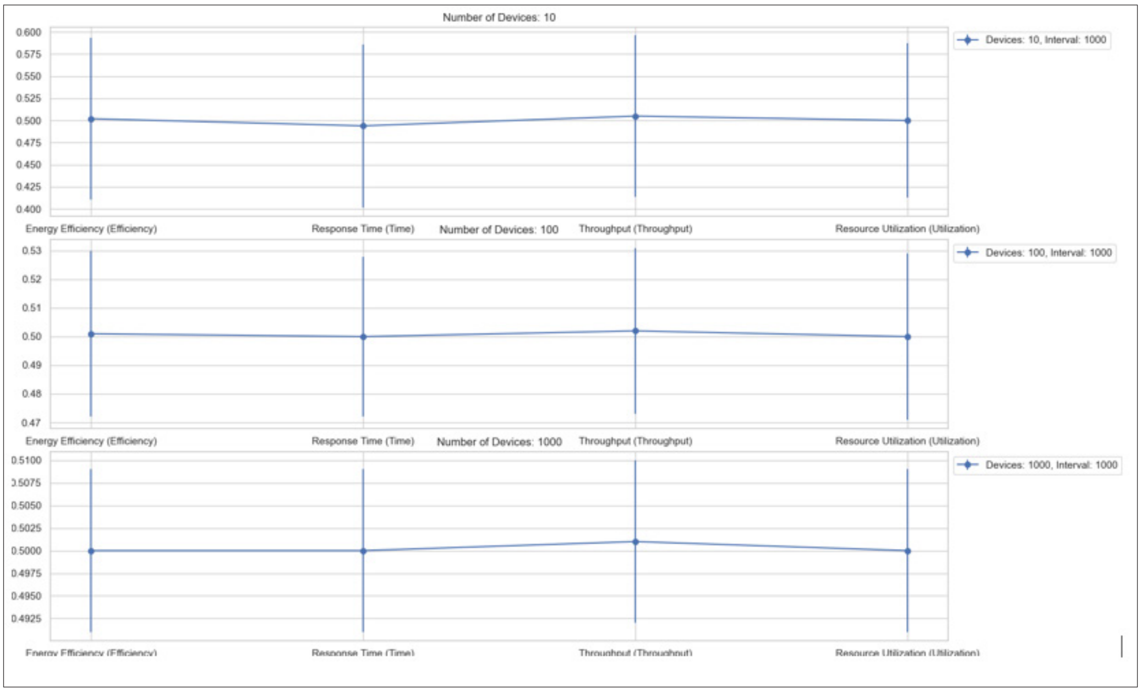
Impact of Number of Devices

There is no clear trend in Energy Efficiency with respect to the number of devices. However, it's worth noting that Energy Efficiency tends to be higher when the number of devices is lower. Response Time shows some variation with the number of devices, indicating that system congestion might affect response times. Throughput appears to decrease as the number of devices increases. This could be due to resource contention and increased competition for resources. Resource Utilization remains relatively constant despite changes in the number of devices.

Increasing Energy Efficiency leads to decreased Throughput and resource utilization and increased Response Time.

