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AHCS: Advanced Health Care System for Critical Care Integrated with AI and Fog Computing in IoT Environments

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This paper employs the Pure Edge simulator to analyze the effectiveness of the edge and cloud computing structures addressing task completion time and resource consumption. In the simulation, 'TRADE OFF' and 'ROUND ROBIN' algorithms are used to compare the 'EDGE AND CLOUD' and 'CLOUD ONLY' orchestration architectures with respect to a number of edge devices. The proposed 'EDGE AND CLOUD' architecture achieves a balance of the computational load and has a relatively healthy average execution delay and an improved task success rate. In contrast, the 'CLOUD ONLY', where all task processing resides in the cloud, has more task failures because of latency, even if it provides total immediacy of processing and storage. A comprehensive analysis and comparison have been done, which suggests that hybrid architectures have significant potential to enhance feasibility and efficiency in distributed computing systems.

Keywords: Smart Healthcare, IoT, Machine Learning, Intelligent System.

1. Introduction

Using a cross-disciplinary approach with the help of modern technologies that can improve patient outcomes as the centerpiece, an advanced healthcare system for patients in critical care can be asserted. Such an advanced healthcare system for patients in critical care is defined by applying the latest medical technologies, AI and IoT, for effective patient care and data collection and analysis. In such systems, passive patient monitoring is made possible through IoT-based medical devices that acquire and send significant patient health parameters to AI systems for evaluation to enable the early intervention of patient complications and obtain specific treatment approaches [1–3].

The usage of AI in critical care has incorporated predictive analytics in these systems and has been shown to augment the chances of timely reactions, foresee and address changes, including patient decline, and reduce the length of stay while increasing survival rates [4–6]. All these systems have also been stated to foster an interdisciplinary approach that encourages each healthcare personnel to work with data from other teams and make decisions [7–9]. Such an endorsement of inter professional working also allowed healthcare to be more patient-centric, where the focus of all the services was on structures that fit the individual patient and their preferences, thereby upholding the quality of care [2, 10–15].

1. Overview of AI and IoT integration in healthcare

The healthcare sector has been redefined with the incorporation of Artificial Intelligence (AI) and the Internet of Things (IoT), which has resulted in improved patient care and efficient delivery of medical services. The combination of AI and IoT has, unlike any other, initiated a complete structure for the real-time capturing, interpretation, and use of these means, which is essential for contemporary healthcare practices. Healthcare AI includes using ML algorithms and data analysis to model possible out- comes for patients, recommend tailored treatments, and enhance diagnostic precision. AI algorithms can analyze millions of data entries in electronic medical files to track events that would ordinarily escape the eye of human evaluation and support prompt disease diagnosis and control [8, 16, 17]. Such vast sums of data, as AI possesses, would undoubtedly be efficient in generating predictive models targeted at patient care [5, 7]. The IoT, however, comprises a myriad of interconnected devices that gather various health-related metrics and information and send them out in real-time. Such devices range from hands-free health monitoring devices to advanced medical devices, each playing a role in the structure of the data and the ecosystem. Such timely data allows for prolonged patient monitoring while minimizing the requirement to physically visit a healthcare center often [5, 18, 19]. The IoT devices had the potential to do analysis. Figure 1 depicts a healthcare monitoring fog computing architecture that provides room for sensor units, fog nodes, cloud servers, and monitoring systems. Health metrics such as temperature, heart rate, and blood pressure differences from patient to patient throughout the hospital are collected using hospital sensors. In the Intensive Care Unit, specific ICU sensors obtain required data, such as active monitoring of the patient's vital signs and life-sustaining medical equipment. It is used to process cloud information, and fog nodes send it to the cloud after analyzing it to minimize latency and bandwidth costs. This also makes the processing much faster, and the resources within the cloud are more optimized. The cloud internal server contains the AI monitoring service, which internally develops algorithms to analyze the data processed to give out insights and forecasts based on patients and other devices. The people's data deposited in the cloud server offers backup for several health care facts that could be applied. The generated insights are incorporated into the patient monitoring system to monitor health levels, identify irregularities, and notify healthcare personnel for timely response. Besides, equipment monitoring uses the performance and condition of medical equipment to forecast when maintenance will be required to avoid breakdowns.

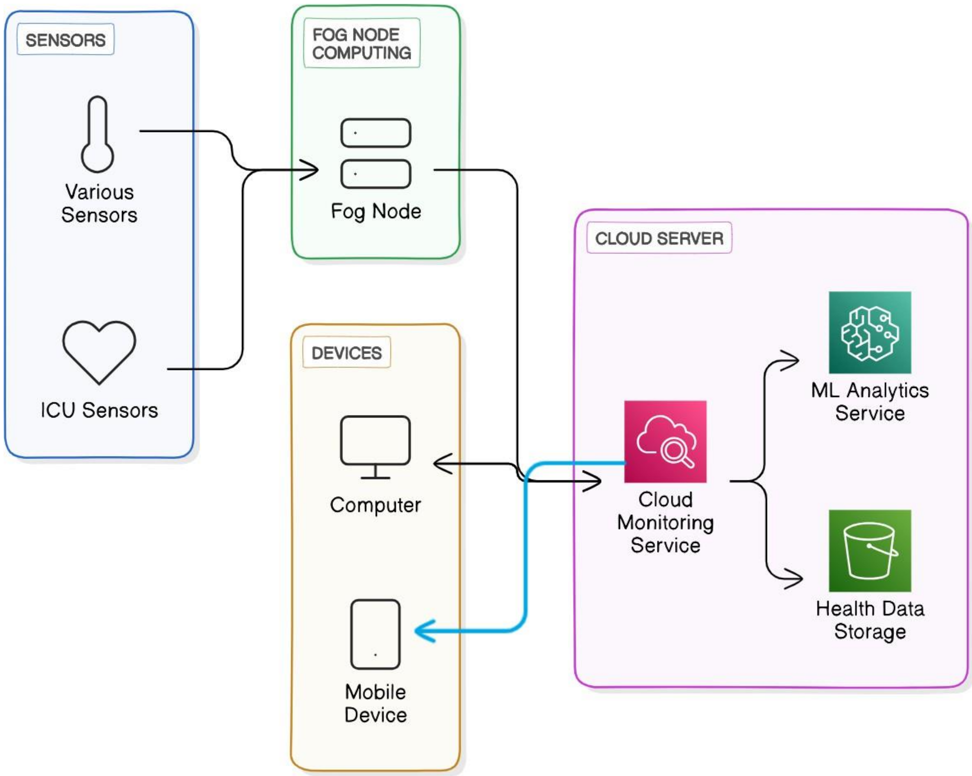


Fig. 1: Typical Advanced Health care System in Hospitals using AI and IoT

Motivation

This paper is inspired by the need to develop better solutions to current computing challenges as technology advances and the world becomes a global village. With the increase of IoT devices and demand for data-intensive applications, traditional cloud computing structures have substantial problems handling modern applications' Low Latency and High Bandwidth requirements. From this perspective, edge computing is developed as a solution that assigns computational resources closer to data sources, reducing response time. Still, equitable distribution of edge and cloud resources is not an easy task, therefore the need to study hybrid models that map tasks regarding changing conditions. To deal with these challenges, this research assesses the potential of 'EDGE AND CLOUD' and 'CLOUD ONLY' orchestration models and their advantages and drawbacks. By analyzing such dynamics, we can identify how such systems can be optimized to meet the needs of future applications, reduce communication overhead and response time, and improve usability.

Organization of the Article

For clarity, the paper follows a layout that examines the performance of both edges and cloud computing structures. It starts with an Introduction that outlines the emergence of the need for optimized computing based on the IoT and data-intensive applications and presents problems of cloud computing and the potential of edge computing solutions. Thus, the literature survey demonstrates previous research and issues regarding edge and cloud architectures, advantages and disadvantages, and the research gaps that need to be addressed by this work. In the proposed section of the paper, Proposed Methodology, the authors present the general approach to assessing these architectures and describe the Pure Edge simulator as an analytical tool. The Experimental Setup of this section explains in detail all specifications of parameters and configurations utilized during the simulations. On the other hand, the Different Node Configuration subsection examines the type and the number of edge devices used and their performance implications. The Results and Discussion section synthesizes and compares the concerned outcomes of the two studied architectures of 'EDGE AND CLOUD' and 'CLOUD ONLY' based on parameters like overall task delay and energy utilization. Last but not least, the paper's conclusion and future direction section gives a brief rundown of conclusions drawn from this study and relates them to the problem of designing distributed computing systems while proposing areas for future studies, such as adaptive orchestration of resources and architectures and the integration of new systems.

2. Literature Survey

The Internet of Health Things (IoHT) is brought forward in Cristiano et al. [20] as a powerful means of smart vital signs tracking and management in healthcare settings, improving the old isolated model. It envisions the Interconnection of medical devices through IoHT for better data utilization and informatization processes for patient diagnosis and preventive measures. The method includes looking at relevant literature about collecting and combining patient vital signs data at the hospital level, testing the idea of warning scores as heuristics, and planning neural networks for data fusion and time series forecasting. It has been shown that the IoHT has the potential to drive better effectiveness, manage resources better, and reduce the health deterioration of patients. However, the main issues are the lack of sufficient interoperability with the already available health systems and the problems of confidentiality and privacy of user information. The research suggests that this approach should always be adopted for patient management, as it constitutes what IoHT is meant to accomplish in hospital wards.

