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COMPARATIVE ANALYSIS OF CLOUD AND FOG COMPUTING PERFORMANCE BASED ON MODELING

This study presents a comparative performance analysis of cloud and fog computing architectures based on simulation modeling. Cloud computing offers numerous advantages, including scalability, on-demand resource allocation, simplified deployment of applications and services. However, this evolution critically depends on efficient data transmission - a domain where principles of radio physics, such as signal propagation, interference management, and channel optimization, play a pivotal role. Fog computing extends cloud capabilities to the network edge, enabling localized processing and reducing response time. Using the Eclipse IDE and Java, two network models were developed to analyze key metrics: energy consumption, transmission delay, and network traffic under varying node topologies. The simulation results show that fog computing significantly reduces latency and distributes energy consumption more efficiently than traditional cloud systems. Correlation matrix analysis reveals that while latency and energy usage in cloud systems increase sharply with the number of devices, fog architectures exhibit better scalability and resilience. These findings highlight fog computing as a viable solution for real-time and IoT applications requiring low-latency responses and efficient resource distribution.

Keywords: cloud technology, fog computing, performance, comparative analysis Eclipse.

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Модельдеу арқылы бұлт және тұман есептеулердің өнімділігін салыстырмалы талдау

Бұл зерттеу симуляциялық модельдеуге негізделген бұлтты және тұманды есептеулер архитектурасының салыстырмалы өнімділігін талдауды ұсынады. Бұлттық есептеулер ауқымдылықты, сұраныс бойынша ресурстарды бөлуді, қолданбалар мен қызметтерді оңайлатылған орналастыруды қоса алғанда, көптеген артықшылықтарды ұсынады. Дегенмен, бұл эволюция деректерді тиімді тасымалдауға, яғни сигналдың таралуы, кедергілерді басқару және арнаны оңтайландыру сияқты радиофизика принциптері шешуші рөл атқаратын салаларға өте тәуелді. Тұмандық есептеулер бұлттың мүмкіндіктерін желі шетіне дейін кеңейтеді, локализацияланған өңдеуді қамтамасыз етеді және жауап беру уақытын қысқартады. Eclipse IDE және Java көмегімен негізгі өнімділік көрсеткіштерін талдау үшін екі желі моделі әзірленді: қуатты тұтыну, беру кідірісі және әртүрлі түйін топологиялары бойынша желілік трафик. Модельдеу нәтижелері тұманды есептеу кідірістерді айтарлықтай азайтатынын және дәстүрлі бұлттық жүйелерге қарағанда энергияны тұтынуды тиімдірек бөлетінін көрсетеді. Корреляциялық матрицалық талдау бұлттық жүйелердегі кідіріс пен қуат тұтыну құрылғылардың санына қарай күрт өскенімен, тұмандық архитектуралар жақсырақ ауқымдылық пен тұрақтылықты көрсетеді. Бұл нәтижелер тұманды есептеуді нақты уақыттағы және төмен кідіріс жауаптарын және ресурстарды тиімді бөлуді қажет ететін IoT қолданбалары үшін өміршең шешім ретінде көрсетеді.

Түйін сөздер: бұлтты есептеулер, тұманды есептеулер, өнімділік, Eclipse салыстырмалы талдау.

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Сравнительный анализ производительности облачных и туманных вычислений на основе моделирования

В этой работе представлен сравнительный анализ производительности архитектур облачных и туманных вычислений на основе имитационного моделирования. Облачные вычисления предлагают многочисленные преимущества, включая масштабируемость, распределение ресурсов по требованию, упрощенное развертывание приложений и услуг. Однако эта эволюция критически зависит от эффективной передачи данных, т.е. области, где принципы радиофизики, такие как распространение сигнала, управление помехами и оптимизация канала, играют ключевую роль. Туманные вычисления расширяют возможности облака до границы сети, обеспечивая локализованную обработку и сокращая время отклика. Используя Eclipse IDE и Java, были разработаны две сетевые модели для анализа ключевых показателей: энергопотребление, задержка передачи и сетевой трафик при различных топологиях узлов. Результаты моделирования показывают, что туманные вычисления значительно сокращают задержку и распределяют энергопотребление более эффективно, чем традиционные облачные системы. Анализ корреляционной матрицы показывает, что, хотя задержка и энергопотребление в облачных системах резко возрастают с количеством устройств, туманные архитектуры демонстрируют лучшую масштабируемость и устойчивость. Эти результаты подчеркивают туманные вычисления как жизнеспособное решение для приложений реального времени и IoT, требующих ответов с низкой задержкой и эффективного распределения ресурсов.

