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Ranking and Validation of Variables Determining Fog Computing Performance in IoT Applications

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Abstract: ***Cloud computing capabilities are extended to the network's edge with fog computing, which offers low-latency processing and storage, making it essential for Internet of Things (IoT) applications. Numerous network and computational factors, however, can significantly influence a substantial impact on fog computing systems' performance. The main objective of this study is to rank and validate the most important elements that affect fog computing performance, particularly when it comes to Internet of Things applications. We investigate five key variables: Packet Loss Rate (PLR), Queue Time, Latency, Channel Utilization, and Throughput, in terms of their influence on the overall performance of fog nodes and IoT systems. Through a comprehensive evaluation using both theoretical models and experimental data, we establish a ranking for these variables based on their direct impact on fog computing performance. The analysis shows that Packet Loss Rate emerges as the most critical factor, as higher packet loss can severely degrade the reliability of communication between fog nodes and IoT devices. This is followed by Queue Time, which represents the delay incurred in processing incoming data requests; longer queue times contribute to increased system latencies and reduced throughput. Latency itself, although related to the aforementioned factors, ranks third as it directly affects the responsiveness of real-time applications. Channel Utilization, a measure of how effectively the communication channel is used, ranks fourth, influencing the overall network capacity and bandwidth efficiency. Lastly, Throughput is ranked fifth, as it is closely tied to the network's ability to transmit data efficiently but has a secondary effect compared to other variables in terms of performance degradation. These rankings were validated through consultation with industry experts, confirming the crucial roles that PLR and Queue Time play in optimizing fog computing performance. These findings provide valuable insights for researchers and practitioners seeking to improve the design and implementation of fog computing systems, highlighting the need for targeted optimizations in the most impactful variables to achieve enhanced performance in IoT environments.***

Keywords: Fog computing, IoT, Packet Loss Rate, Queue Time, Latency, Channel Utilization, Throughput, Performance ranking, Network optimization

1. Introduction

Fog computing is essential in the quickly developing Internet of Things space because it enables real-time data processing at the network's edge, reducing latency and enhancing application performance (Zhou L. L., 2021). Key performance indicators have a significant impact on the fog layer's effectiveness. To make sure fog computing systems can effectively handle and analyze data from a variety of IoT devices, it is essential to recognize and modify these features (Wang Y. L., 2024). Understanding these factors not only enhances specific IoT applications but also boosts overall reliability and scalability of fog computing systems in a data-intensive setting. Figure 1 below provides a summary of the variables which determine fog computing performance.

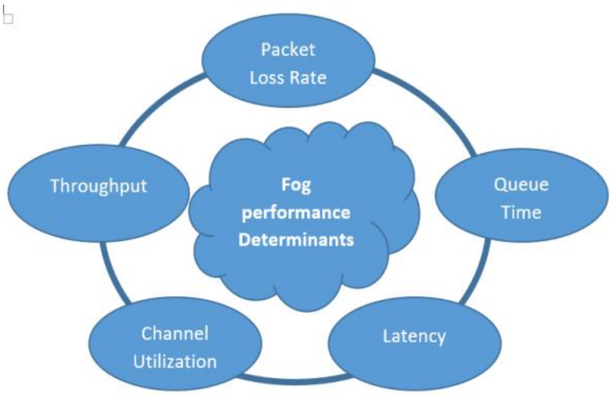

Figure 1: Variables determining fog computing performance

Fog layer extends the concepts of cloud computing to the network edge by distributing processing resources over numerous nodes, including routers, switches, and local servers (Amin, 2022). By processing data closer to its source, this distribution aims to improve data efficiency and decrease reaction times. Even with these developments, latency issues still exist, which affects fog computing systems' effectiveness and performance. Optimizing these systems requires an understanding of the different variables and how they affect fog performance.

2. Related Work

Numerous studies have examined the effectiveness of fog computing in Internet of Things (IoT) applications, with a number of them concentrating on the effects of different network and system characteristics. Since packet loss has a direct impact on distributed systems' dependability and quality of service, numerous studies have looked into the function of packet loss rate (PLR) in fog computing. Zhang et al. (2022), for example, investigated the connection between PLR and fog node communication and showed that higher packet loss causes noticeable delays and performance deterioration in real-time Internet of Things applications. In a similar vein, queue time has been found to be a significant determinant of fog computing performance.