Frederico et al. [21] consider environmental and health research through disruptive technologies like AI, blockchain, and IoT. Proposals for a high-level reference architecture are furnished in the study, where the authors pose integration issues while stressing the benefits of the technologies to enhance data capture, analysis, and decision-making. Nevertheless, it highlights challenges and under-explored data inter- operability, privacy, and governance areas. It draws implications in relation to health surveillance of such great opportunities, stressing, however, that the challenges must be managed before the expansion of those technologies.

Latif et al. [22] investigates how disruptive technologies like AI, Blockchain, and IoT can further research the environment and health in Canada. The methodology used in this paper employs a descriptive research design with a narrative review of the literature. This kind of information shows how these technologies are supposed to improve the processes of collecting data, analyzing it, and making decisions by easing how they are integrated and using at least a high-level reference architecture to help with their integration issues. Other critical aspects of data concerning research bring the understanding of challenges of these technologies in interoperability, privacy, and governance, raising the call for more research into integration and study of more advanced ethical and security issues.

Shumba et al. [23] focuses on applying IoT integration with AI to improve health- care through wearables. The work focused on advanced sensing technologies and machine learning, which are real-time, to cater to health monitoring and response requirements. The strategy includes looking at current IoT healthcare models and making suggestions for making flexible and modular models based on edge computing and intelligence on the device itself to get around problems with latency and privacy. It has been shown that the new and advanced architecture presented in this research is responsible for the enhancement of healthcare services through the availability of timely interventions after processing data in real-time. The criticality of the speed of response, usability, ease of use, and cost as non-functional requirements essential for the effective deployment of healthcare applications has also been emphasized.

Manickam et al. [24] focused on IoT-AI interdependence to provide more precise healthcare through wearables. An advanced health monitoring system with sensing technologies and an integrated real-time machine learning algorithm has been shown. The findings prove that the suggested system allows timely actions due to the availability of information and enables comprehensive data processing, resulting in improved healthcare services.

Al Mudawi and Naif have presented [25] proposed an intelligent IoT-based system for continuously monitoring ICU patients, is proposed as a solution to the challenges of delayed detection and overwhelming workloads in intensive care units. The study describes a method where real-time vital sign parameters and biochemical parameter data could be collected in an ICU by deploying IoT devices to be further processed by fog nodes for reduced latency and enhanced data security. The results looked quite promising in that the solution's effectiveness was felt in monitoring multiple health parameters, pro- viding prompt alerts to healthcare providers to monitor patients remotely. Research gaps remain in effectively implementing one system with one action towards improved data security while integrating machine learning techniques to establish an effective prediction or alert based on the signals presented within the unit. While this study identifies fog computing as the other option to improve the operations and processes of monitoring in ICUs, it also highlights the need for further research to seal identified gaps regarding dependability and scaling.

Minopoulos et al. [26] discusses how integrating IoT, WSN, Big Data Analytics, and Cloud Computing can improve healthcare systems. It describes these emerging technologies as having promising application areas to improve current medical constraints of efficient illness detection and treatments. The methodological process suggests the development of a new system architecture that integrates the latest technologies with advanced networks to establish a smart health- care system. Results indicate that this integration could improve diagnosis accuracy and medical treatment speed for enhanced healthcare delivery. Research gaps include a need for better infrastructure in some regions and challenges related to data management and privacy issues. This paper treats the employment of the cited technologies as an essential vehicle for enhancing healthcare quality and performance. It pinpoints the various challenges, such as technology investment, compliance with privacy laws, and similar hurdles that inhibit widespread employment in hospitals, a debate that has continued for decades.

Alshamrani and Mazin [27] have shown the exploitation of emerging technologies and Advanced Networks for a Smart Healthcare System. It examines the integration of IoT, WSN, Big Data Analytics, and Cloud Computing to enable smart healthcare systems. The method proposed a new system architecture that combines clouds and state-of- the-art networks, along with the mentioned technologies, in an intelligent healthcare system setup. Results show that this combination would further enhance the accuracy and speed of diagnosis and treatment, providing much needed assistance in health- care delivery. There are many research gaps, such as infrastructure development in certain areas, digitization, data management, and privacy hurdles. The study acknowledges the importance of introducing these technologies to improve quality and efficiency in health care while pointing out the obstacles to full scale implementation. Wang et al. [28] essay combines IoTs, WSNs, Big Data Analytics, and Cloud Computing to make healthcare systems smarter. It does this by pointing out that these technologies can help traditional medicine resolve some of its problems by making it easier to find and treat illnesses. The methodology of the two-track study concept proposes a novel system of these technologies and advanced network techniques within intelligent healthcare systems. Results indicate that such integration could enhance the accuracy and speed of medical diagnosis and treatment, benefiting patient care. However, research gaps include a need for better infrastructure in some areas and consideration of data management and privacy challenges. The authors recognized an impending need to adopt these technologies to improve health- care quality and efficiency while highlighting the bottlenecks against their widespread adoption.

Puri et al. [29] proposes a decentralized healthcare system using AI and blockchain to achieve safety, transparency, and efficiency in patient data management. The proposed framework can authenticate IoT devices and secure health records by implementing smart contracts and AI-powered blockchain technology. The methodology involved deploying a rule- based AI system integrated with smart contracts to check for malicious nodes and guarantee communication integrity. Real-time experiments improved device energy consumption, data request time, throughput, average latency, and transaction fees. The research gaps included the development of lightweight algorithms for minimizing energy and gas consumption and applying trusted AI technology for system reliability improvements. The study draws attention to the potential of using blockchain and AI in alleviating security and privacy challenges in managing healthcare data, timely informing these gaps for the future work needed.

Alahi et al. [30] proposes a decentralized healthcare system using AI and blockchain to benefit from increased security, transparency, and efficiency in patient data management. The methodology uses a rule-based AI system and smart contracts to track down malicious nodes and ensure data integrity. As a result of executing real time experiments, the device energy consumption, data request time, throughput, average latency, and transaction fees have better performance. Research gaps include the need for lightweight algorithm development to minimize energy and gas consumption and the incorporation of trustworthy AI that can further bolster the system's reliability. The study has shown the potential of blockchain and AI technologies to address security and privacy issues in healthcare data management, highlighting future research and development aspects.

Dang et al. [31] have shown how IoT-based technologies can revolutionize healthcare. It has been shown that how new communication networks, including 5G and the not-too-distant 6G, can transform healthcare into the remote monitoring and treatment of patients. The methodology encompasses an extensive survey of applications within IoT and health to propose an all-in-one computing architecture for IoHT, enhancing real-time functionalities. The outcomes substantiate that convergence towards cloud, edge, and fog computing in IoT systems shows a notable decrease in response time and energy consumption for such services. However, research remains with impediments clouded with data privacy considerations, interoperability, and adequate infrastructure to supplement these technologies. The findings elaborate on issues addressing these hurdles, channeling future research strategies to transform existing barriers to improving healthcare delivery quality and efficacy.

Table 1: Research Gaps Identified in Various Studies

Study	**Research GAP**
Cristiano et al [20]	-Lack of sufficient interoperability with existing health systems. -Challenges related to confidentiality and privacy of user information.
Frederico et al. [23]	-Under-explored areas of data interoperability. -Privacy and governance challenges that need to be addressed before expanding disruptive technologies.
Latif et al. [22]	-Need for more research into integration issues of disruptive technologies. -Advanced ethical and security issues remain under-explored.
Shumba et al. [23]	-Need for flexible and modular IoT healthcare models to address latency and privacy issues. -Emphasis on non-functional requirements like speed of response, usability, and cost.
Manickam et al. [24]	-Further exploration needed on the integration of IoT and AI for precise healthcare. -Challenges in ensuring timely actions and comprehensive data processing.
Al Mudawi and Naif [25]	-Effective implementation of a unified system for improved data security. -Integration of machine learning techniques for better prediction and alert systems. -Dependability and scalability of fog computing in ICUs need further research.
Minopoulos et al. [26]	-Need for better infrastructure in certain regions. -Challenges related to data management and privacy issues. -Investment and compliance with privacy laws remain hurdles.
Alshamrani and Mazin [27]	-Infrastructure development and digitization challenges. -Data management and privacy hurdles. -Obstacles to full-scale implementation of smart healthcare systems
Wang et al. [28]	-Need for improved infrastructure in some areas. -Consideration of data management and privacy challenges. -Bottlenecks against widespread adoption of smart healthcare technologies.
Puri et al. [29]	-Development of lightweight algorithms to minimize energy and gas consumption.

	-Application of trusted AI technology for system reliability improvements.
Alahi et al. [30]	-Development of lightweight algorithms to minimize energy and gas consumption. -Application of trusted AI technology for system reliability improvements. -Need for lightweight algorithm development to reduce energy and gas consumption. -Incorporation of trustworthy AI to enhance system reliability.
Dang et al. [31]	-Data privacy considerations remain a significant challenge. -Interoperability and adequate infrastructure to support emerging technologies. -Need for strategies to overcome existing barriers to improve healthcare delivery

3. Proposed Methodology

The proposed methodology is based on the extensive literature survey presented in Section 2. The method utilizes fog computing along with ML and IoT, as the hospital infrastructure comprises various sensors and actuators from the ICU to the general ward. Many of them are time-centric, as saving lives is a critical task. Most of the research revolves around the essential care of the patients, while other issues, such as electricity management, housekeeping, safety, and security of the visitors, vehicles, etc., remain untouched.

