

Analysis of Multi-Node QoS in Shrimp Pond Monitoring System with Fog Computing

Anisah¹⁾, Rizal Munadi²⁾, Yuwaldi Away³⁾, Al Bahri⁴⁾, Andri Novandri⁵⁾*

^{1,2,3,4,5)}Universitas Syiah Kuala, Banda Aceh, Indonesia

¹⁾a_nisah@mhs.usk.ac.id, ²⁾rizal.munadi@usk.ac.id, ³⁾yuwaldi@usk.ac.id, ⁴⁾albahri@usk.ac.id,
⁵⁾andrie.nov11@gmail.com

Submitted : Nov 28, 2023 | **Accepted** : Dec 3, 2023 | **Published** : Jan 1, 2024

Abstract: Most of Indonesia's territory consists of oceans, presenting a significant potential for developing the fisheries sector. Shrimp is among Indonesia's flagship commodities with substantial export potential. Internationally, Indonesia holds the fourth position as the largest exporter of frozen shrimp globally. However, shrimp cultivation faces various challenges, including declining water quality due to factors such as water sources and weather, which can adversely affect harvest yields. To preempt potential failures, employing smart devices and technology in shrimp cultivation offers an effective and efficient solution for monitoring and management. This study aims to analyze water quality monitoring in ponds considering the speed of data transmission from end devices to fog using Quality of Service (QoS) parameters like delay/latency, throughput, and packet loss. Data transmission tests were conducted at data rates of 5 Mbps and 10 Mbps, with a bandwidth of 1500 Mbps. The study involves three sensors—water temperature, pH, and salinity—placed in shrimp ponds. Test results showed a decrease in throughput by 1.54% at the sensor node and 2.99% at the sink node when packet data delivery encountered barriers like obstacles. There was a 74.13% increase in latency when the delivery distance extended to 35 meters. The achievable delivery range with low latency was up to 10 meters with barriers and 25 meters without. Thus, latency and throughput values vary depending on the presence of barriers and transmission distance. Barriers tend to increase latency and decrease throughput.

Keywords: Fog Computing, Quality of Service, Sensors, Water Quality

INTRODUCTION

The shrimp cultivation process requires significant effort, especially in managing water quality such as water temperature, salinity, and pH levels to prevent crop failure (Damayanti & Sugiarto, 2022; Mashari et al., 2019). Uncertainties in weather can also lead to a decline in water quality, resulting in reduced yields and production (Fuady et al., 2013). To address these issues, Internet of Things (IoT) technology has been implemented to monitor water quality in ponds. The use of IoT technology serves several functions, including data collection, transmission, and processing over the internet (Anwar & Abdurrohman, 2020; Komarudin et al., 2021). One infrastructure of IoT enabling resource and application access over the internet is cloud computing. Cloud computing comprises three parts: characteristics, service models, and implementation models (Amjad et al., 2017; Marcheriz & Fitriani, 2023). However, besides this option, another alternative is fog computing. The advantage of fog computing lies in its ability to handle downtime issues more swiftly. The primary difference between fog computing and cloud computing is decentralization and flexibility (Singhal & Singhal, 2021). The

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

benefits of fog computing include reducing latency, saving bandwidth, cutting operational costs, and enhancing security (Wawan Setiawan et al., 2022). The primary objective of implementing fog computing is to extend cloud services to the network edge, closer to data sources, and provide part of the computing and storage that was initially handled by cloud computing. Thus, it not only reduces the volume of data transmitted to the cloud but also addresses latency and privacy issues (Atlam et al., 2018; Datta et al., 2015; Nuridhuha et al., 2020).

In the study by (Maulana et al., 2016), IoT and fog computing technologies were employed to address online monitoring of water quality in shrimp ponds. This research utilized Wireless Sensor Network (WSN) and IoT applications to measure the water quality of shrimp ponds, including parameters such as water temperature, pH, salinity, and Dissolved Oxygen (DO). The research results indicated that the use of WSN and IoT applications had an effectiveness rate of 95.31% compared to conventional methods based on time effectiveness. Additionally, in the study conducted by (Pauzi et al., 2017), the monitoring process of shrimp pond water quality also utilized IoT technology with an additional application called Blynk. The measured water quality parameters included temperature, pH, and DO levels. Concerning the implementation of fog computing, a study by (Zainudin et al., 2021) attempted to apply fog computing in a smarthome application. Based on their research, the computation process time for monitoring temperature and humidity reached 0.152 seconds, adjusting the brightness of the lamp took 0.339 seconds, and face recognition computation took 6.602 seconds.

