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A Fuzzy Inference Model for Evaluating Data Transfer in LTE Mobile Networks via Crowdsourced Data

Julio Ernesto Zaldivar-Herrera[1], Luis Pastor Sánchez-Fernández[1,*], Luis Manuel Rodríguez-Méndez[2], María Teresa Zagaceta-Álvarez[2]

[1] Instituto Politécnico Nacional, Centro de Investigación en Computación, Mexico

[2] Instituto Politécnico Nacional, Escuela Superior de Ingeniería Mecánica y Eléctrica, Mexico

{jzaldivarh2021, lsanchez}@cic.ipn.mx, {lrodriguezm, mzagaceta}@ipn.mx

Abstract. Improving the Quality of Service (QoS) in the data transfer of 4G Long-Term Evolution (LTE) mobile networks has been a significant concern. Previous analyses have focused on enhancing network infrastructure using statistical tools, computational algorithms, and fuzzy models to improve mobile network operators. Those works are based on simulated data or data collected by a specialised modem without providing user information. In this study, we propose a fuzzy inference model to evaluate QoS Key Performance Indicators and signal parameters using data acquired by user equipment through collaboration or crowdsourcing. This fuzzy inference model provides specialists with a new method for assessing the QoS and offers users relevant information on the quality of data transfer service in LTE networks. The evaluation is based on fuzzy QoS, and effectiveness indices are classified into five levels: Very poor, Poor, Acceptable, Good, and Very good. Furthermore, the model can evaluate other data samples different from those used in this proposal. Finally, this method can assess the data transfer of 5G networks, making respective adaptations.

Keywords. Quality of service, key performance indicators, long-term evolution, crowdsourcing, fuzzy inferences system, assessment indices.

1 Introduction

As technology continues to develop, the demand for activities and the number of mobile devices have increased, resulting in a significant increase in data transfer over mobile broadband networks [1, 2, 3].

Consequently, there has been a rise in the use of Over-the-Top services [4]: video, audio, voice, or data applications transmitted over fixed or mobile internet platforms [5]. User can now access various multimedia applications through their devices, requiring reliable connectivity at any time and place.

This translates into the need for adequate Quality of Service (QoS) from mobile network operators (MNOs) [6]. Technological advances in multimedia offerings have forced operators to adopt a user-centric and quality of experience (QoE) approach [7].

Telecommunications regulatory bodies recommend evaluating QoS. However, ensuring QoS in the 4G mobile network is a significant challenge due to constant changes in the network [8]. The International Telecommunication Union (ITU) mentions that the QoS planned by network operators is typically different from the level users experience and could even be much lower than expected [9].

QoS is a set of measurable quality parameters called key performance indicators (KPIs). These indicators provide the necessary information for planning, performance analysis, and network optimization and can be either technical or non-technical [10]. As mentioned by the ITU, examples of technical KPIs are call success rate, call drop

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rate, and upload and download connection speeds, among others.

Non-technical KPIs are customer-focused and may include parameters such as billing accuracy and failures [9]. Inadequate KPI data can limit service efficiency, increase operating costs, and negatively affect users [10]. Correct data is beneficial to network operators and users, as well as for research purposes. For example, an ensemble learning scheme for indoor-outdoor classification based on cellular data from a commercial LTE mobile network has been presented in [11], where the data was obtained with a single-user equipment (UE) model.

Numerous studies have focused on LTE mobile networks' data transfer KPIs and QoS. A comprehensive guide to standardized QoS assessment models is presented in [12]. Graphical comparisons of KPIs with received signal parameters have also been performed [13].

However, this study does not consider obtaining an index to determine the QoS of the LTE mobile network. On the other hand, to increase revenues from network services provided by the MNOs, the base station (eNodeB) performance is evaluated when a higher priority QoS is enabled for some LTE users [14]. In that study, the commercial network and UE were used. The study mainly focused on improving the infrastructure of the MNOs, but it is a very relevant work for the 4G network in general.

Other studies focus on the development or use of LTE mobile network simulators. In those studies, the network capacity is calculated. Improvements in the scheduling process for the network are proposed to impact both the QoS and QoE, thus increasing the spectral efficiency in terms of network throughput or packet delay prediction [7], [15, 16, 17, 18].

In addition, other research works aim to improve QoS and QoE during video transmission over LTE networks by evaluating and analysing various configurations and parameters [19 20 21 22 23]. Although, in these studies, there is an interest in increasing QoS and QoE, their main focus remains improving the services of the MNOs.

Several studies use experimental data collected from a smart city to conduct statistical analysis on the QoS of mobile networks. They present statistical descriptions and probability distribution functions for the KPIs to aid comprehension [10]. However, the experimental data contains some missing values estimated for each network parameter using the PCHIP algorithm and statistical error analysis [24]. The measurements in both cases were taken using a specialised modem. The Egil model [25] is also proposed to estimate signal loss using the quadratic regression method. While these investigations offer valuable statistical insights for the 4G LTE mobile network, they require a large data sample, which the current proposal aims to avoid.

The scientific literature encompasses various computational models, including a gradient-based iterative process to determine the optimal tilt configuration for the LTE eNodeB antenna [25].

Several sets of rules have been proposed to optimise resource allocation in downlink scheduling, and their performance has been evaluated by comparing the Knapsack and Priority-only algorithms [26]. The QoS-aware downlink scheduling algorithm (QuAS) was presented in [27] to enhance the QoE for peripheral users. Additionally, an innovative approach aims to maximise QoE by sharing an available channel among video traffic flows, incorporating genetic algorithms and random neural networks [23].

Despite these efforts offering alternatives to improve QoS and QoE, it is necessary to present relevant information to the user, such as knowledge of the actual QoS and effectiveness that users are experiencing.

On the other hand, Zadeh's fuzzy set theory is an extension of classical binary logic and has had a lasting impact on artificial intelligence [28]. The essential advantage of the fuzzy approach over binary logic lies in its flexible decision boundaries, providing greater adaptability to specific application domains [29].

Fuzzy logic draws inspiration from our understanding of human cognition in decision-making systems, making it widely accepted as an explainable artificial intelligence among interdisciplinary experts. It effectively deals with input variables, their ranges, limits, and variations, facilitating design, verification, and continuous improvement [30, 31, 32].

In the context of LTE networks, fuzzy systems have been employed in Call Admission Control to reduce call drop and call blocking probabilities, as well as mitigate co-channel interference [23, 33] and [34].

To reduce costs and minimize negative impacts on the user experience of self-organizing networks, a problem-solving rule learning method based on fuzzy logic controllers and data mining techniques was proposed in [35].

To assess the QoS of LTE networks, particularly during the handover process, a Sugeno-type fuzzy model was employed to analyse four QoS KPIs across four applications [36]. Furthermore, a novel study compared the Sugeno-type fuzzy model against an Adaptive Neuro-Fuzzy Inference System (ANFIS) model tailored explicitly for QoS calculations in heterogeneous LTE networks [37].

However, it is worth noting that both investigations relied on simulated data and failed to propose a fuzzy index that effectively correlates KPIs with received signal parameters. As a result, users should receive more easily understandable and explainable information regarding the LTE network's QoS.

This paper introduces a novel fuzzy inference model for evaluating QoS and data transfer efficiency in LTE mobile networks. It incorporates two user-friendly fuzzy indices for swift categorisation of QoS and effectiveness, benefiting both network evaluators and end-users. The information repository used to evaluate the fuzzy model was collected through crowdsourcing.

The structure of the paper is as follows: Section 2 presents the methodology and information repository, followed by the results in Section 3, a comprehensive discussion in Section 4, and concluding remarks in Section 5.

2 Materials and Methodology

This section shows the phases that were attended to develop the fuzzy inference system. Fig. 1 introduces the methodology of our proposed model inspired by [38] and features six distinct stages: Fig. 1(a) acquisition of an information repository compiled through crowdsourcing; Fig. 1(b) selection of KPIs and signal parameters to be used as input variables, alongside data filtration to discard any outliers; Fig. 1(c) proposal of membership functions for the input variables and two fuzzy indicators; Fig. 1(d) creation of the fuzzy rules considering six input variables for QoS and two for effectiveness; Fig. 1(e) implementation of defuzzification using the Centroid Method; and Fig. 1(f) obtaining fuzzy indices for both QoS and effectiveness.