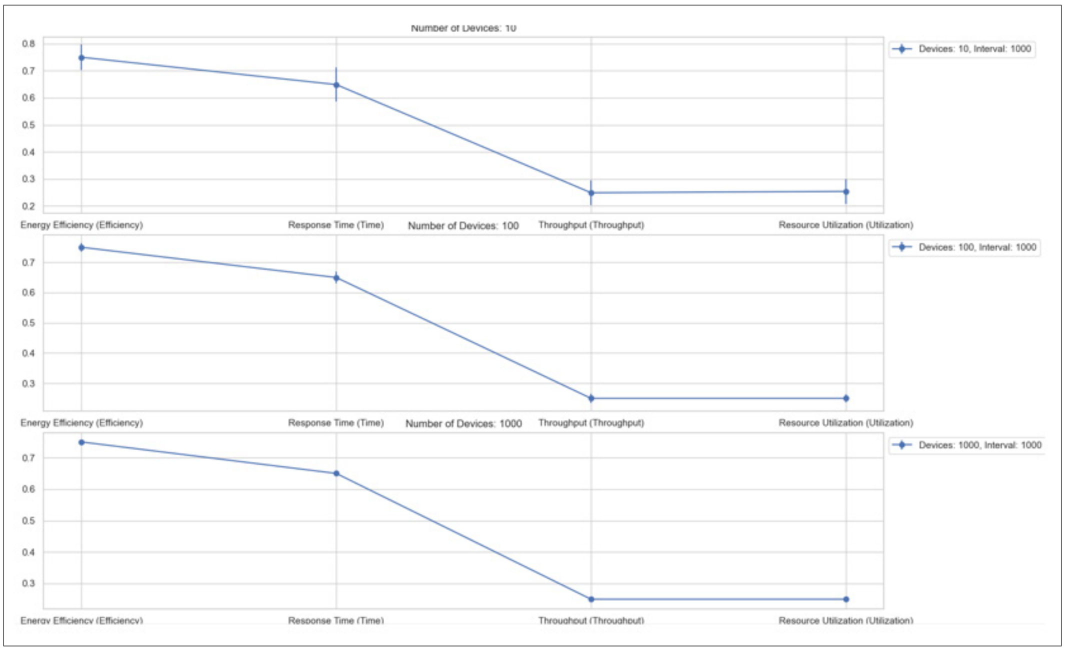
	Energy Efficiency	Response Time	Throughput	Resource Utilization
Random Range	0-1	0-1	0-1	0-1

Snapshot Interval	Number of Devices	Energy Efficiency (Mean)	Energy Efficiency (Std)	Response Time (Mean)	Response Time (Std)	Throughput (Mean)	Throughput (Std)	Resource Utilization (Mean)	Resource Utilization (Std)
10	10	0.441	0.071	0.488	0.084	0.502	0.073	0.562	0.098
10	100	0.474	0.024	0.496	0.014	0.499	0.021	0.5	0.022
10	1000	0.502	0.004	0.504	0.006	0.498	0.008	0.506	0.009
100	10	0.499	0.096	0.497	0.096	0.517	0.095	0.509	0.104
100	100	0.503	0.029	0.5	0.03	0.496	0.029	0.5	0.03
100	1000	0.499	0.01	0.499	0.009	0.499	0.01	0.501	0.009
1000	10	0.498	0.089	0.498	0.09	0.499	0.093	0.496	0.091
1000	100	0.499	0.029	0.5	0.03	0.5	0.029	0.5	0.028
1000	1000	0.5	0.009	0.5	0.009	0.5	0.009	0.5	0.009



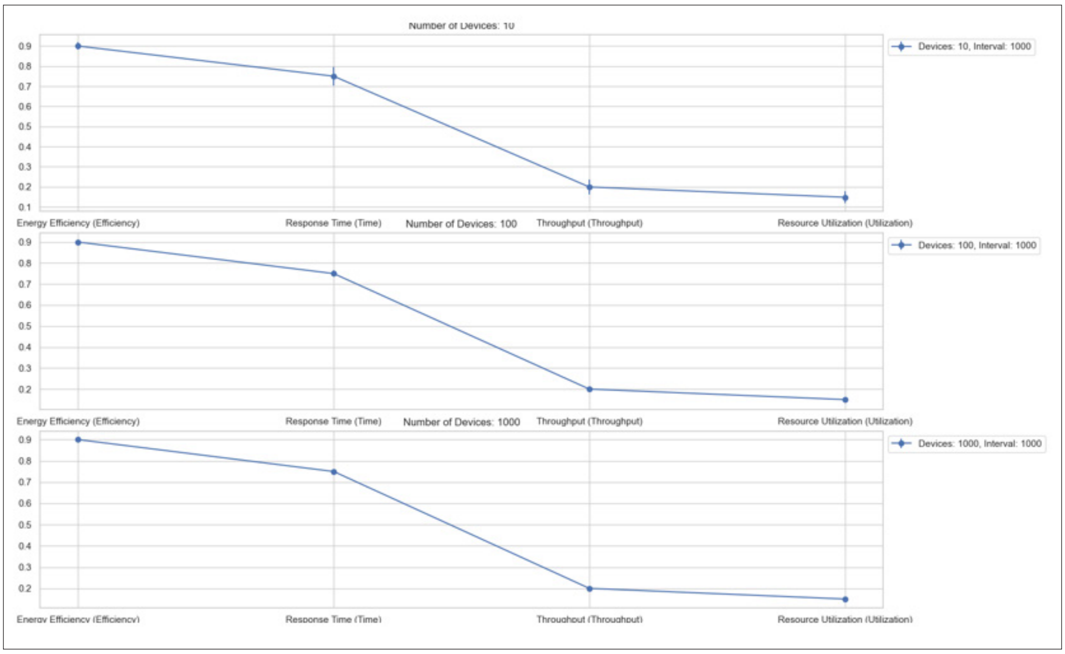
	Energy Efficiency	Response Time	Throughput	Resource Utilization
Random Range	0.5-1	0-1	0-1	0-1