Based on this study, there is a need for research aimed at designing a fog computing model with a multi-node IoT-based approach to monitor the water quality of shrimp ponds in Ujung Batee, Aceh Besar. The parameters to be tested in this research include water temperature, pH, and salinity. The computational process will be conducted using data transmission speeds ranging from 5 Mbps to 10 Mbps and a bandwidth of up to 1500 Mbps. Analysis will be carried out by measuring the data transmission speed from the end device to the fog computing system while considering Quality of Service (QoS) parameters such as latency, throughput, and packet loss.

LITERATURE REVIEW

Quality of Service (QoS) refers to the ability to manage network traffic so that the provided services can meet specific standards. The main goal of QoS is to ensure a good user experience in network usage, especially in terms of speed, latency, reliability, and service quality. This can be applied in various contexts such as computer networks, telecommunications, and the internet. QoS parameters include throughput and latency. Throughput is the amount of data successfully transferred between two points in the network within a certain period. High throughput is required for applications that require large data transfers. Latency is the time taken for data to travel from source to destination. Low latency is highly essential in real-time applications (Samann et al., 2021).

Fog computing is a distributed computing model that leverages existing computational resources at the network edge, such as routers, switches, and gateways, to process data and store information, thus reducing latency and the load on the cloud (Nurcahya et al., 2023). This concept is similar to cloud computing, but differs in the location where data processing occurs. Fog computing places computational and storage capacities near the data source, at the network edge, to manage and analyze data locally before sending it to the cloud. The scheme of fog computing can be seen in Fig. 1. Fog computing aims to enhance system efficiency and responsiveness by reducing delays in data processing. This is relevant in environments where bandwidth limitations or the need for rapid responsiveness are crucial, such as in the Internet of Things (IoT), sensor networks, autonomous vehicles, or applications requiring real-time data processing. By utilizing fog computing, applications can respond faster because data can be processed locally without the necessity to be sent to the cloud, thereby reducing the load on the network and enhancing overall computational efficiency (Bellavista et al., 2019).

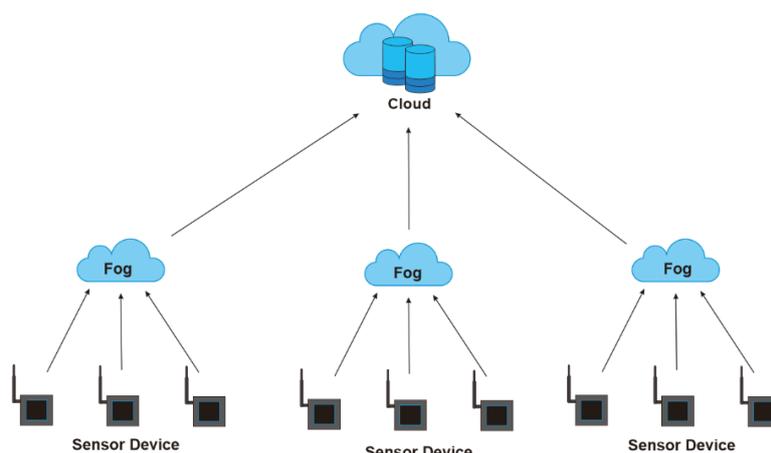


Fig. 1 Fog Computing Scheme

Wireless Sensor Network (WSN) is a network composed of numerous sensors interconnected wirelessly. Each sensor within this network is equipped with the ability to detect, measure, and monitor its surrounding physical environment. The sensors in a WSN operate cooperatively to gather data from their environment, then forwarding it to nodes or other devices within the network that lead to the data processing center. Information collected by these sensors can be used for various applications, such as environmental monitoring, early detection of natural disasters, health monitoring systems, resource management, or security applications. As depicted in Fig. 2, WSN typically consists of several key elements: sensor nodes responsible for collecting and forwarding data, and sink nodes where data from the network is collected and processed. WSN holds advantages in its ability to monitor large areas at relatively low costs without requiring complex cable infrastructures. However, there are challenges in terms of power management, data security, and efficiency in transmitting data in environments often limited in their power resources (Al-Jarrah et al., 2019; Zhao, 2014).

