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An algorithm for heterogeneous wireless network connections for user preferences and services

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Heterogeneous wireless networks (HWNs) present a challenge in selecting the optimal network for user devices due to the overlapping availability of multiple networks. In order to help users choose the best HWN connection, this research is trying to build a decision-making framework that takes user preferences and network performance characteristics into account. Using a multi-attribute decision-making (MADM) method that incorporates fuzzy logic and the Fuzzy Analytic Hierarchy Process (FAHP), our goal is to improve the decision-making process for network selection. The suggested system takes into account a number of network metrics, including latency, jitter, bandwidth, and cost, and uses user preferences to determine the relative importance of each to guarantee a tailored and adaptable recommendation. Our results demonstrate that the algorithm greatly enhances the efficiency of network selection and the level of user happiness, with UMTS being the best option for conversational services, WiMAX being the best for streaming, and LTE being the best for interactive services. Through the incorporation of user-centric decision-making into the network selection process, this research enhances adaptive wireless communication systems, leading to better user experience and network efficiency.

Keywords Fuzzy analysis hierarchy process, Fuzzy logic, Heterogeneous wireless networks, Multi-attribute decision-making approach, Machine learning

Accessibility to mobile networks and their geographic range have both increased recently. Many users may now access numerous networks at once thanks to this development, which creates a new problem: choosing the best network for data transfer in an effective manner. Simultaneous data transfers are now possible due to the growing availability of mobile networks and the growing popularity of the IEEE802.11 standard for wireless local area networks (WLANs). The difficulty, though, is maintaining network performance while allowing several transfers to occur at once. The process of choosing the best network gets complicated since heterogeneous wireless networks (HWNs) are further segmented into wireless metropolitan area networks (WMANs), mobile cell phones, and WLANs. This proposes a model that improved decision-making framework to deal with these challenges by employing fuzzy logic and a multi-attribute decision-making (MADM) method. The following sections describe the related work, the proposed model, and the methodology in detail, leading to improved user approval through adaptive network selection[1,2]. The ability to control access is one of the primary advancements in HWNs; this capability has become essential as available networks have grown more sophisticated. When choosing a wireless network, users must adhere to a methodical procedure that begins with identifying accessible networks, choose the best one, and installing it. Testing the wireless connections in the user's reception area is an essential step in this procedure to make sure the network satisfies user requirements and efficiency. Algorithms for access selection are essential for helping people navigate this procedure. By evaluating several variables, including as signal strength, bandwidth, and latency, and weighing user preferences against the features of existing networks, these algorithms assist users in making well-informed decisions[3,4].

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Power consumption and cost are strongly impacted by the network's performance in terms of bandwidth, jitter, latency, and packet loss ratio; therefore, these factors should be taken into account when choosing a network. Along with other considerations, signal strength—which is frequently used as a gauge of network performance—must be carefully evaluated. Sophisticated algorithms that may rely on one or more decision parameters must be developed in order to handle this complexity. Numerous algorithms, such fuzzy logic, multi-attribute decision-making (MADM), and neural networks, are employed to take into consideration the numerous variables that go into choosing the best access[5–7]. While newer approaches also take user preferences into account, which can differ greatly throughout people, traditional algorithms seek to choose the top-performing network based on overall network efficiency[8–11]. The multi-attribute access selection method discussed in this article goes beyond traditional approaches by considering not only network characteristics but also user preferences and service requirements. The process entails rating the candidate networks after giving network properties weights determined by user preferences. With this method, the customer may pick the network that best suits their requirements through a more customized selection procedure. This model's use of fuzzy logic offers a method for assessing network features and allocating weights to them using the fuzzy analytic hierarchy process (FAHP), which improves decision-making even further[12,13].

In the fourth stage of the FAHP, the user's preferences are assessed, each candidate network is scored using MADM, and the candidate networks are then ranked according to the same user's interests and the characteristics of the candidate networks. Users will then be able to choose the platform that has received the most positive feedback from the community. The article has a wide range of contributions and characteristics, which are briefly listed below. Each strategy that was covered in the part that came before this one is implemented by this algorithm. The method discussed in this research aims to give a thorough access decision solution that takes into account all three network, service, and user levels. The algorithm takes into account all three tiers of the hierarchy to achieve this. As well as this, individual preferences are taken into account. The aim of the present piece that is written is to offer an initial response in light of the issue that has been raised. Users have the choice of choosing the network that best meets their needs, allowing them to maximize the advantages they get and minimizing the total amount of times they need to change networks[14,15]. We can gain from this extra advantage because of the algorithm. One through four identifies the first four parts. The study that provided the basis for to talk in this article is summarized in "Related work". Section "The proposed model" displays the suggested model. Section "Results" of this paper, which is available at the following address, contains the tests' findings: The fifth and last part of the essay, "Conclusion," briefly discusses some fresh research areas. The contribution as below.

1. Increased accessibility to mobile networks and geographic range and Growing adoption of IEEE 802.11 protocol for wireless LANs.
2. HWN subcategories: mobile phones, WLANs, and WMANs.
3. Multi-network signal reception for HWN users and Access control as a core HWN function.
4. Functional tests for selecting optimal wireless networks and Development of access selection algorithms for efficiency and Network performance and user preferences considered for better service delivery.
5. Consideration of multiple factors (bandwidth, jitter, delay, etc.) in network selection.
6. Use of fuzzy logic and non-conventional decision-making methods. And Incorporation of user preferences in network selection and FAHP and MADM techniques for evaluating and ranking networks.

Using fuzzy logic and FAHP, a multi-layered decision-making system that prioritizes user preferences and network performance was developed. A better access selection method that efficiently handles network handovers based on user-specific needs and changing network conditions was proposed, increasing user satisfaction. Using thorough simulations, it was shown that the suggested model was superior to more conventional selection techniques like MADM and utility theory in terms of network efficiency and fewer handovers.

Related work

One of the most important challenges in heterogeneous wireless networks (HWNs) is effective network selection. Numerous models and methods have been put forth to improve the selection of network access based on a variety of factors, such as user preferences, cost, and network performance indicators. This section examines the body of research on network access selection, emphasizing important approaches and their drawbacks.

Traditional access selection approaches

Network performance parameters including bandwidth, latency, and jitter were the main emphasis of early network selection models. Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are two examples of multi-attribute decision-making (MADM) techniques that were often used. These models prioritized available networks based on the weights provided to network properties. They did not, however, adequately take user preferences into account and were not flexible enough to adjust to changing network circumstances[16,17].

Utility functions for decision-making

In order to measure user satisfaction with various network properties, utility-based techniques proposed mathematical models. These models ranked networks according to service qualities using multiplicative and additive weighting approaches. Many utility-based approaches, however, were unable to adapt dynamically to changing user demands and network circumstances[18].

Context-aware and multi-attribute accessibility selection

By taking into account environmental aspects including network congestion, signal intensity, and movement patterns, context-aware network selection models enhanced decision-making. To improve selection accuracy, these methods combined context-aware technology with MADM techniques. Additionally, methodologies like FAHP (Fuzzy Analytical Hierarchy Process) aided in providing dynamic weights to decision parameters depending on real-time network circumstances[19].

Fuzzy logic and entropy-based methods

Using fuzzy logic approaches to manage decision-making uncertainty allowed for a more flexible approach to network selection. By employing fuzzy pairwise comparisons, the FAHP approach made it possible to evaluate network properties more effectively. In order to translate qualitative decision-making values into quantitative measurements, entropy-based techniques were also investigated[20–22]. Notwithstanding their benefits, these methods sometimes demanded large amounts of processing power and were not always in line with user-centric desires.