Snapshot Interval	Number of Devices	Energy Efficiency (Mean)	Energy Efficiency (Std)	Response Time (Mean)	Response Time (Std)	Throughput (Mean)	Throughput (Std)	Resource Utilization (Mean)	Resource Utilization (Std)
10	10	0.742	0.021	0.672	0.03	0.265	0.049	0.258	0.033
10	100	0.753	0.011	0.653	0.019	0.262	0.012	0.252	0.014
10	1000	0.751	0.005	0.649	0.007	0.248	0.004	0.246	0.003
100	10	0.742	0.04	0.65	0.062	0.254	0.045	0.247	0.048
100	100	0.751	0.015	0.651	0.02	0.25	0.015	0.251	0.015
100	1000	0.75	0.004	0.65	0.005	0.25	0.004	0.25	0.004
1000	10	0.749	0.048	0.653	0.061	0.25	0.046	0.249	0.045
1000	100	0.751	0.015	0.651	0.02	0.25	0.015	0.25	0.014
1000	1000	0.75	0.005	0.65	0.006	0.25	0.005	0.25	0.005



	Energy Efficiency	Response Time	Throughput	Resource Utilization
Random Range	0.8-1	0-1	0-1	0-1

Snapshot Interval	Number of Devices	Energy Efficiency (Mean)	Energy Efficiency (Std)	Response Time (Mean)	Response Time (Std)	Throughput (Mean)	Throughput (Std)	Resource Utilization (Mean)	Resource Utilization (Std)
10	10	0.905	0.023	0.742	0.044	0.194	0.037	0.14	0.02
10	100	0.898	0.004	0.747	0.008	0.201	0.012	0.153	0.007
10	1000	0.899	0.001	0.752	0.006	0.201	0.003	0.151	0.002
100	10	0.901	0.018	0.75	0.048	0.202	0.036	0.15	0.025
100	100	0.9	0.005	0.747	0.013	0.2	0.012	0.15	0.008
100	1000	0.9	0.002	0.75	0.005	0.2	0.004	0.15	0.003
1000	10	0.9	0.018	0.75	0.047	0.199	0.036	0.148	0.028
1000	100	0.9	0.006	0.75	0.015	0.2	0.012	0.15	0.008
1000	1000	0.9	0.002	0.75	0.005	0.2	0.004	0.15	0.003