Further explanation of these stages can be found in subsections 2.1-2.5.

2.1 Information Repository

The information repository was gathered using crowdsourcing by teams of users equipped with mid-range mobile phones (UE) in the central Alameda zone of Mexico City during the first two months of 2021. This information was facilitated by the Telecommunications Engineering branch of the Postgraduate Sciences program (PCIT), part of the Postgraduate Studies and Research Section (SEPI) at the Higher School of Mechanical and Electrical Engineering (ESIME), Zacatenco unit of the National Polytechnic Institute (IPN).

Crowdsourced measurements from an end-user perspective prove crucial in enhancing the overall QoS, facilitating the acquisition of valuable information beyond the mere network layer and into the user and application layers. This approach allows a deeper understanding of any challenges or quality issues users face within the network [39].

Mid-range phones during this data-gathering process do not influence or impact the fuzzy indices obtained in this work. Device range classification is based primarily on RAM, screen resolution, and processor performance.

On the other hand, the transceiver and antenna are similar across all mobile phones to ensure good reception and transmission quality provided by MNOs.

In selecting the location, the downtown area of Mexico City stands out for its rich blend of economic, cultural, and social activities. A particularly strategic zone within this area is the public park of Alameda Central, enveloped by museums, theatres, hotels, offices, restaurants, and commercial stores.

This dynamic environment attracts many office workers, residents, tourists, and visitors participating in recreational activities, generating a significant demand for mobile data transfer.

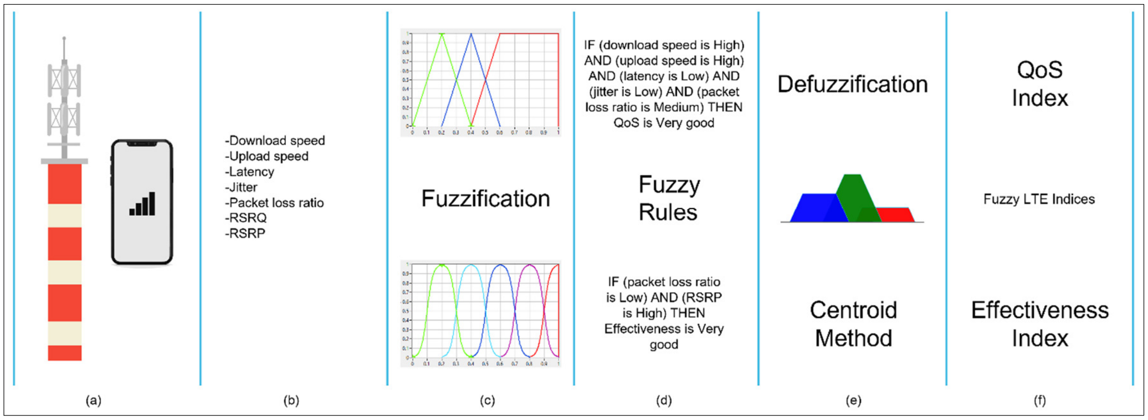

Fig. 1. Fuzzy model methodology: (a) information repository; (b) five QoS KPIs of data transfer and two LTE network signal parameters; (c) fuzzification process based on membership functions; (d) fuzzy rules (372); (e) defuzzification process with the centroid method; and (f) fuzzy QoS and effectiveness indices of the 4G LTE network

To assess the QoS of LTE network data transfer, we have considered the recommendations of prominent organisations such as ITU [9], the European Telecommunications Standards Institute (ETSI) [40], and the Body of European Regulators for Electronic Communications (BEREC) [41]. These guidelines indicate that the appropriate KPIs for this evaluation are download speed, upload speed, latency, jitter, and packet loss rate.

Notably, the packet loss rate is not explicitly included in the information repository but can be derived by applying Eq. (1), as both received and sent packets are available in the repository. Additionally, we propose incorporating the reference signal received quality (RSRQ) parameter to account for the transmission medium.

$$\text{packet loss rate} = \frac{\text{packets received}}{\text{packets sent}}\ [\%]. \tag{1}$$

Furthermore, we derive the data transfer effectiveness index to complement the evaluation of the LTE network service. The packet loss rate is the corresponding KPI for assessing this index. Moreover, as with the QoS, we introduce a signal parameter to consider the transmission medium: the reference signal received power (RSRP).

Ookla [42], the organization responsible for the crowdsourcing measurements, provided the data dictionary of the information repository available in Table A1. However, it is worth noting that the samples reported include outliers, which require a filtering or debugging process that we outline in Section 2.2.

2.2 Filtering the Information Repository

It is necessary to verify the data to ensure an accurate network performance evaluation, as mentioned in [43]. Each parameter has a specific valid range indicated in the data dictionary or the reports published by the company that carried out the measurements [44].

The mobile broadband service reports an average latency of 50 ms, with values ranging from 1 ms to 100 ms. Jitter has a maximum allowable value of 30 ms; any value higher than this is considered invalid. The packet loss rate should fall between 0% and 1%, and values outside this range are discarded. Likewise, the valid range for RSRP is from -120 dBm to -44 dBm, with -44 dBm being the maximum value. For RSRQ, the acceptable values range from -19.5 dB to -3 dB, with -19.5 dB being the minimum value.

For the download and upload speeds, we used the recommendations from the telecommunications regulatory body in Mexico, the Federal Telecommunications Institute [45], and the 2021 Mexico Median Country Speeds report [44]. These state that the valid range for download speed is 4 Mbps to 300 Mbps, and upload speed is 1 Mbps to 100 Mbps. Table 1 presents the range of values used as filters for each parameter.

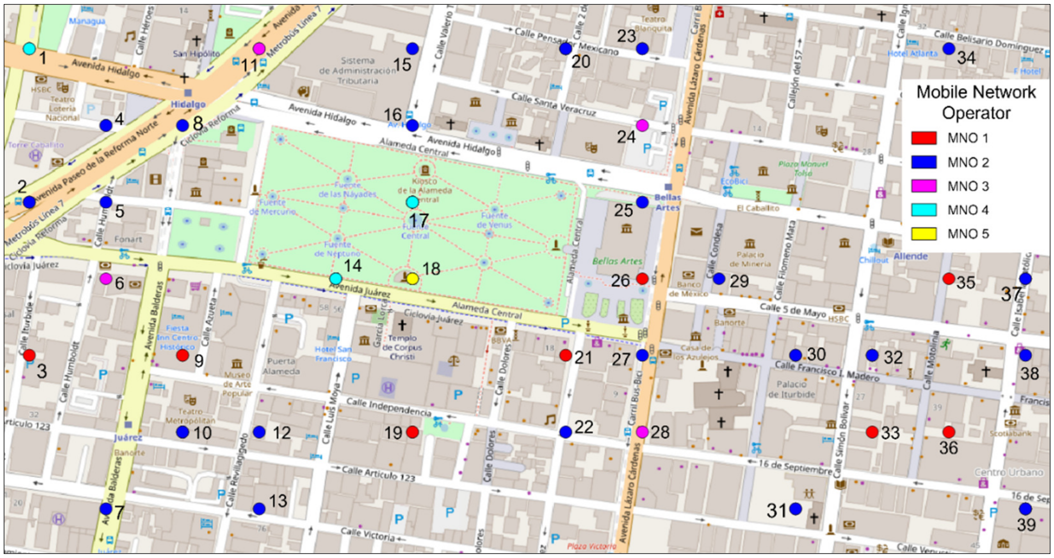

Fig. 2. Map showing the geographical location where information was obtained. The colors indicate different network operators named with the following terminology: MNO 1 is AT&T, MNO 2 is Telcel, MNO 3 is Altan Redes, MNO 4 is Movistar, and MNO 5 is Unefón

Applying these filters to the information repository resulted in a reduction of data samples from 607 to 385, which were geolocated across 39 different locations, as seen in Fig. 2.