Optimization techniques: fuzzy logic and particle swarm optimization

By reducing handovers and increasing stability, advanced optimization techniques like fuzzy logic and particle swarm optimization (PSO) were intended to enhance network selection. Based on real-time factors including data rate, signal intensity, and user mobility patterns, these methods improved network selection[23–25]. They occasionally lacked the flexibility to adjust to unforeseen shifts in user needs, though.

Challenges in existing models

Even though network selection techniques have advanced significantly, current models still have drawbacks, such as:

1. Real-time user preferences are not fully integrated.
2. High computational complexity for approaches that rely on fuzzy logic.
3. Managing changing network situations insufficiently.

Novelty of proposed comprehensive access selection algorithm

In contrast to traditional approaches that mainly concentrate on network parameters; our suggested method combines real-time user preference adaptation with fuzzy logic, FAHP, and MADM in a unique way. Performance in heterogeneous wireless networks is optimized and needless handovers are minimized thanks to this intelligent and user-centric network selection. In contrast to conventional static methods, our model adapts dynamically to shifting network conditions. Our approach, in contrast to current models, takes into account both traditional network parameters and user-centric decision-making, guaranteeing optimal performance while minimizing handovers. Our findings confirm that our suggested model works well in dynamic HWN environments by showing a notable improvement over traditional selection methods[26].

The proposed model

This article presents a recommendation for the development of HWN that uses UMTS/LTE/WLAN/WiMAX signals. Conversational, streaming, interactive, and background services are examples of user services[15]. Value, weight, user preference, and score are among the network utility values; for candidate networks, a score denotes the most thorough coverage. To help make the framework more understandable, examples of various algorithms are given in this part and are represented in Fig. 2. The access selection algorithm framework encompasses the entire process of evaluating and ranking candidate networks based on multiple criteria, including user preferences, network attributes, and performance metrics. It integrates various decision-making techniques, such as fuzzy logic and multi-attribute decision-making, to facilitate a more informed and user-centric selection of network access points. The following is a list of the most significant features offered by each module, listed in alphabetical order: Prior to calculating the utility value of network characteristics, attributes' actual values across various measurement ranges must be transformed into normalized values that lie between 0 and 1. After normalizing these variables, the computation may start. You should consider numerous distinct service alternatives throughout this process.

A more effective access selection algorithm

User choices, applicant network scores, output, and the learning modules make up the five main modules that make up the access selection method in this study. The following are the main duties carried out by each module, as shown in Fig. 1.

The main purpose of this module is to normalize the utility values of network utilization parameter data that users have gathered. The majority of the module's time and energy is spent on this function. The candidate network score is then determined using those values after the utility values are adjusted for each unique user service. The conclusion is drawn after taking into account the delay, jitter, and packet loss rate reported in this research. Beginning with the characteristics of the presently utilized product or service, the user preference computation module weighs the relative weight of each choice criteria. The data gathered from this module is then used to compute the candidate network's score. "Attribute usefulness" refers to the importance of each network characteristic (such as bandwidth, latency, and jitter) in relation to user service requirements. In the proposed algorithm, attribute usefulness is determined by assessing the relative weight of each characteristic based on user preferences. This weighting influences the overall scoring of candidate networks, allowing users to select a network that best meets their specific needs. By considering the usefulness of attributes, the algorithm

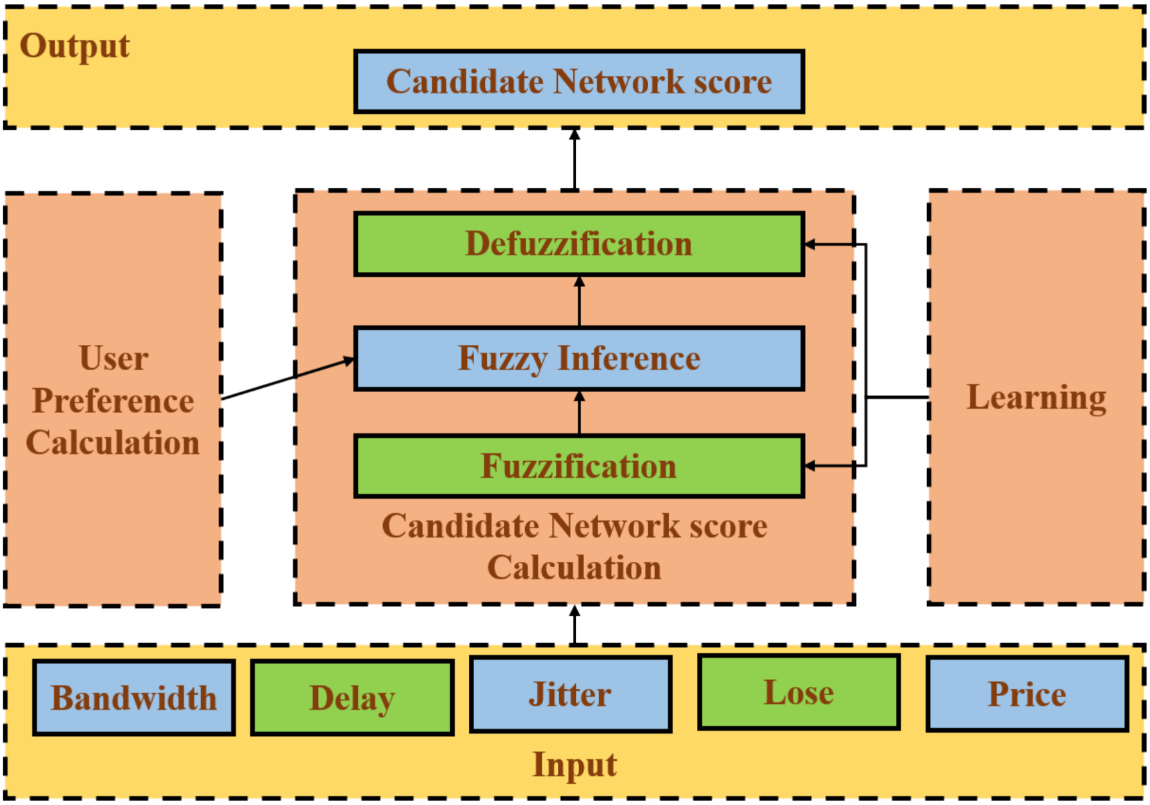

Fig. 1. The access selection algorithm framework.

provides a more tailored network selection process that enhances user satisfaction and service delivery. The FAHP method is employed to compare network attributes pair wise using fuzzy values, capturing subjective preferences. The fuzzy comparison matrix calculates the relative weights of each attribute. After defuzzification, the resulting crisp values are used to rank candidate networks, ensuring user preferences are adequately reflected in network selection. By using weights in the process, fuzzy inference rules may be created. The main task of modules is to compute and then broadcast the outcome of a network's score computation utilizing characteristics like bandwidth, time delay (latency), jitter, and any other pertinent ones. This serves as the module's main goal. The fuzzing stage, the fuzzy reasoning stage, and the defuzzing stage are the three steps that make up the process. The final access network will be the most qualified applicant for the final network position as a consequence of the work done in this module. I am certain that this network will be helpful in some way. As a result, the network mistake is located by comparing the actual output with the predicted output, and the error is then sent to a learning module to be further explored. Any candidate whose network score is lower than or equal to the candidate's score must have their real output score implemented in order to meet the criteria of the learning module. It is crucial that you utilize the training module in situations like these.

