A Two-Stage Assessment Approach for QoS in Internet of Things based on Fuzzy Logic

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***Abstract*—In the sphere of IoT, one of the most significant issues is quality of service (QoS), which is critical for both developers and customers. As a result, IoT platform developers are working to enhance models that will meet consumer expectations in terms of IoT services meeting their expected specified levels of quality. The multidimensional architecture of the IoT platform, combined with the ambiguous mindset of consumers' thinking, makes QoS evaluation a difficult process. As a result, this study seeks to solve these issues and proposes a new paradigm for assessing QoS in IoT ecosystems. The proposed approach evaluates QoS in two steps, with the goal of assessing QoS at all levels. To address the issue of uncertainty, the metric values and QoS were represented using a fuzzy logic method. The model correctly estimated the QoS for 50 services in the dataset, and the results show that 16 services are classed as high quality, while 25 are rated as medium quality and the rest rated as low quality.**

Keywords*—IoT; internet of things; QoS; quality of services; fuzzy logic; evaluate; assess

I. Introduction

The IoT service is a key component in IoT ecosystems and is actually considered to be the backbone of it. Obviously, service plays a crucial role in any IoT platform as it is always the center of attention for both providers and consumers, for after all, it is the source from which both ends of the equation are potentially going to benefit. In general, the concept of services as defined by [1] is the commercial transaction between two parties in which one party allows another to access specific resources. Recent years have witnessed a significant development in IoT market, in turn, the number of IoT services have increased rapidly. This rapid increase in IoT services has been on the rise due to the dramatic increase in the number of devices, that are considered the main source of IoT services. There is no unanimous opinion on the number of things that will connect to the Internet [2]. According to most surveys undertaken by reputable companies such as Gartner, HIS Markit, and Ericson, the number of internet-connected devices will reach nearly 30 to 50 billion in 2021. (excluding smartphones, tablets, and computers) [3]. However, according to a recent estimate which conducted by [4], the number of linked devices worldwide will approach 75 billion by 2025. This reported big jump in the number of devices gives an indication of the massive number of IoT services that we will have and underpins the projection of a significant increase in the number of IoT services in the near future.

This consequential growth in IoT market motivates huge number of consumers to adopt IoT services. However, one of the big challenges that face most of the consumers is how to find the services fulfilling their specific requirements among massive numbers of services that have similar functionality but different in non-functional attributes. Therefore, the IoT developers endeavor to develop IoT platforms that would allow consumers to have access to services meeting their requirements. One of the most requirements most consumers seek and are concerned with is the quality of Services (QoS). According to [5], QoS is the overall performance of a telecommunication system, computer network, or IoT platform, explicitly, the performance perceived by network or platform users, and there are numerous metrics used to measure performance. As QoS is a key metric in measuring the performance of IoT platforms, many researches have been conducted with the view to tackling the issue of QoS in terms of QoS metrics and assessment methods. Researcher in [6] addressed the challenge of how to meet the consumers QoS-based demand whereas [7] discussed the problem of how to calculate the aggregate QoS of a composite service.

As we have noticed, QoS has significant impact on IoT performance. Hence, many researches have been developed in order to address the all issues related to the QoS in IoT platforms. QoS assessment is one of the most challenging issues that must be taken into consideration in any IoT platform, for more explanation, to develop a convenient IoT platform that would allow consumers to get the services with the desirable level of quality, it is necessary first to have a convenient approach for assessment of the QoS. However, developing an assessment approach for QoS in IoT is a rather challenging task for several reasons including: initially, the architecture of IoT platforms is made up of many layers and each layer has a conspicuous impact on the QoS. Thus, firstly, we assume that assessment the QoS for one layer and ignore the other layers will give a result that doesn’t express the QoS for all IoT platform, secondly, calculate the QoS for all layers but deal with each result of layer individually also will affect the final result of QoS for IoT platform. On the other side, the non-functional attributes (QoS metrics) are represented in numerical values, in contrast, humans always think in inexact ways in their daily life, and used linguistic terms such as Short/tall, close/far, and hot/cold. Therefore, we assume that the way of representing the metrics of QoS has a great impact in the final results.

The goal of this work is to address the issues raised above by offering a new method for assessing QoS in IoT ecosystems. The suggested model examines QoS in two steps, with the goal of computing QoS at the all layers. To address the uncertainty issue, we employed the fuzzy logic approach to describe metric values and compute QoS.

II. Background

A. IoT Service Profile

The IoT service profile consists mainly of three models: Service profile, service model and service grounding, Fig. 1.

1) Service model: This model addresses the functional component of services at a high level; it specifies what a service does and is mostly used for service discovery [8].

2) Service profile: Mainly used for service selection. The goal of this section is to aid service selection by semantically describing the service's non-functionality. There are several QoS attributes that used to specify the non-functional of services such as: accuracy, reliability, security, reputation etc..

3) Service grounding: This section contains information about the message format and transfer protocol that are required for service invocation. Some models, for example, employ WSDL to deliver messages over common network protocols [9].