The latitude and longitude coordinates of these 39 geolocated points can be found in Table A2. Out of the 385 valid data samples, measurements are available for each day of the first two months of 2021, representing five MNOs. However, it is essential to note that not every georeferenced point contains data for each day and each operator. Considering this, membership functions for the fuzzy inference model are proposed and presented in Section 2.3.

2.3 Membership Functions: Input Variables

The fuzzy inference model evaluates seven input variables: five are linear data transfer QoS KPIs, while the other two are logarithmic signal parameters. Consequently, the membership functions for the linear variables are of triangular and trapezoidal types. On the other hand, the membership functions for the logarithmic variables are sigmoidal.

Eqs. (2) and (3) give the parameterisation for the triangular and trapezoidal membership functions [46]. The triangular membership function is defined by three parameters, a, b, and c, as follows:

$$\mu(x; a, b, c) = \begin{cases} 0, & x \leq a, \\ \dfrac{x-a}{b-a}, & a \leq x \leq b, \\ \dfrac{c-x}{c-b}, & b \leq x \leq c, \\ 0, & c \leq x, \end{cases} \tag{2}$$

where the parameters a, b, and c, with $a<b<c$, determine the triangle's three corners. Meanwhile, the trapezoidal membership function is defined by four parameters, a, b, c, and d, as follows:

$$\mu(x; a, b, c, d) = \begin{cases} 0, & x \leq a, \\ \dfrac{x-a}{b-a}, & a \leq x \leq b, \\ 1, & b \leq x \leq c, \\ \dfrac{d-x}{d-c}, & c \leq x \leq d, \\ 0, & d \leq x, \end{cases} \tag{3}$$

where the parameters a, b, c, and d, with $a < b \leq c < d$, determine the value of x for the four corners of the trapezoid. The input membership functions for the QoS KPIs, i.e., download speed, upload speed, latency, jitter, and packet loss rate, are depicted in Figs. 3–7.

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These linear membership functions have been fitted within the ranges described in Section 2.2. Three linguistic values are considered for all input variables: Low, Medium, and High.

For instance, as depicted in Fig. 3, when the download speed falls from 0 to 4, it is classified under the linguistic value of Low. In the range of 4 to 38, the linguistic variable Medium exhibits a degree of membership that increases linearly with a high positive slope.

Similarly, Fig. 4 illustrates that upload speed follows a comparable pattern from 1 to 14.

However, this high positive slope is not observed for latency (1 to 50), jitter (0 to 15), and packet loss rate (0 to 0.005), as shown in Figs. 5-7, respectively. In these cases, the membership functions increase with a lower slope.

Conversely, for download and upload speeds starting from 38 and 14, respectively, the membership degree of the linguistic variable Medium decreases with a steeper negative slope than latency, jitter, and packet loss rate starting from 50, 15, and 0.005, respectively. Furthermore, the linguistic variable High reaches its maximum values for download speed, upload speed, and latency, beginning from 72, 29, and 99.

The sigmoidal membership function and its parameters are defined by Eq. (4):

$$\mu(x; a, c) = \frac{1}{1+e^{-a(x-c)}}. \quad (4)$$

Here, a controls the slope at the crossing point $x = c$. As stated in [47], the sign of the parameter a determines whether the sigmoidal membership function is intrinsically open to the right or left, making it suitable for representing concepts such as "very large" or “very negative”.

Fig. 8 illustrates the sigmoidal membership functions for the variables RSRP and RSRQ. Both variables were rescaled and normalised using the following expression (Eq. 5):

$$\frac{(x - x_{min})}{(x_{max} - x_{min})}, \quad (5)$$

where x_{min} represents the minimum valid value of the variable to be normalised, x_{max} is the maximum value of the variable, and x is the variable to be normalised. For RSRP, the range of values to be normalised is from –120 dBm to –44 dBm, while for RSRQ, the range is from –19.5 dB to –3 dB. These sigmoidal membership functions were initially fitted with expert knowledge, followed by a manual adjustment.

Table 1. Filters for each data transfer QoS KPI or signal parameter considered

Parameter	Unit	Filter
Latency	ms	1 to 100
Jitter	ms	0 to 30
Packet loss rate	%	0 to 1
RSRP	dBm	-120 to -44
RSRQ	dB	-19.5 to -3
Download speed	Mbps	4 to 300
Upload speed	Mbps	1 to 100

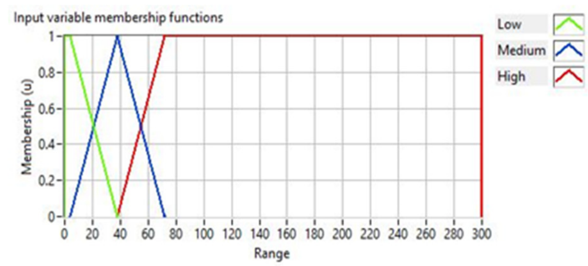

Fig. 3. Trapezoidal and triangular membership functions for download speed

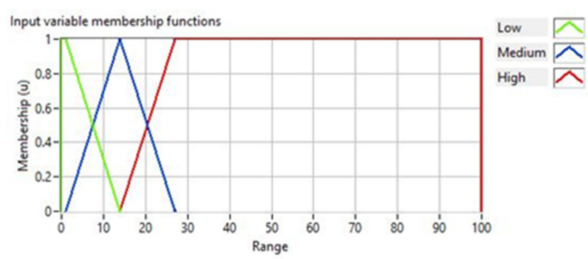

Fig. 4. Trapezoidal and triangular membership functions for upload speed

2.4 Membership Functions: Output Variables

The QoS and effectiveness indices are the output variables obtained from the fuzzy inference model. Fig. 9 illustrates sigmoid-shaped membership functions for both indices because each output is evaluated with at least one non-linear variable. Additionally, linguistic values such as Very poor,

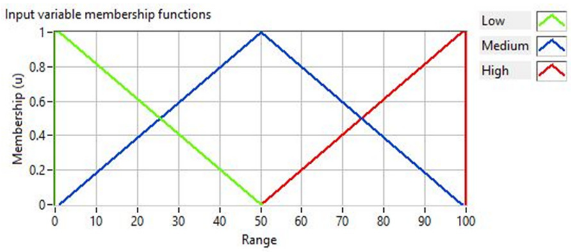

Fig. 5. Trapezoidal and triangular membership functions for latency

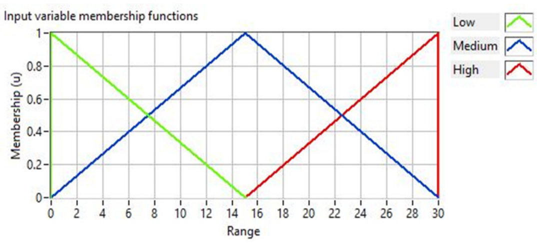

Fig. 6. Triangular membership functions for jitter

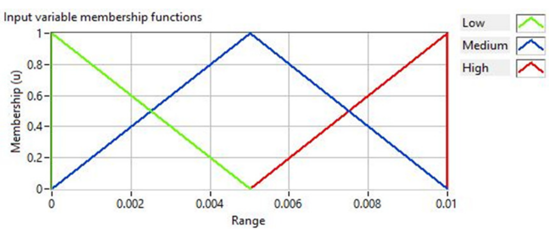

Fig. 7. Triangular membership functions for packet loss rate

Poor, Acceptable, Good, and Very good have been considered to establish a quality evaluation scale for both indices.

On the other hand, the fuzzy quality index is determined by evaluating the following input variables: download speed, upload speed, latency, jitter, packet loss rate, and RSRQ. This index depends on the values of the input variables. For instance, if the download speed, upload speed, and RSRQ have a High value, while the latency, jitter, and packet loss rate have a Low value, the resulting quality is classified as Very good.