Ключевые слова: облачные технологии, туманные технологии, производительность, сравнительный анализ Eclipse.

Introduction

Today’s computing paradigms have evolved from distributed parallel computing to network-based and cloud computing. Cloud computing offers numerous advantages, including scalability, on-demand resource allocation, reduced management effort, a flexible pay-as-you-go pricing model, and simplified application and service deployment [1-3]. However, the behavior of these complex systems can exhibit non-linear characteristics, particularly under high load or in unpredictable network conditions. Cloud computing is now widely adopted across various industries, including manufacturing, healthcare, telecommunications, and finance. However, despite its extensive use, cloud computing still has certain limitations.

One fundamental limitation of cloud computing is the connectivity constraint between the cloud and end-user devices. This connection is established via the Internet, which is not always suitable for cloud applications that require low latency [3]. Examples of such applications include connected vehicles, wildfire detection and suppression, smart grids, and content delivery [4-6]. Additionally, cloud applications are often distributed and composed of multiple components [7]. As a result, certain components may be deployed across different cloud environments (e.g [8-10]), increasing latency due to overhead associated with inter-cloud communication.

Fog computing (FC) has emerged as a computational paradigm designed to address these challenges [11]. The concept is actively promoted by the OpenFog Consortium, which has released several official documents on the topic [12]. FC is often referred to as “the cloud closer to the ground”, as it extends the traditional cloud architecture to the network edge. In this model, latency-sensitive components can be processed at the network periphery, while non-time-sensitive and resource-intensive components remain in the cloud. Figure 1 illustrates the core advantages of FC.

Thus, FC represents a promising approach to overcoming existing limitations of cloud-based solutions. While it has traditionally been discussed in the context of the Internet of Things (IoT), its applicability extends to a broader range of use cases, including industrial automation, intelligent transportation systems, and distributed monitoring systems [11-12]. However, several challenges remain, such as the development of unified standards, efficient management of distributed resources, and ensuring data security. Future research should focus on optimizing resource allocation between cloud and fog nodes, as well as refining coordination mechanisms across different computing layers.