Liu et al. (2023) emphasizes how crucial it is to optimize queue management in order to decrease processing delays and enhance reaction times in fog nodes, especially for latency-sensitive Internet of Things operations like industrial automation or autonomous driving.

In fog computing, latency has been thoroughly investigated, with an emphasis on lowering end-to-end delays in edge computing settings. In order to satisfy the demanding real-time requirements of several IoT applications, low-latency processing in fog nodes is essential, according to research by Kumar et al. (2024), which examines how excessive latency impairs the responsiveness of IoT devices. The function of channel utilization has also been investigated; Wang et al.'s study from 2023, highlights how it affects network efficiency and how available bandwidth is distributed between fog nodes and IoT devices.

Research by Zhao et al. (2022) shows that high throughput guarantees adequate data transfer capabilities for fog systems, but its efficacy is frequently dependent on the optimization of other factors like PLR and Queue Time. Throughput has been linked to overall system performance. Few studies provide a comprehensive ranking and validation of these variables specific to fog computing in IoT, despite the fact that these individual elements have been researched separately. This emphasizes the necessity of integrated approaches to performance improvement.

3. Methodology

In this work, we use the Random Forest Recursive Feature Elimination (RFE) technique to rank the important factors that affect fog computing performance in Internet of Things (IoT) applications. By facilitating edge processing in Internet of Things settings, fog computing creates additional difficulties with regard to resource management, latency, and network efficiency. Finding and ranking the most important performance metrics is essential for fog computing system optimization. Packet Loss Rate (PLR), Queue Time, Latency, Channel Utilization, and Throughput are among the characteristics taken into account in this work. Each of these elements has a major impact on how effective and efficient fog computing systems are overall in practical Internet of Things applications.

We use Random Forest, an ensemble learning technique renowned for its resilience and capacity to manage intricate, high-dimensional datasets, to rank these variables. To determine feature importance, Random Forest constructs several decision trees, which is perfect for figuring out how much each variable contributes to a prediction model. We use the Recursive Feature Elimination (RFE) strategy, which iteratively removes the least significant features according to their effect on model performance, to improve this feature selection procedure. By lowering dimensionality, avoiding overfitting, and keeping only the most important variables, RFE contributes to increased model correctness.

A synthetic dataset is created for this research in order to replicate IoT setups with different conditions for every variable. The dataset makes it possible to validate the ranking approach and conduct controlled experiments. We systematically determine the most important performance parameters that affect fog computing by combining RFE with Random Forest. The quantitative ranking of variables produced by this method can help guide future fog computing system optimization efforts, particularly in latency-sensitive Internet of Things applications. Figure 2 below shows the process flow in the ranking algorithm applied.

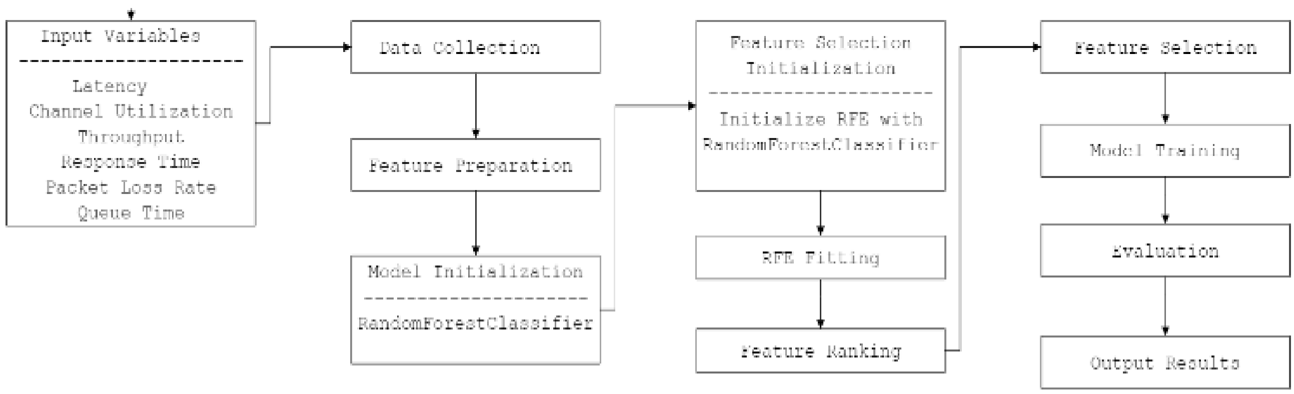

Figure 2: Process flow for raking fog computing performance determinant variables