Similarly, the fuzzy effectiveness index, which assesses packet loss rate and RSRP as input variables, will yield a Very good value when the packet loss rate is Low and the RSRP is High. The fuzzy rules that complement the membership functions are described in detail in Section 2.5.

2.5 Fuzzy Rules

Fuzzy rules of the type if–then were proposed using the AND (minimum) connector in the antecedent for both fuzzy indices. Each input variable is associated with three linguistic variables. The general expression for this set of variables is given by Eq. (6):

$$\mathrm{T}(\mathrm{variable}) = \{\mathrm{Low}, \mathrm{Medium}, \mathrm{High}\}, \tag{6}$$

where T represents the set of the variable in question (e.g., download speed, latency, etc.), and Low, Medium, and High are the linguistic variables in the set. The following expression was used to determine the number of rules:

$$\mathrm{Q} = \mathrm{M}^{\mathrm{N}}, \tag{7}$$

where M is the size of the linguistic variable set, N is the number of input variables, and Q is the number of rules.

First, we obtained the number of rules for the QoS fuzzy index by considering six input variables and three linguistic variables, resulting in 729 rules for QoS. Similarly, the effectiveness index yielded nine fuzzy rules after considering two input variables and three linguistic variables. Thus, the total number of rules for both indices is 738, encompassing all possible combinations of input variables using the AND connector.

We considered reducing the number of rules to avoid redundancy and computational cost associated with many of them. For this purpose, the rules were analysed from the point of view of expert knowledge in mobile networks. We proposed a weighting scheme for the input variables, giving higher importance to the KPIs variables relative to the signal parameter ones since regulatory bodies recommend KPIs for the QoS evaluation.

For the QoS case, where five of the six input variables are KPIs, and one is a signal parameter, a weighting of 7/36 was assigned to each of the five KPIs and 1/36 to RSRQ. The sum of the weights for all six variables is equal to 1, namely:

$$\frac{7}{36}+\frac{7}{36}+\frac{7}{36}+\frac{7}{36}+\frac{7}{36}+\frac{1}{36}=1. \tag{8}$$

Likewise, different weights were assigned to the input variables for the fuzzy effectiveness index. A weight of 3/4 was proposed for the KPI and 1/4 for

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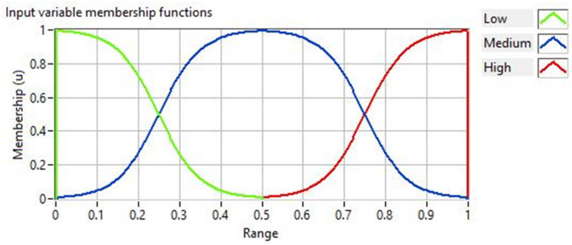

Fig. 8. Sigmoidal membership functions for the RSRP and RSRQ (the graphical representation is the same for both)

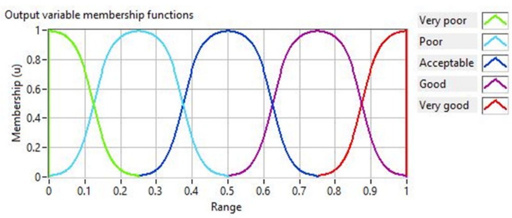

Fig. 9. Sigmoidal membership functions for the QoS and Effectiveness indices (the graphical representation is the same for both indices)

the RSRP. The sum of the weights for both variables is again equal to one.

After applying the weights mentioned earlier to the 738 rules, we found coincidences in two different types of groups, each containing three rules. In the first group, five of the six variables in the antecedent held the same value, and the consequent had the same result for all three rules. Consequently, these rules could be merged into one. Consider the following rules as an example:

R_{L1}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is High) **AND** (RSRQ is Low) **THEN** QoS is Very poor.

R_{L2}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is High) **AND** (RSRQ is Medium) **THEN** QoS is Very poor.

R_{L3}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is High) **AND** (RSRQ is High) **THEN** QoS is Very poor.

Observing rules R_{L1}, R_{L2}, and R_{L3}, we can see that the linguistic values for download speed (Low), upload speed (Low), latency (High), jitter (High), and packet loss ratio (High) are repeated in the antecedent. However, the RSRQ variable carries different linguistic values for each rule (Low, Medium, and High).

On the other hand, the consequent consistently yields the same value for QoS (Very poor). Since the RSRQ variable covers all three linguistic possibilities in this group without affecting the QoS result, we can merge these three rules into one. As a result, the RSRQ variable is removed, obtaining rule R_1:

R_1: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is High) **THEN** QoS is Very poor.

A similar situation occurs with the second group of rules shown below. In the antecedent, the variables maintaining the same linguistic value are download speed, upload speed, latency, jitter, and packet loss ratio, while the RSRQ variable varies its linguistic value. In the rule's consequent, the QoS has two different outcomes.

R_{L25}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **AND** (RSRQ is Low) **THEN** QoS is Poor.

R_{L26}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **AND** (RSRQ is Medium) **THEN** QoS is Acceptable.

R_{L27}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **AND** (RSRQ is High) **THEN** QoS is Acceptable.

Here, two rules share the same linguistic value, while the third rule differs. Thus, we can merge two rules into one, reducing the number of rules from three to two. In the antecedent of rules R_{L25}, R_{L26}, and R_{L27}, we can observe that only the RSRQ variable changes its linguistic value among the three possibilities: Low, Medium, and High.

On the other hand, in the consequent, the QoS value remains "Acceptable" for rules R_{L26} and R_{L27}, while for rule R_{L25}, it is classified as "Poor." Keeping this in mind, we merge rules R_{L26} and R_{L27} into rule R_{13}. However, it should be noted that to avoid affecting the result of this group, rule R_{12} is placed before the merged rule R_{13}, as shown below:

R_{12}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is

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Table 2. File format for KPIs and signal parameter data in the information repository

Download Speed (Mbps)	Upload Speed (Mbps)	Latency (ms)	Jitter (ms)	Packet Loss Rate (%)	RSRP	RSRQ
21.92	26.436	31	9.2	0	0.36	0.70588235
67.943	27.148	32	7.8	0	0.36	0.70588235

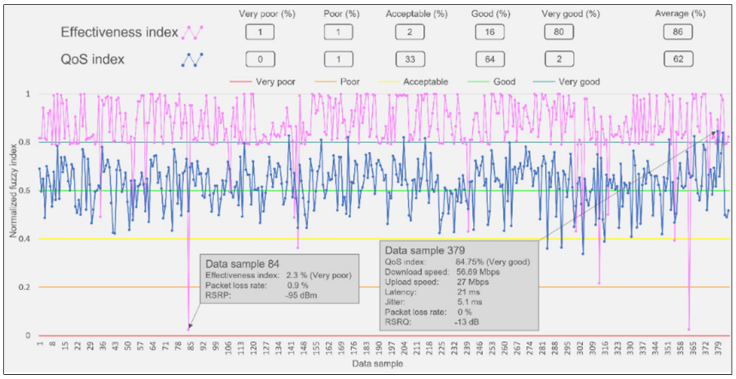

Fig. 10. QoS and effectiveness fuzzy indices for the 385 data samples evaluated in the study zone

Low) **AND** (packet loss ratio is Low) **AND** (RSRQ is Low) **THEN** QoS is Poor.

R_{13}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **THEN** QoS is Acceptable.

Consequently, after merging sets of three rules, the total number of rules was reduced from 738 to 372. Some representative rules are presented below. A summary of these rules can be found in Table A3.

R_1: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is High) **THEN** QoS is Very poor.

R_{12}: **IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **AND** (RSRQ is Low) **THEN** QoS is Poor.

R_{182}: **IF** (download speed is Medium) **AND** (upload speed is Medium) **AND** (latency is Medium) **AND** (jitter is Medium) **AND** (packet loss ratio is Medium) **THEN** QoS is Acceptable.

R_{351}: **IF** (download speed is High) **AND** (upload speed is High) **AND** (latency is Low) **AND** (jitter is High) **AND** (packet loss ratio is High) **AND** (RSRQ is High) **THEN** QoS is Good.

