A New Approach Based on an Intelligent Method to Classify Quality of Service

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Computer networks are used more frequently for time-sensitive applications like voice over internet protocol and other communications. In computer networks, quality of service (QoS) can be crucial since it makes it easier to assess a network's performance and offers mechanisms for enhancing its performance. As a result, understanding the QoS provided by networks is essential for both network users and service providers to assess how well the transmission requirements of different applications are satisfied and to implement improvements to network performance. Next-generation monitoring systems must not only detect network performance deterioration instantly but also pinpoint the underlying cause of quality of service problems to achieve strict network standards. A brand-new fuzzy logic-based algorithm is suggested as a solution to this issue. Thus, the proposed approach was evaluated and compared with probabilistic neural networks (PNN) and Bayesian classification, as well as network performance measurement, latency, jitter, and packet loss. All approaches correctly classified the QoS categories, although generally, the fuzzy approach outperformed PNN and Bayesian. An improved comprehension of the network performance is acquired by precisely determining its QoS.

Povzetek: Razvit je nov algoritem za odkrivanje vzroka za poslabšano kvaliteto storive v omrežjih.

1 Introduction

Quality of service (QoS) enhances the operation of computer networks by facilitating traffic prioritization, resource reservation, traffic shaping and policing, packet scheduling, and queue management. These responsibilities are becoming increasingly crucial for the efficient delivery of multimedia traffic. Due to the time-sensitive nature of multimedia applications, if their traffic metrics, such as delay, jitter, and packet loss, exceed acceptable bounds, the user experience may suffer[1]. Therefore, analyzing the QoS provided by networks is crucial for both network users and service providers to determine how successfully the transmission requirements of various applications are met and to apply measures to improve network performance. Nonetheless, assessing QoS in multimedia networks presents obstacles[2]. These include a high volume of traffic, the network's dynamic behavior, limited resources (such as bandwidth), the diversity of transmission requirements among applications, and the computational demands of collecting and evaluating traffic data. Consequently, when the areas lacked harmony, the quality of service was negatively impacted in the disadvantaged regions. One method is to observe network performance to identify harmonious and deficient places. Monitoring performance reveals the quality of services as measured by a variety of evaluation metrics[3]. As a result, it is possible to take action to develop disability awareness in these regions. Thus, improves the quality of service according to the feedback of evaluation metrics. [4]. It enables the use of a different variable to forecast the system's behavior. In all instances, the approach is viewed as an alternate realization that approximates the system, and its objective is to evaluate and comprehend the system's behavior under many alternative actions or decisions[5].

Nowadays, network many approaches are utilized by researchers in various domains, including academic education and engineering. By assessing their system through network simulation, engineers can create and model a new system to obtain performance.

In addition, it can be used to evaluate the effect of the various parameters and investigate the system's unique behavior. Examining the network's performance based on the quality of the apps as perceived by the users. Other research has shown efficient QoS assessment using artificial intelligence[6]. According to their findings, measured QoS is a reliable indication of network functioning and resource availability. Quantitative tools are required to analyze and interpret end-to-end transmission measurements for packets to

Table 1: Summarization table on the related works.