Figure 1 and Figure 2 depicts the system's core consisting of sensors meant to collect information from various hospital settings. The sensors are systematically ordered into discernible clusters; each cluster has a purpose.

The patient's vital parameters in the ICU sensors, such as heart rate, blood pressure, and oxygen saturation, will be monitored. This data would continuously be evaluated and sent to the fog node for real-time processing.

General ward cluster:

General Ward Sensors monitor the patient's vital signs and ambient conditions that can affect a patient's comfort and safety. Data is sent to the fog node for processing. Electrical Assets Cluster: The sensor of electrical assets monitors the status and performance of electrical equipment and sends operational data to the fog node for analysis of maintenance and efficiency.

Housekeeping Cluster:

Housekeeping sensors ensure cleanliness and hygiene by monitoring cleaning schedules and supplies. This information is returned to the fog node for further optimization of housekeeping operations.

Parking Cluster:

Parking sensors monitor the availability and security of space into parking spaces and send real-time data to the fog node for effective management.

Staff Cluster:

Staff Sensors track employees location and activities, optimizing workforce management through communication with the fog node.

Doctors Cluster:

Doctor Sensors monitor availability and patient interaction with doctors and send the data to a fog node for scheduling and resource assignment.

Logistics Cluster:

Logistics sensors monitor the movement and condition of medical supplies and equipment, feeding information about inventory for the fog node to manage.

Safety and Security Cluster:

Safety and Security Sensors ensure hospital safety through surveillance and access control, sending security data to the fog node for threat detection and response. Fog Node Computing: This mediates a processing layer that controls data from multiple clusters before transmitting data to the cloud server. This reduces latency while enhancing the bandwidth utilization efficiency due to on-site data processing execution.

Cloud Server:

This can be a central data reservoir that depends on sophisticated analytics and machine learning techniques to generate insights about what to notify.

Cloud Monitoring Server:

It interfaces with end-user devices, enabling clinicians to monitor and manage information through access from computers and mobile devices.

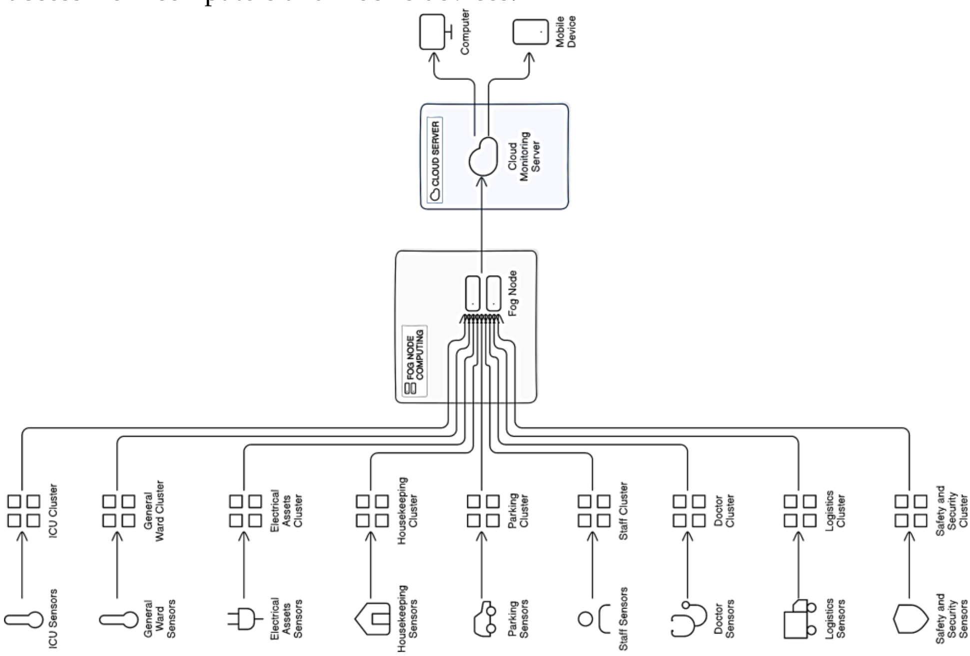


Fig. 2: Proposed Advanced Health Care System

3.1 Experimental Setup

The experiment consists of edge devices (Arduino Nano), fog computing nodes (Raspberry Pi), a cloud server (Amazon), and an Edge Data Center. The use case scenario has been created with the help of the Pure Edge Sim simulator shown in Figure 3. The whole setup has been completed on Windowoperating system (Window 11) and Intel i-3 sixth generation. Further, the eclipse 2024-09 software with JAVA IDE has been installed to run the simulator.

Table 2 depicts the initial consideration of different setup components for a pure edge sim simulator. Different applications, cloud servers, edge data centers, edge devices, and simulator parameters, along with movable nodes, are required to simulate the real-world use case in the simulator.

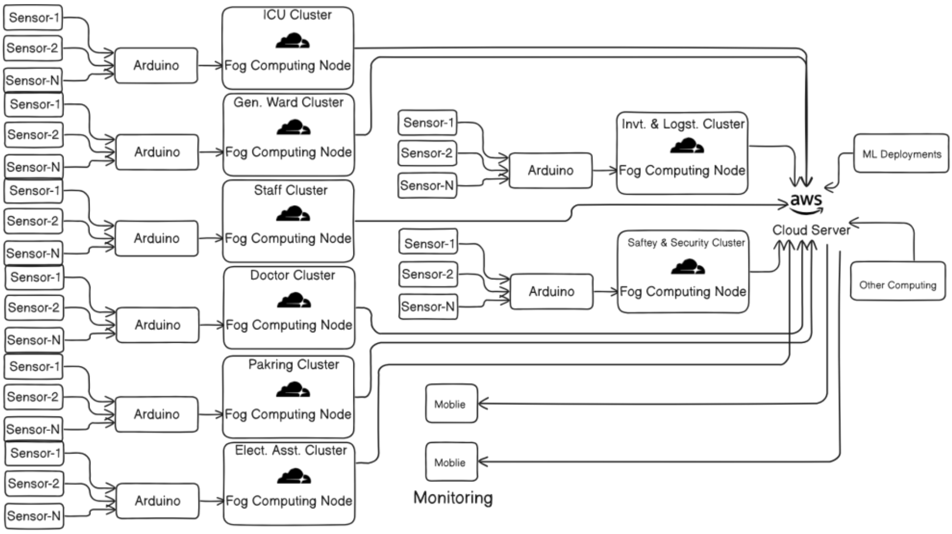


Fig. 3: Experimental Setup in Pure Edge Sim

Table 2: Components and their configuration in Pure Edge Sim

Components	Configuration	No. of Devices
Applications	As per experimental setup mentioned in section 3.2	
Cloud Server	As per experimental setup mentioned in section 3.2	
Data Centers	As per experimental setup mentioned in section 3.2	
Edge Devices	As per experimental setup mentioned in section 3.2	
Movable Nodes	As per experimental setup mentioned in section 3.2	

3.2 Node Configuration

To run the simulation, we first created XML files for different nodes like a cloud server, fog computing nodes, edge devices, connections, etc.

a. Application Configuration: The XML application file is a configuration document ofthe Pure Edge simulator that defines many application specifications that can be simulated within the system. Applications such as augmented reality and Heavy Comp App are defined within this file by specifying particular parameters that define each application and affect their performance within the simulation. It is, therefore, classified as a ‘Hard Real-time’ application with very high timing necessities; this application produces 20 tasks per minute, and its latency is 0.02 seconds. The application has so far been utilized in 20% of the devices and has a container size, request size, and results size of 20 kilobytes with a task length of 500 million instructions (MI). The ‘Augmented reality’ app, named ‘Soft Real-time’, has a more frequent rate of task creation at 30 tasks per minute; its latency is about 0.5 seconds to describe, which, indeed, describes looser timing constraints. It appears in 30% devices and has larger container and request sizes at 1500 kilobytes with results size at 50 kilobytes and task length at 5000 MI. Finally, ‘Heavy Comp App’ falls in ‘Normal’, with very low task generation rates at 3 tasks per minute and great latency at 300 seconds, so there is no sensitivity to latency. The application was said to be running on 50% of the devices, in that the largest container and request sizes stand at 2200 and 2500 kilobytes,respectively, while the size of

```xml
<?xml version="1.0"?>
<applications>
    <application name="Health">
        <type>Hard Real-time</type> <!-- the type of this application, can be used to differentiate between applications during the orchestration, you can write anything -->
        <rate>20</rate> <!-- how many tasks are generated each minute -->
        <usage_percentage>20</usage_percentage> <!-- percentage of devices using this type of applications -->
        <latency>0.02</latency> <!-- latency in seconds -->
        <container_size>20</container_size> <!--application/container size in kilobytes -->
        <request_size>20</request_size> <!-- the offloading request that will be sent to the orchestrator and then to the device where the task will be offloaded in kilobytes -->
        <results_size>20</results_size> <!-- the results of the offlaoded task in kilobytes -->
        <task_length>500</task_length> <!--MI: million instructions -->
    </application>
    <application name="Augmented reality">
        <type>Soft Real-time</type>
        <rate>30</rate>
        <usage_percentage>30</usage_percentage>
        <latency>0.5</latency>
        <container_size>1500</container_size>
        <request_size>1500</request_size>
        <results_size>50</results_size>
        <task_length>5000</task_length>
    </application>
    <application name="HEAVY_COMP_APP">
        <type>Normal</type>
        <rate>3</rate>
        <usage_percentage>50</usage_percentage>
        <latency>300</latency> <!-- a great number represents no latency-sensitivity -->
        <container_size>2200</container_size>
        <request_size>2500</request_size>
        <results_size>200</results_size>
        <task_length>30000</task_length>
    </application>
</applications>
```

