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Forensic-Aware Load Balancing for Fog-Enabled IoT Resources Using Hierarchical Clustering Analysis

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ABSTRACT

Due to increasing amounts of apps using IoT, there has been a focus on properly managing resources, having low latency communication, and processing real-time data across distributed computing environments. While cloud computing allows for scalability of storage and processing power, it also introduces potential delays as a result of its architecture in terms of requirements for bandwidth for latency-dependent applications. Fog computing expands cloud-based functions to the edges of the network, thus providing distributed computing and networking capabilities. In the case of heterogeneous devices, the main problems relate to workload management, resource management, and forensic preparedness. This paper presents a resource load-balancing architecture that supports forensic awareness for fog OS-based IoT resources. Hierarchical clustering is implemented to provide an optimized load balancing system to monitor the resources and distribute workload. This data workload classification scheme identifies the various categories of data based on their processing requirement and allocates resources accordingly. The intelligent data migration framework will be used with all data processed in order to have a forensic awareness about any data that would be affecting the performance of the system, through the systematic tracking of workloads and resource management, allowing evaluation of this framework and its implementation to be done in the iFogSim simulation environment using various configurations of the network. Analysis of test samples shows that, on average, newer designs will have marked improvements over traditional structures (cloud-based) regarding latency, execution costs, network usage, energy use, and elapsed time. This same analysis also supports using hierarchical clusters and using a fog-cloud-based forensic-aware load balancer type with these hierarchical clusters to have an elasticity mechanism for resource optimization and to minimize response times to requests, which will maximize a system's ability to provide visibility and to use IoT-enabled devices in real-time applications.

Keywords: Fog Computing, Internet of Things, Load Balancing, Digital Forensics, Forensic Readiness, Resource Allocation, Hierarchical Clustering, Cloud Computing, iFogSim

1. INTRODUCTION

The cloud computing technology provides access to storage space, computational power, and software services through the internet network. Cloud computing has three categories of service: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). Its rental pricing policy enables individuals to purchase the required cloud computing services on demand [1, 2].

The development of IoT applications creates huge amounts of data through sensors, smart devices, health care, industrial equipment, and intelligent transportation. The requirements for these applications include communication, data processing, and quick response time. However, such requirements are hard to meet due to the long distance between these applications and data centers [3, 4].

Fog Computing is an enhancement of Cloud Computing, where computation and data storage are moved near end devices. As a result, computing is done at a place that lies between cloud and Internet of Things devices. Fog Computing can be useful for applications that require low latency and quick response time [5].

While there are benefits of using fog computing, deploying it on the edge creates extra work and resource constraints. Nodes used for fog computing are not as powerful as those available in cloud data centers; hence, task assignment should be done in such a manner that no node is overloaded since this could result in inefficient usage and low performance of the applications [6].

Load balancing is a process that aims to distribute workloads among resources in a distributed system for optimum efficiency. Classical methods were designed for cloud environments, and thus may not cover certain issues like resource allocation dynamically and the unique characteristics of fog-IoT environments. With an increasing number of devices connecting, more intelligent methods are required [7, 8].

The objective of resource allocation and workload scheduling studies in fog computing is to enhance resource utilization and accomplish the tasks effectively. Research on fog computing employs optimization techniques, machine learning, workload offloading, and resource virtualization to maximize resource utilization and efficiency. Majority of researches concentrate on either workload migration between the fog nodes or resource allocation inside a cloud setting. There has been limited study on the integration of both workload migration and resource allocation in a fog and cloud environment [9, 10].

Optimization and increased efficiency through clustering can be achieved. Clustering involves grouping similar objects together to facilitate proper resource management. Hierarchical clustering is one type of unsupervised machine learning that has its strengths in comparison with other approaches to clustering. Specifically, hierarchical clustering provides representation of resources at different levels and creates dynamic clusters due to various parameters, including processing capability and types of workload [11].

In the latest research, there is a strong focus on the need for an intelligent resource management system in the context of fog-cloud systems that can support scalable and real-time applications. There are various issues to be addressed, including workload adaptation, migration coordination, VM allocation, and increased energy efficiency. Another issue is that most existing strategies ignore the hierarchical structure of the available resources [12, 13].