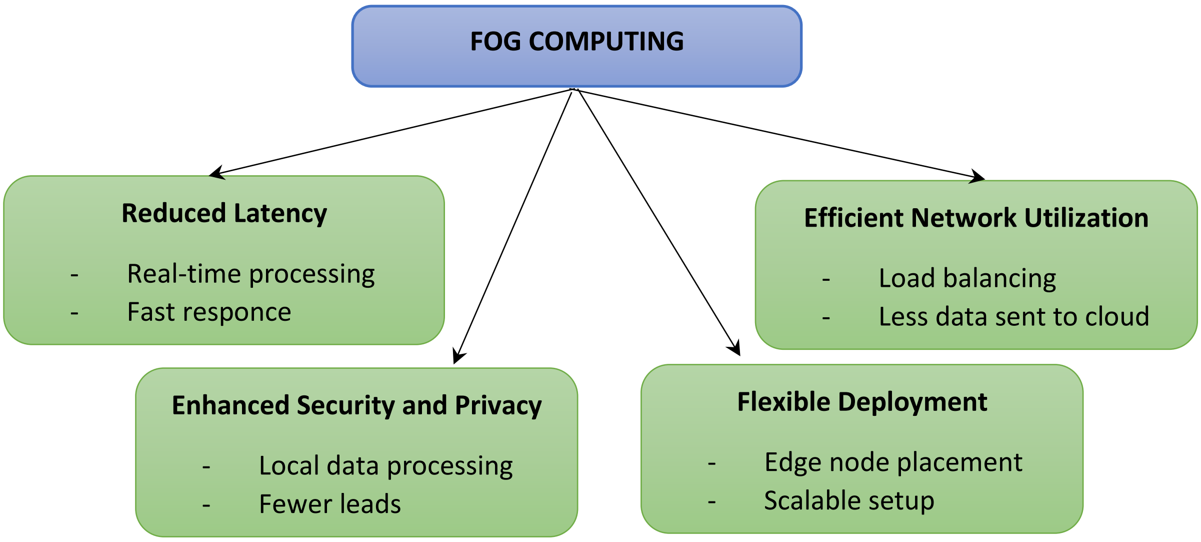

Figure 1 – Key advantages of Fog Computing

When designing cloud and computing systems, it is crucial to develop an optimal routing system that can dynamically adapt to varying network conditions and security requirements. An essential aspect of this process is achieving an optimal balance between resource distribution and minimizing the number of network nodes, which directly impacts the energy efficiency of the system [13-14].

Among the primary factors influencing system performance are network traffic characteristics. In cloud-centric models, frequent data transmissions to remote servers can increase latency. Conversely, fog computing facilitates edge processing, reducing delays but demanding efficient load distribution across fog nodes.

A comparative performance evaluation of cloud and fog computing requires simulation-driven modeling of real-world scenarios, including load balancing, power consumption, and transmission delay analysis. Addressing these aspects – energy efficiency, traffic reduction, and latency minimization – is paramount in selecting the most appropriate computational architecture for a given application context.

Problem Statement

This study aims to improve the deployment efficiency and performance of distributed systems by utilizing fog computing technologies. While cloud computing offers significant benefits, its limitations, particularly those related to latency and resource allocation, require exploration of alternative paradigms. Fog computing, with its capability to process data closer to the source, represents a promising solution.

The central goal of this research is to perform a comparative analysis of cloud and fog computing in terms of energy consumption, network traffic, and latency. These metrics are evaluated with respect to different network topologies and varying numbers of nodes to determine the scalability and adaptability of each computing model.

To ensure reproducibility and accuracy, all experiments will be conducted using the Java programming language within the Eclipse integrated development environment. The results of this modeling-based study will provide a foundation for designing more efficient, responsive, and sustainable computing infrastructures.

Methods

To simulate and evaluate the performance of cloud and fog computing architectures, we develop a series of experiments using the Java programming language within the Eclipse integrated development environment (IDE) [15]. Java offers robust libraries for concurrent and network-based programming, making it well-suited for modeling distributed computing systems.

Eclipse was chosen due to its comprehensive support for modular development, debugging tools, and integration with external simulation libraries. The modeling environment allows for flexible configuration of network topologies, node behaviors, and communication patterns, which is essential for accurately assessing system performance under different conditions.

The experimental setup involves simulating various network configurations to analyze how key performance metrics – such as energy consumption, traffic volume, and data transmission delay – respond to changes in system topology and node count.

To evaluate the performance differences between cloud and fog computing systems, we developed a simulation model representing typical data transmission scenarios. The architecture includes two core variants: a cloud-based system (Fig.2) and dog-enhanced system (Fig.3). Both models simulate message flow from sensors to a processing server and back to an actuator, thus completing a closed feedback control loop.

In the modeled systems, sensor nodes serve as data sources, periodically sending measurements to a central server for processing and decision-making. After performing predictive analysis or control logic, the server returns commands to end-user devices connected to actuators. These operations are computationally intensive and typically require the power of remote cloud servers. However, transmitting large volumes of data to remote cloud centers introduced noticeable latency, which may be unacceptable for real-time or latency-sensitive applications. To mitigate this, the fog-based model introduces intermediate processing nodes – fog servers – positioned closer to the data sources. These fog nodes perform preliminary data processing and reduce the load on cloud servers by transmitting only aggregated or refined data upstream.