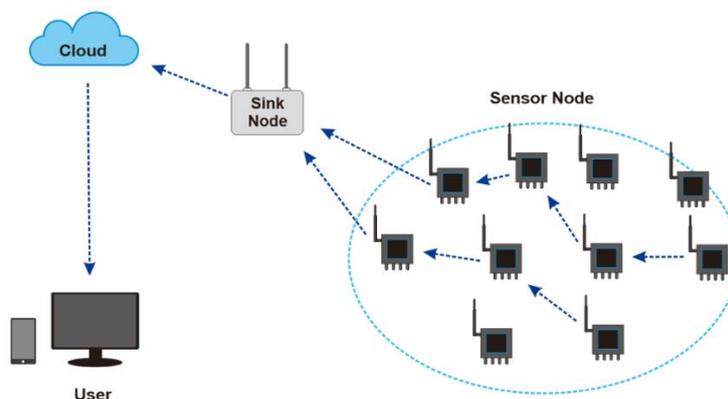


Fig. 2 Wireless Sensor Network

Water quality refers to the physical, chemical, biological, and even aesthetic characteristics or conditions of water (Simanungkalit et al., 2023). In shrimp farming, water quality is exceptionally vital as shrimp are aquatic organisms highly sensitive to their surrounding environment. Optimal water quality is key to successful shrimp cultivation. Primary parameters in assessing water quality for shrimp ponds include water temperature, salinity, and pH levels. Optimal water temperature plays a crucial role in shrimp growth and health. Extremely high or low temperatures can affect shrimp metabolism and health. Shrimp typically thrive in water with specific salinity levels; inappropriate salinity levels can induce stress in shrimp. Maintaining the balance of water pH is crucial because extreme changes in acidity or alkalinity can affect shrimp health and growth. Regular monitoring of water quality parameters helps maintain the appropriate balance, ensuring attention to the environmental conditions in shrimp ponds and thereby ensuring the health and success of shrimp cultivation (Kamiseti et al., 2012; Ramadhan et al., 2020).

*name of corresponding author



METHOD

The pond layout in this study comprises a total of 5 ponds with an area per ponds of less than 1 hectare, typically ranging between 3000-5000 m². Three sensor nodes were placed in each shrimp pond. The distance between the sensors ranged from 1 meter to 2.5 meters. As illustrated in Fig. 3, each sensor node is connected to the sink node through a wireless network to collect data from each sensor. Sensor node 1 monitors water temperature to assess the pond’s temperature. Sensor node 2 measures pH levels to determine the acidity in the water. Meanwhile, sensor node 3 measures salinity to assess the salt content in the water.

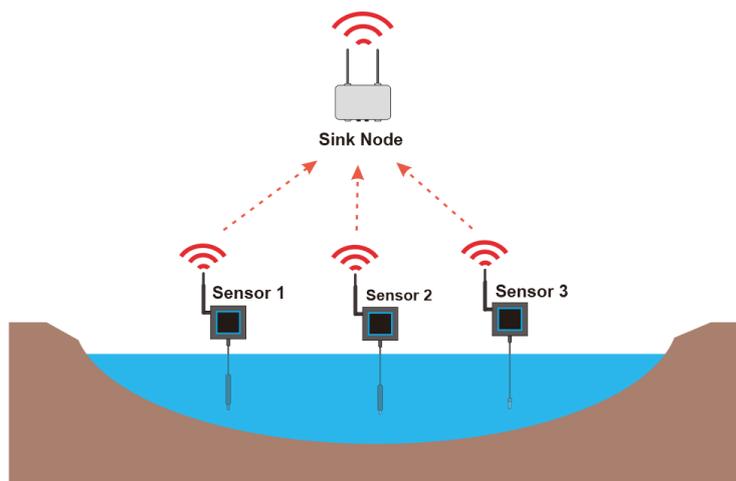


Fig. 3 Connection between Sensor Nodes and Sink Node

In its application, the sink node labels data according to each sensor node. This is done to facilitate data filtering by the fog node and enable easy identification of the sensor nodes to be executed. Once all data is labeled and received by the sink node, the next step involves storing the data to be sent to the fog node and accessed in the cloud. Access to the cloud is only possible when connected to the internet. Fig. 4 illustrates the configuration of the data transmission process from the nodes to the cloud, using the fog node.