Load Balancing (LB) framework for IoT resources enhanced with fog computing through Hierarchical Cluster Analysis (HCA) is proposed in this paper. This LB framework combines fog-cloud load balancing (LB-WF), Intelligent Data Migration (IDM), and Resource Clustering (RC) in one unified approach. The load distribution depends on PC capability to process the workload, whereas resource clustering is done based on HCA to facilitate VMs allocation. Simulations using iFogSim were conducted in terms of delay, execution cost, networking utilization, power consumption, and execution time.

Contributions of this research include the following:

- Load balancing approach by integrating fog and cloud to support real-time IoT applications
- Data migration scheme by intelligently transferring workloads from fog and cloud
- Cluster analysis in hierarchy for resource allocation and management of VMs
- Evaluation of the proposed approach through iFogSim simulation in different network scenarios
- Analysis on latency, execution cost, network usage, energy consumption, and execution time

2. RELATED WORK

The Fog Computing architecture enables the control of computation and storage operations closer to the edge of the network, thereby enhancing the efficiency of IoT systems through decentralization. With this technique, latency is lowered while reducing bandwidth consumption and response delays encountered in the centralized cloud model. In fog computing, load balancing plays an important role in the efficient utilization of resources and providing better service quality. Optimal load balancing increases the effectiveness of resource utilization along with reducing the workload process time [14]. Songhorabadi et al. conducted surveys for fog computing resource management techniques by classifying them as service, application, and resource-based [15]. Similarly, Kashani et al. presented a review of load balancing algorithms that were either approximated, exact, heuristic, or hybrid, and analyzed problems associated with resource management in heterogeneous fog environments [16].

Allocation of resources is essential for high-performing fog computing. According to Alsadie, efficient management strategies are those that enhance the operation of fog networks by resource allocation, scheduling, and load balancing [17]. Resource allocation was identified by Martinez et al. to be one of the major concerns influencing the quality of service (QoS) and scalability of fog computing infrastructure [18]. The dynamic resource allocation framework based on Bayesian learning put forth by Etemadi et al. showed promising results in terms of effective usage and efficiency of fog resources [19].

Load balancing involves distribution of tasks among IoT devices, fog nodes, and cloud data centers. Two-stage task offloading technique was recommended by Malik et al. for minimizing task failure and energy consumption in geographic fog networks [20]. The Energy Makespan Scheduling model was put forward by Ijaz et al. to distribute workloads through multi-objective optimization and attained significant energy saving as well as time reduction [21]. Ibrahim et al.'s new technique for offloading tasks is based on thresholds that enable prioritization of tasks based on latency, which helps enhance response time of applications through optimum workload allocation [22]. Prasad et al. further emphasized the importance of efficient task offloading in smart city applications where computational requirements and storage demands continuously fluctuate [23].

Recent developments in optimization techniques and efficient resource management have improved IoT through fog computing. The authors Gill et al. utilize particle swarm optimization technique to develop an optimal cloud-based resource management scheme for fog computing [24]. A team of scientists from the Teoh et al. study used genetic algorithm and machine learning to improve predictive maintenance, producing results that demonstrated faster completion time, cost effectiveness, and energy savings [25]. The approach proposed by Kumar et al. for workload prediction employs autoencoders, coupled with optimization of fog nodes using Crow Search Optimization (CSO), which has demonstrated superior performance to state-of-the-art approaches in terms of throughput, response time, and execution costs [26].

In contemporary distributed computing environments, the technique of clustering is used to achieve load balancing and resource organization. The Fog computing architecture suggested by Sharma and Saini uses artificial neural network technology, time-based scheduling, and clustering, although the latter tends to increase response time but ensures better energy consumption efficiency [27]. According to Essalhi et al., clustering contributes significantly towards achieving efficient energy consumption in the context of Fog-IoT communication as well as load balancing [28].

Hierarchical clustering involves forming many clusters to find out the relationship within data, which means we do not determine the number of clusters beforehand. The formation of clusters comes from the relationship of data. For instance, Idrees and Idrees used Huffman coding with hierarchical clustering to address issues related to workload management and data compression [29]. Many researchers have worked on the implementation of fog and cloud computing for its effective use. Researchers working on fog and cloud computing hybridization are Karatas & Korpeoglu [30], who have suggested a way to manage data by using fog and cloud computing. Their system made use of geographical dispersion for minimizing data retrieval time. Al-Joboury & Al-Hemiary [31] are also among the researchers who implemented the idea of fog and cloud computing hybridization in order to reduce packet losses and increase throughput.