B. IoT Architecture from QoS Prospective

Form QoS prospective, IoT architecture made up of three layers, the perception layer, the network layer and the application layer, Fig. 2. In the perception layer we find the IoT devices from which services publish. The network layer represents the medium communication used to transfer services such as WiFi, ZigBee. The application layer is the interface where the end users access the services. Each layer has its own QoS metrics and based on these metrics the quality of services will be computed.

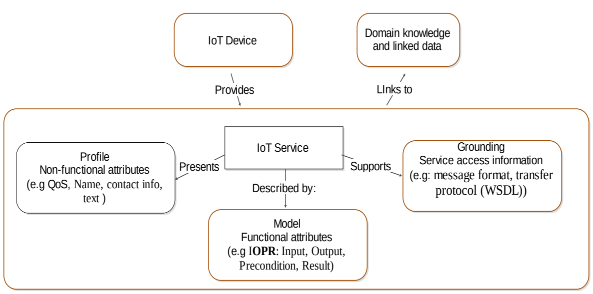

Fig. 1. Shows IoT Service Profile.

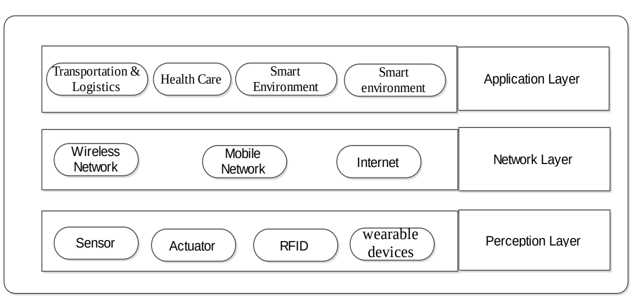

Fig. 2. Architecture in IoT from QoS Prospective.

1) QoS of Perception Layer: This layer is the backbone of the IoT and it is described as the five sense organs of loT ecosystems [10]. In this layer we find the IoT devices. These can be the edge devices such as sensors, actuators, RFID, cameras, GPS, wearable devices that interact with their environment. Several QoS metrics can be defined under this layer and they include:

a) Accuracy: Accuracy is one of the parameters that play vital role in QoS. Accuracy of sensor as defined by [11] is the greatest uncertainty between a sensor's actual value and the standard value defined at output settings.

b) Precision: Precision refers to the sensors' capacity to measure the deviation in the output obtained when the same signal is measured repeatedly under the same conditions [11].

c) Reliability: Reliability provides a high degree of trust and trustworthiness during the operation of IoT systems [12]. The reliability also reflects the ability of systems to recover and self-configure in the changing environment.

d) Sensor Time Constant (τ): A sensor constant time is defined as the time required for the sensor reading/output to reach to 63.2% of its total step change in measurement" [13].

e) Response Time: It is defined as the time taken by the sensors to change its output state with the change in input parameters. The Sensors that have low response time are more desirable for any application [11].

2) QoS of Network Layer: Network layer connects the IoT devices to other smart objects, servers, and network devices, it is considered as an intermediate between the application layer and perception layer [14] [15]. Several QoS metrics can be defined under this layer and they include:

a) Bandwidth: Represetns the measured amount of data that transmitted over netwrok at a given period of time. For accessing, the ones with a high available bandwidth are preferred for accessing [11].

b) Reliability: If the backet arrives at its destination without any loss or security breach, the service is considered reliable. [15].

c) Availability: Availability represented as the percentage of time, in a specific time interval, during which network components such as (a server, cloud service, or other machine) can be used for the task that it was mainly designed and created for [16] [17].

d) Security: There is an increasing demand for security among the IoT users. Most of the users want to ensure that the network used to provide IoT services is secure and the information provided will be treated confidentially [18].

3) QoS of Application (Cloud) Layer: It is responsible of providing the user with application-specific services. or what the user interacts with [19]. Several QoS metrics which can be defined under this layer and they include:

a) Price: The price of getting services in IoT is one of the metrics that reflects the QoS.

b) Reputation: Reputation of IoT services is measured based on the individual's experience and reviews. Many services selection approaches are customized based on the preferences [20].

c) Availability: As in sensor layer the availability also used as metric of QoS in application layer. It can be defined as a probability ratio that the service is operational and accessible when selected [21].

III. Related Work

The non-functional or QoS attributes are the key criteria when IoT end users need to select specific service to perform specific task. Therefore, it is important to develop an approach that allows providers of services to evaluate the QoS before making them available for the end users. Recently, many researches have been developed in order to improve tools to calculate or assess the QoS.