Ref	Methodology	Performance/Results
[27]	• Fuzzy C-Means • Kohonen Unsupervised Neural Networks	• QoS evaluation can be undertaken in a variety of ways and exposes the quality of application delivery. The ability of fuzzy c-means clustering (FCM) and Kohonen unsupervised neural networks to distinguish between Good, Average, and Poor QoS for voice over IP (VoIP) traffic was evaluated. • FCM and Kohonen categorized VoIP traffic successfully into Low, Medium, and High QoS classes. FIS, regression model, and MLP integrated the QoS measures (delay, jitter, and packet loss percentage ratio) with information from the formed clusters and displayed the overall QoS.
[28]	• Naive Bayes	• They use a Naive Bayes estimator to classify traffic according to application. Our study makes use of hand-classified network data as input to a supervised Naive Bayes estimator in a novel way. demonstrate the high degree of precision that can be achieved with the Naive Bayes estimator, and demonstrate further the enhanced precision of refined forms of this estimator. • The results indicate that with the simplest Naive Bayes estimator, we can achieve approximately 65% accuracy on per-flow classification, and with two powerful refinements, we can improve this value to greater than 95 %.
[29]	• Artificial Neural Networks	• An artificial neural network has demonstrated potential for QoS evaluation in wired and wireless networkAn innovative QoS evaluation method employing artificial neural networks (ANNs) for real time protocol (RTP) traffic analysis is described. • In these investigations, NS2 software was used to model communication networks. Initial classification of network traffic parameters into several QoS classes was performed using an unsupervised learning Kohonen neural network.
[30]	• Congestion Window	• The authors proposed in is to improve healthcare for patients to minimize delay and packet loss. The network measurement was calculated based on the Congestion Window of Transmission Control Protocol (TCP). • The analysis of all parameters is calculated based on the output of the simulator which is the trace file. However, the proposed study doesn't show the network format supported and the statistical results are calculated in external tools.
[31]	• Script Languages	• They evaluate the performance of several mobile ad-hoc network routing protocols based on several metric measurements. Based on four crucial measures, including packet delivery ratio, average end-to-end delay, normalized routing overhead, and throughput, • The evolution's performance varies with the number of mobile nodes and packet sizes. However, the authors use script language to perform all the experiments which makes the process of the evaluation require more time with understating other script languages.
[32]	• Video Streaming System	• Show the difficulties encountered by the Researcher in the realm of video streaming due to its susceptibility to transmission quality differences. In streaming applications, it is advantageous to be able to quantify Quality of Service (QoS). Using the information from QoS measurements, video traffic can be modified to conform to the network's transmission limitations. • This project aims to examine the concept of Quality of Service, study alternative QoS monitoring approaches, and design a system that monitors the end-to-end QoS of several concurrent video streaming sessions.
[26]	• Probabilistic Neural Network • Bayesian	• The probabilistic neural network (PNN) and Bayesian classification were built to investigate VoIP communication delay, jitter, and packet loss percentage ratio. • Both methods successfully categorized the transmission of VoIP packets into low, medium, and high QoS categories; however, the Bayesian approach performed more accurately than the PNN algorithm overall. By accurately specifying the network's QoS, its performance is better understood.
[33]	• Hierarchical Fuzzy	• The method for operationally analyzing the condition of network elements is predicated on the creation and employment of intelligent agents. The production of intelligent agents as hierarchical fuzzy situational networks. • where control solutions are built based on addressing a hierarchical series of optimization issues using fuzzy mathematical programming methods, as opposed to conventional approaches based on the application of reference conditions.

analysis. Table 1 shows related work in which quality has been calculated in various ways, including computer performance and results. So in this present work, we introduce a new method for calculating the classified quality called Fuzzy Quality of Service (F-QoS). The proof of its validity has been compared with a probabilistic neural network (PNN) and Bayesian classification algorithm.

This paper is organized as follows: In Section 2, it presents the network quality of service and its problems. In Section 3, the proposed method is proposed. Finally, the conclusion of this paper is presented in Section 4.

2 Network Quality of Service

The ability to assign various applications, users, or data flows different priorities or to guarantee a specific degree of performance for the data flow is known as quality of service. For instance, it is possible to ensure the desired information's speed, delay, instability, likelihood that messages would be lost in the transmission, and/or error rate. In this part, the issues related to the quality of service are divided into three stages (network performance, network monitoring, and factors affecting the network)[7], [8]. With everyday network demands increasing, performance measurement is more vital than ever. Effective network performance correlates with improved user satisfaction, whether to internal employee efficiencies or customer-facing network components like an e-commerce website. This makes performance testing and monitoring a no-brainer. Bandwidth difficulties, network outages, and bottlenecks can quickly become an Information Technology (IT) disaster when delivering services and applications to end customers. The best way to ensure long-term user satisfaction is to utilize proactive network performance management solutions that detect and diagnose performance issues.

Since network performance cannot be predicted, the only legal methods for maintaining network quality include measuring network performance before, during, and after upgrades and continuously monitoring performance. In addition to measuring and monitoring network performance characteristics, it is essential to interpret and implement these measurements[8]. This stage is important to check the performance through several metrics to achieve the quality of results. All metrics are calculated as shown in Equations 1-5, [9], [10].

$$Throughput = \frac{P_a}{P_f} \tag{1}$$

where P_a are the packets received and P_f is the number of forwarded packets over a specific time interval.

$$Goodput = \frac{MP_a}{TP_f} \tag{2}$$

where MP_a are the maximum number of packets received and TP_f is the total amount of packets sent

$$Jitter = D_{i+1} - D_i \tag{3}$$

Where D_{i+1} is the delay of $i_{th} + 1$ packet and D_i is the delay of the i_{th} packet.

$$Delay = R_{i+1} - R_i \tag{4}$$

Where R_{i+1} is the time packet received of $i_{th} + 1$ packet and R_i is the previous time packet received of the i_{th} packet.

$$End\ to\ end\ delay = T_d - T_s \tag{5}$$

Where T_d is the packet receive time at the destination and T_s , packet send time at the source node.