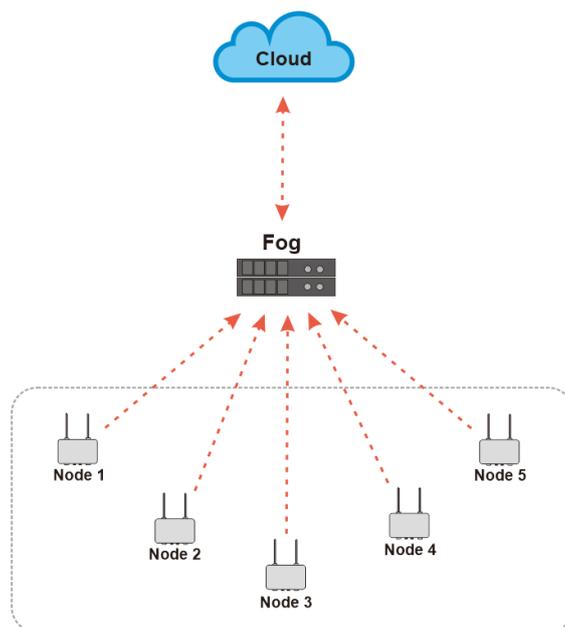


Fig. 4 Configuration of Data Transmission from Nodes to Cloud

*name of corresponding author



In the testing process, several stages of the scheme were conducted to measure QoS. These stages include throughput testing and latency testing. During throughput testing, data was transmitted from the sensor node to the sink node. This measurement was divided into two schemes: testing without obstacles and testing with obstacles. The next stage involved latency testing, which also consisted of two schemes. The first scheme tested based on the amount of packet data transmitted, measuring the latency from each sensor node. The second scheme involved testing based on the transmission distance between nodes, conducting transmissions both with and without obstacles.

RESULT

Throughput Testing

The throughput testing was conducted in two stages: throughput testing without obstacles and throughput testing with obstacles. The results of the throughput testing without obstacles are shown in Fig. 5. The sensor node achieved the highest throughput at a distance of 12 meters, reaching 0.135 bps, while the lowest throughput occurred at 22 meters, at 0.117 bps. The throughput values fluctuated with the transmission distance, with an overall average of 0.13 bps. At the sink node, the highest throughput was recorded at a distance of 16 meters, reaching 0.137 bps, while the lowest throughput occurred at 28 meters with a value of 0.131 bps. The throughput values at the sink node also exhibited fluctuations, with an overall average of 0.134 bps.

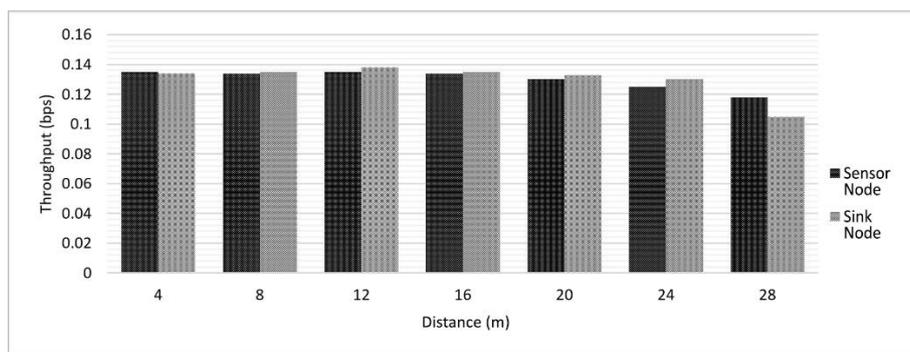


Fig. 5 The Comparison of Throughput without Obstacles between Sensor Node and Sink Node

Meanwhile, the results of throughput testing with obstacles are presented in Fig. 6. On the sensor node, throughput reaches its peak at distances of 4 and 12 meters, with a value of 0.135 bps, while the lowest value is recorded at a distance of 28 meters with 0.118 bps. Throughput values vary with transmission distance, with an overall average of 0.128 bps. On the sink node side, the highest throughput occurs at a distance of 12 meters with a value of 0.138 bps, while the lowest value is recorded at a distance of 28 meters with 0.105 bps. Throughput values on the sink node also experience fluctuations, with an overall average of 0.13 bps.

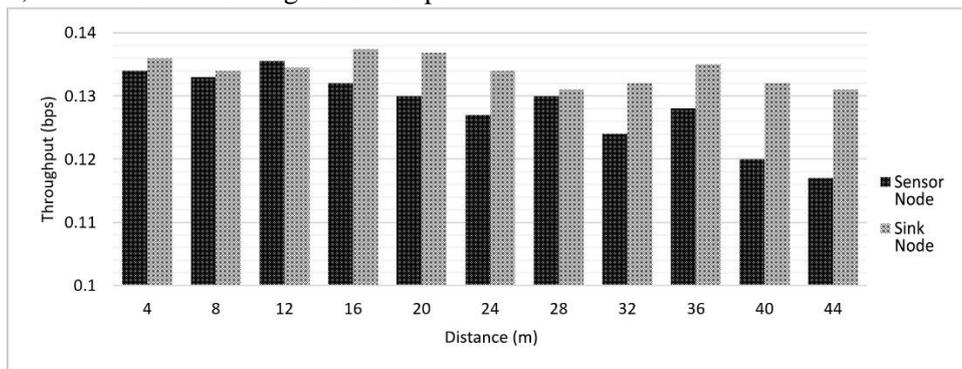


Fig. 6 The Comparison of Throughput with Obstacles between Sensor Node and Sink Node