Figure 2 illustrates the architecture of the cloud computing system. It consists of multiple sensor devices (D1, D2, ..., D10), a central router, and a remote cloud server. Data flows upward from the sensors to the router and then to the server. In the fog computing variant (Fig.3), additional fog nodes are placed between the sensors and the cloud, enabling edge-level computation and reducing end-to-end latency. Data from sensors D1, D2, and D3 are sent to fog server Fog1, data from sensors D4, D5, D6 are sent to fog server Fog 2, data from sensors D7, D8, D9 are sent to fog server Fog 3 respectively. The number of branches coming from fog servers can be increased, however, as the number of devices increases, the delay of data packets will increase.

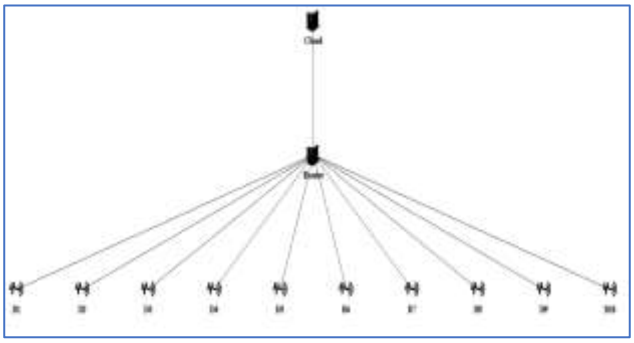

Figure 2 – Cloud Computing System Architecture

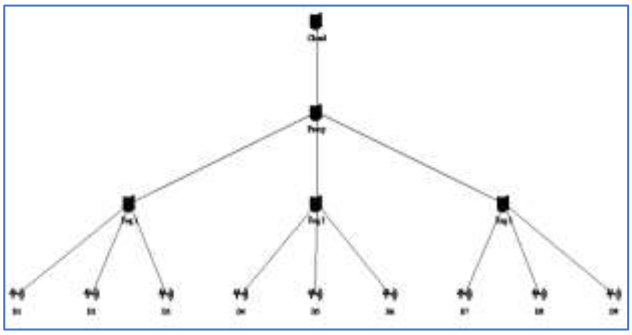

Figure 3 – Fog Computing System Architecture

This simulation setup allows for controlled analysis of how varying network topologies and the number of nodes affect energy efficiency, data traffic, and system responsiveness in both architectures. This scheme was also tested for the degree of optimality of systems using fog technologies [16].

Results and Discussion

The input parameters used in the simulation for the cloud computing architecture are presented in Table 1.

Table 1. Simulation Parameters for Cloud Computing

Parameter	Cloud Server	Router
MIPS	44 800	2 800
RAM (Mb)	40 000	4 000
Uplink Bandwidth (Mb)	100	10 000
Downlink Bandwidth (Mb)	10 000	10 000
Level	0	1
Power in Active Transmission (W)	16·103	107.339
Power in Idle Mode (W)	16·83.25	83.43

These parameters include computing capacity in MIPS (Million Instructions Per Second), memory (RAM), uplink and downlink bandwidths, network hierarchy level, as well as power consumption in both active and idle modes. The input values for the fog computing simulation are listed in Table 2.

The last two rows in Tables 1 and 2 represent the power consumption of devices under two operational modes: transmission and idle. For the cloud server, the idle power consumption is indicated as 16×83.25 W, which equals 1332 W. This value assumes that the cloud data center comprises 16 identical units, each consuming 83.25 watts in idle mode. Similarly, the transmission power is calculated as 16×103 W, yielding a total of 1648 W. These aggregated power values reflect a more realistic representation of energy usage in large-scale cloud infrastructures, where multiple servers operate simultaneously.

Table 2. Simulation Parameters for Fog Computing

Parameter	Cloud Server	Proxy Server	Cloud Server
MIPS	44 800	2 800	2 800
RAM (Mb)	40 000	4 000	4 000
Uplink Bandwidth (Mb)	100	10 000	10 000
Downlink Bandwidth (Mb)	10 000	10 000	10 000
Level	0	1	2
Power in Active Transmission (W)	16·103	107.339	107.339
Power in Idle Mode (W)	16·83.25	83.43	83.43

This approach ensures that simulation parameters better approximate real-world scenarios and enables more accurate performance and energy-efficiency comparisons between cloud and fog computing models. Further analysis compares these parameters with those obtained for fog computing architectures, in order to identify potential benefits in responsiveness and resource efficiency. The results of the simulations are used to assess the scalability and performance trade-offs between the two models under varying network loads.