Fig. 4: Application Configuration using XML

the result is at 200 kilobytes with a large quantity of task length at 30000 MI. All these parameters dictate the orchestration and resource allocations of simulation processes, which reflect different computational and networking demands for eachtype of application.

b. Cloud Server Configuration: An XML file explicitly describes attributes related to a cloud data center associated with the Pure Edge simulator within the simulation framework. It describes a single data center and contains a set of critical parameters that influence its properties related to operation. ‘idle Consumption’ is specified as 0, so the data center would not consume power if it is idle. In addition, ‘max Consumption’ has a value of 5776, understood as maximum power consumption in watts at full loads. The flag for ‘is Orchestrator’ is false; the data center current is not supposed to behave like a task orchestrator; it is not responsible for allocating tasks across the network. The data center has 200 processing cores, each with a potency of running operations at 40,000 million instructions per second (MIPS), thereby providing significant computing power. Additionally, it has 16,000 megabytes of RAM that improves the processing capacity of data and the execution of tasks, plus storage space amounting to 1,000,000 megabytes capable of handling vast data storage operations. Specifications collectively outline the role and functionalities of the data center as part of the simulation environment that impacts the management of computation requirements andinteractions with other network entities.

c. Edge Data-centers Configuration: XML file that describes a configuration document designed for the Pure Edge simulator. In terms of simulation, four edge data centers need to be placed, and they are ‘dc1’, ‘dc2’, ‘dc3’, and ‘dc4’, which further represent specific attributesthat govern their operational functionalities. All data centers are a type of periphery because they are dealing with processing data closer to its source and not in a cloud setup. Each data center has an ‘idle Consumption’ of 100 watts and a ‘max Consumption’ of 150 watts, which means a profile of consumption. Not one of these data centers orchestrates tasks since the ‘is Orchestrator’ is set to false. Each data center has 10 processing cores that can carry out operations at a staggering 40,000 million instructions per second, or MIPS. Also accompanying the CPU are 16,000 megabytes of RAM and 200,000 megabytes of storage, all of which impart rather sizeable computing and storage capabilities. The data centers on purpose are placed at specific coordinates: ‘dc1’ at (500, 500), ‘dc2’ at (500, 1500), ‘dc3’ at (1500, 500), and ‘dc4’ at (1500, 1500), thus forming a grid. The network topology is determined by the connections connecting the data centers in a cyclic: ‘dc1’ to ‘dc2’, ‘dc2’ to‘dc3’, ‘dc3’ to ‘dc4’, and ‘dc4’ back to ‘dc1’ which ensures easy flow of data and well- distributed tasks within the network. This will, therefore, allow for edge computing with minimal latency in data transmission by processing it locally.

```xml
<?xml version="1.0"?>
<cloud_data_centers>
    <datacenter>
        <idleConsumption>0</idleConsumption>
        <maxConsumption>5776</maxConsumption>
        <isOrchestrator>false</isOrchestrator> <!-- it has a task orchestrator or not  -->
        <cores>200</cores>
        <mips>40000</mips>
        <ram>16000</ram>
        <storage>1000000</storage>
    </datacenter>
</cloud_data_centers>
```

Fig. 5: Cloud Configuration using XML

d. Edge Devices Configuration: The XML file in the above description represents the configuration document of the Pure Edge simulator to specify different specs regarding various edge devices used in this simulation environment. Four types of edge devices have differing characteristic influences on their operations and interactions within the network. The first group consists of smartphones, described by cellular connectivity, the ability to travel at a velocity of 1.4 m/s, and their reliance on battery energy worth 18.75 Watts-hours. This part of devices is 30 percent, pro- duces things, and owns 8 cores that will calculate 10,000 million instructions per second or MIPS for each. It has been accompanied by 4,000 megabytes of RAM and 128,000 megabytes of storage. The following part of the device form resembles the Raspberry Pi Model B+, supports Wi-Fi, does not roam around, and is free from batteries. This category accounts for 10% of the devices; it does not have a work- load, has 4 cores that can perform 4,000 MIPS each, and has 4,000 megabytes of RAM and 32,000 megabytes of storage capacity. The third type is almost a laptop as it uses Wi-Fi, is immobile and has a battery power of 56.2 Watts. It accounts for 20% of the appliance and does not make work; it has 8 cores, 20,000 MIPS per core, 8,000 megabytes of RAM, and 1,024,000 megabytes of storage. The fourth type of device is a sensor, connected through Wi-Fi, and it is a stationary one that depends on no batteries to serve its purpose. It accounts for 40% of the appliance. It makes work but has no computing capability. Its cores, MIPS, RAM, or storage are zero. All the edge computing scenarios can be simulated by the configurations with device types that differ in their computations and connectivity requirements.

```xml
<?xml version="1.0"?>
<edge_datacenters>
    <datacenter name="dc1">
        <periphery>true</periphery>
        <idleConsumption>100</idleConsumption>
        <maxConsumption>150</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <location>
            <x_pos>500</x_pos>
            <y_pos>500</y_pos>
        </location>
        <cores>10</cores>
        <mips>40000</mips>
        <ram>16000</ram>
        <storage>200000</storage>
    </datacenter>
    <datacenter name="dc2">
        <periphery>true</periphery>
        <idleConsumption>100</idleConsumption>
        <maxConsumption>150</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <location>
            <x_pos>500</x_pos>
            <y_pos>1500</y_pos>
        </location>
        <cores>10</cores>
        <mips>40000</mips>
        <ram>16000</ram>
        <storage>200000</storage>
    </datacenter>
    <datacenter name="dc3">
        <periphery>true</periphery>
        <idleConsumption>100</idleConsumption>
        <maxConsumption>150</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <location>
            <x_pos>1500</x_pos>
            <y_pos>500</y_pos>
        </location>
        <cores>10</cores>
        <mips>40000</mips>
        <ram>16000</ram>
        <storage>200000</storage>
    </datacenter>
```


Fig. 6: Edge Data Centers Configuration using XML (Continue...)

```xml
    <datacenter name="dc4">
        <periphery>true</periphery>
        <idleConsumption>100</idleConsumption>
        <maxConsumption>150</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <location>
            <x_pos>1500</x_pos>
            <y_pos>1500</y_pos>
        </location>
        <cores>10</cores>
        <mips>40000</mips>
        <ram>16000</ram>
        <storage>200000</storage>
    </datacenter>
    <network_links>
        <link>
            <from>dc1</from>
            <to>dc2</to>
        </link>
        <link>
            <from>dc2</from>
            <to>dc3</to>
        </link>
        <link>
            <from>dc3</from>
            <to>dc4</to>
        </link>
        <link>
            <from>dc4</from>
            <to>dc1</to>
        </link>
    </network_links>
</edge_datacenters>
```

Fig. 6: Edge Data Centers Configuration using XML

e. **Simulation Parameters Configuration:** The simulations parameters properties file is a complex file that contains all the information about the environment where the Pure Edge simulator is functioning. This simulation will take 10 units with updated information for every unit and a pause break of 3 units. Real-time charts are turned on and set to update when the number counts up to 10, but they automatically turn off and cannot be saved. The simulation area is large and adjusted to be 2000 x 2000 units. Edge devices have a range of 10 units, while edge data centers have 1000 units in coverage. Coordinators are supported on edge devices, allowing for collaborative task execution across the net- work and with batches of 100 tasks scheduled to improve efficiency. The simulation is set up to expect a fixed number of edge devices, between 500 and 500, with a counter size 400. This model includes WAN, MAN, Wi-Fi, Ethernet, and Cellular networks with specific bandwidths, latency, and energy consumption. The simulation architecture is specified as ‘EDGE AND CLOUD’ to enable the execution of tasks at either edge data centers or the cloud. At the same time, the orchestration parameters of the algorithm are set at ‘TRADE OFF’ and ‘ROUND ROBIN’ as the trade-off can be made for various factors. The feature that the log is not being saved and the output folder is cleared after execution is also included in the file, along with the options for logging and output management. This configuration enables a complex and selectable emulation of scenarios related to edge computing, including evaluating various network arrangements and operational models.

```xml
<?xml version="1.0"?>
<edge_devices>
    <!-- here you can define the types of edge devices, and how many devices
        of this type there will be in this case , there are 4 types of devices(defined
        here), 30 percent of all devices will be of the first type, this percentage
        is defined here <percentage> -->

    <device> <!-- this is a smartphone, for example -->
        <connectivity>cellular</connectivity><!-- the type of network connection -->
        <mobility>true</mobility><!-- the device is mobile or fixed -->
        <speed>1.4</speed><!-- the speed of the device in meters per second : 1.4m/s equals 5km/h, 0 = non mobile-->
        <minPauseDuration>100</minPauseDuration><!-- the minimum delay before moving to a new location-->
        <maxPauseDuration>400</maxPauseDuration><!-- the maximum delay before moving to a new location-->
        <minMobilityDuration>10</minMobilityDuration><!-- the minimum delay before stopping-->
        <maxMobilityDuration>60</maxMobilityDuration><!-- the maximum delay before stopping-->
        <battery>true</battery> <!-- relies on battery? -->
        <percentage>30</percentage> <!-- percentage of this device type -->
        <batteryCapacity>18.75</batteryCapacity> <!-- battery capacity in Watt-Hour -->
        <initialBatteryLevel>100</initialBatteryLevel> <!-- initial battery percentage. e.g. set it to 50 in order to generate devices with 50% remaining energy-->
        <idleConsumption>1</idleConsumption><!-- idle energy consumption in Watt-->
        <maxConsumption>3.3</maxConsumption><!-- max energy consumption in Watt,
            when device cpu is use at 100% -->
        <isOrchestrator>false</isOrchestrator> <!-- it has a task orchestrator or not -->
        <generateTasks>true</generateTasks> <!-- it generates data/tasks or not -->
        <cores>8</cores><!-- how many tasks can this device execute in parallel -->
        <mips>10000</mips> <!-- MIPS (million instructions per second) per CPU core -->
        <ram>4000</ram>
        <storage>128000</storage>
    </device>
    <device> <!-- this is a raspberry pi model B+-->
        <connectivity>wifi</connectivity>
        <mobility>false</mobility>
        <speed>0</speed>
        <minPauseDuration>0</minPauseDuration>
        <maxPauseDuration>0</maxPauseDuration>
        <minMobilityDuration>0</minMobilityDuration>
        <maxMobilityDuration>0</maxMobilityDuration>
        <battery>false</battery>
        <percentage>10</percentage>
        <batteryCapacity>0</batteryCapacity>
        <initialBatteryLevel>0</initialBatteryLevel>
        <idleConsumption>1.6</idleConsumption>
        <maxConsumption>5.1</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <generateTasks>false</generateTasks>
        <cores>4</cores>
        <mips>4000</mips>
        <ram>4000</ram>
        <storage>32000</storage>
    </device>
```