R_{363}: **IF** (download speed is High) **AND** (upload speed is High) **AND** (latency is Low) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **THEN** QoS is Very good.

R_{364}: **IF** (packet loss ratio is High) **AND** (RSRP is Low) **THEN** Effectiveness is Very poor.

R_{366}: **IF** (packet loss ratio is High) **AND** (RSRP is High) **THEN** Effectiveness is Poor.

R_{368}: **IF** (packet loss ratio is Medium) **AND** (RSRP is Medium) **THEN** Effectiveness is Acceptable.

R_{370}: **IF** (packet loss ratio is Low) **AND** (RSRP is Low) **THEN** Effectiveness is Good.

R_{372}: **IF** (packet loss ratio is Low) **AND** (RSRP is High) **THEN** Effectiveness is Very good.

In rule R_1, when there is poor data download and upload speed performance, high latency, jitter, and packet loss, the QoS is classified as "Very poor." On the other hand, for rule R_{12}, the QoS is "Poor" when the download speed is less than 21 Mbps, the upload speed is less than 7.5 Mbps, latency is between 75 ms and 100 ms, jitter is between 22.5 ms and 30 ms, packet loss ratio is between 0.25% and 0.75%, and the RSRQ is

Table 3. Fuzzy indices range corresponding to linguistic variables

Fuzzy QoS Index × 10^2 (%)	Fuzzy Effectiveness Index × 10^2 (%)	Linguistic variables
0 to 0.2	0 to 0.2	Very poor
0.2 to 0.4	0.2 to 0.4	Poor
0.4 to 0.6	0.4 to 0.6	Acceptable
0.6 to 0.8	0.6 to 0.8	Good
0.8 to 1	0.8 to 1	Very good

Table 4. Input and output variables used in evaluating QoS for the area of study

Data Sample	Download Speed (Mbps)	Upload Speed (Mbps)	Latency (ms)	Jitter (ms)	Packet Loss Rate (%)	RSRQ (dB)	QoS ×10^2 (%)
5	38.928	23.443	37	6.6	0	–11	0.700233
33	23.104	6.268	50	8.9	0	–13	0.600372
149	9.383	1.23	41	12.6	0	–14	0.5004
158	36.921	41.222	16	9.1	0	–15	0.810547
304	4.474	4.241	21	19.3	0.003597122	–17	0.337567
331	4.643	10.326	71	15.7	0	–8	0.408525
379	56.694	27	21	15.1	0	–13	0.847512
157	0	–81	0.99994181				
300	0.003355705	–109	0.43180837				
374	0.003355705	–77	0.60668714				

Table 5. Input and output variables used in the evaluation of effectiveness for the area of study

Data Sample	Packet Loss Rate × 10^2 (%)	RSRP (dBm)	Effectiveness × 10^2 (%)
19	0	–108	0.7983722
60	0.003355705	–97	0.54166604
84	0.009950249	–95	0.02383161
145	0.003937008	–115	0.36244197

higher than –7.125 dB (i.e., Low download and upload speeds, High latency, jitter, and RSRQ; Medium packet loss ratio).

Rule R_{182} demonstrates that QoS is "Acceptable" when each variable fall within their medium range, i.e., download speed between 21 Mbps and 55 Mbps, upload speed between 7.5 Mbps and 20.5 Mbps, latency between 25 ms and 75 ms, jitter between 7.5 ms and 22.5 ms, packet loss ratio between 0.25% and 0.75%, and RSRQ

Table 6. Distribution of QoS by operator in the study area

QoS	MNO 1 (%)	MNO 2 (%)	MNO 3 (%)	MNO 4 (%)	MNO 5 (%)
Very poor	0	0	0	0	0
Poor	0	2	0	0	0
Acceptable	36	35	27	45	0
Good	62	60	71	55	86
Very good	2	3	2	0	14
Average	64	61	65	58	68

Table 7. Distribution of service effectiveness by operator in the study area

Effectiveness	MNO 1 (%)	MNO 2 (%)	MNO 3 (%)	MNO 4 (%)	MNO 5 (%)
Very poor	0	1	0	0	0
Poor	0	2	0	0	0
Acceptable	0	5	0	0	0
Good	8	20	14	18	0
Very good	92	72	86	82	100
Average	90	84	89	88	99

between –15.375 dB and –7.125 dB (all variables have a value of Medium). Rule R_{351} states that if high values are observed for download speed (55 Mbps) and upload speed (20.5 Mbps) and low values for latency (25 ms), jitter (7.5 ms), packet loss ratio (0.25%), and RSRQ (–15.375 dB) (i.e., High download and upload speeds, Low latency, jitter, and packet loss ratio), then the QoS is classified as "Good".

Similarly, rule R_{363} states that the QoS is classified as "Very Good" when the download and upload speeds are higher than 55 Mbps and 20.5 Mbps, respectively. The latency, jitter, and packet loss ratio are lower than 25 ms, 7.5 ms and 0.25%, respectively (i.e., High download and upload speeds, Low latency, jitter, and packet loss ratio).

If the packet loss rate exceeds 0.75% and the RSRP values are below –101 dBm (packet loss rate is High and RSRP is Low), then the effectiveness is categorised as "Very poor" in rule R_{364}. Rule R_{366} classifies the effectiveness as "Poor" if the packet loss rate is higher than 0.75% and the RSRP is –63 dBm (packet loss rate and RSRP are both High).

The effectiveness is considered "Acceptable" in rule R_{368} when the packet loss rate falls between 0.25% and 0.75%, and the RSRP is between –110 dBm and –63 dBm (packet loss rate and RSRP are both Medium).

If the packet loss rate and RSRP are below 0.25% and –101 dBm, respectively (Low packet loss rate and RSRP), then the effectiveness is categorised as "Good" in rule R_{370}. Similarly, in rule R_{372}, if the data transfer is optimal with a packet loss rate below 0.25% and RSRP greater than –63 dBm (Low packet loss rate and High RSRP), the effectiveness is classified as "Very good."

3 Results

The fuzzy inference model algorithm was developed and programmed in software with specialised fuzzy logic libraries. The program