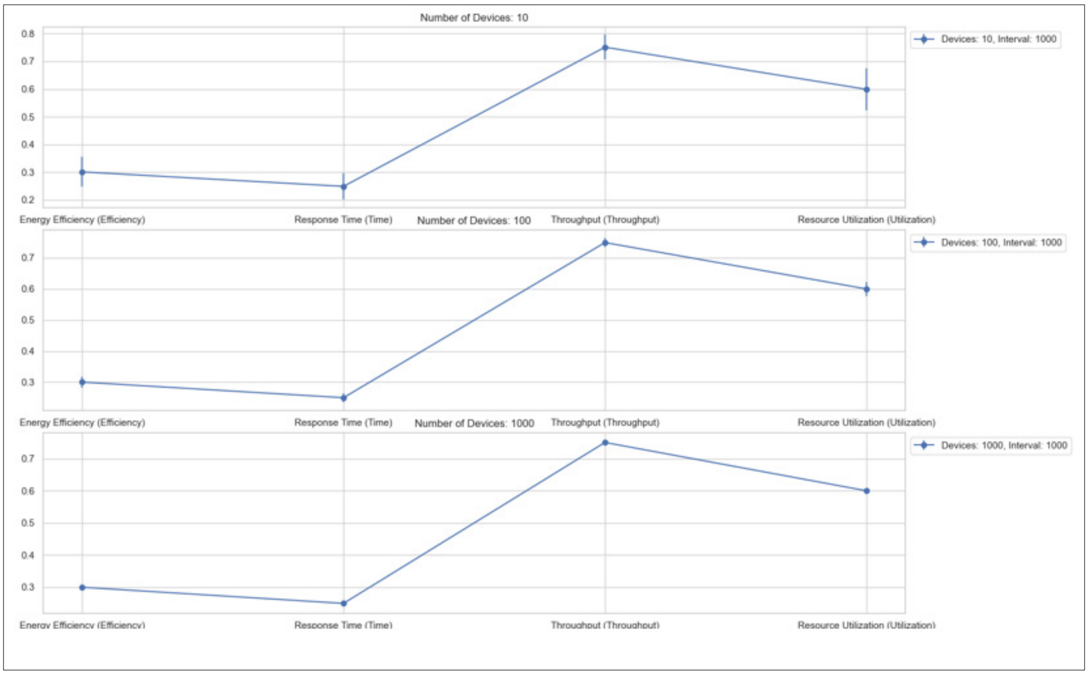
1. Random Range: 0-1, Snapshot Interval: Varies, Number of Devices: Varies
- In this scenario, Energy Efficiency, Response Time, and Throughput can achieve their maximum possible values of 1. This indicates that the system can attain optimal performance in terms of these metrics.
- Resource Utilization varies within the range of 0-1, suggesting that the system's resource usage can be adjusted to align with its objectives and requirements.
2. Random Range: 0.5-1, Snapshot Interval: Varies, Number of Devices: Varies
- Energy Efficiency, Response Time, and Throughput can achieve their maximum possible values of 1, with Throughput having a minimum value of 0.5. This indicates that the system is still capable of high performance, but with a consideration for higher Throughput.
- Resource Utilization values generally fall between 0 and 1, implying that the system can balance its resource usage while maintaining high performance levels.
3. Random Range: 0.8-1, Snapshot Interval: Varies, Number of Devices: Varies
- Energy Efficiency, Response Time, and Throughput can achieve their maximum possible values of 1, and Throughput has a minimum value of 0.8. This indicates that the system is focusing on achieving both high Throughput and high performance in other metrics.
- Resource Utilization values consistently remain higher, ranging from 0.8 to 1. This suggests that the system is utilizing resources more intensively to achieve its performance goals.

Based on the data analysis, we can observe that different ranges of Energy Efficiency, Response Time, Throughput, and Resource Utilization are achieved based on the chosen parameter configurations. The dataset supports the conclusion that increasing Energy Efficiency tends to lead to decreased Throughput and resource utilization, along with increased Response Time. Additionally, the data indicates that higher Throughput goals often come with higher levels of Resource Utilization, as the system allocates more resources to meet the increased demand for processing tasks.