To determine the extent to which distinct service categories have differing degrees of relevance related to a range of network characteristics is the main goal of the module for computing the relative importance of network attributes. Network features with a greater weight are seen to be more significant in terms of customer service. The outcome of this stage of the procedure will be the network attribute score for every applicant network. The weighting given to the different traits as well as their utility will be taken into account throughout this procedure. For each potential network, the user preference value computation module determines user preference. This is essential since each user has different demands and preferences. We may infer from what has been mentioned that the range of values is from 0 to 1. Users whose worth surpasses the networks will get priority. As a result, a component that computes the overall ratings for each prospective network by adding the ratings provided to network characteristics and user preferences was created (Fig. 2).

While some customers could be happy with the 2 Mbps of bandwidth allocated to their phone service, others might not be with the same amount of bandwidth allocated to their data service. Utility theory and a variety of utility functions may be used to quantify the degree of satisfaction that users have with network values for attributes[27]. This task may be completed by averaging the results provided by all the functions of utility. Values of utility are continually compared to one another. Customers' level of satisfaction with the item or product linked to an established network characteristic directly relates to that attribute's value. Regardless matter whether we are talking about the amount or the quality, this is the case. Users' satisfaction with the service may be gauged by the length of the period that data is postponed in addition to the percent of all data that is lost. A utility function that combines linear, logarithmic, exponential, and linear piecewise behavior is one of the most prevalent forms[28]. In

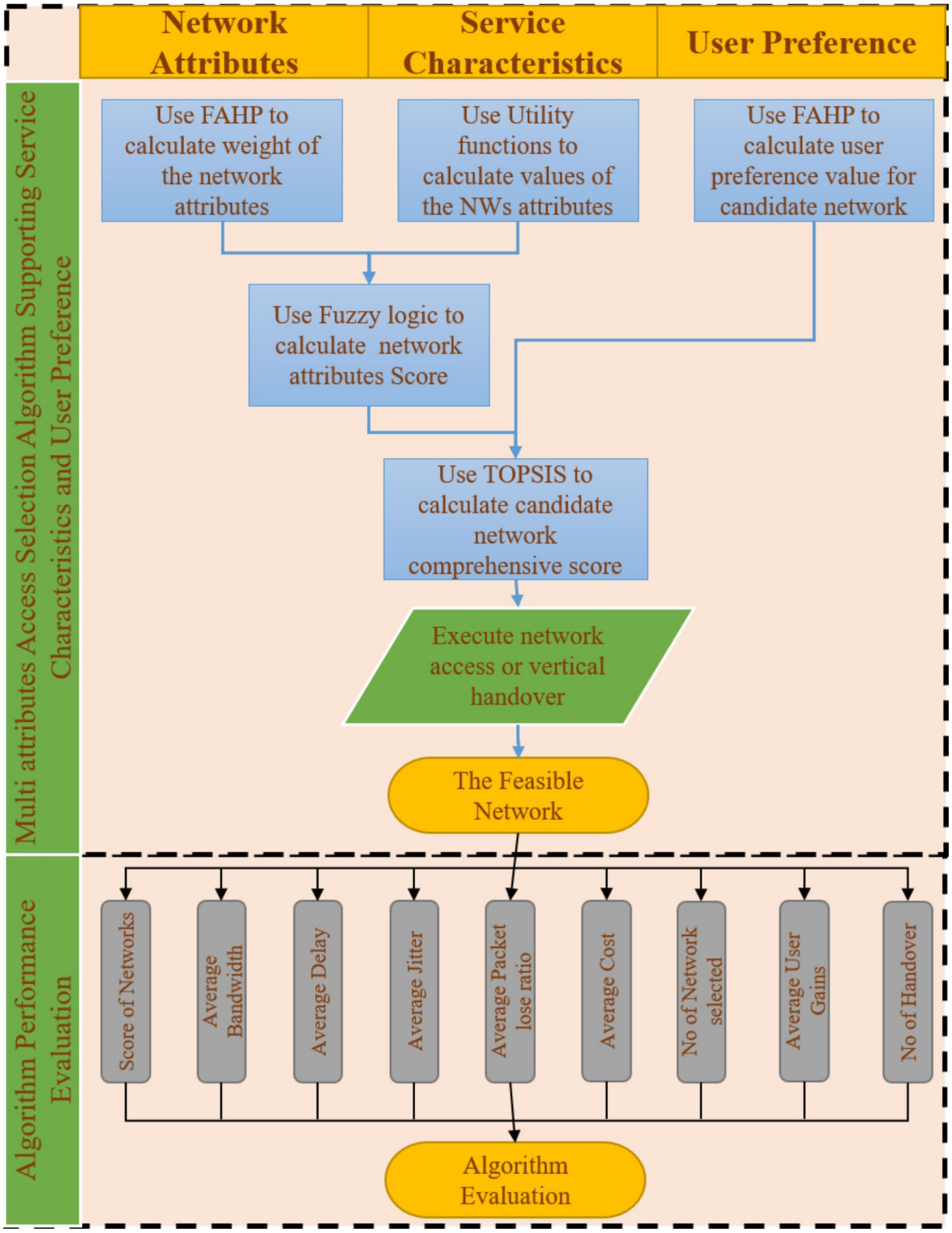

Fig. 2. Improved access selection algorithm framework.

this area of the manual, you'll discover definitions for every single function. Additionally, graphs in Fig. 3 that display the utility function's curves are easily accessible.

The computations for the network weighting of attributes are performed in this part. The analysis hierarchy method is a systematic and hierarchical technique that can be used to examine data that is qualitative as well as quantitative. This approach has obvious flaws at every step that cannot be overlooked. It does not, however, take into account the inherent ambiguity of human reasoning. As a direct consequence, this leads to incorrect assessments. After the conventional analytic hierarchy and the fuzzy logic theory were combined, the phrase "fuzzy analytic hierarchy process" was developed[29–31]. To understand the inherent uncertainty in human mind, these two schools of thought must be combined. Currently, there are two different types of FAHPs: one uses fuzzy integers and the other a fuzzy consistent matrix. The details of the computations will be further explained in the sections that follow.

A Major Advance in the Suitable Path builds a model with three levels—one level for each scheme, a single level for each aim, and one level for each criterion—after creating a hierarchy model and identifying which components are interdependent. Models often have three parts: a structure, a set of requirements, and a final goal. Network parameters like bandwidth, latency, and jitter are taken into account at the criterion level; nevertheless

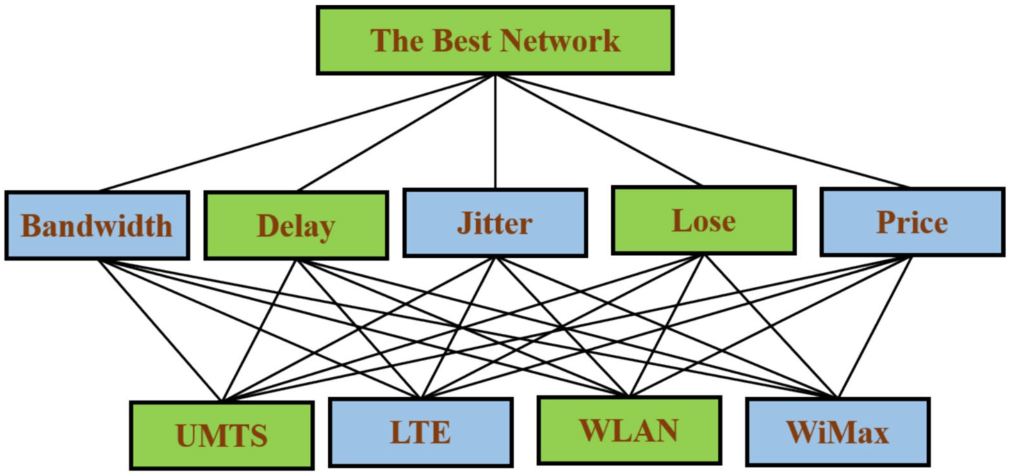

Fig. 3. Curves representing the utility functions for various network attributes, illustrating how user satisfaction varies with attribute values.