However, despite the advancements made in areas such as resource management, workload scheduling, and load balancing, there still exist some unsolved problems. Studies have tended to focus on only one parameter, either delay or energy-efficient resource allocation, ignoring the fact that there are connections between the fog and the cloud. As such, tissue of workload management has not been effectively addressed using a combination of fog and cloud technologies [32-33].

Recently, AI-based research has demonstrated effectiveness of intelligent, explainable and optimization-based approaches in academic writing assistance, collaborative learning and NLP prompt optimization, by doing this illustrating their potential applicability in AI-based decision-making methods in diverse domains [34-37].

3. PROPOSED METHODOLOGY

The technique is made up of two phases. In the first phase, cloud-based VMs are employed to reduce the energy consumption of idle VMs while allocating resources within the servers. In the second phase, network load balancing reduces latency and jitter to ensure that time-dependent applications run at maximum efficiency. In the fog computing paradigm, the user decides where data will be stored and allocated both locally and in the cloud environment that are shown in figure 1.

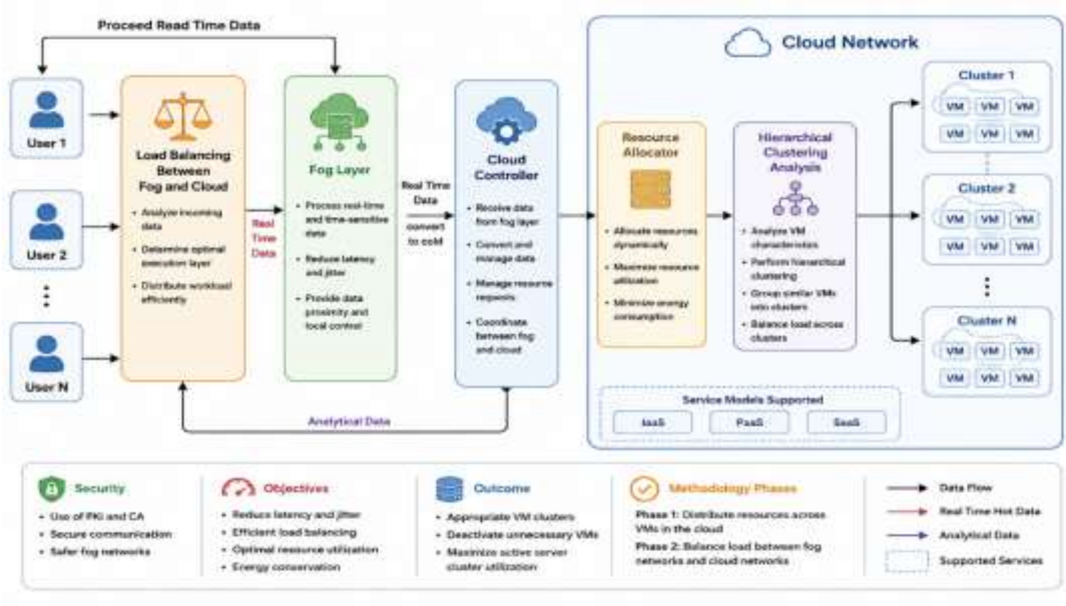

Figure 1: Proposed Load Balancing for Fog-Enabled IoT Resources

It seeks to develop a load balancing algorithm using fog and cloud computing systems. The request goes to the Load Balancer, which determines whether the processing will be done in the fog node or cloud node that are shown in figure 2. Processing of the request takes place in the fog node whereas the analysis is done in the Cloud Controller.