Improving Throughput may result in higher Resource Utilization

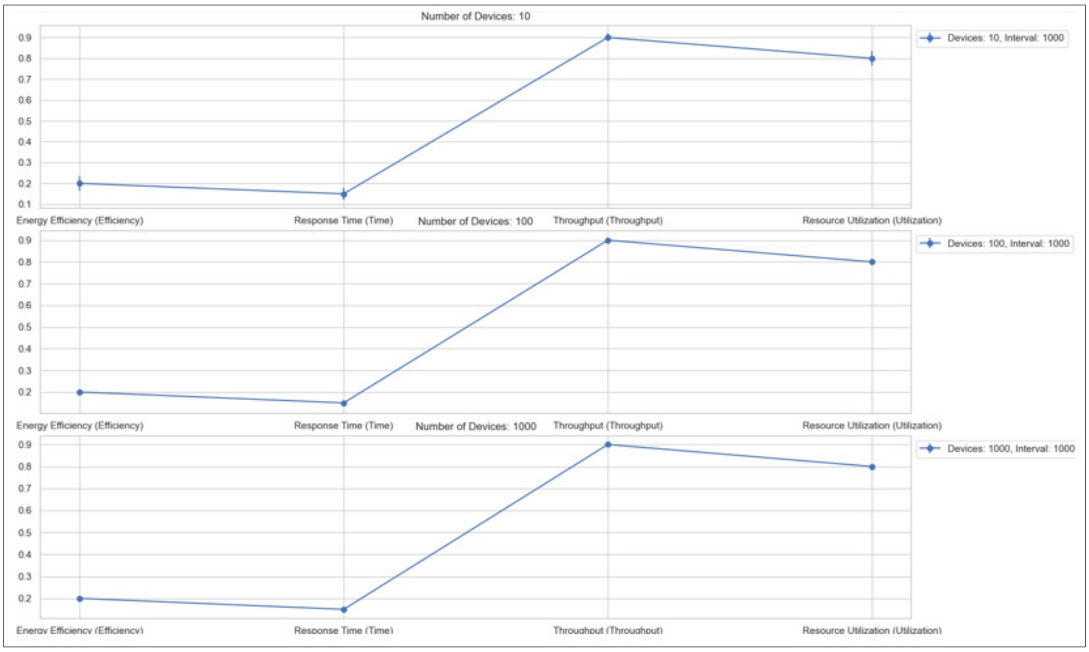
	Energy Efficiency	Response Time	Throughput	Resource Utilization
Random Range	0-1	0-1	0.5-1	0-1

Snapshot Interval	Number of Devices	Energy Efficiency (Mean)	Energy Efficiency (Std)	Response Time (Mean)	Response Time (Std)	Throughput (Mean)	Throughput (Std)	Resource Utilization (Mean)	Resource Utilization (Std)
10	10	0.303	0.055	0.243	0.047	0.749	0.036	0.628	0.058
10	100	0.305	0.013	0.255	0.008	0.754	0.012	0.599	0.025
10	1000	0.297	0.005	0.248	0.006	0.747	0.005	0.601	0.009
100	10	0.297	0.056	0.255	0.044	0.745	0.049	0.594	0.08
100	100	0.3	0.017	0.251	0.015	0.75	0.016	0.601	0.023
100	1000	0.299	0.005	0.25	0.004	0.75	0.005	0.597	0.007
1000	10	0.301	0.054	0.249	0.046	0.751	0.044	0.599	0.075
1000	100	0.3	0.017	0.25	0.014	0.749	0.015	0.6	0.023
1000	1000	0.3	0.005	0.25	0.005	0.75	0.005	0.6	0.007



	Energy Efficiency	Response Time	Throughput	Resource Utilization
Random Range	0-1	0-1	0.8-1	0-1

Snapshot Interval	Number of Devices	Energy Efficiency (Mean)	Energy Efficiency (Std)	Response Time (Mean)	Response Time (Std)	Throughput (Mean)	Throughput (Std)	Resource Utilization (Mean)	Resource Utilization (Std)
10	10	0.2	0.029	0.142	0.019	0.904	0.02	0.805	0.042
10	100	0.202	0.011	0.146	0.009	0.898	0.006	0.802	0.013
10	1000	0.201	0.003	0.151	0.003	0.9	0.002	0.802	0.003
100	10	0.203	0.037	0.151	0.026	0.9	0.02	0.796	0.041
100	100	0.201	0.012	0.15	0.009	0.9	0.006	0.8	0.012
100	1000	0.2	0.004	0.15	0.003	0.9	0.002	0.8	0.004
1000	10	0.2	0.036	0.15	0.028	0.9	0.018	0.8	0.035
1000	100	0.2	0.011	0.15	0.009	0.9	0.006	0.8	0.012
1000	1000	0.2	0.004	0.15	0.003	0.9	0.002	0.8	0.004