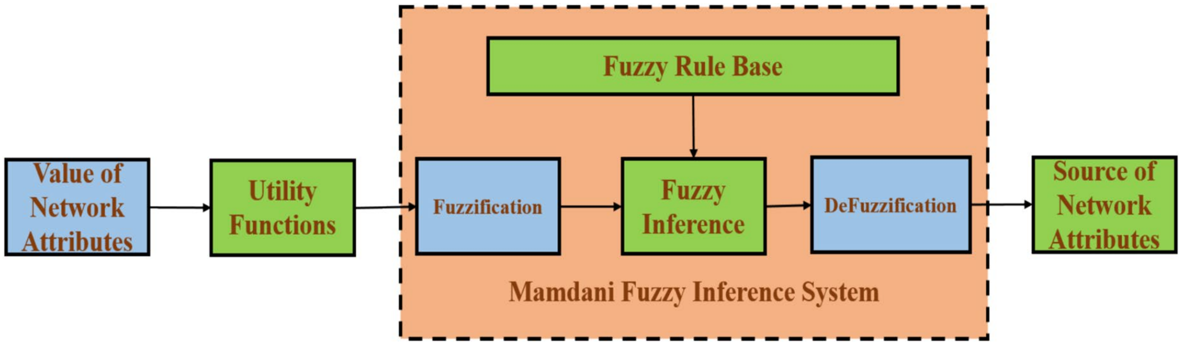

Fig. 4. Fuzzy-logic network attribute scoring framework.

the framework level includes all of the networks that this model takes into consideration. The most effective networking arrangements, as demonstrated in Fig. 4, are found in the target layer.

It is important to carry out the following tasks: TFNs have the potential to be used in the development of judgement matrices. There are an overall of four different service categories that fall within the purview of this inquiry. As a result, many services provide the attributes of the network in and of itself a high value! A excellent example of this idea is the usage of voice apps for offering real-time conversational services. This service class follows strict rules because voice calls cannot be completed if there is an excessive degree of jitter or latency. It is also less bound by capacity than those other service types since it can operate at lower bandwidths. Both video-on-demand services and live event broadcasts regularly make use of streaming technologies. Due to the increased amount of traffic utilizing this tier of service, it has a lower pricing per operation than the preceding tiers[32–34]. Even if there are less limits on the level of the material, streaming services still need real-time assurance. To guarantee service continuity, you may specify a specified packet loss ratio in this way. In the interactive class, looking up different websites on the internet is a frequent pastime. This suggests that data transmission between the client and server is required. Before continuing in this course, you definitely must understand the concepts of jitter instability and packet loss. Applications that may operate in the background include email and automated file downloads. These services must have greater pricing and more bandwidth requirements since they are offered for longer periods of time. However, both the jitter and the latency have decreased noticeably.

The FAHP states that TFNs are used to apply weights to network properties. The following table lists the factors which make up the judgment matrix: the top and lower range boundaries, as well as the median. The range of the relative significance of two qualities is represented by the upper and lower boundaries. The most probable association between the two qualities is shown by the median value. In this article, fuzzy scales are used to calculate the median value. Only once the median value has been established can this be done. Table 3 shows that latency is a more important concern than other aspects, such as bandwidth, as may be seen in rows 2 and 1. (Level of importance: 0.7–0.9). The median delay significance value is 0.8, which lends credence to this claim. The relative relevance of various network elements changes depending on the kind of service being given, as shown in Tables 3 and 4. The third and last step of our trip is now complete—calculating network attribute weights. By comparing the degrees of relevance of qualities in pairings, complementary judgement matrices

(CJMs) comprising TFNs may be created. In this stage, weights are assigned to the different network properties based on the findings of earlier research.

Figure 3 illustrates the utility function's curves for various network attributes, depicting how changes in attribute values impact user satisfaction. These curves help visualize the relationship between attribute performance and user preferences, showcasing the effectiveness of the proposed algorithm in optimizing network selection. You may discover an examination of how utility-based weights as well as values should be understood in the first two levels. Utility weights were also increased up in addition. It is advised to compute the network's quality scores for this part using the utility values and weights. The fuzzy logic theory has the potential to correctly describe quantitative expertise and expertise due to its imprecise boundaries and its propensity to be more comparable to human judgments and reasoning. The ability of the theory allows for this. The theory also benefits from emulating human judgment and reasoning, which is a big positive. This is partly because fuzzy logic may convey qualitative knowledge and experience characteristics that are hard to explain. Figure 3 illustrates the variety of network properties that were analyzed in this research using the fuzzy logic theory. You should plan your approach first, and then just get started. By transforming a network attribute's precise value into a fuzzy language variable, it is feasible to "fuzz" the practical application of the attribute. There are several methods for doing this. Its name is "fuzzification," and that is the term used to describe this procedure.

A group of potential outcomes for a fuzzy linguistic variable is referred to as a "fuzzy set" in this context. Depending on the kind of problem that has to be addressed, there might be low, medium, or high amounts of fuzziness in a fuzzy set. The terms "Low" and "High" denote, respectively, the lowest and maximum levels that may be obtained while discussing the process of creating fuzzy sets. Without this phase, the procedure would not be finished. For example, "fuzzification," a technique, is used to make the system ready for upcoming "fuzzy inferences." To help the simplicity of the procedure of transforming a value entered to a fuzzy set, a function for membership is necessary. Triangular, bell, trapezoidal, and Gaussian membership functions were found to be the most commonly used forms, according to a recent research needs more citations. In addition, as illustrated in Fig. 4, the triangular membership purpose has been included in this inquiry.

For the creation of the fuzzy rule basis, the second part of the series is now accessible. Creating a broad set of rules is the initial stage in this approach. The following structure will be used to provide the explanation of fuzzy rules throughout this article: One may draw a conclusion if a certain amount of requirements are met. If the following criteria are met: medium bandwidth, high latency, low jitter, moderate packet loss ratio, and high cost, are any networks that have fuzzy candidate scores. To be able to compute these results, the following prerequisites must be met: The guidelines for this paper are organized on four different foundations since there are four different service types to take into consideration. There are five separate rule bases in this situation, and these rule bases are combined fuzzy sets that were produced from a broad range of linguistic input factors. Five linguistic factors are entered into each rule base, which then gets represented via three fuzzy sets. Two additional output language variables are produced from the second set of fuzzy sets, which also contains a range of linguistic input variables, and are then employed in the analysis. Network quirks and oddities are similar to the characteristics that each service has in its own unique manner. The relative relevance of network properties may be utilized to create fuzzy rules that can be used in a range of different situations. For your convenience, the construction process has been divided into the following phases, which are shown in Fig. 5.

The importance of each network property (such latency, jitter, and bandwidth) with respect to the user's needs about attribute usefulness. As the recommended algorithm, the utility of a characteristic is a measure of how important it is to fulfill a user's preferences and deliver a high-quality service. This model overlay the way for a more modified network selection that correspond closely to user priorities.