2.1 Monitoring Network

Network management's information-gathering job is network monitoring. Network monitoring programs are designed to collect data for network management applications. The purpose of network monitoring is to collect pertinent data from various network components so that the network can be monitored and controlled based on the collected data. Most network devices are placed in remote areas [11]. The lack of physically attached terminals on these devices makes it difficult for network management software to monitor their states. Network monitoring techniques are expanded to include network-wide monitoring as more network devices are deployed to create more extensive networks.

Network size and complexity have grown as more people connect via them. The rate of network expansion has accelerated due to the growth of the Internet. Because of the size and complexity of today's networks, network monitoring apps must utilize effective techniques to ascertain the state of their networks so that network management applications may fully govern them and offer users high-quality, reasonably priced networking services. Understanding the expected results is crucial while monitoring networks. Network monitoring apps can determine the most effective network monitoring techniques by understanding the goals of network monitoring[12].

There are two primary objectives for network monitoring [7], [10]:

- **Performance monitoring**

Performance monitoring is the measurement of the network's performance. There are three crucial aspects of performance monitoring. First, performance monitoring data is typically used to plan for future network growth and identify present network utilization issues. Second, the duration of performance monitoring must be sufficient to develop a model of network behavior. Third, selecting what to measure is crucial. In a network, there are too many measurable things. However, the list of objects to be measured must be relevant and cost-effective. This collection of elements to be measured is referred to as network indicators because they represent network characteristics.

- **Faults Monitoring**

This involves measuring network difficulties. In fault monitoring, there are two crucial aspects to consider. First, defect monitoring involves multiple network layers. When an issue develops on a network, it might occur at many layers. Therefore, it is essential to determine which layer is problematic. Second, fault monitoring necessitates the establishment of typical network characteristics over an extended period. There are always errors in the network, but the presence of errors does not indicate that the network is experiencing continuous issues. Some of these errors are expected. For example, network link noise can result in transmission problems. The network has an issue only when the number of mistakes has risen over usual. Consequently, a record of regular behavior is essential.

2.2 Factors Affecting Network

Monitoring and optimizing methods for critical network performance indicators, such as application downtime and packet loss, are a part of network performance management. Two logical outcomes of a successful network management program are an increase in network availability and a reduction in response time when issues arise. A holistic approach to network performance management must consider all essential problem manifestation categories[7].

- **Infrastructure**

The entire network infrastructure comprises network hardware like routers, switches, and cables, network software like operating and security systems, and network services like IP addressing and wireless protocols. It's critical to describe the network's overall traffic and bandwidth patterns from an infrastructure perspective. This network performance measurement will reveal which flows are the busiest over time and may develop into future problem areas. Instead of only reacting to any performance problem, identifying the infrastructure's over-capacity components might result in preventative modifications or upgrades to reduce future downtime[13].

- **Network Problems**

The network's inherent performance limits frequently receive a lot of attention. The performance of the network can be affected by several factors, and defects in any of these areas can have a systemic impact. These components must be constructed to satisfy all anticipated system needs due to the significance of hardware requirements to capacity planning. For instance, a memory shortage or an inadequate bus size on the network backplane may cause more packet loss or a decrease in network performance[14].

- **Applications**

While issues with network hardware and infrastructure may directly affect how users interact with a particular application, it is important to consider how the programs themselves, as fundamental parts of the network architecture, may affect user experience. Ineffective software may take an excessive amount of bandwidth and degrade the user experience. As application complexity rises, diagnosing and tracking performance becomes more critical. Window sizes and keep-alive are two application parameters that influence network performance and capacity.