A study conducted by [22] investigated the problem of how to find the best service providers that offer smart parking services. The researchers identified 25 parameters that play a vital role in identifying the QoS in such a service. In [23], investigated the most suitable QoS criteria for optimal services selection problem in composition and classify them to the negative and positive criteria. In order to develop a good services evaluation model for IoT environment, a model based on multi-objective decision making (MODM) is proposed by [24]. The parameters that used to assess the QoS are: battery energy cost RE, CPU cost RC, memory usage RM, user-friendly RU and network bandwidth usage RB. The result obtained showed that this model successfully evaluated the QoS. A model based on fuzzy logic is developed by [25] in order to propose an assessment method to evaluate the level of QoS in IoT. The authors used execution time and reliability as the measurement metrics to the QoS. Fuzzy Logic Estimating Level (FLEL) estimates the QoS level by performing many tests. To evaluate the model, the researchers compares the proposed model with the existing model such as a Randomization Test (RT) and the estimating method by a Single Test in Steps (STS), and the result revealed that the efficiency of the FLEL is close to the STS and RT or even higher through the comparison of Average Paased Times APTs. in [26], a model developed to assess the QoS in IoT network layer. The parameters used in this study are end to end delay, energy consumption, energy fairness, jitter, throughput, routing load, packet delivery ratio and normalized routing overhead. The QoS of each parameter is evaluated by testing the performance of each parameter by increasing and decreasing the number of nodes in IoT network. The result obtained showed that, as the number of nodes grows, the performance of QoS measures such as end-to-end delay, energy consumption, energy fairness, routing load, and normalized routing overhead improves.

In [27], a model for evaluating QoS is developed based on five attributes. The attributes are classified in two categories: positive attributes (reliability, reputation, security) and negative attributes (cost, response time). To compute the QoS, the weight for each attribute is identified based on users' preferences, then the QoS is aggregated for negative and positive attribute separately using tow aggregation formulas.

To improve the services selection, [28] developed QoS model based on three components of IoT (things, communication and computing). The model provides description to the services in all three components. The aim of this study is to improve the services selection by considering the QoS in the three mentioned components. Evaluation of the quality of services in the proposed model passes through three steps: first the QoS parameters will be identified; secondly, the weight of each QoS parameter is calculated using Analytic Hierarchy Process (AHP) method. In the last steps the IoT services are ranked by using Order Preference by Similarity to Ideal Solution (TOPSIS). To validate the model, it compared with AHP, the evaluation showed that execution time taken by AHP- TOPSIS is less that than the time taken AHP.

A QoS model was established by [21] in order to compute QoS in the application layer. The main goal of this study is to tackle the issues of selecting the ideal service among similar functionally identical services and varied non-functionality needs. They classified the QoS factors into two categories: the first one is Business Quality Type (BQT), which assesses the quality of services from a business view point, the factors in this type like Reputation and Execution Price. The second type is System Quality Type (SQT). This type relates to the processing time of system and used factors such as Reliability, Availability and Response Time.

As we have seen, though the assessment of QoS in IoT ecosystems has been addressed by many researchers, however, some of the adopted solution developed based one specific layer and ignore the other layers. Moreover, most of the proposed solution did not consider the fuzziness of the QoS attributes. Therefore, in this paper is going to address all these issues by proposing new approach for computing the QoS in IoT ecosystems.

IV. Assessment QoS Model

In this research our assessment QoS model is based on a new approach. The model is based on three-layers IoT architecture as shown in Fig. 2. We used the fuzzy logic system to assess the QoS in each layer. The assessment of QoS performed in two stages (Fig. 3).

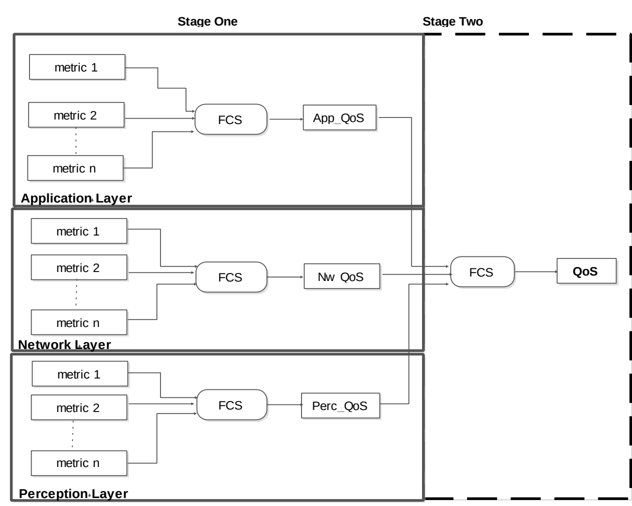

Fig. 3. Show the Two Fuzzy Stages of Assessment QoS for IoT Services.

In the first stage we have three FCSs which assess the QoS in perception layer, network layer and application layer. The metrics of each layer represent the inputs of the FCS. The result of this stage is three outputs named Perc_QoS, Nw_QoS and App_QoS, which represent the QoS of perception layer, network layer and application layer, respectively.