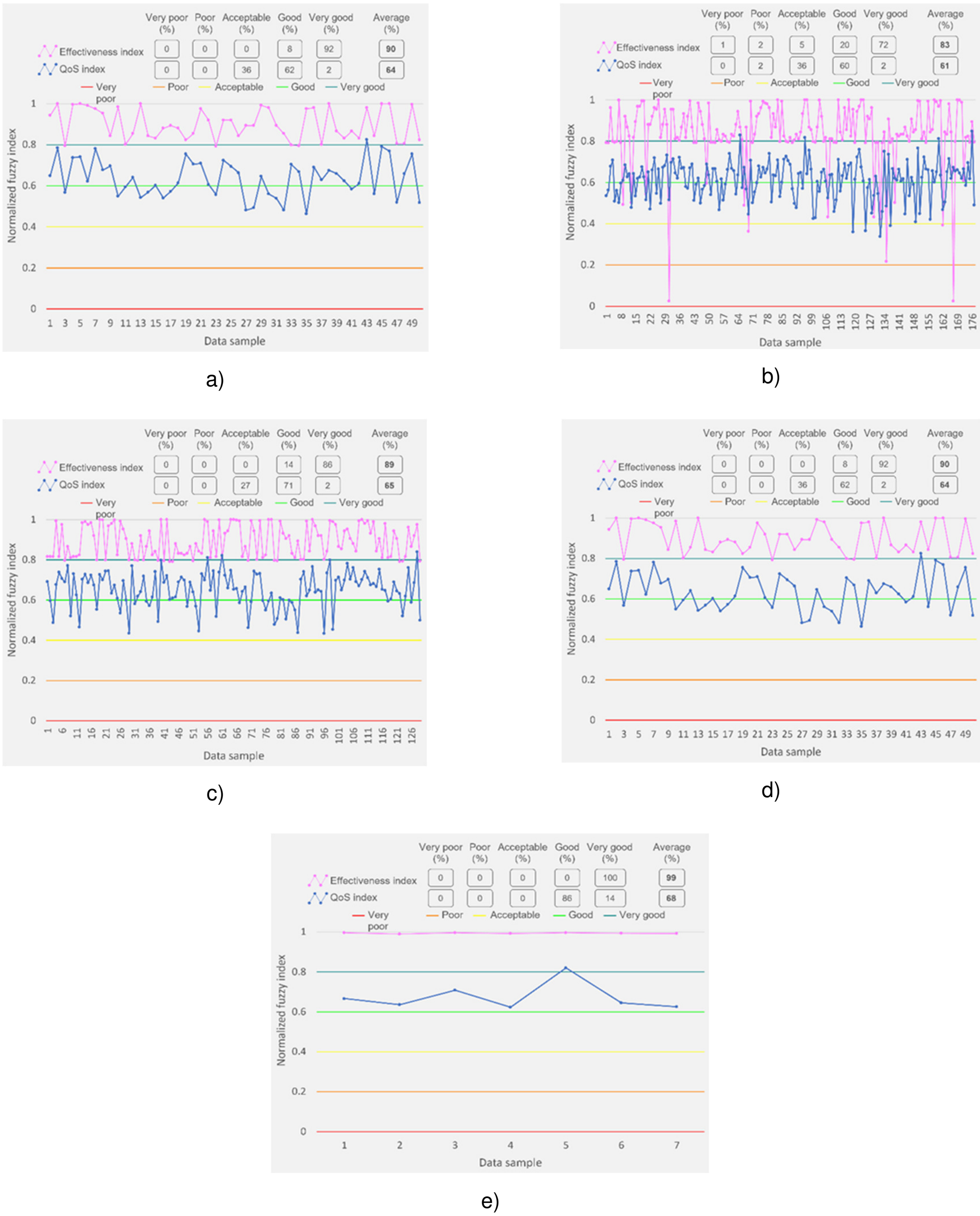

Fig. 11. Fuzzy QoS and effectiveness indices obtained by the mobile network operators (MNO): (a) MNO 1, (b) MNO 2, (c) MNO 3, (d) MNO 4, and (e) MNO 5

allows for manual or automatic evaluation of the input variables through the following steps:

1. Select the manual or automatic evaluation mode for the data rows.

Table 8. Fuzzy QoS index for MNO 1 by location

No.	Location no.	Latitude	Longitude	MNO	QoS Index	Category
1	3	19.434	–99.149	1	0.64829325	Good
2	9	19.434	–99.147	1	0.67515632	Good
3	14	19.435	–99.145	1	0.70858523	Good
4	17	19.436	–99.144	1	0.57596928	Acceptable
5	18	19.435	–99.144	1	0.61902345	Good
6	19	19.433	–99.144	1	0.66704351	Good
7	20	19.438	–99.142	1	0.62331306	Good
8	21	19.434	–99.142	1	0.58415889	Acceptable
9	26	19.435	–99.141	1	0.61081482	Good
10	30	19.434	–99.139	1	0.82497577	Very good
11	31	19.432	–99.139	1	0.55999562	Acceptable
12	32	19.434	–99.138	1	0.77987155	Good
13	33	19.433	–99.138	1	0.51886548	Acceptable
14	35	19.435	–99.137	1	0.65858975	Good
15	36	19.433	–99.137	1	0.75429903	Good
16	37	19.435	–99.136	1	0.51764475	Acceptable

2. Prompt the user to provide a plain text file containing the information repository data. This file comprises seven columns, each representing a KPI or a received signal parameter.
3. Request the file containing the fuzzy rules.
4. Evaluate each row from the repository data file using the Mamdani fuzzy method.
5. If the evaluation mode is manual, proceed to the next step. Otherwise, return to step 4 until all rows in the repository data file have been evaluated.
6. Calculate the fuzzy quality and effectiveness indices.

The structure of the information repository file should follow the format presented in Table 2. This file should not contain headers, only the seven-column data representing the five KPIs and two signal parameters.

The proposed fuzzy inference model employs seven LTE network parameters to assess 4G data transmission quality and efficiency. The two descriptive indices summarise the percentage of QoS and the percentage of effectiveness, allowing even users without technical expertise to evaluate and interpret the results quickly.

However, it is essential to note that while LTE network indices provide an interpretable measure of network QoS, they do not replace the KPIs or parameters recommended by regulators, which are the basis of the fuzzy model.

We use a dataset of 385 samples from the central Alameda zone of Mexico City to evaluate the model. The input variables for the fuzzy quality index are download speed, upload speed, latency, jitter, packet loss rate, and RSRQ.

On the other hand, the variables for the effectiveness index are packet loss rate and RSRP.

Fig. 12. Thematic map of the data transfer QoS index for MNO 1

Fig. 13. Thematic map of the effectiveness index for MNO 1

To facilitate interpretation, the values obtained for both fuzzy indices are normalised and classified into five levels associated with the five linguistic variables used in the fuzzy rules: Very poor, Poor, Acceptable, Good, and Very good. The normalised value is divided into five equal sections of size 0.2, each representing a different linguistic variable.

For instance, the range from 0 to 0.2 corresponds to the "Very poor" category, while the range from 0.2 to 0.4 means "Poor". Similarly, the range from 0.4 to 0.6 indicates "Acceptable, the range from 0.6 to 0.8 is "Good", and the range from 0.8 to 1 represents "Very good". In other words, the numerical values can be represented by qualitative variables, as summarised in Table 3, which reflect the QoS perceived by the user QoE.

Fig. 10 gives a visual representation of the results for both fuzzy indices. The horizontal lines highlight the minimum value for each linguistic variable category.

For example, the horizontal axis appears in red at the 0 level to indicate the minimum value for the "Very poor" category. Similarly, the horizontal axis is orange, yellow, green, and dark green at the 0.2, 0.4, 0.6, and 0.8 index levels representing the minimum values for the "Poor", "Acceptable", "Good", and "Very good" categories, respectively.

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Table A1. The telecommunications department of IPN ESIME Zacatenco provided the information repository

Field Name in Extract	Definition	Data type	Max Field Size
test_id	A unique ID for every speed test performed based on the platform.	number	11
test_date	Date and time of the test in UTC (default). Previously, this data was presented in Pacific time (default).	datetime	19
download_kbps	The result of the download portion of the test was measured in kilobits per second.	number	11
upload_kbps	The result of the upload portion of the test was measured in kilobits per second.	number	11
latency	The result of the latency portion of the test was measured in milliseconds.	number	6
client_city	The city where the test was conducted. If this field is labelled unknown and the location type field equals 2, we cannot confidently assign a city to the record, and it is only accurate to the region level.	text	255
client_latitude	The latitude of the device conducting the test. If the location type equals 2, this value is approximate.	number	10
client_longitude	The longitude of the device conducting the test. If the location type equals 2, this value is approximate.	number	10
network_operator_name	The device displays the name of the network operator. This field is generally accurate but is not reliable. Custom versions of Android, including carrier-specific versions, may modify this string, and carriers have used different spellings and brandings on their network names. 2020-05-28: When Ookla can more accurately identify the active network operator via Android CellIdentity APIs, it will overwrite the network_operator_name based on Ookla-maintained MCCMNC-to-network relations.	text	255
MCC	A Mobile Country Code (MCC) is a three-digit code specific to the country where the network operator is located. A list of codes and countries can be found here.	number	3
mnc	Mobile Network Code (MNC). A three-digit identifier is specific to a network operator within a given country. Each mobile network can be uniquely identified when combined with the Mobile Country Code. A comprehensive list of Mobile Network Codes can be found here, but each country regulates their MNCs individually so that codes may appear or change without any notice.	number	3
pre_connection_type	A number representing the device's connection type as detected before the test begins. Please see the connection type table for an explanation of each type. Connection type as detected before the test starts: 0 = Unknown,1 = Cell, 2 = Wi-Fi, 3 = GPRS, 4 = EDGE, 5 = UMTS, 6 = CDMA, 7 = EVDO0, 8 = EVDOA, 9 = OnexRTT, 10 = HSDPA, 11 = HSPA, 12 = IDEN, 13 = EHRPD, 14 = EVDOB, 15 = LTE, 16 = HSUPA, 17 = HSPAP, 18 = GSM, 19 = TDSCDMA, 20 = IWLAN, 21 = LTE-CA, 22 = Ethernet, 23 = Bluetooth, 24 = NR	number	4
post_connection_type	A number representing the device's connection type as detected at the end of the test. Please see the connection type table for an explanation of each type. Connection type as witnessed at the end of the test: 0 = Unknown,1 = Cell, 2 = Wi-Fi, 3 = GPRS, 4 = EDGE, 5 = UMTS, 6 = CDMA, 7 = EVDO0, 8 = EVDOA, 9 = OnexRTT, 10 = HSDPA, 11 = HSPA, 12 = IDEN, 13 = EHRPD, 14 = EVDOB, 15 = LTE, 16 = HSUPA, 17 = HSPAP, 18 = GSM, 19 = TDSCDMA, 20 = IWLAN, 21 = LTE-CA, 22 = Ethernet, 23 = Bluetooth, 24 = NR	number	4
brand	The consumer-facing brand of the device.	text	255
manufacturer	The device manufacturer.	text	255
model	User device's model.	text	255
jitter_a	The latency variance over time determines the internet connection's stability.	number	4