Next, a correlation matrix for the cloud network was constructed. A correlation matrix is a table showing the correlation coefficients between several variables [17]. Each element of this matrix reflects the degree of linear dependence between two variables. Using correlation analysis helps identify the most sensitive performance indicators and can be beneficial for optimizing the distribution of computational tasks between cloud and fog resources.

Figure 4 presents a heatmap of the Pearson correlation matrix, illustrating the relationships between various performance metrics in a cloud computing network. The correlation values range from 0.4 to 1.0, with darker shades representing stronger positive correlations. The analysis reveals that parameters such as total latency (TL Total latency), energy consumption of the cloud server (E cloud), total energy consumption of fog nodes (Total E fog), total energy consumption of end devices (Total E device), and total network usage show a high degree of correlation with the number of devices and the number of fog servers. This indicates that as the number of connected devices increases, system load also increases in terms of computation, energy consumption, and network utilization.

The same network parameters for fog computing systems were considered. Figure 5 displays the Pearson correlation matrix [18] visualized as a heatmap, representing the relationships among different performance indicators in the fog computing network. Unlike the cloud architecture, this matrix shows a broader variation in correlations, including both strong and weak dependencies between parameters.

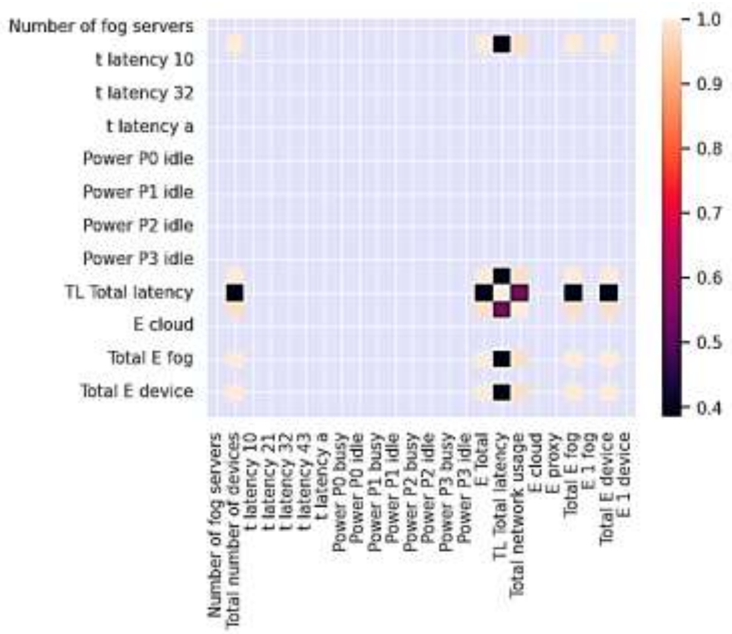

Figure 4 – Correlation matrix for the cloud-based network

Notably, the "Total numbers of devices" is strongly positively correlated with "Total network usage" and "Total energy consumption (E Total)", indicating that an increase in connected devices leads to higher load on network bandwidth and energy demands across the system. However, is minimal or even negative correlation between the number of devices and latency metrics such as "*t latency* 21" and "*t latency* 43", which refer to the time delay from node 2 to 1 and from 4 to 3, respectively. This suggests that in fog-based architecture, localized data processing can help reduce the impact of network size on transmission delays.