*name of corresponding author



Latency Testing

Latency testing was conducted in two stages: latency testing concerning transmission distance and latency testing concerning packet data. Latency testing concerning distance involved placing sensor nodes in ponds with varying inter-node distances. The comparative results graph can be seen in Fig. 7. Based on the obstacle-based testing results, the furthest delivery distance achievable with low latency was 10 meters. Meanwhile, for obstacle-free conditions, it was 25 meters.

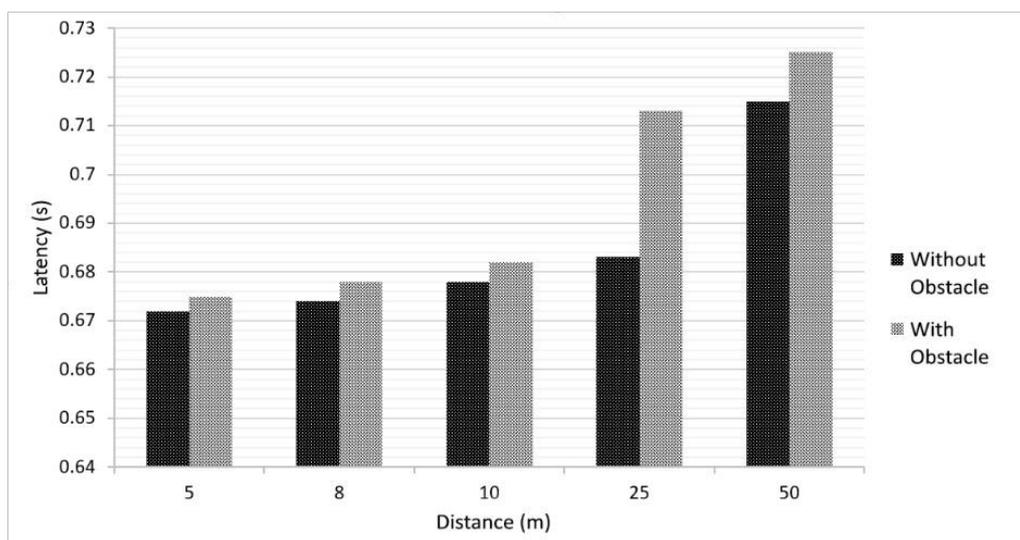
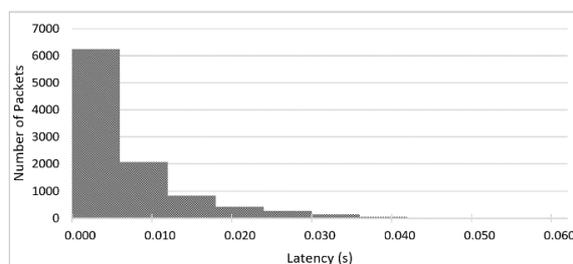
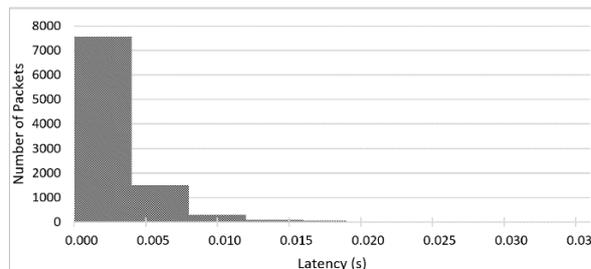


Fig. 7 The Comparison of Latency between Sensor Nodes and Sink Node Concerning Transmission Distance

Furthermore, latency testing concerning packet data was conducted on each sensor node, including water temperature, salinity, and pH, aiming to identify and evaluate latency values, both maximum and minimum, as well as packet loss. Latency testing on the water temperature sensor node used a data rate of 10 Mbps, bandwidth of 1500 Mbps, with a latency threshold of 0.07209 seconds. The test results indicated a maximum latency of 0.00953 seconds, minimum latency of 0.00019 seconds, and a packet loss of 1.21%. Latency testing in the data delivery scheme from the water temperature sensor node to the sink node is depicted in Fig. 8(a). With a packet size of 6300 bytes, the recorded latency was 0.039 seconds, nearing 0.04 seconds. The lowest latency occurred at a distance of 4 meters, at 0.347 seconds, while the highest was at 45 meters, at 0.386 seconds. In the data delivery scheme from the sink node to the fog node, the lowest latency was recorded at a distance of 4 meters, at 0.279 seconds, while the highest was at 45 meters, at 0.311 seconds.