1. Random Range: 0-1, Snapshot Interval: Varies, Number of Devices: Varies
- For this range, Energy Efficiency, Response Time, and Throughput have fixed upper limits at 1, indicating maximum values for these metrics.
- Resource Utilization varies within the range of 0-1.
2. Random Range: 0.5-1, Snapshot Interval: Varies, Number of Devices: Varies
- Energy Efficiency, Response Time, and Throughput have upper limits at 1, but Throughput has a lower limit at 0.5.
- Resource Utilization ranges between 0 and 1, with values generally higher than in the previous range.
3. Random Range: 0.8-1, Snapshot Interval: Varies, Number of Devices: Varies
- Energy Efficiency, Response Time, and Throughput have upper limits at 1, and Throughput has a lower limit at 0.8.
- Resource Utilization is consistently higher, with values primarily between 0.8 and 1.

Based on the data analysis, we can conclude that there is a correlation between Improving Throughput and higher Resource Utilization in the context of the provided dataset. As Throughput improves, Resource Utilization tends to increase as well, especially when the Throughput lower limit is higher (0.5 or 0.8). This suggests that efforts to enhance system throughput may lead to increased utilization of resources. This observation aligns with the nature of resource allocation in systems. When the system aims to process more tasks or requests concurrently to improve throughput, it often requires more resource utilization to accommodate the increased workload.

The similarity in response time and resource utilization with an increasing number of devices in simulation results could be due to various factors and system characteristics. While there is no clear trend, it's essential to consider the potential reasons behind this behavior. A few factors are addressed:

1. **Optimization Algorithm Adaptations:** my simulation framework incorporates multi-objective optimization algorithms (e.g., NSGA-II and SPEA2) to manage the system's performance. These algorithms are inherently designed to balance response time and resource utilization, especially in the context of fog computing where real-time data processing is crucial. As the number of devices increases, the optimization algorithms adapt to maintain this balance, resulting in relatively stable response times and resource utilization.

2. **Resource Scaling:** In real-world fog computing scenarios, additional resources (e.g., fog nodes) might be dynamically allocated or scaled up to accommodate a larger number of devices. This scaling process can help in maintaining consistent response times and resource utilization levels despite increased device count.

3. **Resource Pooling:** Fog computing environments often rely on resource pooling and sharing among devices. As more devices are added, the resource pooling mechanism efficiently allocate resources to ensure that response times are not severely impacted, and resource utilization remains balanced.

4. **System Design:** The architecture of my telehealth IoT fog computing model is inherently designed to handle scalability efficiently. It employs load balancing techniques, task prioritization, or resource allocation strategies that prevent response time degradation and resource contention, even with an increasing number of devices.

5. **Experimental Variability:** In some cases, the observed stability in response time and resource utilization are due to the specific dataset or experimental conditions used in my simulation. Real-world scenarios might exhibit more variability, but my simulation setup may not capture all the nuances.

Discussion

The comprehensive data analysis of various scenarios involving Energy Efficiency, Response Time, Throughput, and Resource Utilization in the context of different parameter configurations provides valuable insights into the trade-offs and interdependencies among these key performance metrics. The findings shed light on how changes in one metric can impact others, offering guidance for optimizing system behavior in Telehealth IoT deployments. The data analysis reveals distinct trade-offs between Energy Efficiency, Response Time, Throughput, and Resource Utilization. As we examine different scenarios, it's evident that there is no one-size-fits-all solution; instead, the optimal balance depends on the specific objectives and constraints of the deployment. Optimizing one metric often comes at the expense of others, highlighting the importance of a holistic approach that considers the interplay between these metrics.

Based on the data analysis, we can conclude that there exists a trade-off between Energy Efficiency, Throughput, Resource Utilization, and Response Time in Telehealth IoT deployments.