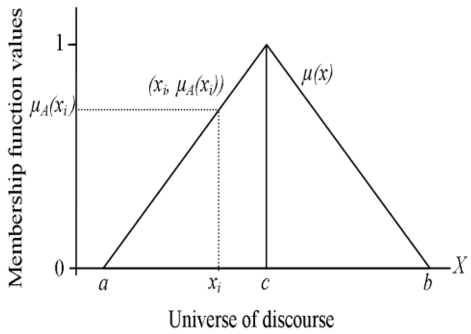

Figure 1 :Membership function (x, µA(x))

- **Security Issues**

Network security aims to protect data integrity, confidentiality, and intellectual property. As a result, the need for robust security is undeniable. Managing and mitigating network security issues necessitates device scanning, data encryption, virus protection, authentication, and intrusion detection, all of which take network bandwidth and can have a detrimental impact on performance. Because security breaches and virus-related downtime are among the most expensive performance issues, any performance loss caused by security systems must be carefully weighed against the potential downtime or data integrity disasters they prevent[15].

3 The Proposed Method

Quality rating is one of the most important things related to computer networks. In light of this, an intelligent technique based on fuzzy logic has been proposed to classify the overall quality service decision. Thus, it consists of five inputs (for five measures), while the output is represented by the fuzzy value between zero and one. As the quality rating is either low, medium, or high, the proposed work was compared. The proof of its validity has been compared with a probabilistic neural network (PNN) and Bayesian classification algorithm.

This proposal will be in two parts, the first part is the system's design, and the second part is the analysis and results of the system.

3.1 System Design

Fuzzy Logic (FL) is a method for making robots more intelligent and enabling them to think in a fuzzy manner similar to human thinking [16]. A fuzzy control system is considered a knowledge-based system that implements the skill of a human being, operator, or engineer, which can be simply represented by the set of terms from natural language forming fuzzy linguistic rules (list of IF-Then rules)[17].

Information analysis in FL is done using fuzzy sets, and each fuzzy set is expressed by a linguistic term from a natural language, such as low, high, or very high. These sets allow the partial membership of an object to a

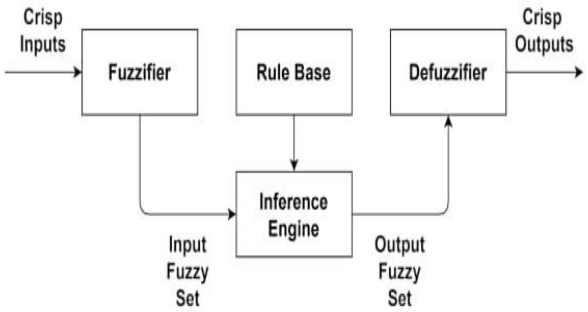

Figure 2: Fuzzy structure

specific set. As shown in Figure 1**,** if X represents a group of objects and each object is denoted by x, commonly X is known as the "universe of discourse," and hence a fuzzy set A in X consists of a set of pairs ordered in (x, $\mu_A(x)$) form as in Eq.(6) [18]:

$$A = \{(x, \mu_A(x) / x \in X\} \qquad \textbf{(6)}$$

MA *(x)* is the membership function of the object x in A.

The membership function is the line or curve that reflects a specific membership value that takes the range [0...1] for each given point in the universe of discourse. A membership function (μ) for an input (x_i) can be expressed by Eq. **(**7**)** [18]:

$$0 \le \mu(x_i) \le 1 \qquad \textbf{(7)}$$

Membership functions employed in fuzzy systems vary in shape or form, including piecewise linear, triangular, singleton, trapezoidal, Gaussian, etc. [18]. The membership function of the triangular form is used in the fuzzy system of this thesis to calculate membership values. The triangular membership function is illustrated in Eq. (8**):**

$$\mu(x;a,c,b) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{c-a} & a \le x \le c \\ \dfrac{b-x}{b-c} & c \le x \le b \\ 0 & b \le x \end{cases} \qquad (8)$$

where a and b are the start and end limits of the triangular membership interval, respectively, and c is the center of that interval.

In FL systems, linguistic rules are expressed in the following manner: IF antecedent(s) THEN consequence(s), whereby both propositions, antecedents, and consequences, include linguistic variables. In fuzzy rules, antecedents use logical operators to build a collection of fuzzy sets. These rules may be provided by a human specialist or derived from numerical data. The beneficial fuzzy rules may be stated in any way by a collection of IF-THEN expressions [19].