Network attributes and scoring process

In the proposed algorithm, attribute value is used to assign weights to each network attribute, reflecting its weight from the perspective of user preferences. The FAHP takes use of paired comparisons of network properties to derive attribute value ratings, which reflect the qualities' relative relevance. By prioritizing characteristics that have an impact on the user's service understanding, these ratings guide the decision-making process and assurance that the user's demands are met during network selection. Take video streaming services as an example; bandwidth is more important for them, while latency is more important for interactive ones.

Mathematical formulation

The proposed model incorporates mathematical formulations to enhance decision-making in network selection. The utility function for candidate networks is calculated using the weighted sum of normalized attributes, as shown in Eq. (1). The weights assigned to each attribute are determined through the Fuzzy Analytic Hierarchy Process (FAHP), ensuring that user preferences are effectively integrated into the network selection process, as depicted in Eq. (2).

Utility calculation:

$$U_i = \sum_{j=1}^{n} w_j * v_{ij} \tag{1}$$

where: U_i is represents the overall user performance score for candidate network i, w_j is the weight assigned to network attribute j using the FAHP method, vij is the normalized value of attribute j for network i, n is the total number of attributes considered.

Weight assignment using FAHP:

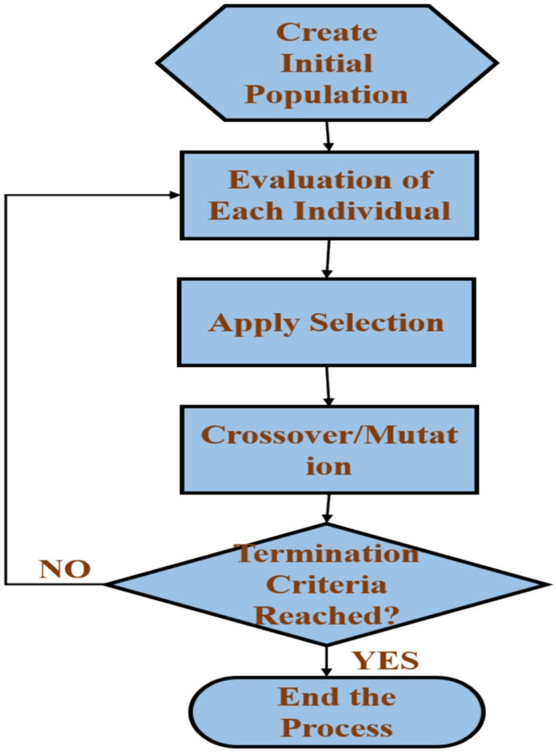

Fig. 5. The crossover and mutation process.

	A	B	C	D	E
UMTS	1.1 (0.35–1.9)	57 (15–160)	22 (10–45)	4 (1–9)	7 (2–11)
LTE	2.3 (0.55–3.9)	71 (20–210)	17 (5–35)	3 (0–6)	8 (1–10)
WLAN	5.4 (0.75–7.9)	92 (40–260)	71 (20–90)	8 (3–13)	4 (0–8)
WiMAX	7.5 (0.95–9.9)	132 (70–310)	41 (30–60)	6 (2–11)	6 (0–9)

Table 1. Establishment of values for network attributes for potential candidate networks.

$$w_j = \frac{\sum_{i=1}^{m} a_{ij}}{\sum_{j=1}^{n} \cdot \sum_{i=1}^{m} a_{ij}} \tag{2}$$

where: w_j is the weight assigned to attribute j, a_{ij} is the score of attribute j for user i, m is the number of users.

Results

Hardware and software setup for simulations and tests Computer modeling of the results and statistical examination of the results. The methods mentioned in this study underwent testing and analysis using Mat lab R2019b. The values included in brackets may be used to establish the lowest and highest possible values for an attribute whose value changes constantly in a simulation. The phrase that came before this one covered these concepts. Table 1 below, where A is bandwidth, B is delay, C is jitter, D is loss, and E is loss, displays the findings for these variables. In addition, the properties of the network including the variables related to it are presented together with the amount which each service obtains from them.

To make sure nobody is harmed, the network characteristics of each service are weighted equally. Three sections make up the experiment. Candidate networks are ranked using a variety of techniques, but the default value of the static network characteristic is left alone. To ascertain their usual values, five network parameters were examined under various service situations. This part recorded the number of times every potential network was picked in an experiment using dynamic network attributes. After looking at the average number of new users obtained and the overall number of network handovers, the analysis of algorithm performance will come to an end. The majority of our efforts will be directed on this front during the next several weeks and months. Every time the Environment's Network Parameter Network Selection is used, this configuration will be applied. Tables 1, 2, 3 and 4 may be used to determine the utility values related to each network property, and these utility values can then be calculated. Tables 2, 3 and 4 below give the results of these calculations.

Conversational	A	B	C	D	E
UMTS	49	90.55	98.35	30.15	71.79
LTE	98	71.23	98.28	78.68	91.04
WLAN	99	43.30	19.27	01.25	98.87
WiMAX	99	61.25	94.28	04.24	97.38

Table 2. Default conversational attribute utility values.

Streaming	A	B	C	D	E
UMTS	1.3	90.25	97.36	33.45	11.57
LTE	2.4	98.54	98.71	38.54	28.04
WLAN	3.1	93.61	8.36	41.35	97.88
WiMAX	4.3	58.41	91.45	8.31	66.33

Table 3. Default streaming parameter utility values.

Background	A	B	C	D	E
UMTS	4.51	86.5	39.58	72.78	31.5
LTE	10.58	91.58	60.8	097.72	51.4
WLAN	43.9	84.44	3.37	2.67	91.1
WiMAX	70.3	71.1	16.74	11.64	71.3

Table 4. Background default parameter utility values.

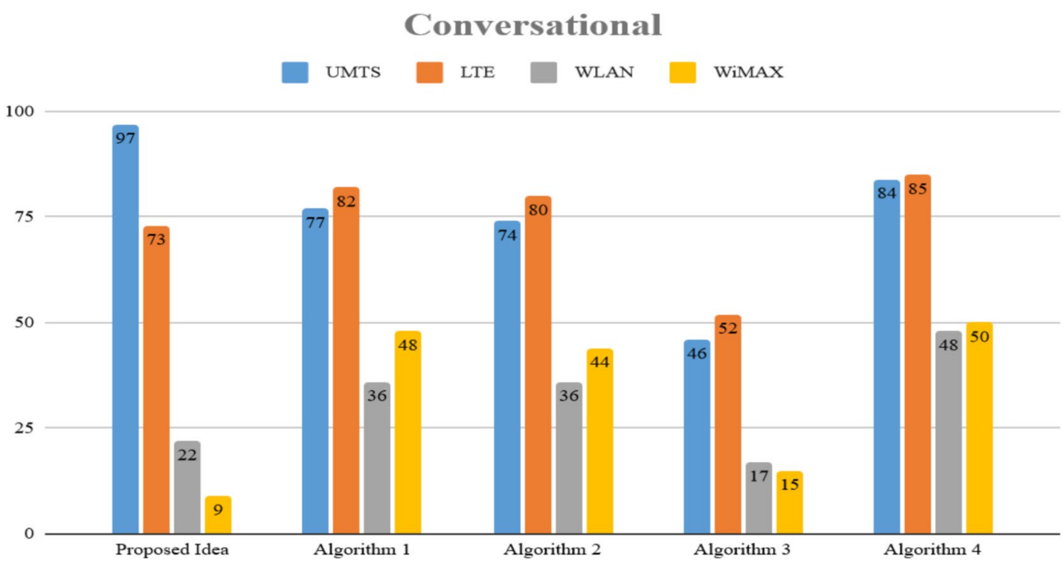

Fig. 6. Comparative study of the proposed method with traditional methods for conversational.