In the second stage the Perc_QoS, Nw_QoS and App_QoS obtained from first stage will be inputs of the FCS of the second stage. The result of this stage is the QoS which represents the final output of the system. The methodology that we used to perform the two stages mentioned is fuzzy control system which based on Lotfi A. Zadeh's fuzzy logic theory, which was developed in the 1960s to offer mathematical rules and functions that allowed natural language queries. The general idea behind the Fuzzy Logic is to mimic the way humans think [29], which tends to think in approximate rather than precise terms [30]. In other word, fuzzy logic is a method for describing and processing vague information that is commonly used by humans in their daily lives. Unlike traditional propositional logic, fuzzy logic assigns numeric values between 0 and 1 to each proposition in order to reflects uncertainty [31]. It is possible to calculate the degree to which an item belongs using fuzzy sets. For example, if a person is.83 tall, they are considered "rather tall." Fuzzy logic determines the shades of gray between black and white and true and false. The fuzzy logic control system typically consists of three major components, which are as follows:

(1) fuzzifier (2) inference rules and (3) defuzzifier. These components represent the sequences processes of the fuzzy logic controller (Fig. 4).

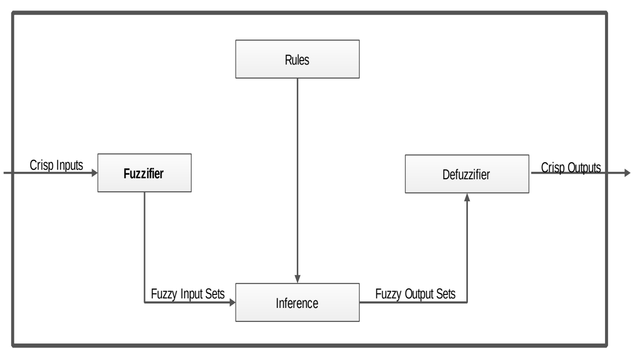

Fig. 4. Shows Fuzzy Logic Control System Architecture [32].

A. Fuzzification

This is the first step in developing FCS which explains the process of converting a set of crisp data into a set of linguistic variables using the membership functions (fuzzy sets) [33]. Fuzzification is a useful tool for dealing with vague and uncertain information, which can be objective or subjective. The membership function chart can be drawn in a variety of ways, including triangles, trapezoids, bell curves, or any other shape that accurately represents the distribution of information inside the system. A triangular fuzzy number is represented by a triplet (a, b, c), as shown in Fig. 5, and the membership function is calculated by equation (1):

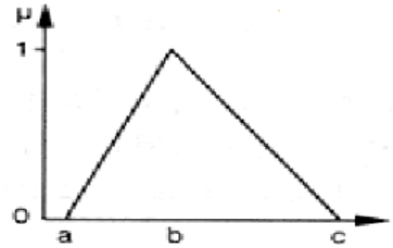

Fig. 5. Shows a Triangular Fuzzy Shape [34].

$$\mu(x) = \begin{cases} \frac{x-a}{b-a} a \le x \le b \\ \frac{c-x}{c-b} b \le x \le c \\ 0 \quad otherwise \end{cases} \tag{1}$$

A trapezoids fuzzy number is defined by four variables (a, b, c, d), as shown in Fig. 6, and the membership function is calculated by Equation (2):

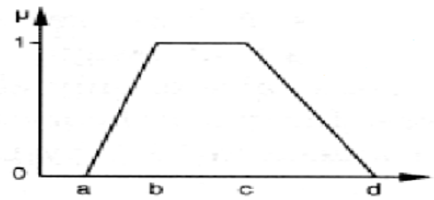

Fig. 6. Shows a Trapezoid Fuzzy Shape [35].

$$\mu(x) = \begin{cases} \frac{x-a}{b-a} a \le \mathrm{x} \le b \\ 1 \quad b \le \mathrm{x} \le c \\ \frac{d-x}{d-c} c \le \mathrm{x} \le d \end{cases} \tag{2}$$

B. Inference Mechanism

This is the main intelligent control of this system. Forming the rules base doesn't has systemic tools that can be used as standard in developing the fuzzy logic controller [30]. As a controller designed as expert system, thus, developing the rule base depend on intuitive knowledge and the experience.

C. Defuzzification

After examining the fuzzy rules, the defuzzification component of fuzzy logic converts the fuzzy data values into real-world data values, and these real-world data values are determined by the defuzzification method. Different methods are used for defuzzification process such Center of Gravity (SOG), Weighted Average method, Mean of Maxima (MOM) and Smallest of Maxima (SOM). These methods are set by the controller designer.

V. Implementation and Results

Based on the above definition and steps of developing FCS, we used Fuzzy Logic Designer in MATLAB to develop the proposed model. Our purpose of this research is to assess the QoS of IoT service in all layers. As shown in Fig. 3, the calculation of QoS will be performed in two stages:

A. Stage One

In this stage we develop three FCSs for the three layers. For straightforwardness we selected tow metrics in each layer to represent inputs for FCS. Upcoming in this we will describe in details the steps of building the FCS for the three layers:

1) Fuzzification: For each layer we choose two QoS metrics to represent the inputs of the FCS. For example, we choose price and reputation for application layer, bandwidth and reliability for network layer and accuracy and response time for perception layer. Then we identified the fuzzy set of each input and outputs in each layer as showed in Table I and Table II.