In a fuzzy system, the input space is produced by the set of antecedent parts in the rules, and the consequents of the fuzzy rules generate the output space. Both of them are defined by the collection of fuzzy sets. Having a fuzzy logic system consisting of p inputs and a single output together with M fuzzy rules, the L^{th} rule has the arrangement in Eq(9) [20]:

$$R^L\text{: IF } x_1 \text{ is } F_1^L \text{ and ... and } x_p \text{ is } F_p^L \text{ THEN } y \text{ is } G^L \qquad (9)$$

where F_1^L .. F_p^L and G^L refer to the variables represented by linguistic terms that form fuzzy sets, and L is the number of rules that takes a value from 1 to M. Figure 2. Illustrates the structure of the standard fuzzy logic.

There are four parts needed to build a fuzzy logic system. These are [18], [14], [21]:

- **Fuzzification**

In this module, the numerical (i.e., crisp values) inputs are turned into membership values (i.e., fuzzy values) using the relevant fuzzy sets. The obtained fuzzy values are consistent with the fuzzy sets expressions in the fuzzy rule base.

The grade or degree of belongingness obtained using any membership function is the fuzzy value with a range [0...1]. In most cases, fuzzy variables consist of more than one membership function related to them. As a result, the fuzzification process will produce several membership values for a single crisp input [22].

- **Rule base**

The performance of a system to be managed or controlled using fuzzy logic is characterized according to a collection of IF-THEN rules of this component. Rules can be considered practical guidelines from practical backgrounds to deal with knowledge. Fuzzy roles act as the bridge that connects the input and output spaces[23].

- **Inference Engine**

In this component, fuzzy concepts are utilized to imitate human decision-making. It performs matching between fuzzy facts and the antecedents group of the fuzzy rules. When a match is founded in an antecedent of a rule, it is denoted by the rule's firing.

The inference engine strives to infer the appropriate fuzzy outputs by incorporating fuzzy implications and rules of inference in FL. The process is done through the inference engine and generally comprises two steps:

a) The collection of antecedents related to all of the rules of inference is compared to the crisp or numerical input to select the set of rules that applies current situation.

b) Trimming the fuzzy set that characterizes the meaning of the fuzzy rule to the point at which the crisp input has matched the consequent part of the fuzzy rule. After that, the trimmed output values of each fuzzy rule are gathered and aggregated.

- **Defuzzification**

After the inference engine processes have been done, the produced linguistic variables are converted to a crisp numerical value. Defuzzification, then is the opposite of the fuzzification process as it inversely results from the numerical output of the crisp domain according to the inferred output of the fuzzy domain. There are several

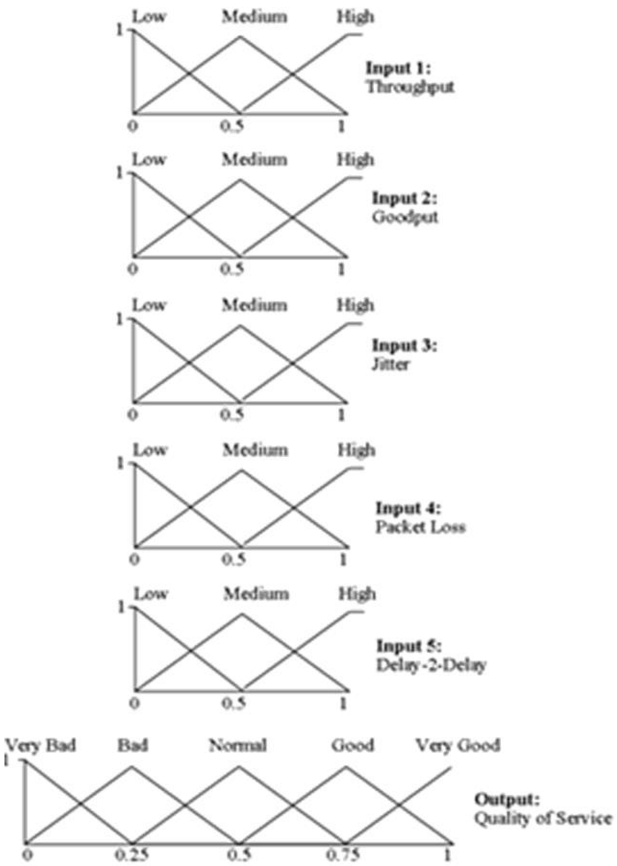

Figure 3: The membership function into five inputs with one output

defuzzification techniques, including the center of gravity (COG), middle of maximum (MOM), center of the area (COA), etc.[24].

$$CoG = \frac{\sum_{i=1}^{n} U_i * c_i}{\sum_{i=1}^{n} U_i} \quad (10)$$

Where CoG represents the center of gravity and Ui represents the output of rule base i, Ci represents the center of the output membership function for n rule bases.