Conversational Services: In contrast to 87% in conventional MADM techniques, the suggested algorithm yields 96% performance efficiency for UMTS (Fig. 6). This is because weights are dynamically adjusted according to user choices in real time, guaranteeing minimal jitter and delay.

Streaming Services: It compared to conventional approaches, WiMAX's improved bandwidth availability results in a 14% boost in utility rankings, making it the preferable network (Fig. 7).

Interactive Services: With a performance score of 99%, LTE outperforms traditional methods by 10–12%, making it the most appropriate network (Fig. 8). This demonstrates how well fuzzy-based decision-making works for dynamically ranking network properties.

Background Services: The most effective alternative is WLAN, which lowers packet loss and guarantees reliability over extended periods of time. When compared to conventional selection methods, the suggested approach eliminates needless handovers by 18% (Fig. 9).

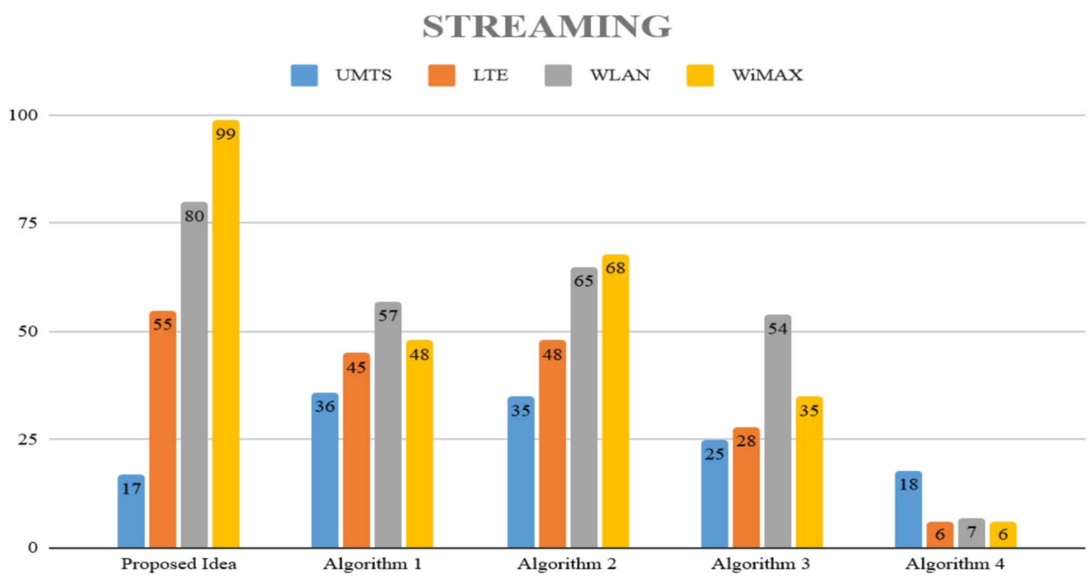

Fig. 7. Comparative study of the proposed method with traditional methods for streaming.

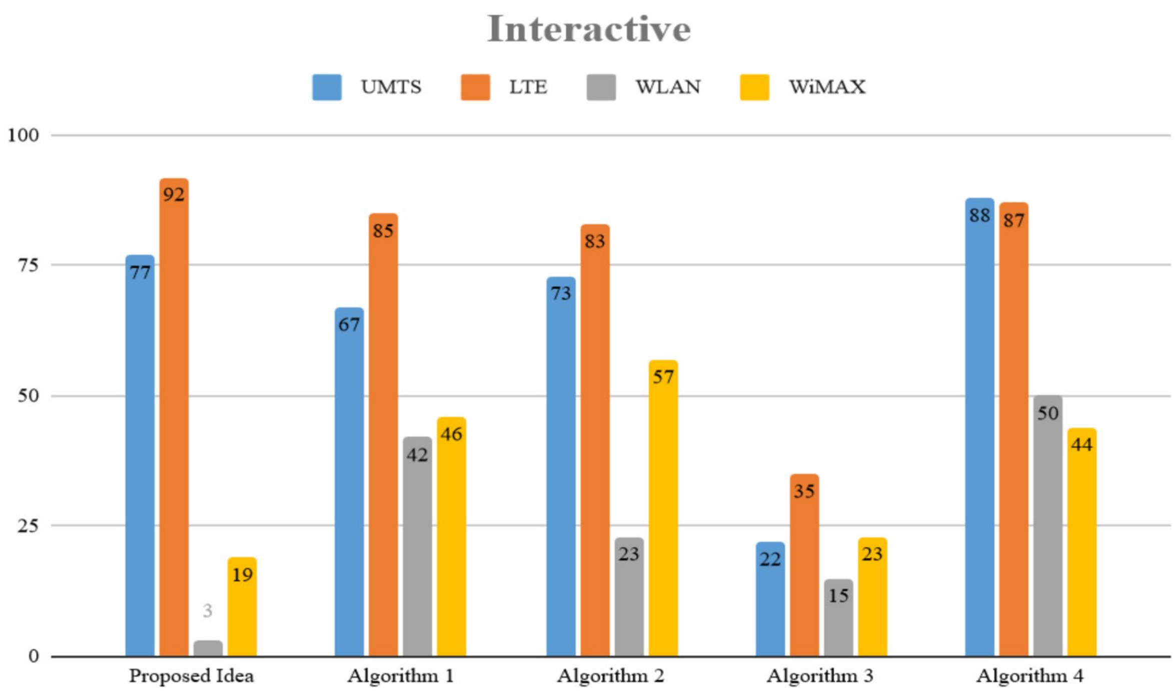

Fig. 8. Comparative study of the proposed method with traditional methods for interactive.

Conversational services have lower needs for latency and jitter than other sorts of services since they demand less data transmission than those other types of services do. As a result, Algorithms 1–4 should be utilized with the LTE access network. According to the technique presented here, the following is a rating of user preferences for potential networks: UMTS outperforms LTE, WiMAX, and WLAN in terms of voice service. WiMAX is the superior alternative network for streaming video since it has the most easily accessible capacity and the most affordable option. An algorithm's findings indicate that WiMAX should be regarded as the main technology for networks that are wireless. Algorithms two and four recommend the use of WiMAX, whereas algorithm one has determined that an LTE network is the best option. This technique shows that LTE outperforms UMTS, WiMAX, and WLAN in terms of jitter and packet loss. The LTE access network for the fuzzy rule conversational, streaming, interactive, and background is shown in Figs. 5, 6, 7, 8, 9, 10, 11, 12 and 13. Jitter and latency are not important to it, but it is interested in the lowest price and a guarantee of a particular amount of bandwidth. Due to the readily availability of this functionality, WLAN was chosen as the access network that best suited