Thus, if the index is above the minimum value of one category and below the next, it will correspond to the lower category.

For example, consider the effectiveness index result for sample 84, the lowest value depicted in Fig. 10. Although it surpasses the minimum of the

ploss_sent_a	The number of packages sent to the host server from the device. To determine packet loss percentage, take the ploss_recv divided by ploss_sent. 100% means zero packet loss since 100% of the packets were sent and received.	number	5
ploss_recv_a	The number of packages received by the host server from the device. To determine packet loss percentage, take the ploss_recv divided by ploss_sent. 100% means zero packet loss since 100% of the packets were sent and received.	number	5
tr_latency_a	The time is taken for the packet to be received after the first hop in the traceroute.	Number	5
tr_ip_1_a	This is the IP address of the second hop of the traceroute during a test.	text	15
earfcn_a	EARFCN stands for E-UTRA Absolute Radio Frequency Channel Number. In LTE, the carrier frequency in the uplink and downlink is designated by EARFCN, which ranges between 0 and 65535. EARFCN uniquely identify the LTE band and carrier frequency. ... EARFCN is independent of channel bandwidth.	number	8
rsrp_a	Reference Signal Received Power. LTE metric displaying the received power of the reference LTE signal, similar to the old school "signal strength". Range: -40 to -140, where -140 is the worst and -44 is the highest the device will report	number	4
rsrq_a	Reference Signal Received Quality The received quality of the LTE reference signal. Range: -19.5 to -3, where -3 is best	number	5
rssnr_a	Reference Signal Signal-to-Noise Ratio is Perhaps the most important KPI, but it needs to be reported more adequately in Android OS. It's the ratio between the noise and signal of the LTE data transmission. The range is -30 to +30, where +30 is best	number	3
cqi_a	CQI stands for Channel Quality Indicator. As the name implies, it is an indicator carrying the information on how good/bad the communication channel quality is. LTE has 15 different CQI values ranging from 1 to 15 and mapping between CQI and modulation scheme. In HSDPA, the CQI value ranges from 0 to 30. 30 indicates the best channel quality, and 0,1 tells the poorest channel quality.	number	2
cellbandwidth_a	Cell bandwidth in kHz	number	6

Table A2. Geographic coordinates of the 39 points where the information repository is distributed

No.	Latitude	Longitude	No.	Latitude	Longitude	No.	Latitude	Longitude
1	19.438	–99.149	14	19.435	–99.145	27	19.434	–99.141
2	19.436	–99.149	15	19.438	–99.144	28	19.433	–99.141
3	19.434	–99.149	16	19.437	–99.144	29	19.435	–99.14
4	19.437	–99.148	17	19.436	–99.144	30	19.434	–99.139
5	19.436	–99.148	18	19.435	–99.144	31	19.432	–99.139
6	19.435	–99.148	19	19.433	–99.144	32	19.434	–99.138
7	19.432	–99.148	20	19.438	–99.142	33	19.433	–99.138
8	19.437	–99.147	21	19.434	–99.142	34	19.438	–99.137
9	19.434	–99.147	22	19.433	–99.142	35	19.435	–99.137
10	19.433	–99.147	23	19.438	–99.141	36	19.433	–99.137
11	19.438	–99.146	24	19.437	–99.141	37	19.435	–99.136
12	19.433	–99.146	25	19.436	–99.141	38	19.434	–99.136
13	19.432	–99.146	26	19.435	–99.141	39	19.432	–99.136

"Very poor" category, it is below the minimum of the "Poor" category. Hence, this value is classified as "Very poor."

On the contrary, the QoS index result for data sample 379, the highest value depicted in Fig. 10, is 84.7512%.

This index considers the download speed, upload speed, latency, jitter, packet loss rate, and RSRQ, with values of 56.69 Mbps, 27 Mbps, 21 ms, 5.1 ms, 0%, and –13 dB, respectively.

Furthermore, Fig. 10 illustrates that the resulting values for QoS are distributed across four of the five categories.

Most values fall into the "Good" category at 64%, followed by 33% in the "Acceptable" category.

Table A3. Most relevant fuzzy rules to obtain the fuzzy indices of quality and effectiveness

No.	Fuzzy Rules
1	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is High) **THEN** QoS is Very poor.
2	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is Medium) **THEN** QoS is Very poor.
3	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is Low) **AND** (RSRQ is Low) **THEN** QoS is Very poor.
4	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is High) **AND** (packet loss ratio is Low) **THEN** QoS is Poor.
⋮	⋮
12	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **AND** (RSRQ is Low) **THEN** QoS is Poor.
13	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is High) **AND** (jitter is Low) **AND** (packet loss ratio is Low) **THEN** QoS is Acceptable.
14	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is Medium) **AND** (jitter is High) **AND** (packet loss ratio is High) **THEN** QoS is Very poor.
15	**IF** (download speed is Low) **AND** (upload speed is Low) **AND** (latency is Medium) **AND** (jitter is High) **AND** (packet loss ratio is Medium) **AND** (RSRQ is Low) **THEN** QoS is Very poor.
⋮	⋮
182	**IF (download speed is Medium) AND (upload speed is Medium) AND (latency is Medium) AND (jitter is Medium) AND (packet loss ratio is Medium) THEN QoS is Acceptable.**
183	**IF (download speed is Medium) AND (upload speed is Medium) AND (latency is Medium) AND (jitter is Medium) AND (packet loss ratio is Low) AND (RSRQ is High) THEN QoS is Good.**
184	**IF (download speed is Medium) AND (upload speed is Medium) AND (latency is Medium) AND (jitter is Medium) AND (packet loss ratio is Low) THEN QoS is Acceptable.**
185	**IF (download speed is Medium) AND (upload speed is Medium) AND (latency is Medium) AND (jitter is Low) AND (packet loss ratio is High) THEN QoS is Acceptable.**
⋮	⋮
351	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is High) AND (packet loss ratio is High) AND (RSRQ is High) THEN QoS is Good.**
352	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is High) AND (packet loss ratio is High) THEN QoS is Acceptable.**
353	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is High) AND (packet loss ratio is Medium) THEN QoS is Good.**
354	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is High) AND (packet loss ratio is Low) AND (RSRQ is High) THEN QoS is Very good.**
⋮	⋮
360	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is Low) AND (packet loss ratio is High) AND (RSRQ is High) THEN QoS is Very good.**
361	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is Low) AND (packet loss ratio is High) THEN QoS is Good.**
362	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is Low) AND (packet loss ratio is Medium) THEN QoS is Very good.**
363	**IF (download speed is High) AND (upload speed is High) AND (latency is Low) AND (jitter is Low) AND (packet loss ratio is Low) THEN QoS is Very good.**
364	**IF (packet loss ratio is High) AND (RSRP is Low) THEN Effectiveness is Very poor.**
365	**IF (packet loss ratio is High) AND (RSRP is Medium) THEN Effectiveness is Very poor.**
366	**IF (packet loss ratio is High) AND (RSRP is High) THEN Effectiveness is Poor.**
367	**IF (packet loss ratio is Medium) AND (RSRP is Low) THEN Effectiveness is Poor.**
368	**IF (packet loss ratio is Medium) AND (RSRP is Medium) THEN Effectiveness is Acceptable.**
369	**IF (packet loss ratio is Medium) AND (RSRP is High) THEN Effectiveness is Good.**
370	**IF (packet loss ratio is Low) AND (RSRP is Low) THEN Effectiveness is Good.**
371	**IF (packet loss ratio is Low) AND (RSRP is Medium) THEN Effectiveness is Very good.**
372	**IF (packet loss ratio is Low) AND (RSRP is High) THEN Effectiveness is Very good.**