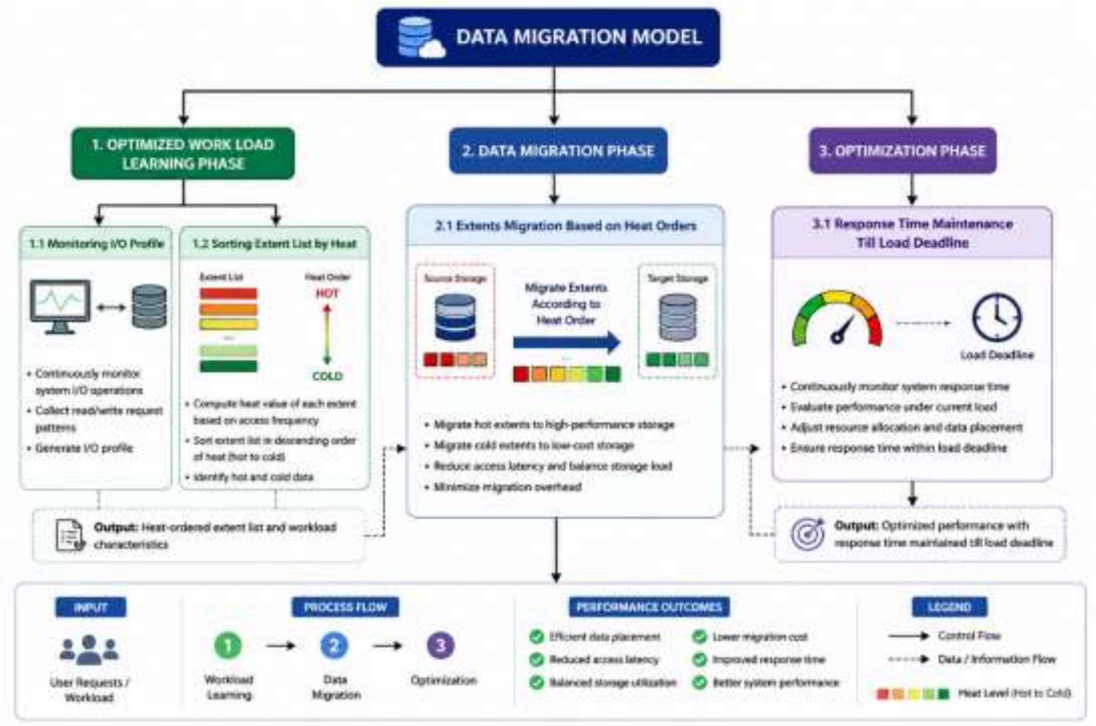

Figure 2: Data Migration Model for Optimization

The Three-Stage Data Migration System for efficient resource allocation and utilization: Optimum Workload Learning: gather I/O statistics to classify the data according to their usage frequency. Data Migration: data transfer such that hot data is placed in fast storage while cool data is located in slow storage. Optimization: constant monitoring to ensure optimum system performance considering resource usage and migration.

A brief description of the model: The Data Migration Model facilitates communication between Clients and Cloud through the use of the fog layer. Data Migration helps to reduce latency time in communication between cloud and fog by fast processing of data, which is done in real-time and bulk methods that representing figure 3 and 4.

In real-time, data flows from the user to the fog layer and is delivered promptly by the Fog Gateway. We use a hierarchical clustering-based approach to allocate resources in an attempt to enhance utilization and minimize power consumption of the cloud system.

The creation of the VM determines the attributes, capabilities, status, and type of VM. We then group similar VMs based on parameters such as client priority, cloudlet price, and instruction size and use these clusters for certain services.