4. Results

Table 1: Results for Ranking of variables using machine learning model (RF-RFE)

Feature	Rank
Packet Loss Rate	1
Queue Time (ms)	2
Latency (ms)	3
Channel Utilization	4
Throughput (Mbps)	5

Packet Loss Rate is prioritized first because it directly affects data integrity and reliability. High packet loss can lead to re-transmissions and degraded application performance, making it critical to address for any fog computing application. Next, Latency is essential, as it measures the delay in data transmission. In fog computing, low latency is vital for real-time applications, such as IoT devices, where even small delays can significantly affect performance.

Queue Time follows closely, as it reflects the waiting time for data processing. Reducing queue time enhances system responsiveness, contributing to a better user experience and efficient resource utilization. Throughput (Mbps) ranks next, representing the data transfer rate. While high throughput is important, it is often influenced by the preceding factors, as high packet loss and latency can hinder overall throughput.

Lastly, Channel Utilization measures bandwidth efficiency. Although important, its significance is generally derived from the other variables, making it the least critical in this specific context. This order ensures a comprehensive approach to optimizing fog computing performance. Response time was excluded as a performance variable because it overlaps with latency and queue time, which already capture essential delays in data processing and transmission. These variables provide more direct insights into the efficiency of data handling in fog environments. Additionally, response time may not offer unique advantages in specific contexts where real-time performance is paramount, as the emphasis shifts to metrics like packet loss and latency that significantly impact application quality. By focusing on these key indicators, researchers can streamline analysis and optimize system performance more effectively.

Validation of variable ranking using industry experts.

The study sampled 30 ICT experts with IOT-related Certifications. After the first expert is identified, a pervasive approach was used to link up the next expert in the industry. The necessary education back ground include IOT certification on the common IOT professional courses. This is because the IOT specialty is still in its early stages, and the specialists are not evenly distributed in the industries. Also, statistically, the variability level of the population is very low, therefore the sample size is considered sufficient to provide accurate and reliable estimates of population parameters, to minimize sampling errors, and detect meaningful effects or relationships with adequate statistical power. A pilot study was carried out by administering questionnaires to ten industry experts with a intention of testing the data collection tool for consistency. The Cronbach's alpha values was realized sing the following formula:

$$\alpha = \left(\frac{k}{k-1}\right)\left(\frac{sy^2 - \varepsilon s_i^2}{s^2 y}\right)$$

= (6/5)((6.62-2.33)/6.62)
= 0.8

This confirms that the data collection instrument is reliable and therefore suitable for the study.

Analysis of variable ranking by industry experts using Kendall's coefficient of concordance

There were a total of 35 respondents to the survey, slightly above the target of 30.

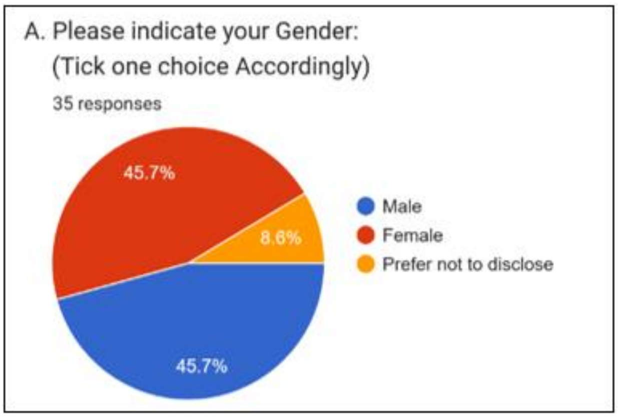

Figure 2: Distributions of respondents by gender

There was generally gender balance among the respondents, with 45.7% indicating male and female respectively. 8.6% of the respondents did not declare their gender as per figure 2 above.