We used triangular and trapezoid shapes to represent the fuzzy set for all inputs and outputs in the three layers.

2) The rule base: The inputs identified in the fuzzification step will be applied to a set of IF/then control rules in this step. The results of this step are combined to produce a set of fuzzy outputs. In our proposed model we have 2 inputs for each layer, and each input has 3 fuzzy sets, as showed in the Table I. Therefore, the number of control rules that we need will be based on the equation (3) below:

$$\text{Number of control rules} = n^m \tag{3}$$

where n = the number of fuzzy sets and m = the number of inputs.

By applying the above rule, number of control rules = 3^2 = 9 rules (for each FCS).

In this paper we used (And) as conjunction operator to form the rules as showed below:

If (metric1 is membership function1) and (metric2 is membership function2) then (output is output membership function).

TABLE I. SHOWS THE FUZZY SETS FOR INPUTS

Layer	**Input Parameters**	**Fuzzy set**	**Universe of Discourse**
Application Layer	Price	Cheap, medium, Expensive	0 – 15
	Reputation	Low, Medium, High	0 – 100
Network Layer	Bandwidth	Low, Medium, High	0-100
	Reliability	Low, Medium, High	0-100
Perception Layer	Accuracy	Low, Medium, High	0-100
	Response time	Fast, Medium, Slow	0-1

TABLE II. SHOWS THE FUZZY SETS FOR OUTPUTS

Output Parameters	**Fuzzy set**	**Universe of Discourse**
App_QoS	Low, Medium, High	0 -10
Nw_QoS	Low, Medium, High	0 -10
Perc_QoS	Low, Medium, High	0 -10

3) The defuzzification: Since the outputs from the previous step still fuzzy and uncertain, a defuzzification process is needed. The function of the defuzzification is to convert back the linguistic variable obtained from the previous step into numerical value in order to make the fuzzy output suitable to use in real application [36]. we used the MOM fuzzification method in order to get the results. From this step we received three outputs which represent the QoS for IoT services in perception layer, network layer and application layer, these outputs are Perc_QoS, Nw_QoS and App_QoS respectively.

B. Result of Stage One

To test the new model, we used the random function in MATLAB to generate a data set of 50 services. By applying the model to this stage, the model successfully calculates the QoS for all 50 services in perception layer, network layer and application layer. The Table III shows random samples of results obtained in this stage.

TABLE III. SHOWS SAMPLE OF RESULTS OF STAGE ONE

Service_ID	App_QoS	Nw_QoS	Perc_QoS
1	5.00	5.10	5.10
5	5.00	5.10	3.50
8	8.50	8.50	4.20
9	5.00	8.50	5.10
10	1.10	5.10	0.10
11	5.00	1.40	7.50
12	5.00	8.50	5.10
13	1.30	8.50	0.10
16	1.10	1.40	7.60
17	5.00	5.10	0.10
21	1.40	1.10	3.20
24	1.10	8.50	5.10
31	5.00	1.50	3.90
33	8.50	0.80	7.40
35	5.00	5.10	7.90
50	8.50	8.50	0.10

C. Stage Two

The FCS for this stage is based on the outputs of the FCSs of stage one. As we mentioned before, we received three outputs from the FCSs of stage one, which are: App_QoS, Nw_QoS and Perc_QoS. These outputs will be the inputs of the FCS for this stage. To develop the FCS, we follow the same steps as in the first stage.

1) Fuzzification: In this step we identified the fuzzy set of the inputs parameters as shows in Table IV.

The result of this stage is one output which represents the QoS. And as the purpose of this research is to assess the Quality of IoT service and put it into three categories (high quality, medium quality and low quality), we identified the fuzzy set of the output based on these categories, Table V.

TABLE IV. SHOWS THE MEMBERSHIP FUNCTION FOR INPUTS

Inputs Parameters	Fuzzy set	Universe of Discourse
App_QoS	Low, Medium, High	0 –100
Nw_QoS	Low, Medium, High	0 –100
Perc_QoS	Low, Medium, High	0-100

TABLE V. SHOWS THE MEMBERSHIP FUNCTION FOR OUTPUTS OF FCS FOR STAGE TWO

Outputs Parameters	Fuzzy set	Universe of Discourse
QoS	Low, Medium, High	0 –10

We used triangular and trapezoid shapes to represent the fuzzy set for all inputs and output in FCS Fig. 7(a-b-c-d).