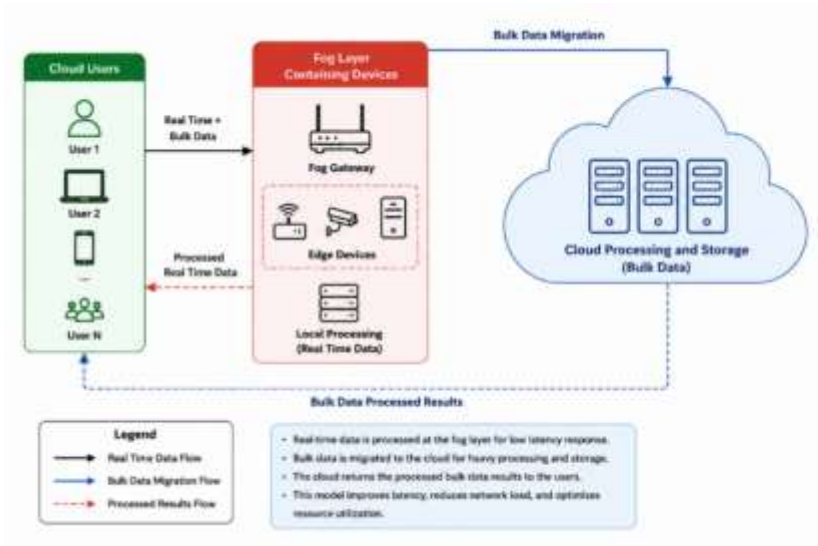

Figure 3: IaaS for Fog

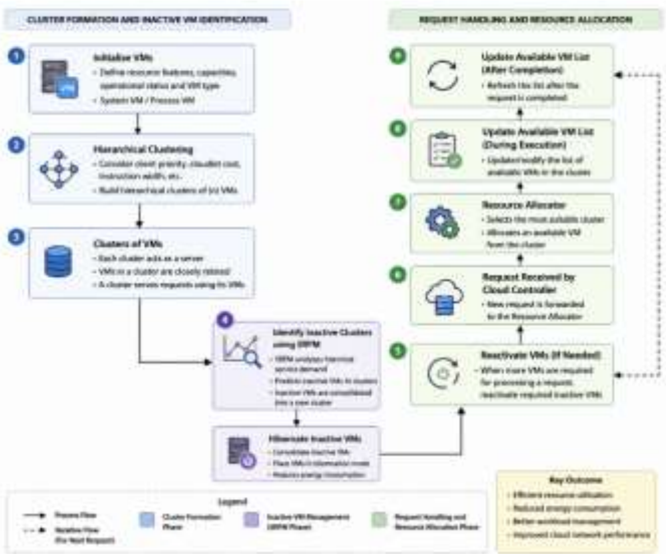

Figure 4: Resource Allocation using Hierarchical Clustering and SRPM

4. RESULTS AND DISCUSSION

The suggested simulation employs a smart monitor and emergency healthcare system that ensures immediate medical attention. In the Timer, constant monitoring causes alarms to go off for critical conditions. These alarms are passed to the Interface, and then to the Checker for evaluating the patient's condition. The Potency Calculator calculates the appropriate dosage based on the illness, which is stored in the Cloud Storage. Finally, the Selector identifies the best candidate for medication, followed by administration using the Actuator Injector that are shown in figure 5.

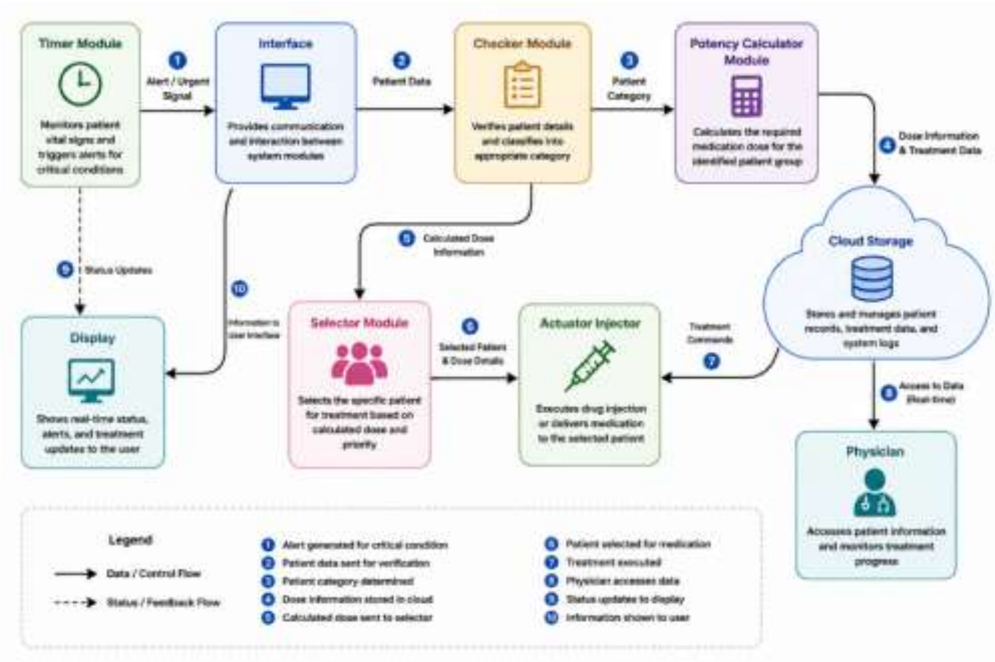

Figure 5: Application Model of Patient-Medicine Administration

Using iFogSim, an extension of CloudSim for fog computing, a cloud-fog environment is simulated, and QoS metrics such as latency, energy consumption, cost of execution, and network usage are analyzed. CloudSim, set relevant parameters, and initialize a fog broker in order to initiate cloud-fog communication. Create a cloud-fog infrastructure with suitable compute and network characteristics for fog computing. Introduce gateways, observers, sensors, and actuators for generating, observing, and processing information. Use tuples for measuring latency, energy consumption, cost of execution, network usage, and execution time. The figure 6 from one module to another must be aggregated in order to determine average latency and energy usage.