(a)

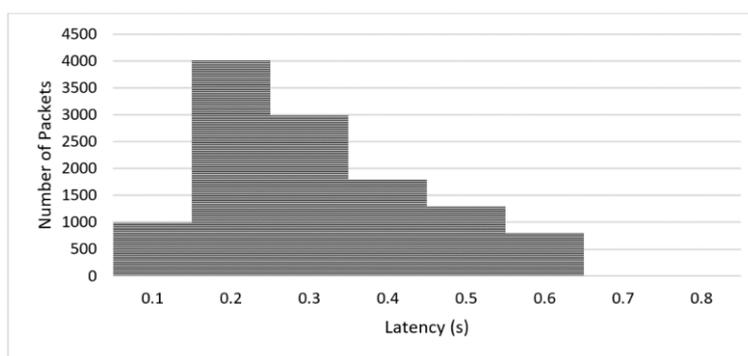


(b)

*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.



(c)

Fig. 8 Latency Graph Based on Data Transmission to The Sink Node at Each Sensor Node (a) Water Temperature, (b) Salinity, (c) pH

Then, on the salinity sensor node, a data rate of 5 Mbps was employed, with a bandwidth of 1500 Mbps and a latency threshold of 0.07455 seconds. According to the test results, the maximum latency recorded was 0.00543 seconds, with a minimum latency of 0.00019 seconds, and a packet loss of 0.76%. Latency testing in the data transmission scheme from the salinity sensor node to the sink node is shown in Fig. 8(b), using a packet count of 7800 bytes.

Furthermore, on the pH sensor node, a data rate of 5 Mbps and a bandwidth of 1500 Mbps were used, with a latency threshold of 0.07455 seconds. The test results showed a maximum latency of 0.00543 seconds, a minimum latency of 0.00019 seconds, and a packet loss of 0.76%. The latency test results in the data transmission scheme from the pH sensor node to the sink node can be seen in Fig. 8(c) using a packet size of 4000 bytes, with a latency reaching 0.2 seconds. The lowest latency was recorded at a distance of 4 meters, with a latency value of 0.42 seconds, while the highest occurred at a distance of 45 meters, reaching 0.426 seconds. In the data transmission scheme from the sink node to the fog node, the lowest latency occurred at a distance of 4 meters with a value of 0.341 seconds, while the highest latency was recorded at a distance of 45 meters, reaching 0.371 seconds.

DISCUSSIONS

Based on the test results, it's evident that the throughput of both the sensor node and sink node is significantly affected by the transmission distance. At the sensor node, there's a fluctuation in throughput from the highest value at a distance of 12 meters to the lowest at distances of 22 and 28 meters. Similarly, at the sink node, a similar pattern emerges where the highest throughput occurs at distances of 12 and 16 meters but decreases at a distance of 28 meters. In situations with an obstacle, both the sensor node and sink node show a decrease in average throughput compared to conditions without obstacles. This indicates that the presence of obstacles negatively impacts the system's ability to transmit data with optimal throughput. There's a fluctuation in throughput at both the sensor node and sink node with an increase in transmission distance, suggesting limitations in data transmission capabilities at specific distances. The test results indicate that the presence of obstacles leads to reduced throughput in both types of nodes, sensor nodes, and sink nodes, indicating that obstacles have the potential to hinder efficiency in data transmission.

Additionally, the latency test results for sending data packets from the water temperature sensor node to the fog node show a value of 0.512 seconds at a distance of 10 meters and 0.825 seconds at a distance of 45 meters. Testing from the salinity sensor node to the fog node recorded a latency of 0.475 seconds at a distance of 10 meters and 0.711 seconds at a distance of 45 meters. As for the pH sensor node, the recorded latency is 0.312 seconds at a distance of 10 meters and 0.725 seconds at a distance of 45 meters. There is a significant variation in latency among sensor nodes at the same distance. The water temperature sensor node has the highest latency at both distances, followed by the salinity sensor node, and the pH sensor node has the lowest latency at a distance of 10 meters. However, at a distance of 45 meters, the water temperature sensor node still has the highest latency, followed by the pH sensor node.

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

This indicates that the farther the data transmission distance, the higher the latency experienced by each sensor node.