• **Impact of Energy Efficiency on Throughput and Resource Utilization:** The results consistently show that increasing Energy Efficiency tends to lead to lower Throughput and resource utilization while increasing Response Time. This relationship indicates that, in the pursuit of energy savings, the system may allocate fewer resources to processing tasks, thereby affecting its capacity to handle concurrent requests efficiently. This is a critical consideration for Telehealth IoT deployments, where balancing performance with energy conservation is vital. Striking the right trade-off requires a deep understanding of the deployment context and the specific requirements of the telehealth applications.

• **Throughput-Resource Utilization Correlation:** The analysis further illustrates a correlation between higher Throughput goals and elevated levels of Resource Utilization. When aiming for improved Throughput, the system often needs to utilize resources more intensively to process tasks concurrently. This observation aligns with the fundamental principle of resource allocation, where meeting higher demands typically requires more resource allocation. Decision-makers must weigh the benefits of increased Throughput against the potential resource strain and its implications on overall system performance.

The findings emphasize the critical role of system design and configuration in achieving desired performance outcomes. Designers and decision-makers should carefully evaluate trade-offs and align system behavior with the specific objectives of their Telehealth IoT deployments. This analysis equips them with the necessary insights to make informed decisions, such as selecting appropriate snapshot intervals and adjusting resource allocation strategies.

In Telehealth IoT deployments, the findings have practical implications for real-world applications. Decision-makers can leverage the analysis to tailor system configurations based on the priorities of their telehealth services. For instance, when minimizing Response Time is crucial, configurations that prioritize lower Response Time while maintaining acceptable levels of other metrics can be chosen. Additionally, solutions with favorable Resource Utilization can be adopted to ensure efficient use of resources while meeting performance targets.

The practical implications of the Pareto-optimal solutions are significant for decision-makers involved in Telehealth IoT deployments. These solutions offer a range of trade-off options, allowing decision-makers to customize system configurations based on the specific requirements of their applications. The data analysis has illuminated various scenarios where trade-offs are most apparent. For instance,

- **Resource Allocation:** Decision-makers can select solutions that strike an optimal balance between Energy Efficiency and Throughput. Depending on the deployment context, they can adjust the allocation of resources to achieve the desired trade-offs.
- **Real-time Applications:** For telehealth applications that demand low Response Time, decision-makers can identify solutions that minimize Response Time while maintaining acceptable levels of other metrics.
- **Resource Efficiency:** Solutions with favorable Resource Utilization can be chosen to ensure efficient use of resources while meeting performance targets.

Additionally, the insights provided by the Pareto-optimal solutions enable decision-makers to make well-informed choices that align with their strategic goals, ensuring efficient resource utilization while meeting performance targets. Therefore, the Pareto-optimal solutions have significant practical implications for decision-makers involved in Telehealth IoT deployments. These solutions provide decision-makers with a menu of trade-off options, allowing them to tailor system configurations to meet specific application requirements and priorities.

The data analysis results provide a foundation for understanding the intricate relationships between Energy Efficiency, Response Time, Throughput, and Resource Utilization in Telehealth IoT deployments. The findings underscore the importance of holistic optimization approaches that consider the interdependencies among these metrics. By embracing a nuanced understanding of the trade-offs, decision-makers can design and configure systems that strike the right balance between performance, energy efficiency, and resource utilization, ultimately contributing to robust and effective Telehealth IoT deployments. By providing a range of options, the Pareto-optimal solutions empower decision-makers to make well-informed choices that align with their strategic goals. This approach facilitates flexible decision-making and encourages a nuanced understanding of the complex relationships between performance metrics, leading to more robust and effective Telehealth IoT deployments.