The cloud data center belongs to the category of fog-cloud Level 0 which provides high processing and storage capacity for carrying out large scale computations and storing information. The computation capacity of 39,860 MIPS along with a RAM of 39 GB is provided. Communication rates include uploading at the rate of 100 MB/s and downloading at the speed of 10 GB/s. The computation price stands at 1 cent per unit.

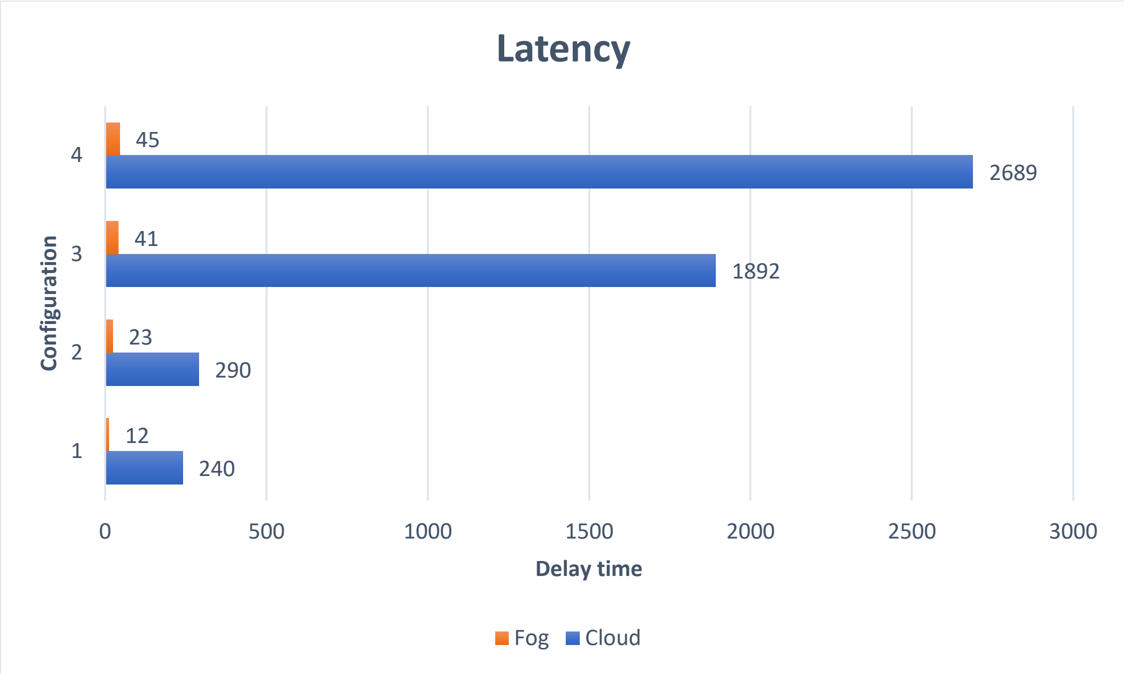

Figure 1: Latency

This serves as the interface for communication between fog nodes and the end devices, making it the second level of abstraction in the fog cloud architecture. This node takes care of transferring information, controlling communication processes, and managing the other observer nodes and processor nodes. Level two is the home of this node, which is beneath the proxy server, allowing for faster, less congested, and higher bandwidth communications. This node gives a processing speed of 2,800 MIPS and RAM capacity of 4 GB for data forwarding, offers up to 10 Gbps download/upload and allows for maximum transfer rate. Latency analysis in fog and cloud was performed with various area-LPU combinations. Latency increases with increase in configuration size in both cases, but the latency increase is much higher for the cloud case especially for small configuration sizes. For example,

- 1 Area, 2 LPUs: Cloud 240 ms, Fog 12 ms
- 2 Areas, 3 LPUs: Cloud 290 ms, Fog 23 ms
- 3 Areas, 6 LPUs: Cloud 1,892 ms, Fog 41 ms
- 4 Areas, 8 LPUs: Cloud 2,689 ms, Fog 45 ms

The results indicate that the integration of fog computing and virtual machine hibernation significantly reduces operational cost, latency, and energy consumption compared to traditional cloud-only environments that are shown in figure 6.