3.2 System Analysis

The system is analyzed using one of the previously proposed systems, and the five scales are extracted, and classifier of the QoS. (For example, sending 32 packets over a grid containing 9 nodes)[25]. After that, the fuzzy approach is used to determine the fitness function value, dependent on the five inputs. The fuzzy approach uses five input parameters which are Throughput, Goodput, and Jitter, packet loss, Delay-end -Delay with a QoS as an output parameter. The following equation shows the calculation of the final quality of the network based on the five inputs.

$$Qos = fuzzy(Th(n_i), G(n_i),.J(n_i),.D(n_i),.D2D(n_i)) \quad (11)$$

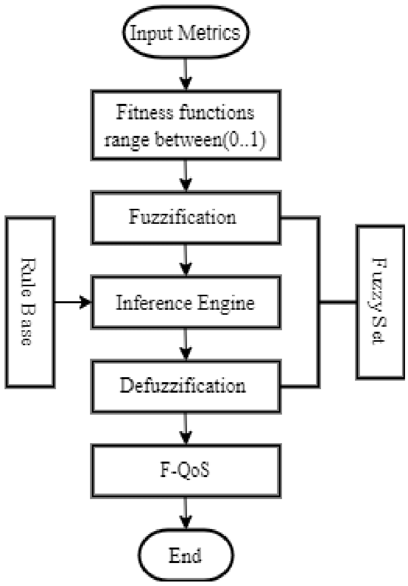

Figure 4: The proposed model

Where Th(n), G(n), J(n), P(n), and D2D(n) are the Throughput, Goodput, and Jitter, packet loss, Delay-end -Delay, respectively, n, number of inputs.

Each measurement produced a probability value between 0 and 1. High levels of likelihood indicated QoS linked with that route. To have a continuous range between 0 and 1 for the three pathways combined, the outputs from the measurement were mapped as 0 to 0.33 for the low QoS packets categorized measurement, 0.34 to 0.65 for medium QoS packets classified, and 0.66 to 1 for high QoS packets classified [26]. Figure 3 shows the division of the membership function into five inputs with one output.

The method processes the fuzzified data using an inference engine that consists of a rule base and multiple techniques for inferring the rules, with a total of 5^5=3125 rules in the fuzzy rule base. For example, when the input is the Throughput is high, the Jitter is medium, the Goodput is high, then packet loss is low, the Delay-end -Delay is low, and the quality output is good. Figure 4 represents the proposed model for rating quality.

Thus, using the proposed model, the five metrics are extracted and analyzed to determine service quality as shown in Figures 5 to 9.