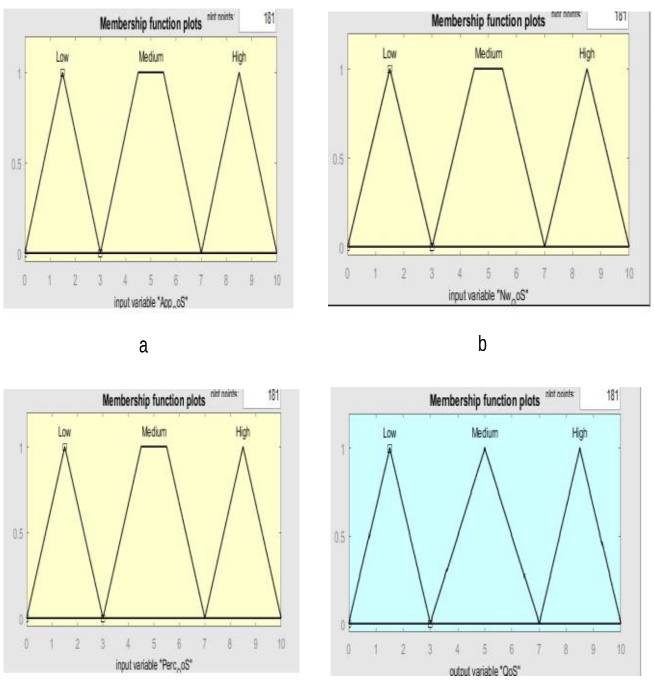

Fig. 7. Shows the Representation Fuzzy Set for Inputs and Output.

2) The rule base: As we have 3 inputs and 3 fuzzy set for each input, and referred to the equation (3), the number of the rules will be = 3^3 = 27 rules.

3) The defuzzification: We received from the previous step the output which represents the QoS. To convert the fuzzy output to crisp form, we used MOM defuzzification method.

D. Result of Stage Two

The result obtained from stage one has become the dataset for stage two. By applying the dataset in this stage, the model successfully calculates the QoS for all 50 services which are based on the three layers. Table VI shows the final result we obtained and which represents QoS of some of the targeted services.

TABLE VI. SHOWS QOS OF SOME OF SERVICES

Service_ID	App_QoS	Nw_QoS	Perc_QoS	QoS
1	5.00	5.10	5.10	5.00
5	5.00	5.10	3.50	5.00
8	8.50	8.50	4.20	8.50
9	5.00	8.50	5.10	8.50
10	1.10	5.10	0.10	1.50
11	5.00	1.40	7.50	5.00
12	5.00	8.50	5.10	8.50
13	1.30	8.50	0.10	1.50
16	1.10	1.40	7.60	1.50
17	5.00	5.10	0.10	5.00
21	1.40	1.10	3.20	1.50
24	1.10	8.50	5.10	5.00
31	5.00	1.50	3.90	5.00
33	8.50	0.80	7.40	8.50
35	5.00	5.10	7.90	8.50
50	8.50	8.50	0.10	8.50

VI. DISCUSSION

Through two stages our model calculated the QoS for 50 services. In the first stage the model calculated the QoS for all services in perception layer, network layer and application layer. Then in the next stage the model used the results of the first stage to calculate the QoS for all targeted services. Unlike other approaches which calculate QoS by focusing on some layers and ignore the other layers, or calculate the QoS in all layers but deal with each layer separately, our model evaluated the QoS in three layers and combined the results of all layers in order to get the final result which represents the QoS for all targeted services.

Based on the final result obtained and reference to the range of fuzzy set of QoS parameters that we identified earlier in the FLC Fig. 7(d), we have successfully classified the all services into three categories: high quality services, medium quality services and low quality services. Based on this classification: the number of high quality services is 16, the number of the medium quality services is 25 and the number of the low quality services is 9.

Our findings show that our model was able to calculate the QoS for all services in the dataset. As a result, the model will be of great assistance to service providers by providing them with convenient tools that allow them to accurately assess QoS before delivering it to end users. In addition, the model enables end users to request services using linguistic terms rather than numerical values. When compared to existing models such as AHP-TOPSIS, our developed model is more flexible while AHP-TOPSIS is very restricted because the end user is required to use numerical values to identify the weight of each metric. To explain this point, for example suppose that we have a user need an IoT services with a medium quality. In AHP-TOPSIS the user must use numeric value as the model does not support fuzziness. The user has to say (“I need a service with quality = 55”), but if there is no service with exact number in registry, the system will replies “null”, maybe in registry there are services with medium quality = 56 or 54, But because the AHP- TOPSIS model is very restricted, the other services will not be recommended to the end user. In our model we have solved this problem by using fuzzy logic technique. Instead of use numbers, end user just has to say (“I need a service with a medium quality”), immediately the model will recommend 25 services that match the user requirement.

To validate the model, we compare its execution time with AHP-TOPSIS. AHP-TOPSIS took 0.0386 second to rank 50 services, whereas our model took 0.2274 second to assess QoS for 50 services. This slight increase in execution time in our developed model is due to the model calculating QoS across all layers and then aggregating the results to obtain the final results.