Table 1. The Comparison of Latency on Each Sensor Node

Sensor Node	Data Rate (Mbps)	Bandwidth (Mbps)	Latency (s)			Packet data (bytes)	Packet Loss (%)
			Threshold	Maximum	Minimum		
Water Temperature	10	1500	0.07209	0.00953	0.00019	6300	1.21
Salinity	5	1500	0.07455	0.00543	0.00019	7800	0.76
pH	5	1500	0.07455	0.00543	0.00019	4000	0.76

In the latency measurements conducted on each sensor node, the accumulated data obtained is presented in Table 1. The water temperature sensor node has a higher data rate compared to the salinity and pH sensor nodes. However, all three sensors have the same bandwidth of 1500 Mbps, indicating variations in speed and the amount of data they can process. The salinity sensor node registers the highest amount of packet data compared to the water temperature and pH sensor nodes, yet with lower packet loss, indicating better efficiency in data transmission. The water temperature sensor node records the highest latency, indicating a higher delay in the data transmission process.

CONCLUSION

Based on the throughput measurements on the sensor nodes without obstacles, an average value of 0.13 bps was obtained. However, when tested with obstacles, the average value decreased to 0.128 bps, reducing throughput by approximately 1.54%. On the other hand, the throughput measurement on the sink node without obstacles showed an average value of 0.134 bps, whereas with obstacles, the average value increased to 0.13 bps, experiencing an increment of about 2.99%. Furthermore, the latency measurement results in data transmission from the sensor node to the fog node indicated an average value of 0.433 seconds at a distance of 10 meters. However, it increased to 0.754 seconds at a distance of 45 meters, experiencing a latency increase of approximately 74.13%. The maximum distance to achieve low latency is 10 meters with obstacles and 25 meters without obstacles. The conclusion drawn from this research indicates that latency values vary depending on the presence of obstacles and the transmission distance. As the transmission distance increases or when obstacles are present, the latency tends to increase. Conversely, when the transmission distance decreases or is obstacle-free, the latency decreases. Obstacles or disruptions during the data transmission process tend to elevate the latency values. Moreover, increasing throughput values can be achieved by expanding the bandwidth.

REFERENCES

- Al-Jarrah, M. A., Al-Dweik, A., Kalil, M., & Ikki, S. S. (2019). Decision Fusion in Distributed Cooperative Wireless Sensor Networks. *IEEE Transactions on Vehicular Technology*, 68(1), 797–811. <https://doi.org/10.1109/TVT.2018.2879413>
- Amjad, A., Rabby, F., Sadia, S., Patwary, M., & Benkhelifa, E. (2017). Cognitive Edge Computing Based Resource Allocation Framework for Internet of Things. *2nd International Conference on Fog and Mobile Edge Computing (FMEC)*, 194–200. <https://doi.org/10.1109/FMEC.2017.7946430>
- Anwar, S., & Abdurrohman, A. (2020). Pemanfaatan Teknologi Internet of Things Untuk Monitoring Tambak Udang Vaname Berbasis Smartphone Android Menggunakan Nodemcu Wemos D1 Mini. *Infotronik : Jurnal Teknologi Informasi Dan Elektronika*, 5(2), 77. <https://doi.org/10.32897/infotronik.2020.5.2.484>
- Atlam, H. F., Walters, R. J., & Wills, G. B. (2018). Fog Computing and The Internet of Things: A Review. *Big Data and Cognitive Computing*, 2(2), 1–18. <https://doi.org/10.3390/bdcc2020010>
- Bellavista, P., Berrocal, J., Corradi, A., Das, S. K., Foschini, L., & Zanni, A. (2019). A Survey on Fog Computing for the Internet of Things. *Pervasive and Mobile Computing*, 52, 71–99. <https://doi.org/10.1016/j.pmcj.2018.12.007>
- Damayanti, A. R., & Sugiarto, S. (2022). Analisis Daya Saing Ekspor Udang Beku Indonesia di Jepang