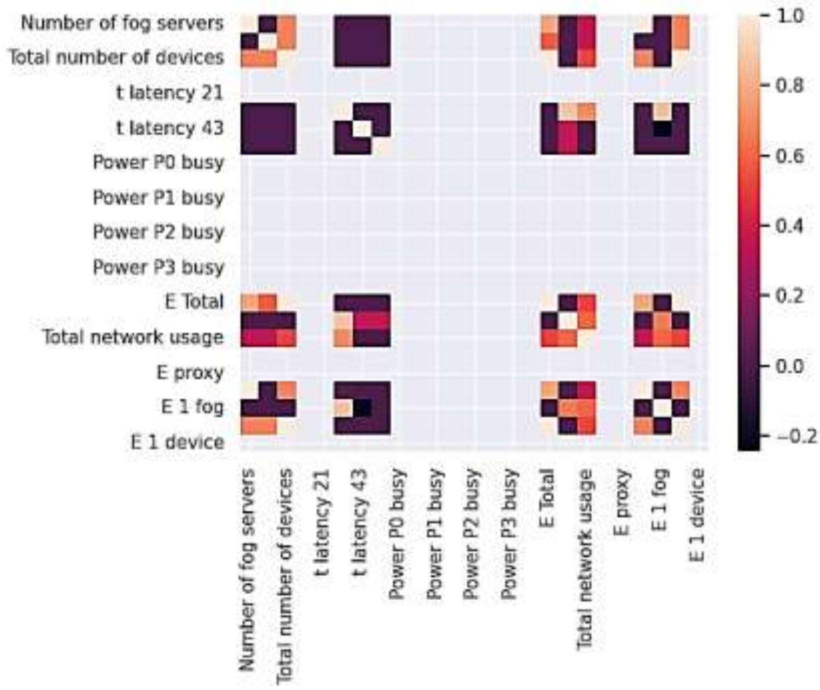

Figure 5 – Correlation matrix for the fog computing network

The energy consumption at individual components (such as *E proxy*, *E*1 *fog*, and *E*1 *device*) varied correlations with power usage at fog servers (*Power P*0 *busy* to *Power P*3 *busy*), emphasizing the distributions nature of energy demands in fog environments. Moreover, the correlation of total energy usage with power metrics highlights that fog nodes play a critical role in balancing energy efficiency and latency.

Overall, this matrix provides valuable insight into the dynamics of fog computing and its effectiveness in decentralizing computing resources, thereby reducing latency while maintaining energy performance.

The correlation matrices in Figures 4 and 5 reveal notable differences in system behavior between cloud and fog computing architectures.

1. Latency Correlation:

Cloud: Latency values exhibit a high positive correlation with the total number of devices and network usage. This indicates that as the network scales, latency increases significantly.

Fog: Latency shows weak or even negative correlation with device count, demonstrating better scalability and responsiveness due to distributed data processing at fog nodes.

2. Energy Consumption:

Cloud: Total energy consumption is strongly correlated with cloud server activity and device count, reflecting centralized energy load.

Fog: Energy consumption is distributed among proxy and fog nodes, with diverse correlations depending on the node and network structure.

3. Network Usage:

Cloud: Highly dependent on the number of devices and directly affects latency.

Fog: Still correlated with device count but less impact on latency, suggesting better bandwidth optimization.

4. Scalability:

Cloud: Performance declines (higher latency and energy use) with network growth.

Fog: More scalable due to localized processing, reducing global traffic and delays.

These results can be conveniently presented in the form of a comparative Table 3.

Table 3. Summary Table: Correlation Analysis Insights

Metric	Cloud Computing	Fog Computing
Latency vs Devices	Strong positive correlation	Weak or no correlation
Energy vs Devices	Strong correlation to centralized cloud node	Distributed correlation (proxy, fog nodes)
Network Usage vs Devices	Strong positive correlation	Moderate correlation
Latency vs Network Usage	High correlation	Low to moderate correlation
Energy Distribution	Centralized (cloud and router)	Decentralized (fog and proxy nodes)
Scalability	Limited due to latency and energy increase	Higher scalability due to localized processing

Conclusion

In conclusion, this study has demonstrated the performance advantages of fog computing over cloud computing in terms of latency, energy consumption, and network efficiency. These improvements are critical for supporting real-time applications and the growing demands of IoT. Future work should investigate the optimization of fog computing architectures from the perspective of radio physics, specifically focusing on dynamic spectrum allocation, adaptive modulation techniques, and energy-efficient wireless transmission protocols to further enhance performance and scalability. Furthermore, the principles of radio wave propagation modeling can be integrated into the simulation models to provide more realistic evaluations of fog computing deployments in diverse environments.

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