VII. Conclusion

Delivering a service that meets certain standards of quality demanded by end users in the realm of IoT has clearly piqued the interest of many academics. As a result, it is essential to first build a model that allows IoT service providers to measure QoS before making them available to users. We solved this issue in this research by building a novel model that allows us to calculate QoS for all targeted services. The main contribution of this model lies in the evaluation of QoS in IoT platforms at the level of three layers. Moreover, the model used the fuzzy logic system in order to support the uncertainty thinking of humans. Over all, the model provides IoT services providers with a convenient tool which allows them to evaluate QoS for all available services. In future work, firstly we will try to improve the performance of the model, then we will use the results obtained from this model to develop a selection model that would allow IoT service consumers to select the kind of services meeting the levels of Quality they anticipate and look for.

References

[1] Barros and D. Oberle, “Handbook of service description: USDL and its methods,” Handb. Serv. Descr. USDL Its Methods, no. February, pp. 1–538, 2012, doi: 10.1007/978-1-4614-1864-1.

[2] M. E. Adam, “Usages of Semantic Web Services Technologies in IoT Ecosystems and its Impact in Services Delivery : A survey,” vol. 4523.

[3] A. Nordrum, “Popular Internet of Things Forecast of 50 Billion Devices by 2020 Is Outdated,” 2016. https://spectrum.ieee.org/tech-talk/telecom/internet/popular-internet-of-things-forecast-of-50-billion-devices-by-2020-is-outdated.

[4] Statista, “Internet of Things (IoT) connected devices installed base worldwide from 2015 to 2025,” Stat. Res. Dep., 2022, [Online]. Available: https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/.

[5] Https://www.iotone.com/, “Quality of Service:,” 2004. https://www.iotone.com/term/quality-of-service/t622 (accessed Sep. 19, 2021).

[6] C.-L. Fok, C. Julien, G.-C. Roman, and C. Lu, “Challenges of satisfying multiple stakeholders,” p. 55, 2011, doi: 10.1145/1988051.1988062.

[7] Y. Yang, M. Dumas, L. García-Bañuelos, A. Polyvyanyy, and L. Zhang, “Generalized aggregate Quality of Service computation for composite services,” J. Syst. Softw., vol. 85, no. 8, pp. 1818–1830, 2012, doi: 10.1016/j.jss.2012.03.005.

[8] D. Martin et al., “Bringing semantics to web services with OWL-S,” World Wide Web, vol. 10, no. 3, pp. 243–277, 2007, doi: 10.1007/s11280-007-0033-x.

[9] U. Bellur, H. Vadodaria, and A. Gupt, “Semantic Matchmaking Algorithms,” Greedy Algorithms, no. November, 2008, doi: 10.5772/5884.

[10] W. D. Fang, W. He, W. Chen, L. H. Shan, and F. Y. Ma, “Research on the application-driven architecture in internet of things,” Front. Artif. Intell. Appl., vol. 293, pp. 458–465, 2016, doi: 10.3233/978-1-61499-722-1-458.

[11] M. Singh and G. Baranwal, “Quality of Service (QoS) in Internet of Things,” Proc. - 2018 3rd Int. Conf. Internet Things Smart Innov. Usages, IoT-SIU 2018, pp. 1–6, 2018, doi: 10.1109/IoT-SIU.2018.8519862.

[12] A. Mavrogiorgou, A. Kiourtis, C. Symvoulidis, and D. Kyriazis, “Capturing the Reliability of Unknown Devices in the IoT World,” 2018 Fifth Int. Conf. Internet Things Syst. Manag. Secur., pp. 62–69, 2018.

[13] B. D. Technologies, “Difference between sensor response time and sensor time constant τ (tau) 63.2%.,” 2019. https://www.baranidesign.com/faq-articles/2019/5/6/difference-between-sensor-response-time-and-sensor-time-constant-tau#:~:text=Sensor Response Time %3D 5*τ,five times the time constant. (accessed Aug. 28, 2020).

[14] Y. Li, Y. Huang, M. Zhang, and L. Rajabion, “Service selection mechanisms in the Internet of Things (IoT): a systematic and comprehensive study,” Cluster Comput., vol. 23, no. 2, pp. 1163–1183, 2020, doi: 10.1007/s10586-019-02984-4.

[15] L. A. K. Subash, D. Janet Ramya and S. Awarded, “Quality of Service in the Internet of Things (IoT) – A Survey,” Res. Teach. Learn. Lett., vol. 21, no. June, 2019.

[16] S. Gridelli, “How to calculate network availability?,” NetBeez, 2014. https://netbeez.net/blog/how-to-calculate-network-availability/ (accessed Nov. 08, 2020).

[17] N. M. M. Alhag and Y. A. Mohamed, “An Enhancement of Data Encryption Standards Algorithm (DES),” 2018 Int. Conf. Comput. Control. Electr. Electron. Eng. ICCCEEE 2018, vol. 1, pp. 1–6, 2018, doi: 10.1109/ICCCEEE.2018.8515843.

[18] R. A. A. Farah and Y. A. Mohamed, “Adaptive Immune-Based System for Network Security,” 2018 Int. Conf. Comput. Control. Electr. Electron. Eng. ICCCEEE 2018, pp. 1–7, 2018, doi: 10.1109/ICCCEEE.2018.8515827.