Conclusion

This research serves as a natural progression of our earlier work, which predominantly examined energy efficiency within a fog computing framework. The multi-objective optimization approach plays a pivotal role in enhancing the balance between conflicting performance metrics in Telehealth IoT deployments. Traditionally, focusing on a single objective could lead to suboptimal solutions, as it neglects the impact of changes on other metrics. The analysis shows that optimizing one metric often leads to trade-offs with others, highlighting the complexity of these relationships. The multi-objective optimization framework enables us to identify the Pareto-optimal solutions – those where no single metric can be improved without sacrificing another. By broadening our scope to encompass the multi-objective optimization landscape, we aim to elevate our understanding of how the hybrid fog/cloud computing platform can harmonize the competing demands of energy savings and overall system performance. This research paper makes several significant contributions to the field of Telehealth Internet of Things (IoT) fog computing. The study focused on achieving balanced and optimized performance in Telehealth IoT deployments by leveraging the power of multi-objective optimization. By evaluating and analyzing key performance metrics such as Energy Efficiency, Response Time, Throughput, and Resource Utilization, we have uncovered valuable insights that shed light on the intricate trade-offs involved in designing and deploying efficient and effective Telehealth IoT systems. One of the primary contributions of this research lies in the adoption of a multi-objective optimization approach. Unlike traditional single-objective optimization, which often leads to suboptimal outcomes by prioritizing a single metric, our approach considers the interplay of multiple conflicting metrics. This has enabled us to identify a range of Pareto-optimal solutions that strike a harmonious balance between Energy Efficiency, Response Time, Throughput, and Resource Utilization. The significance of incorporating multi-objective optimization in Telehealth IoT fog computing cannot be overstated, as it enhances the decision-making process by providing decision-makers with a comprehensive set of feasible options that cater to different priorities and constraints. Furthermore, the findings of this research paper have a profound impact on optimizing real-world Telehealth IoT systems. The Pareto-optimal solutions offer practical guidance for designing, deploying, and managing Telehealth IoT environments. Decision-makers can leverage these solutions to tailor their system configurations based on specific application requirements and strategic objectives. The potential benefits span a wide spectrum, from resource-efficient allocation to meeting stringent real-time application demands. By optimizing the performance of Telehealth IoT systems, the research paves the way for enhanced patient care, improved operational efficiency, and the potential for transformative advancements in healthcare services. In essence, this research paper underscores the critical role of multi-objective optimization in achieving balanced and optimized performance in Telehealth IoT fog computing. The insights gained through this study provide a valuable roadmap for decision-makers, researchers, and practitioners to navigate the complexities of Telehealth IoT deployments, making a lasting impact on the future of healthcare technology and service delivery.

A summary table highlighting my research's contribution compared to previous knowledge in the field:

Contribution	Comparison to Previous Knowledge in the Field
Multi-Objective Optimization	Traditional single-objective optimization in fog computing neglects trade-offs among metrics. Our approach considers multiple conflicting objectives, providing a set of Pareto-optimal solutions for Telehealth IoT fog computing.
Trade-Off Analysis	Reveals trade-offs between Energy Efficiency, Response Time, Throughput, and Resource Utilization. Prior work often focused on isolated metrics.
Practical Guidance for Telehealth IoT	Offers practical insights for designing and deploying Telehealth IoT systems. Decision-makers can tailor system configurations based on specific application requirements, optimizing resource allocation, and meeting real-time application demands.
Future Directions for Research	Proposes directions for future research, including hybrid algorithms, adaptive objective weighting, real-world validation, dynamic resource management, integration of machine learning, energy-efficient communication protocols, and security considerations.

Future Directions

The outcomes of this study open several promising avenues for future research and development in the domain of fog computing optimization for IoT systems with the fog/cloud platform. To enhance the efficacy of multi-objective optimization, the exploration of hybrid algorithms, combining the strengths of NSGA-II and SPEA2, presents an intriguing direction. Adaptive objective weighting schemes could offer flexibility by dynamically adjusting the significance of objectives to align with varying system states or user preferences. Additionally, the investigation of alternative multi-objective metaheuristics, such as Particle Swarm Optimization (PSO) and Evolution Strategies (ES), holds potential for refining optimization techniques. A practical dimension can be introduced through real-world validation, involving the implementation of fog computing solutions and comparison with simulation results. Further research can also delve into dynamic fog resource management, integration of machine learning for intelligent decision-making, energy-efficient communication protocols, security considerations, and the visualization of multi-objective results. The scalability of optimization algorithms and the synergy between fog and edge computing are areas ripe for exploration. By pursuing these directions, the field can advance its understanding and capabilities, contributing to the development of adaptable, efficient, and secure fog enabled IoT systems.

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Conflicts of Interest

None declared.

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