Fig. 7: Edge Devices Configuration using XML (Continue...)

4. Results and Discussion

The simulation has been performed for both edge and cloud models concerning the cloud-only model. The orchestration algorithms like Trade off and 'Round robin' are used for both use cases.

1. **Edge and Cloud Model:** The simulation was run for 6 minutes and 40 seconds. The iteration of the simulation was 10 times. The architecture was Edge and Cloud. The comparison has been performed with Cloud only. Several findings in Table 3 concerning task execution and resource usage across the number of edges can be drawn by investigating the results of the cloud and edge scenarios under the orchestration structure of 'EDGE AND CLOUD' and the utilization of the 'TRADE OFF' and 'ROUND ROBIN' algorithms from the Pure Edge simulator. With the growth in the number of edge devices from 100 to 300, both total task execution delay and waiting time rise, whichshows the increased computational load. Still, the average execution delay remains nearly constant and within an acceptable range of approximately 0.16 seconds, which means efficientmanagement of tasks. The number of generated and successfully executed tasks increases by adding more devices, while there is no failed job because of resources unavailability or longwaiting times, which lets noticing good resource management. However, tasks fail because ofdelay, which rises from 6,000 with 100 devices to 16,735 with 300 devices, and this evidence implies that latency becomes a more important problem as the number of devices grows. Network usage, especially WAN, also rises, as the following points indicate the rising need for data transmission. Energy consumption data reveal that cloud and

edge energy consumption increases with the number of devices. In contrast, the average energy per computing node is reduced, increasing energy efficiency even with scale-up. The findings indicate that distributed computational load between the cloud and edge systems needs to be managed to enhance performance and energy consumption while, at the same time, solving latency issues, particularly in large networks.


```xml
    <device> <!--  this is a laptop for example -->
        <connectivity>wifi</connectivity>
        <mobility>false</mobility>
        <speed>0</speed>
        <minPauseDuration>0</minPauseDuration>
        <maxPauseDuration>0</maxPauseDuration>
        <minMobilityDuration>0</minMobilityDuration>
        <maxMobilityDuration>0</maxMobilityDuration>
        <battery>true</battery>
        <percentage>20</percentage>
        <batteryCapacity>56.2</batteryCapacity>
        <initialBatteryLevel>100</initialBatteryLevel>
        <idleConsumption>1.7</idleConsumption>
        <maxConsumption>23.6</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <generateTasks>false</generateTasks>
        <cores>8</cores>
        <mips>20000</mips>
        <ram>8000</ram>
        <storage>1024000</storage>
    </device>
    <device>
        <connectivity>wifi</connectivity>
        <mobility>false</mobility>
        <speed>0</speed>
        <minPauseDuration>0</minPauseDuration>
        <maxPauseDuration>0</maxPauseDuration>
        <minMobilityDuration>0</minMobilityDuration>
        <maxMobilityDuration>0</maxMobilityDuration>
        <battery>false</battery>
        <percentage>40</percentage>
        <batteryCapacity>0</batteryCapacity>
        <initialBatteryLevel>0</initialBatteryLevel>
        <idleConsumption>1</idleConsumption>
        <maxConsumption>2</maxConsumption>
        <isOrchestrator>false</isOrchestrator>
        <generateTasks>true</generateTasks>
        <cores>0</cores><!-- A sensor that does not have computing capabilities -->
        <mips>0</mips>
        <ram>0</ram>
        <storage>0</storage>
    </device>
</edge_devices>
```


Fig. 7: Edge Devices Configuration using XML

2. Cloud Only Model: With all other parameters the same, the execution time was 5 minutes, 0 seconds. The findings (Table 3) on the Pure Edge simulator under the 'CLOUD ONLY' orchestration architecture with the 'TRADE OFF' and 'ROUND_ROBIN' algorithms present the performance and resource usage when tasks are executed only in the cloud. The authors point out that as the number of edge devices rises from 100 to 300, the total task execution delay goes up from 1,800 to 5,395 seconds. In contrast, the average execution delay stays effectively constant at 0.16 seconds, demonstrating that all the edge devices operate uniformly in terms of processing.

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration architecture	Orchestration algorithm	Edge devices count	Total task s execution delay(s)	Average execution delay(s)	Total tas ks waiting time (s)	Average waiting time(s)	Number of generated tasks	Task s successfully executed	Task not executed	Tasks failed (delay)	Tasks failed (device dead)	Tasks failed (mobility)	Tasks not generated due to the death of devices	Tot al task s executed (Cloud)
CLOUD_ONLY	TRADE_OFF	100	1800	0.1622	0	0	11100	1200	0	9900	0	0	0	11100
CLOUD_ONLY	TRADE_OFF	200	3580	0.16	0	0	22370	2370	0	20000	0	0	0	22370
CLOUD_ONLY	TRADE_OFF	300	5395	0.1599	0	0	33740	3540	0	30200	0	0	0	33740
CLOUD_ONLY	ROUND_ROBIN	100	1800	0.1622	0	0	11100	1200	0	9900	0	0	0	11100
CLOUD_ONLY	ROUND_ROBIN	200	3580	0.16	0	0	22370	2370	0	20000	0	0	0	22370
CLOUD_ONLY	ROUND_ROBIN	300	5395	0.1599	0	0	33740	3540	0	30200	0	0	0	33740

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration architecture	Orchestration algorithm	Edge devices count	Total task s execution delay(s)	Average execution delay(s)	Total tas ks waiting time (s)	Average waiting time(s)	Number of generated tasks	Task s successfully executed	Task not executed	Tasks failed (delay)	Tasks failed (device dead)	Tasks failed (mobility)	Tasks not generated due to the death of devices	Tot al task s executed (Cloud)
EDGE_AND_CLOUD	ROUND_ROBIN	100	1800	0.1622	38.0375	0.0034	11100	5398	0	5702	0	0	0	4295
EDGE_AND_CLOUD	ROUND_ROBIN	200	3580	0.16	711.5625	0.0318	22370	11366	0	11004	0	0	0	7542

EDGE_AND_CLOUD	ROUND_ROBIN	300	5395	0.1599	2309.325	0.0684	33740	17587	0	16153	0	0	0	11457
EDGE_AND_CLOUD	TRADE_OFF	100	1800	0.1622	26.2875	0.0024	11100	5100	0	6000	0	0	0	4392
EDGE_AND_CLOUD	TRADE_OFF	200	3580	0.16	745.05	0.0333	22370	11665	0	10705	0	0	0	8115
EDGE_AND_CLOUD	TRADE_OFF	300	5395	0.1599	2165.3875	0.0642	33740	17005	0	16735	0	0	0	11651

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration architecture	Orchestration algorithm	Tasks successfully executed (Cloud)	Total tasks executed (Edge)	Tasks successfully executed (Edge)	Network usage (s)	Wan usage (s)	Lan usage (s)	Total network traffic (M Bytes)	Containers wan usage (s)	Containers lan usage (s)	Average bandwidth per task (Mbps)	Average CPU usage (%)	Average CPU usage (Cloud) (%)	Average CPU usage (Edge) (%)
CLOUD_ONLY	TRADE_OFF	1200	0	0	0	5622	0	14055	0	0	20	0.0346	1.4516	0
CLOUD_ONLY	TRADE_OFF	2370	0	0	0	11214.8	0	28037	0	0	20	0.0352	2.8871	0
CLOUD_ONLY	TRADE_OFF	3540	0	0	0	16990.4	0	42476	0	0	20	0.0357	4.3508	0
CLOUD_ONLY	ROUND_ROBIN	1200	0	0	0	5622	0	14055	0	0	20	0.0346	1.4516	0
CLOUD_ONLY	ROUND_ROBIN	2370	0	0	0	11214.8	0	28037	0	0	20	0.0352	2.8871	0
CLOUD_ONLY	ROUND_ROBIN	3540	0	0	0	16990.4	0	42476	0	0	20	0.0357	4.3508	0