[19] A. K. Sikder, G. Petracca, H. Aksu, T. Jaeger, and A. S. Uluagac, “A Survey on Sensor-based Threats to Internet-of-Things (IoT) Devices and Applications,” arXiv, 2018, [Online]. Available: http://arxiv.org/abs/1802.02041.

[20] G. S. M. Sathya, M. Swarnamugi, P. Dhavachelvan, “Evaluation of QoS based Web- Service Selection Techniques for Service Composition,” JInternational J. Softw. Eng., vol. 110, no. 9, pp. 73–90, 2017.

[21] A. N. Abu-safe and S. E. Elrofai, “An Efficient QoS-aware Services Selection in IoT using A Reputation Improved- Social Spider Optimization Algorithm,” Res. Sq., 2020, doi: 10.21203/rs.3.rs-38596/v1.

[22] S. Singh and R. K. Tiwari, “Quality of Services in Assets of Smart Parking,” Proc. - 2018 3rd Int. Conf. Internet Things Smart Innov. Usages, IoT-SIU 2018, pp. 1–5, 2018, doi: 10.1109/IoT-SIU.2018.8519885.

[23] Y. Dongre and R. Ingle, “An Investigation of QoS Criteria for Optimal Services Selection in Composition,” 2nd Int. Conf. Innov. Mech. Ind. Appl. ICIMIA 2020 - Conf. Proc., no. Icimia, pp. 705–710, 2020, doi: 10.1109/ICIMIA48430.2020.9074950.

[24] S. Fan, W. Shi, N. Wang, and Y. Liu, “MODM-based evaluation model of service quality in the Internet of Things,” Procedia Environ. Sci., vol. 11, no. PART A, pp. 63–69, 2011, doi: 10.1016/j.proenv.2011.12.011.

[25] B. Jia, L. Hao, C. Zhang, and D. Chen, “A dynamic estimation of service level based on fuzzy logic for robustness in the internet of things,” Sensors (Switzerland), vol. 18, no. 7, pp. 1–13, 2018, doi: 10.3390/s18072190.

[26] & K. Sheikh, A., Ambhaikar, A., “analysis of QoS parameters in IoT network 2021.pdf,” Open J. Sci. Technol., 2021.

[27] X. Zhang, J. Geng, J. Ma, H. Liu, and S. Niu, “A QoS-driven Service Selection Optimization Algorithm for Internet of Things,” Eur. PMC, 2020.

[28] M. S. • G. B. • A. K. Tripathi1, "QoS-Aware Selection of IoT-Based Service.pdf," Arab. J. Sci. Eng., vol. 45(12), no. 10033-10050., 2020.

[29] D. Shannaq, B., & Thakkar, "On The Development of Neural Network Models Using Data Mining Tools," Asian J. Comput. Sci. Inf. Technol., vol. 2, no. 7, 2012.

[30] L. A. Zadeh, "Fuzzy sets," nformation Control, vol. 8, no. 3, pp. 338–353, 1965, [Online]. Available: https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=L.A.+Zadeh%2C+1965%2C+Fuzzy+Sets.&btnG=.

[31] Charles Elkan, "fuzzy logic," 1999, [Online]. Available: https://www.scientificamerican.com/article/what-is-fuzzy-logic-are-t/.

[32] M. Norsuzila Ya'acob et al., "Enhancing Fuzzy Controllers Using Generalized Orthogonality Principle," Intech, vol. 32, pp. 137–144, 1989, [Online]. Available: http://www.intechopen.com/books/trends-in-telecommunications-technologies/gps-total-electron-content-tec-prediction-at-ionosphere-layer-over-the-equatorial-region%0AInTec.

[33] T. Sai, D. Nakhaeinia, and B. Karasfi, "Application of Fuzzy Logic in Mobile Robot Navigation," Fuzzy Log. - Control. Concepts, Theor. Appl., no. March 2012, 2012, doi: 10.5772/36358.

[34] F. Liu, S. Chen, M. Heiner, and H. Song, "Modeling biological systems with uncertain kinetic data using fuzzy continuous Petri nets," BMC Syst. Biol., vol. 12, no. Suppl 4, 2018, doi: 10.1186/s12918-018-0568-8.

[35] H. Fakhrurroja, S. A. Mardhotillah, O. Mahendra, A. Munandar, M. I. Rizqyawan, and R. P. Pratama, "Automatic pH and Humidity Control System for Hydroponics Using Fuzzy Logic," 2019 Int. Conf. Comput. Control. Informatics its Appl. Emerg. Trends Big Data Artif. Intell. IC3INA 2019, no. July 2020, pp. 156–161, 2019, doi: 10.1109/IC3INA48034.2019.8949590.

[36] Y. Bai and D. Wang, "Fundamentals of fuzzy logic control — fuzzy sets, fuzzy rules and defuzzifications," Adv. Ind. Control, no. 9781846284687, pp. 17–36, 2006, doi: 10.1007/978-1-84628-469-4_2.