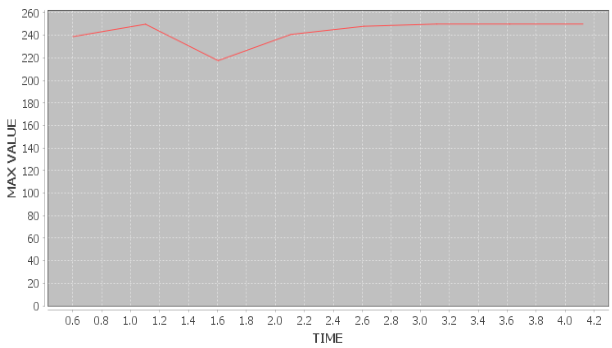

Figure 5: Throughput

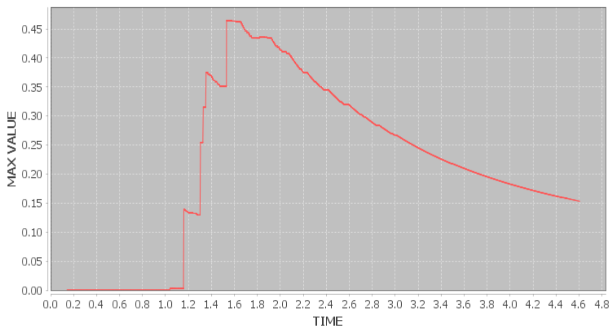

Figure 6: Jitter

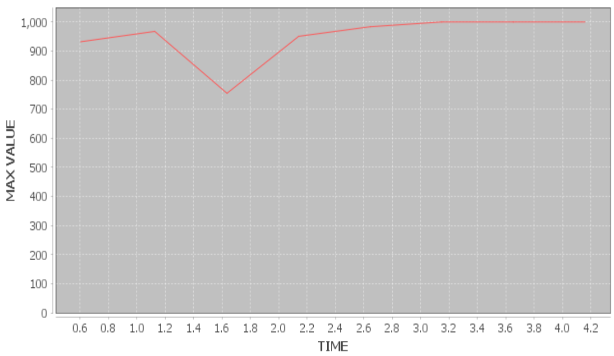

Figure 7: Goodput

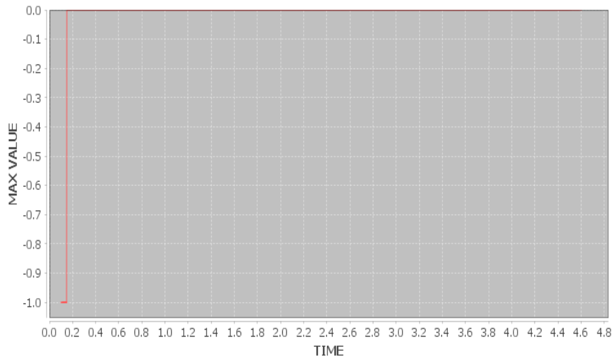

Figure 8: Packet Loss

After applying the tests between the three methods, the results appear to be superior to the proposed method based on the accuracy of the classification and the time taken to conduct the test. Table 2 shows the results of the work.

In Figure 10, we notice that the error rate in rating the quality of service varies. Whereas PNN has an error rate of approximately 51%, Bayesian has an error rate of 44%, and F-QoS has an error rate of 5%. Based on this output, we conclude that the F-QoS algorithm is involved in the quality classification process.

4 Conclusions

Understanding the quality of service provided by networks is essential for both network users and network service providers to assess how well the transmission requirements of different applications are met and to implement improvements to network performance. Thus,

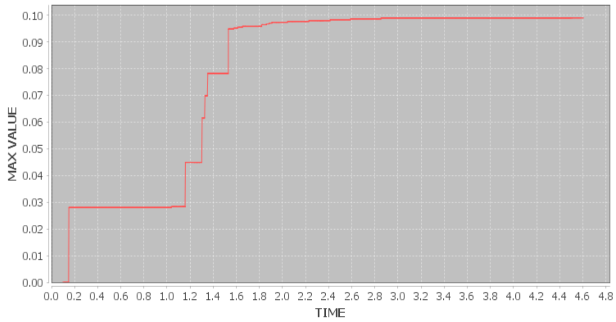

Figure 9: Delay-2-Delay

Table 2: Results of the work

Algorithm	Accuracy	Time
Probabilistic Neural Network	.087	530 µs
Bayesian Algorithm	0.83	401 µs
Fuzzy Quality of Service (F-QoS)	.093	313 µs

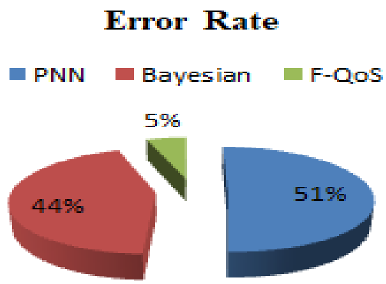

Figure 10: Error Rate in Quality of Service

computer networks have many problems, for example, high network delays or packet loss in data; these problems affect the quality of service. In light of this, you must also identify the root cause of QoS problems to achieve network standards. A new proposal is a Fuzzy Logic algorithm, representing a balance between the five measures for quality classification. A better understanding of network performance is gained through the accurate determination of QoS. Thus, the proposed approach was evaluated and compared with Probabilistic Neural Networks (PNN) and Bayesian classification, measuring network performance, latency, jitter, and packet loss. All methods correctly ranked QoS categories, although the fuzzy approach generally outperformed PNN and Bayesian with a precision of 0.93. In future work, the proposed method will be applied with one of the intelligence swarm protocols in wireless sensor networks to conserve energy quantity and increase network efficiency.

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