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration	Orchestration	Tasks succ	Total tas	Tasks succ	Network	Wan	Lan usage (s)	Total	Contain	Contain	Average ban	Average	Average	Average

architecture	algorithm	essfully executed (Cloud)	ks executed (Edge)	essfully executed (Edge)	usage (s)	usage (s)		network traffic (MBytes)	ers wan usage (s)	ers lan usage (s)	dwidth per task (Mbps)	CPU usage (%)	CPU usage (Cloud) (%)	CPU usage (Edge) (%)
EDGE_AND_CLOUD	TRADE_OFF	0	7520	5520	58.24	0	58.24	9464	0	0	1300	0.4474	0	18.7903
EDGE_AND_CLOUD	TRADE_OFF	0	15280	10680	112.7692308	0	112.7692308	18325	0	0	1300	0.4435	0	36.371
EDGE_AND_CLOUD	TRADE_OFF	0	20800	15590	167.0646154	0	167.0646154	27148	0	0	1300	0.4647	0	56.6935
EDGE_AND_CLOUD	ROUND_ROBIN	0	6540	4740	51.6	0	51.6	8385	0	0	1300	0.4378	0	18.3871
EDGE_AND_CLOUD	ROUND_ROBIN	0	15750	11550	120.7569231	0	120.7569231	19623	0	0	1300	0.4603	0	37.7419

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration architecture	Orchestration algorithm	Energy consumption of computing nod es (Wh)	Average energy consumption (Wh/Computin g node)	Clo ud energy consumption (Wh)	Average Cloud energy consumption (Wh/Data center)	Edge energy consumption (Wh)	Average Edge energy consumption (Wh/Data center)	WAN energy consumption (Wh)	MAN energy consumption (Wh)	LAN energy consumption (Wh)	WiFi energy consumption (Wh)	LTE energy consumption (Wh)	Ethernet energy consumption (Wh)	Dead devices count
CLOUD_ONLY	TRADE_OFF	51.3351	0.5033	14.44	14.44	17.2222	17.2222	10.8368	0	0	10.8368	0	0	0
CLOUD_ONLY	TRADE_OFF	85.2647	0.4221	28.7196	28.7196	17.2222	17.2222	21.6169	0	0	21.6169	0	0	0
CLOUD_	TRA	119.	0.396	43.2	43.2	17.2	17.2	32.7			32.7			

ONLY	DE_OFF	6178	1	799	799	222	222	525	0	0	525	0	0	0
CLOUD_ONLY	ROUND_ROBIN	51.3351	0.5033	14.44	14.44	17.2222	17.2222	10.8368	0	0	10.8368	0	0	0
CLOUD_ONLY	ROUND_ROBIN	85.2647	0.4221	28.7196	28.7196	17.2222	17.2222	21.6169	0	0	21.6169	0	0	0

CLOUD_ONLY	ROUND_ROBIN	119.6178	0.3961	43.2799	43.2799	17.2222	17.2222	32.7525	0	0	32.7525	0	0	0
Orchestration architecture	Orchestration algorithm	Energy consumption of computing nodes (Wh)	Average energy consumption (Wh/Computing node)	Cloud energy consumption (Wh)	AverageCloud energy consumption (Wh/Data center)	Edge energy consumption (Wh)	Average Edge energy consumption (Wh/Data center)	WAN energy consumption (Wh)	MAN energy consumption (Wh)	LAN energy consumption (Wh)	WiFi energy consumption (Wh)	LTE energy consumption (Wh)	Ethernet energy consumption (Wh)	Dead devices count
EDGE_AND_CLOUD	TRADE_OFF	47.017	0.461	5.4553	5.4553	21.8888	21.8888	4.4331	0	2.9703	7.4034	0	0	0
EDGE_AND_CLOUD	TRADE_OFF	76.1102	0.3768	9.6718	9.6718	27.1155	27.1155	7.1509	0	6.7023	13.8532	0	0	0
EDGE_AND_CLOUD	TRADE_OFF	106.4709	0.3526	15.9251	15.9251	31.43	31.43	11.8627	0	9.6816	21.5444	0	0	0
EDGE_AND_CLOUD	ROUND_ROBIN	46.8831	0.4596	5.1766	5.1766	22.0335	22.0335	4.0799	0	3.1325	7.2124	0	0	0
EDGE_AND_CLOUD	ROUND_ROBIN	76.5535	0.379	10.5941	10.5941	26.6364	26.6364	7.7324	0	6.4351	14.1674	0	0	0

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration architecture	**Orchestration algorithm**	**Average remaining power (Wh)**	**Average remaining power (%)**
CLOUD_ONLY	TRADE_OFF	32.797	99.551
CLOUD_ONLY	TRADE_OFF	32.794	99.5353
CLOUD_ONLY	TRADE_OFF	32.7893	99.5101
CLOUD_ONLY	ROUND_ROBIN	32.7773	99.446
CLOUD_ONLY	ROUND_ROBIN	32.7899	99.5132
CLOUD_ONLY	ROUND_ROBIN	32.7873	99.4996

Table 3. Different Parameters Estimation in Cloud and Edge and Cloud Only Use Case Scenario (Continue….)

Orchestration architecture	**Orchestration algorithm**	**Average remaining power (Wh)**	**Average remaining power (%)**
EDGE_AND_CLOUD	TRADE_OFF	32.797	99.551
EDGE_AND_CLOUD	TRADE_OFF	32.7925	99.5268
EDGE_AND_CLOUD	TRADE_OFF	32.7852	99.488
EDGE_AND_CLOUD	ROUND_ROBIN	32.7838	99.4807
EDGE_AND_CLOUD	ROUND_ROBIN	32.7842	99.4828
EDGE_AND_CLOUD	ROUND_ROBIN	32.7961	99.5461

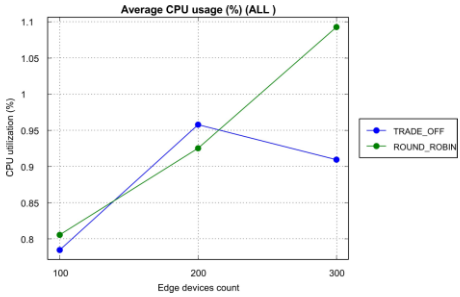
```
# Simulation Parameters File

simulation_time=10
parallel_simulation=false
update_interval=1
pause_length=3

display_real_time_charts=true
auto_close_real_time_charts=true
charts_update_interval=10
save_charts=false

# We chose a larger simulation area 2000x2000 instead of 200x200
length=2000
width=2000

edge_devices_range=10

# To ensure that all devices can reach the edge data centers, and that the edge data center can reach one another, we chose a higher value
# By setting it to 1000 we ensure that all the Edge servers cover all the map ( you can chose a higher value)
edge_datacenters_coverage=1000


enable_registry=false
registry_mode=CLOUD


# To enable the edge data centers to work cooperatively, we have to deploy one orchestrator on each edge device
# This means that the tasks will be transferred to the nearest Edge data center, which will decide where it will be executed: on the cloud,
# on another edge data cetner, or execute it locally on this daat center.
# run the simulation with "enable_orchestrators=true" and then run it with "enable_orchestrators=false" to compare the results
enable_orchestrators=true
# we must set this to EDGE
deploy_orchestrator=EDGE

wait_for_all_tasks=true

# Schedule tasks in batches to reduce the event queue size (to decrease simulation time and memory usage, default = 100)
batch_size=100
```

```
cellular_base_station_nanojoules_per_bit_up_link = 6200
cellular_base_station_nanojoules_per_bit_down_link = 20500
cellular_latency = 0.03


# We select the Edge_and_Cloud architecture in order to execute the tasks on the Cloud or Edge data centers,
# we will also use the Cloud_only architecture for comparison
orchestration_architectures=EDGE_AND_CLOUD
# The used orchetsration algorithm
orchestration_algorithms=TRADE_OFF
```

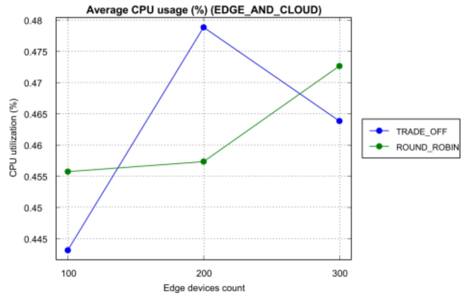
```
save_log_file=false
clear_output_folder=true
deep_log_enabled=false

min_number_of_edge_devices=500
max_number_of_edge_devices=500
edge_device_counter_size=400


realistic_network_model=false
network_update_interval=1

# If true, all data transferred to the cloud will pass through the same wan link and share the same bandwidth,
# this can be needed in some scenarios. This also will cause many tasks to fail due to latency.
# So, you can either increase the wan bandwidth, or adjust the tasks latency sensitivity in applications.xml file.
# When disabled, the the WAN real-time chart will not be displayed.
one_shared_wan_network = false


wan_bandwidth = 1000
wan_latency = 0.06
wan_nanojoules_per_bit = 46.7

man_bandwidth = 1000
man_latency = 0.01
man_nanojoules_per_bit = 0

wifi_bandwidth = 1300
wifi_device_transmission_nanojoules_per_bit = 283.17
wifi_device_reception_nanojoules_per_bit = 137.01
wifi_access_point_transmission_nanojoules_per_bit = 23.8
wifi_access_point_reception_nanojoules_per_bit = 23.8
wifi_latency = 0.005

ethernet_bandwidth = 1000
ethernet_nanojoules_per_bit = 40
ethernet_latency = 0.002

cellular_bandwidth = 100
cellular_device_transmission_nanojoules_per_bit = 438.4
cellular_device_reception_nanojoules_per_bit = 51.97
```