The "Very good" category represents 2% of the values, while the "Poor" category accounts for only 1%. Notably, there is no distribution in the "Very poor" category.

As a result, the average QoS is 62%, indicating a “Good” QoS in the central Alameda zone of Mexico City. Table 4 displays the correlation between the input parameters and the resulting index.

For example, for data sample 304, the obtained QoS was classified as "Poor" at 31.9078%. This low rating is due to shared values in input

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variables, including download speed (4.74 Mbps), upload speed (4.241 Mbps), latency (21 ms), and RSRQ (–17 dB). Low values for download speed, upload speed, and RSRQ worsen QoS, while a low value for latency improves QoS. Additionally, the jitter and packet loss rates have medium values of 19.3 ms and 33.7567%, respectively, which contribute to a QoS score of 50%. Thus, after processing all this information using the fuzzy model, sample 304 is classified as “Poor.”

Furthermore, Fig. 10 shows the results of the effectiveness index, with an average score of 82.1% classified as "Very good." The distribution of values across categories is as follows: "Very good" (80%), "Good" (16%), "Acceptable" (2%), "Poor" (1%), and "Very poor" (1%).

Additional details about the correlation between input variables and the effectiveness index can be found in Table 5. For instance, in the evaluation of sample 157, the resulting effectiveness is 99.994181%, classified as "Very good" due to a 0% packet loss rate and an average RSRP of –81 dBm.

The fuzzy indices categorised by MNO are displayed in Fig. 11 for the study area. The QoS index has a "Good" category for four out of the five MNOs (1, 2, 3, and 5), while MNO 4 received an "Acceptable" rating, as shown in Figs. 11(a), 11(b), 11(c), and 11(e) respectively. This indicates that, in this geographical location, MNOs 1, 2, 3, and 5 maintain a good quality of data transfer service. Meanwhile, MNO 4 lags two points below the quality of the other MNOs.

The average scores are 68%, 65%, 64%, 61%, and 58% for MNOs 5, 3, 1, 2, and 4, respectively. In summary, MNO 5 performs the best in terms of QoS, while MNO 4 has the lowest quality, as presented in Table 6. Moreover, all five operators achieved the "Very good" category in the fuzzy effectiveness index, indicating excellent effectiveness in data transmission in this geographical zone. The average scores for the MNOs 1, 2, 3, 4, and 5 are 90%, 84%, 89%, 88%, and 99%, respectively, as detailed in Table 7 and depicted in Figs. 11(a), 11(b), 11(c), 11(d), and (e).

The fuzzy indices for each MNO are presented as thematic maps below to provide users and regulatory bodies with easily understandable information. The thematic map in Fig. 12 illustrates the QoS for MNO 1, displaying data for 16 of the 39 georeferenced points in the repository. Among these points, ten are categorised as "Good" quality, five as "Acceptable," and one as "Very good." Importantly, no points are classified as "Poor" or "Very poor." Points that are not shown lack measurements for MNO 1. For a summary of these findings, please refer to Table 8.

Furthermore, Fig. 13 demonstrates that in all the 16 locations examined, the effectiveness category is consistently classified as "Very good." It is important to note that this georeferenced analysis was conducted for each MNO. However, as this work focuses on evaluating the LTE mobile network rather than the individual MNOs, the specific results for the other MNOs are not included.

4 Discussion

Numerous studies have examined QoS evaluation with diverse objectives. In [13], the relationship between KPIs and received signal parameters is investigated, although the aim is not to provide a joint index for both parameters.

In [14], the QoS priority is adjusted for some users to evaluate the scheduling of base stations. In addition, several works propose improvements in network resource planning to enhance QoS and user-perceived quality by increasing spectral efficiency [7. 15, 16, 17] or by analysing various configurations and parameters during video transmissions over the mobile network [19].Nonetheless, their objective is primarily to improve the infrastructure of MNOs.

On the other hand, [10, 24, 47] conduct statistical analyses of mobile network QoS, presenting distributions or estimates for missing values, but their approaches require substantially large data samples. Computational models have also been applied, employing various algorithms to optimise base station antenna tilt [25], optimise downlink resource allocation [26, 27], and maximise QoE [23]. Despite their aim to improve QoS and QoE, these proposals do not deliver relevant information to users.

Fuzzy systems have also been explored for LTE networks. [36, 37] assess QoS using Sugeno and ANFIS fuzzy models, yet they do not use measurement data or provide understandable information to users about LTE network QoS.

Following ITU recommendations, this study combines KPIs and signal parameters to evaluate fuzzy indices of QoS and effectiveness in the 4G LTE mobile network. While the proposed fuzzy model can handle any dataset, even if appropriate adjustments are made, it could evaluate data from the 5G network; the results presented here are based on the information repository acquired in the central Alameda zone of Mexico City. This work offers the following contributions:

- Using crowdsourcing measurements allowed for information to be collected by end users through their devices, effectively integrating their perspective on network performance.
- Analyzing the information repository enabled determining the number of input variables and their combinations for each fuzzy index. This process led to designing a fuzzy model, employing membership functions and fuzzy rules that utilize KPIs and signal parameters to derive two fuzzy indexes.
- This fuzzy inference model effectively utilises Telecom expert knowledge and provides accurate evaluations using a small data sample. Its if–then rule-based inference enables easier comprehension of results for experts and users alike, as the indices are classified into five levels.
- Classifying results into these five levels allows for a qualitative understanding of current service quality and effectiveness at specific georeferenced points or within the study area. This aids experts and users in interpreting the mobile network service from a different perspective. Moreover, network operators can share these results to improve transparency.

5 Conclusion

This work proposes a fuzzy inference model to quantify seven LTE network parameters during data transfer using an information repository obtained through crowdsourcing. The ITU recommends specific KPIs and signal parameters for this purpose. We evaluated 385 data samples collected at 39 georeferenced points in the central Alameda zone of Mexico City.

Our model was designed based on the if–then rules derived from analysing the information repository and expert reasoning. As a result, we obtained fuzzy indices for data transfer QoS and effectiveness in the 4G LTE mobile network. This approach addressed the challenge of evaluating the network's QoS with a limited data sample, thanks to the flexibility offered by fuzzy models.

It is essential to clarify that our proposed fuzzy indices are not intended to replace existing descriptors. However, our developed fuzzy inference model brings two significant advantages compared to other works mentioned: a) it requires a smaller data sample to analyse the 4G LTE mobile network, and b) the evaluation results provide regulatory bodies and users with valuable insights into the network's quality. Finally, the realised Fuzzy Inference System can evaluate data from 5G networks, making the corresponding adaptions for this network.

As a part of future work to enhance the robustness of this research, we intend to consider utilising a more extensive information repository with additional data. This includes extending the study duration within the same geographic area for a more comprehensive analysis. Additionally, we plan to enhance the fuzzy model by incorporating an analytic hierarchy process and data for 5G networks.

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*Corresponding author is Luis Pastor Sánchez-Fernández.