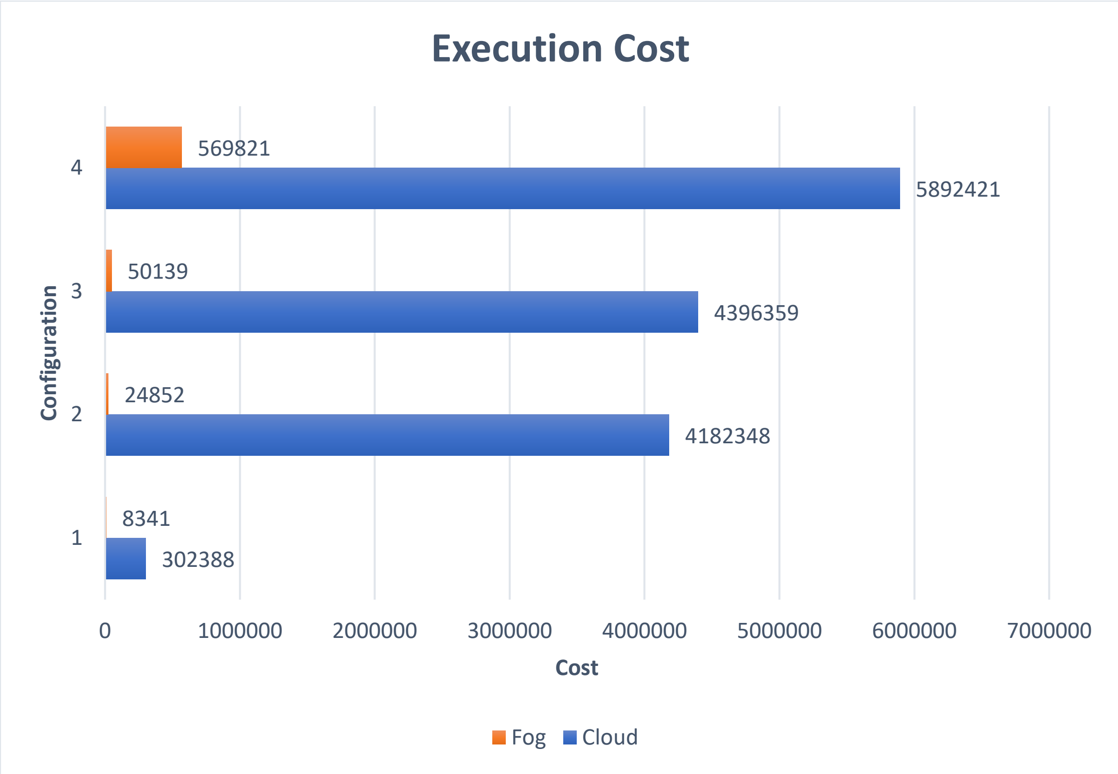

Figure 7: Total Operational Cost

The comparative financial models reveal that fog computing (including VM hibernation) will continue to provide cost-effective solutions compared to just being in the cloud.

- One Site, Two LPUs: Cloud $302,388; Fog $8,341
- Two Sites, Three LPUs: Cloud $4,182,348; Fog $24,852
- Three Sites, Six LPUs: Cloud $4,396,359; Fog $50,139
- Four Sites, Eight LPUs: Cloud $5,892,421; Fog $569,821

From this comparison, it can be concluded that there is a cost savings with fog computing because of the ability to use local resources reducing the data transfer cost associated with VM hibernation.

5. CONCLUSION

The study proves that the integration of fog computing along with load balancing and hierarchical VM clusters increases the performance of IoT networks. Fog and cloud offloading help to minimize latency, network delay, cost, and energy consumption. Also, load balancing helps to create applications with high responsiveness and reduced network delays because of the use of local fog resources.

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