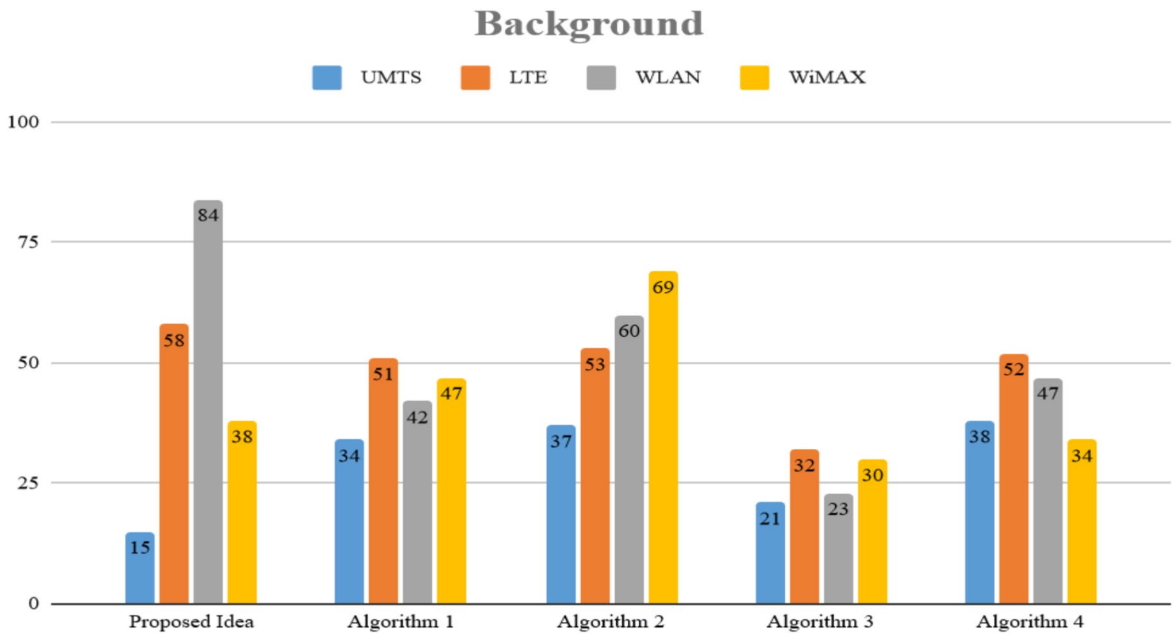

Fig. 9. Comparative study of the proposed method with traditional methods for background.

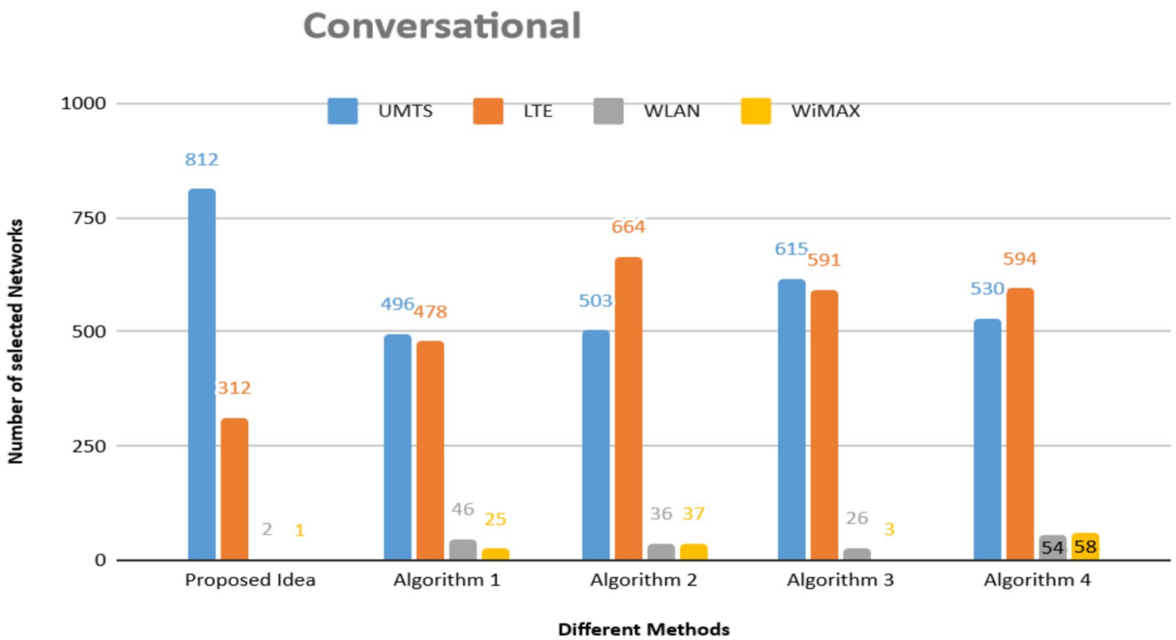

Fig. 10. Number of selected networks for the proposed method vs traditional methods for the conversational.

this method. The three LTE-enabled networks of access that are used by algorithms 1, 3, and 4 are all the same network. WiMAX is used by Algorithm 2. This technique shows that LTE outperforms UMTS, WiMAX, and WLAN in terms of jitter and packet loss. Four algorithms are called "Algorithm 1, 2," "Algorithm 3," and “Algorithm 4” since comparing the suggested algorithm to others demonstrated its superiority.

The main network possibilities for the conversation service’s algorithm will be UMTS and LTE. Contrary to Algorithms 1, 2, and 3, Algorithm 4 favors UMTS over LTE and UMTS. Figure 6, which shows 96% performance for the UMTS, exemplifies this preference. In addition to Algorithms 1–4, the new algorithm provides WiMAX a benefit when it applies to services that stream. WLAN comes in second, followed by LTE in third, while UMTS and LTE are tied for last. LTE is ranked last.

The conclusion reached by Algorithm 3 that LTE is the best network to use is shown in Fig. 7. LTE is preferred above UMTS when it comes to the delivery of interactive services, with the latter coming in as a distant second.