Fig. 8: Simulation Parameters Configuration using XML

Unsurprisingly, there is no waiting time for tasks as all tasks are executed in the cloud, but many tasks are delayed, evidenced by 9,900 failed tasks at 100 devices and 30,200 at 300 devices. This means latency is still a big problem even when cloud resources are on hand. No tasks are at the edge or mist layers, and all are computed in the cloud, highlighting the dependence on centralized resources. There is general growth in usage when there are more devices, specifically WAN usage, because of the increased traffic towards the cloud. Energy density in computing nodes increases with the number of devices, and cloud energy consumption increases to 43.28 Wh from 14.44Wh. By contrast, the edge energy consumption stays high since the edge devices are not engaged in executing tasks. These outcomes point to the difficulties of handling latency and network congestion specifically for the cloud, mainly architecture, pointing to the advantages of incorporating edge resources for decreasing time and enhancing the rate of successful completion of tasks. The figures from 9 through Figure 11 represent various aspects of CPU utilization and energy consumption in cloud and edge computing scenarios. Figure 9 discusses the CPU utilization across different scenarios. Average CPU usage across cloud and edge scenarios is illustrated in subfigures (a) and (b) to indicate how workload has been distributed between these two architectures. Subfigure (c) isolates the average CPU usage among cloud environments, while subfigure (d) does just that for edge scenarios. These visualizations reflect differences in processing demands and efficiency between centralized cloud computing and decentralized edge computing. Figure 10 outlines some parameters for energy consumption metrics. Subfigures (a) through (c) compare energy usage, averaged over the scenarios, between edge only, cloud-only, or a mixture of edge and cloud scenarios. Such information is critical in understanding how different deployment strategies can impact energy consumption. Subfigures (d) through (x) provide a detailed look into the breakdown of energy consumption across different network types, such as LAN, LTE, MAN, WAN, and Wi-Fi in both cloud-only and edge-and-cloud scenarios, highlighting the energy implications of various network setups and their impacts.

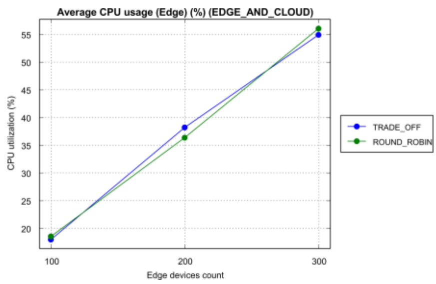


(a) Avg. CPU Usage for Cloud and Edge scenario

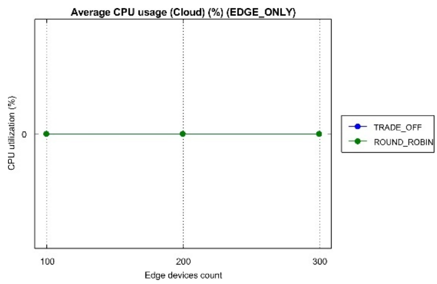


(b) Avg. CPU Usage for Cloud and Edge scenario

Fig. 9: CPU Utilization of Various Scenarios in Edge and Cloud Use Case (Continue…)

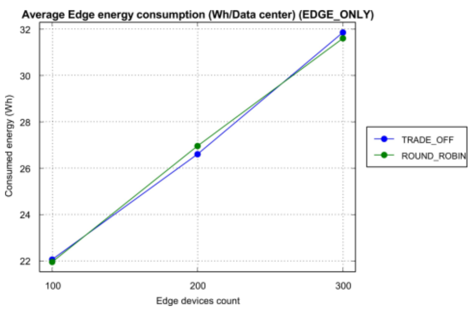


(a) Avg. CPU usage of Cloud



(d) Avg. CPU Usage of Edge scenario

Fig. 9: CPU Utilization of Various Scenarios in Edge and Cloud Use Case



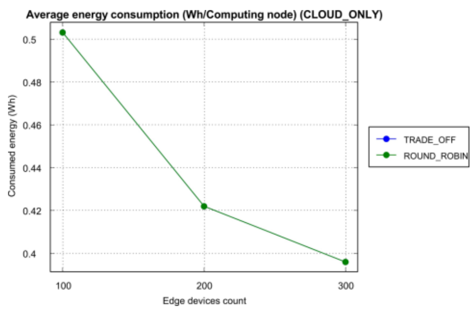
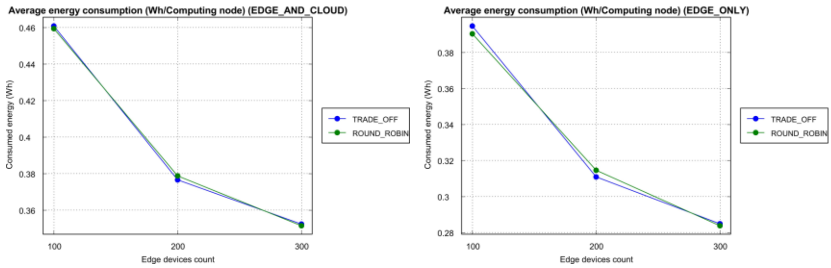


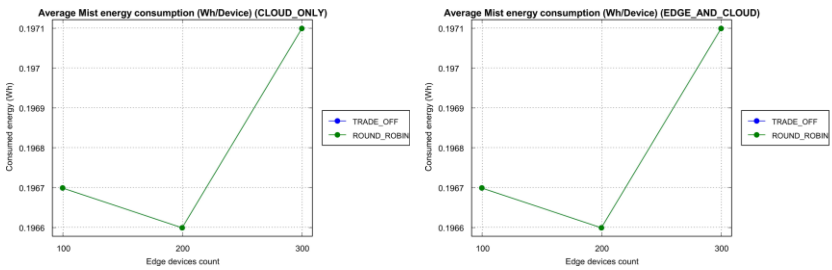
Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)



(a) Avg. Energy Consumption For Edge Only and Edge and Cloud (Wh/Data Center)

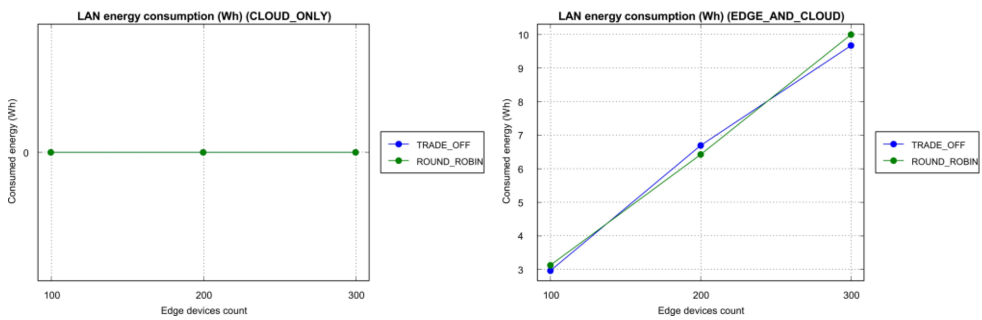
(b) Avg. Energy Consumption For Edge Only (Wh/Data Center)

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)



(c) Avg. Energy Consumption For Cloud Only (Wh/Devices)

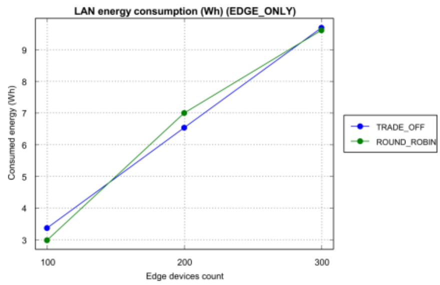
(d) Avg. CPU Usage for Cloud and Edge scenario



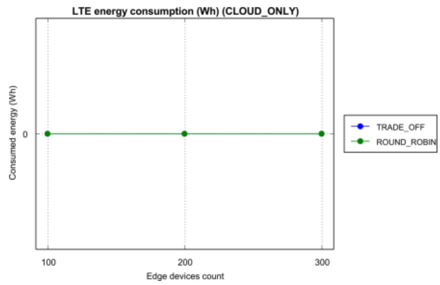
(a) LAN Energy Consumption Cloud Only Scenario

(b) LAN Energy Consumption Cloud and Edge Scenario

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)

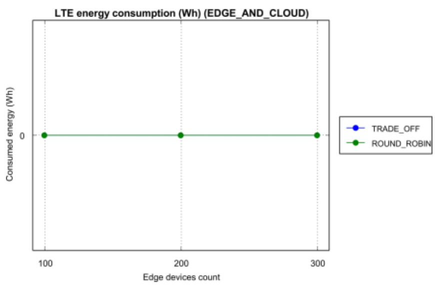


(a)LAN Energy Consumption Edge Only Sce- nario

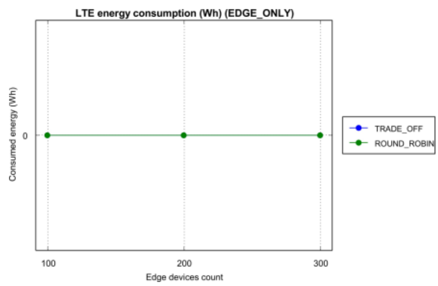


(b) LAN Energy Consumption Cloud Only Scenario

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)

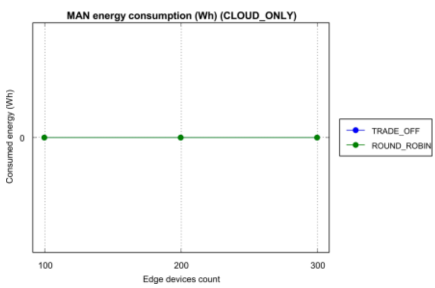


(a) LTE Energy Consumption Edge and Cloud Scenario

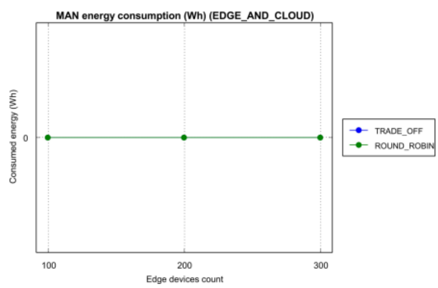


(b) LTE Energy Consumption Edgge Only Scenario

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (Con- tinue...)