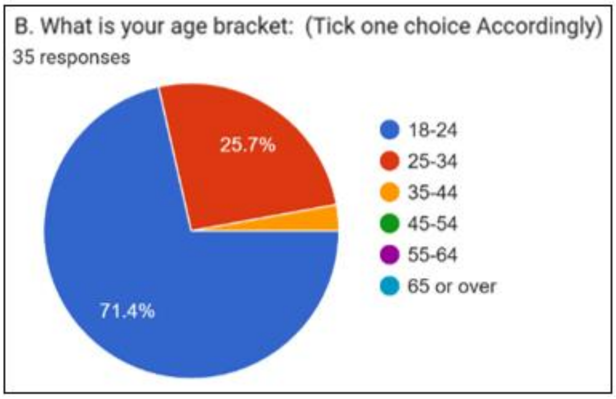

Figure 3: Distribution of respondents by age

Majority of the respondents were fairly young, where 71.4% being between 18-24 years. 2.9% were between 35-44 years of age, as indicated in figure 3 above.

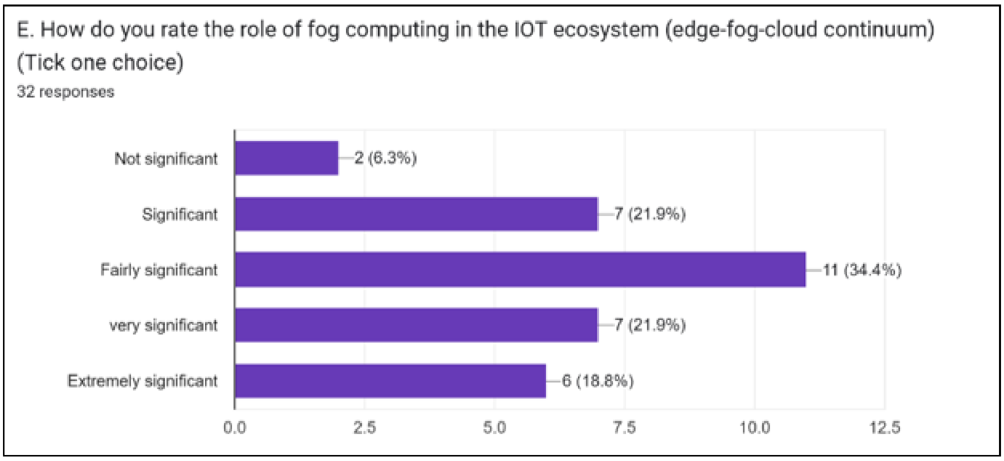

Figure 4: Rating role of fog computing in IOT

More than 93% of the respondents rated fog computing to play a significant role in IOT. The 6.3% were treated as outliers, as indicated in table 4 above.

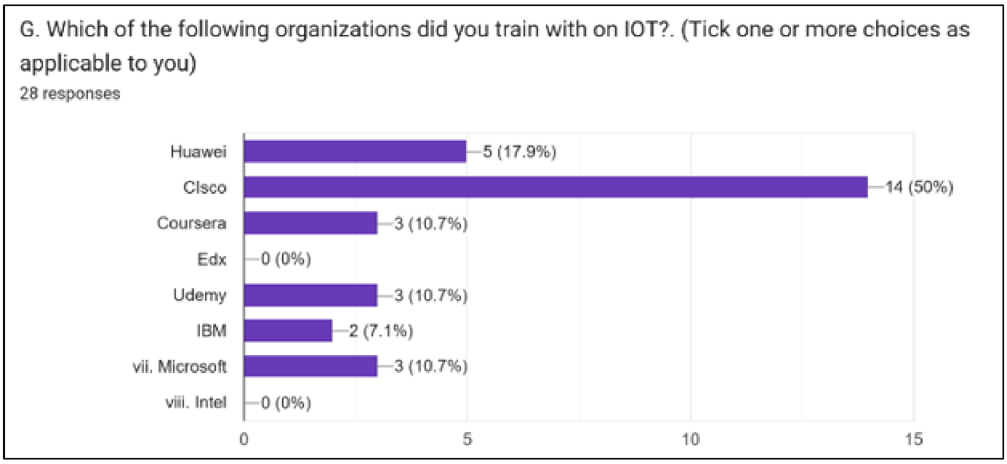

Figure 5: Organizations where respondents have trained IOT with

28 of the 35 respondents have already undergone professional training on IOT, majority of whom have gone through Cisco professional training as indicated in figure 5 above.