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

- dan Faktor-Faktor yang Memengaruhinya Tahun 1989-2019. *Jurnal Dinamika Ekonomi Pembangunan*, 5(1), 16–35. <https://doi.org/10.14710/jdep.5.1.16-35>
- Datta, S. K., Bonnet, C., & Haerri, J. (2015). Fog Computing Architecture to Enable Consumer Centric Internet of Things Services. *IEEE International Symposium on Consumer Electronics (ISCE)*, 85, 6–7. <https://doi.org/10.1109/ISCE.2015.7177778>
- Fuady, M. F., Haeruddin, & Niti Supardjo, M. (2013). Pengaruh Pengelolaan Kualitas Air Terhadap Tingkat Kelulushidupan dan Laju Pertumbuhan Udang Vaname (*Litopenaeus vannamei*) di PT. Indokor Bangun Desa, Yogyakarta. *Management of Aquatic Resources Journal (MAQUARES)*, 2(4), 155–162. <https://doi.org/10.14710/marj.v2i4.4279>
- Kamisetti, S. N. R., Shaligram, A. D., & Sadistap, S. S. (2012). Smart Electronic System for Pond Management in Fresh Water Aquaculture. *IEEE Symposium on Industrial Electronics and Applications (ISIEA2012)*, 173–175. <https://doi.org/10.1109/ISIEA.2012.6496623>
- Komarudin, M., Septama, H. D., Yulianti, T., & Wicaksono, M. A. (2021). Rekayasa E-Aquaculture untuk Pemantauan Tambak Udang secara Realtime dengan Model Multipoint Node. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, 8(2), 395–402. <https://doi.org/10.25126/jtiik.2021824142>
- Marcheriz, I. N., & Fitriani, E. (2023). Design of IoT-Based Tomato Plant Growth Monitoring System in The Yard. *Sinkron*, 8(2), 762–770. <https://doi.org/10.33395/sinkron.v8i2.12226>
- Mashari, S., Nurmawati, R., & Suharno. (2019). Dinamika Daya Saing Ekspor Udang Beku dan Olahan Indonesia di Pasar Internasional. *Jurnal Agribisnis Indonesia*, 7(1), 37–52. <https://doi.org/https://doi.org/10.29244/jai.2019.7.1.37-52>
- Maulana, Y. Y., Wiranto, G., & Kurniawan, D. (2016). Online Monitoring Kualitas Air Pada Budidaya Udang Berbasis WSN Dan IoT. *Journal of Informatics, Control Systems, and Computers*, 10(2), 81–86. <https://doi.org/dx.doi.org/10.14203/j.inkom.456>
- Nurchahya, D., Karimah, S. A., & Mugitama, S. A. (2023). Performance Analysis of Scheduling Algorithms on Fog Computing using YAFS. *Sinkron*, 8(3), 1677–1686. <https://doi.org/10.33395/sinkron.v8i3.12682>
- Nuridhuha, D., Ichsan, M. H. H., & Maulana, R. (2020). Sistem Monitoring Lingkungan Rumah Cerdas berbasis Fog Computing dan nRF24101. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, 4(2), 622–631. <http://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/7004>
- Pauzi, G. A., Syafira, M. A., Surtano, A., & Supriyanto, A. (2017). Aplikasi IoT Sistem Monitoring Kualitas Air Tambak Udang Menggunakan Aplikasi Blynk Berbasis Arduino Uno. *JURNAL Teori Dan Aplikasi Fisika*, 05(02), 1–8.
- Ramadhan, H. P., Kartiko, C., & Prasetiadi, A. (2020). Monitoring Kualitas Air Tambak Udang Menggunakan Metode Data Logging. *Jurnal Teknik Informatika Dan Sistem Informasi*, 6(1), 102–114. <https://doi.org/10.28932/jutisi.v6i1.2365>
- Samann, F. E. F., Zeebaree, S. R. M., & Askar, S. (2021). IoT Provisioning QoS based on Cloud and Fog Computing. *Journal of Applied Science and Technology Trends*, 2(01), 29–40. <https://doi.org/10.38094/jastt20190>
- Simanungkalit, E., Husna, M., & Tarigan, J. S. (2023). Smart Farming on IoT-Based Aeroponik Systems. *Sinkron*, 8(1), 505–511. <https://doi.org/10.33395/sinkron.v8i1.11988>
- Singhal, A. K., & Singhal, N. (2021). Cloud Computing vs Fog Computing: A Comparative Study. *International Journal of Advanced Networking and Applications*, 12(04), 4627–4632. <https://doi.org/10.35444/ijana.2021.12403>
- Wawan Setiawan, Nurul Fajriyah, & Tobias Duha. (2022). Analisa Layanan Cloud Computing Di Era Digital. *Jurnal Informatika*, 1(1), 32–39.
- Zainudin, A., Anisah, I., & Gulo, M. M. (2021). Implementasi Fog Computing Pada Aplikasi Smart Home Berbasis Internet of Things. *CESS (Journal of Computer Engineering, System and Science)*, 6(1), 127–132. <https://doi.org/10.24114/cess.v6i1.20658>
- Zhao, J. (2014). Research on Wireless Sensor Network in Aquaculture. *Applied Mechanics and Materials*, 686, 397–401. <https://doi.org/10.4028/www.scientific.net/AMM.686.397>