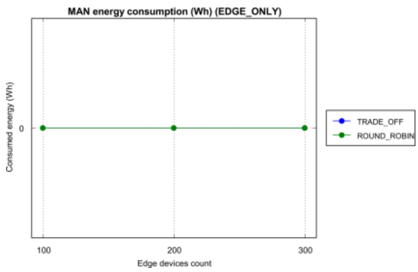


(c) MAN Energy Consumption Cloud Only Scenario

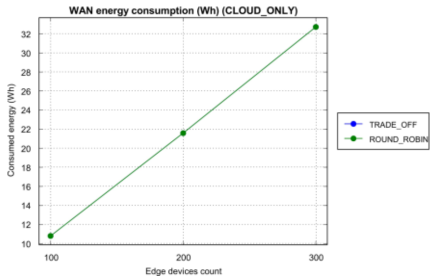


(d) MAN Energy Consumption Edge and Cloud Scenario

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)

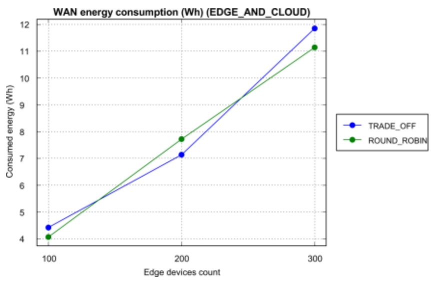


(a) MAN Energy Consumption Edge Only

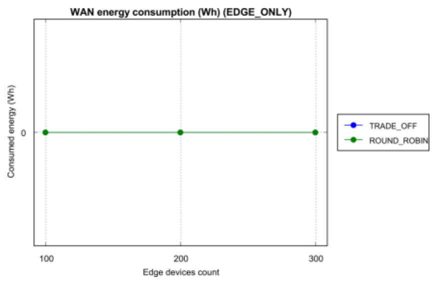


(b) WAN Energy Consumption Cloud Only Scenario

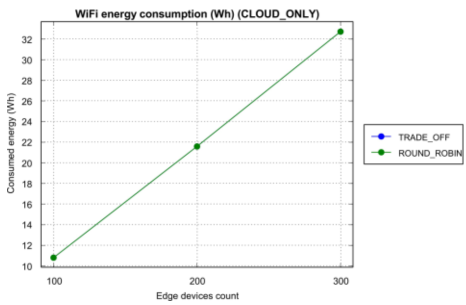
Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)



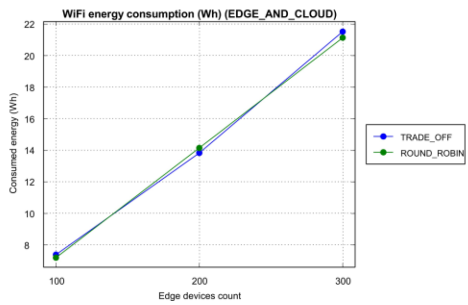
(c) WAN Energy Consumption Edge and Cloud Scenario



(d) WAN Energy Consumption Edge Only Scenario

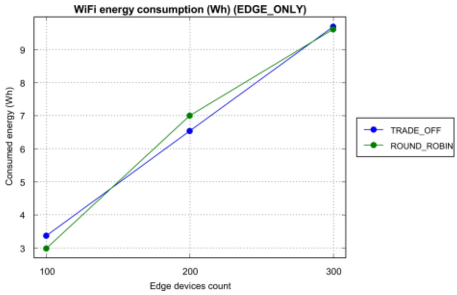


(a) Wi-Fi Energy Consumption Cloud Only Scenario

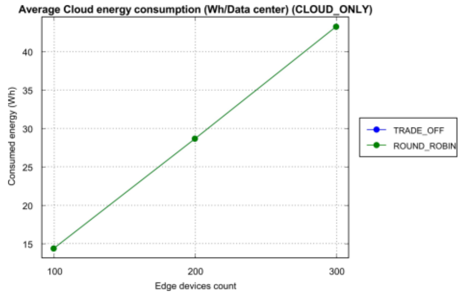


(b) Wi-Fi Energy Consumption Edge and Cloud Scenario

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)

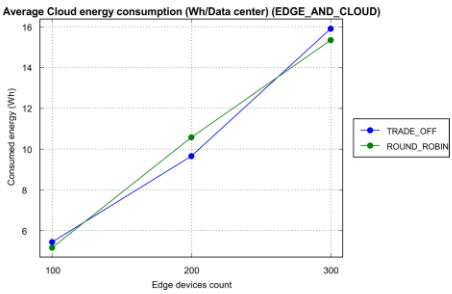


(a) Wi-Fi Energy Consumption Edge Only Scenario

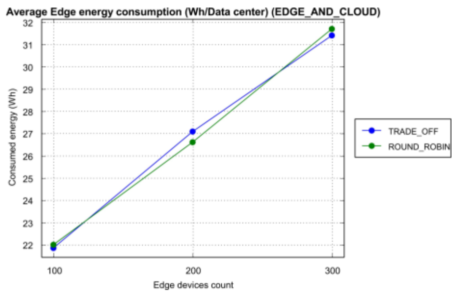


(v) Avg.Energy Consumption Cloud Only Scenario (Wh/Data Center)

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (continue...)

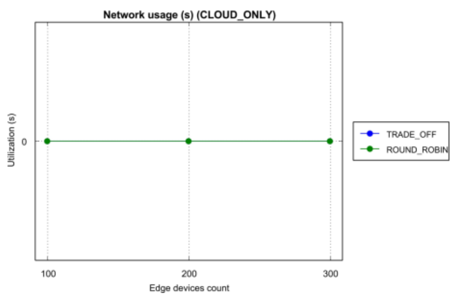


(w) Avg. CPU Usage for Cloud and Edge Sce- nario

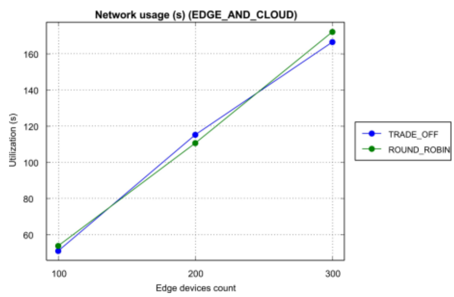


(x) Avg. Edge Energy Consumption in Edge and Cloud Usage Scenario (Wh/Data Center)

Fig. 10: Energy Consumption in Edge and Cloud and Cloud Only Scenario (con- tinue...)



(a) Avg. CPU Usage for Cloud and Edge sce- nario



(b) Avg. CPU Usage for Cloud and Edge sce- nario

Fig. 11: Energy Consumption in Edge and Cloud and Cloud Only Scenario

Figure 11 highlights overall CPU usage and discusses a few other scenarios to repeat the findings from Figure 9. Aligned with repeated emphasis on CPU usage across different configurations, it serves as logic underpinning further research in this area to ensure computational efficiency in hybrid cloud-edge environments is pursued.

In general, these figures collectively reflect the trade-offs of computational efficiency against energy consumption in cloud and edge computing. There is a need to cognizant resource allocating towards possible integrated benefits of considering edge resources for latency reduction and enhanced system performance, especially so for real-time applications. Furthermore, the insights given in these visualizations can somewhat converge onto future research directive avenues such as developing an adaptive orchestration algorithm and energy efficient communication protocols.

Future research should consider the following directions to improve knowledge and utilization of edge and cloud architectures. First, extending research on adaptive orchestration algorithms that dynamically assign tasks according to the current state of the network could provide additional improvement. Furthermore, increasing the scope of the simulation to cover a greater variety of devices and network settings would give an extended indication of system outputs. Other possible future investigations that might help to decrease the negative effect of distributed computing systems on the environment are the studies of methods for energy-efficient communication protocols and hardware enhancements for edge devices. Finally, investigating how the newest technology trends, like 5G and AI for resource allocation, can be implemented into hybrid computing systems may provide further potential for scalability and more efficient designs.

5. Conclusion and Future Direction

The analysis of the simulation results shows key factors that characterize the behavior of efficient edge and cloud computing systems. The 'EDGE AND CLOUD' scenario shows the highest percentage of successful task execution, with no tasks being missed due to resource limitations or long waiting times, and all of this while the number of edge devices is growing. This architecture optimally utilizes edge and cloud services, which decreases latency and increases power-saving results. On the other hand, although WPs are reduced to zero as is the case of the 'CLOUD ONLY'.

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