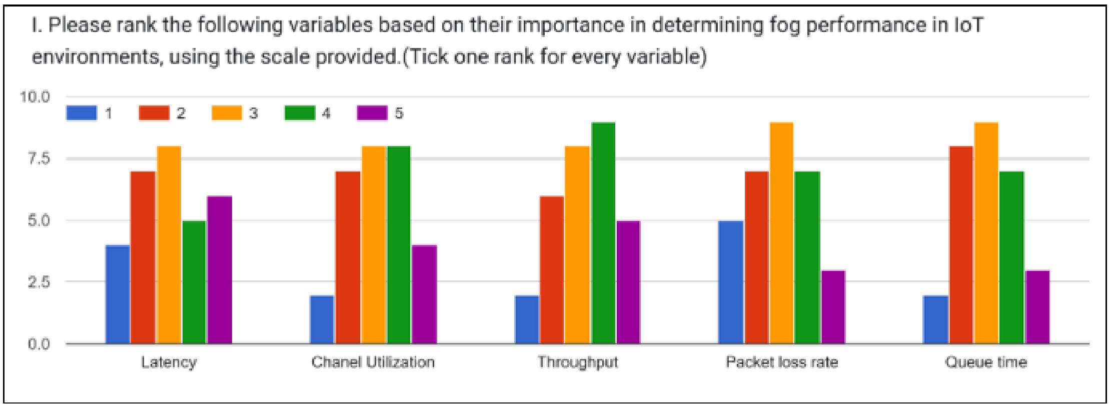

Figure 6: Overall ranking of variables.

In a snapshot, there seems to be a consensus on ranking of the variable as displayed in figure 6 above. Detailed analysis reveals the ranking as indicated below.

Table 2: Summary of data collected from industry experts on variable raking.

RSPD	Latency	Chanel Utilization	Throughput	Packet loss rate	Queue time
A	3	4	5	1	2
B	3	4	5	1	2
C	2	5	4	3	1
D	3	4	5	1	2
E	5	4	3	2	1
F	3	5	4	1	2
G	3	5	4	1	2
H	3	4	5	1	2
I	3	4	3	2	1
J	3	4	5	2	2
K	3	4	5	2	1
L	4	3	5	1	2
M	3	4	5	1	2
N	3	4	5	1	2
O	3	4	5	2	1
P	3	4	5	1	2
Q	3	5	4	1	2
R	4	5	3	2	1
S	3	4	5	1	2
T	3	5	4	2	1
U	3	4	5	2	1
V	3	4	5	1	2
W	1	3	5	3	2
X	3	1	5	3	2
Y	3	4	5	1	2
Z	3	5	4	2	1
AA	3	3	4	2	1
AB	3	4	5	1	2
AC	3	4	5	1	2

Kendall's Value W: =0.728656361
Chi square: =84.52413793
P value: =0.0436568

Kendall's value (W) of 0.728656361 indicates moderate to strong agreement among the respondents. They are largely in agreement, but there is still some variation in how they rank the fog computing performance variables. This suggests that the rankings are fairly consistent**,** but not perfectly aligned. The p-value was computed to be 0.0436568. Since the p-value is less than 0.05, it indicates statistically significant agreement at the 5% level. This means that the observed level of agreement among the raters is unlikely to have occurred by random chance, and the rankings represent a real pattern of consensus. The Chi-square value is 84.52413793 for the ranking output. The relatively large Chi-square statistic supports the notion that the rankings show significant deviation from randomness. It indicates that the observed agreement is not due to chance, further confirming the statistical significance of the rankings.

The moderate to strong agreement (W = 0.73) among the raters, along with the statistically significant p-value (0.0436568)**,** suggests that the rankings of the fog computing performance variables are reliable and meaningful. The raters largely agree on which variables are more important for fog computing performance. Given the statistical significance of the agreement, the rankings of the fog computing variables (Latency, Channel Utilization, Throughput, Packet Loss Rate, and Queue Time) can be considered trustworthy**.** There is a strong pattern of consensus that the raters' rankings are not due to random chance. Since the ranking process shows statistical significance**,** these rankings can be used with more confidence in making decisions about the relative importance of the variables. However, the moderate strength of agreement (W = 0.73) also indicates that further refinement or clarification in the ranking process could strengthen the consensus further.

5. Discussion

To make sure that the system's design and operational priorities match practical applications, industry experts had to validate the ranking of fog computing performance variables. In addition to guaranteeing that the performance measurements are thorough and in line with industry demands, expert validation aids in fine-tuning the ranking of these variables according to their practical usefulness.

A high degree of internal consistency among the experts who took part in the validation process is shown by the Cronbach's alpha value of 0.8. This implies that the respondents strongly agreed on the dependability and significance of the variables in determining fog computing performance, irrespective of their backgrounds. Generally speaking, a Cronbach's alpha of 0.8 is regarded as a good threshold, indicating that the measurement instrument used to collect the experts' data yields reliable and consistent results. In fog computing, where several measures must cooperate to guarantee peak system performance, this consistency is essential.

The findings are further validated by the demographic dispersion of the respondents. The results show a respectable gender diversity, with 45.7% of respondents being male and female (the remaining respondents did not specify their gender). This shows that the findings are reflective of a wide range of industry professionals. By ensuring that the results are not skewed by the viewpoint of one gender, gender diversity in expert validation can offer a more comprehensive understanding of the pertinent performance measures. Furthermore, the comparatively small proportion of responders (1.4%) in the 18–24 age range indicates that the majority of experts have substantial industry experience, giving their assessments and opinions additional weight.

Additionally, fog computing was evaluated as significant in IoT by 93% of respondents, indicating that the industry as a whole recognizes its significance. This high degree of agreement not only highlights fog computing's increasing importance but also supports the widespread belief that improving its performance is essential to the effective deployment of IoT systems. Because fog computing is widely used in edge computing scenarios where latency, throughput, and response times are crucial, the expert validation process offers a crucial basis for giving these metrics top priority in operational and design models.

The most important factors for fog computing performance can be identified with the assistance of expert evaluations. Response time, throughput, and latency are frequently seen as critical measures, particularly in Internet of Things settings where real-time data processing is crucial. Because they have a direct impact on the system's capacity to manage massive data volumes effectively, variables like queue time and packet loss rate also aid in improving the system's performance assessment. Organizations can have a better understanding of how to prioritize these metrics in the design of fog computing systems that are responsive and efficient by validating these factors through expert feedback.

Notably, 28 of the 35 respondents had received professional training in IoT, which greatly increases the validity and applicability of their responses. These professionals' assessments are extremely relevant for assessing important performance measures since they are knowledgeable about the requirements and difficulties of IoT systems and possess both theoretical and practical expertise.

The specialists are skilled at comprehending how each of these factors impacts fog computing systems' total performance because of their training. For example, in real-time IoT applications where rapid data processing is essential, latency and throughput are crucial. Likewise, to guarantee data integrity and reduce transmission delays, queue time and packet loss rate are crucial. The professionals assist in determining which performance aspects should be given priority in order to guarantee effective, scalable, and dependable fog computing systems in Internet of Things environments by validating the significance of these variables. This professional validation procedure yields useful information for fog computing deployment optimization.

6. Conclusion

This study ranked Packet Loss Rate, Queue Time, Latency, Channel Utilization, and Throughput as key determinants of fog computing performance in IoT applications, with Packet Loss Rate and Queue Time proving most critical. Validated by experts, these findings underscore the need to prioritize data reliability and processing delays in system design. While synthetic data provided a solid foundation, real-world testing remains a vital next step. These insights pave the way for more responsive and efficient IoT ecosystems

7. Future Work

Although industry experts' insights have verified the existing technique, large-scale, real-world IoT implementations will be necessary for additional validation. Future research will concentrate on improving the feature selection procedure, validating the model in a variety of use cases and situations, and expanding the rankings' usefulness for fog computing optimization in real-world settings.

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