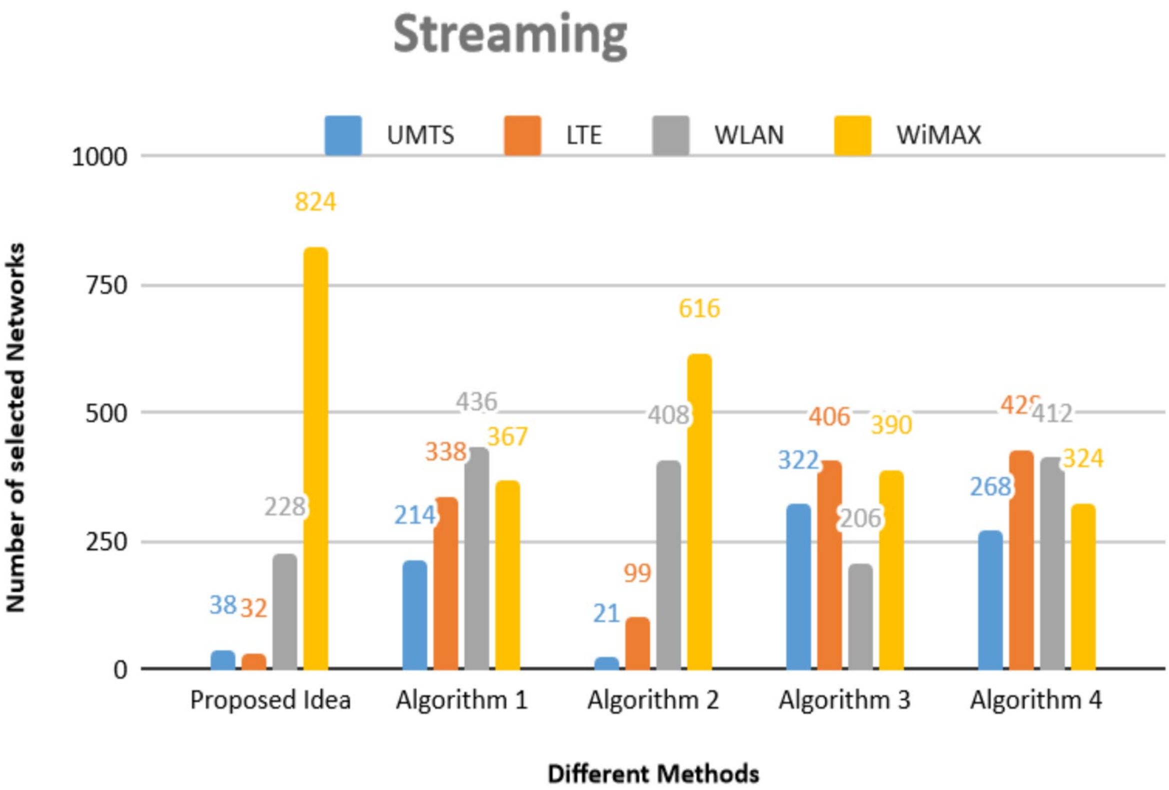

Fig. 11. Number of selected networks for the proposed method vs traditional methods for the streaming.

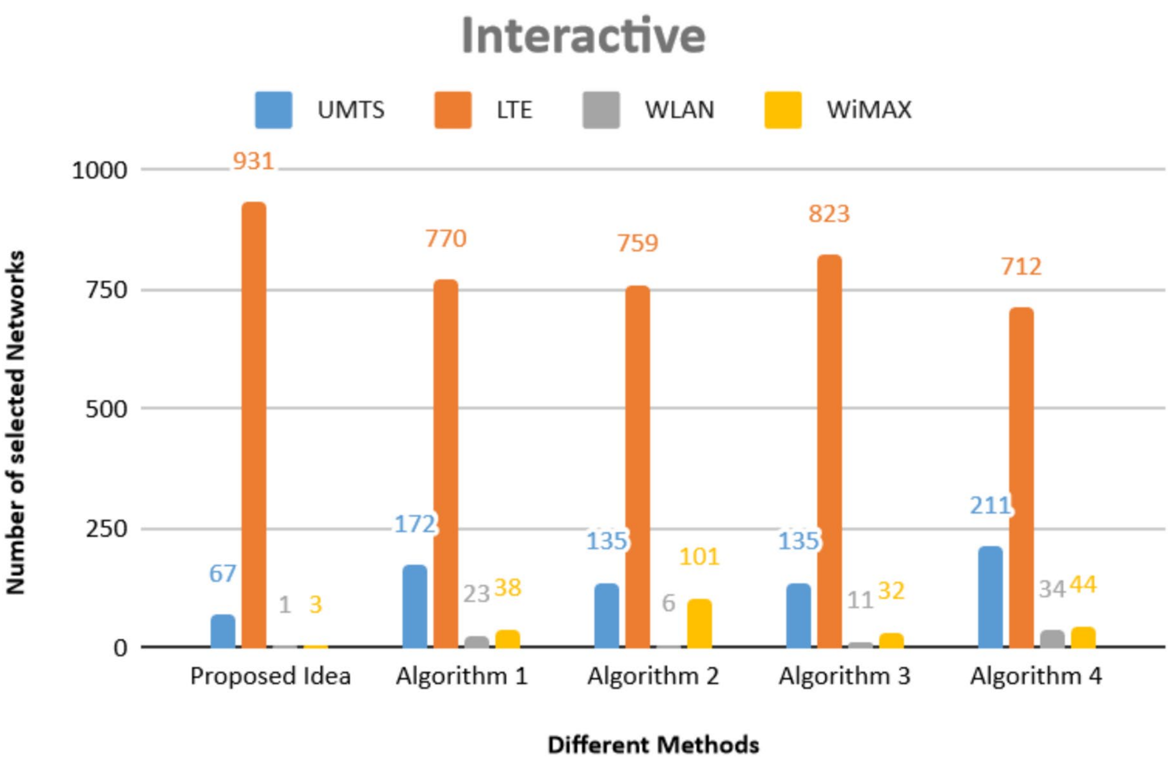

Fig. 12. Number of selected networks for the proposed method vs traditional methods for the interactive.

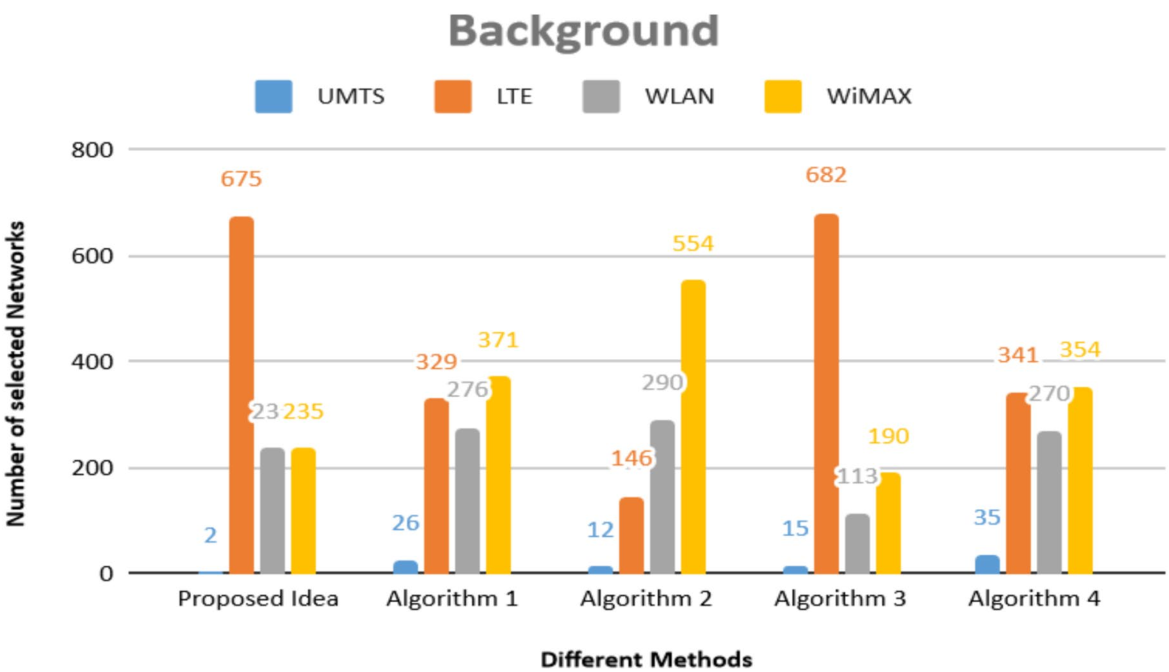

Fig. 13. Number of selected networks for the proposed method vs traditional methods for the background.

99 percent performance for the suggested technique is exhibited in a comparison study of it with conventional methods for interactive in Fig. 8. Figure 9 compares proposed work the existing algorithms.

We wish to provide an algorithm for wireless home networks that takes user and service preferences into account. Fuzzy logic and MADM were used throughout the algorithm development process. The actions involved in each module's calculations are outlined in depth. To discover how customer pleasure may raise the quality of experiences and services, this article will be updated. The method presented in this research may assist users in choosing the best network, resulting in more gains and less switching time. Figures 10, 11, 12 and 13, show various graph forms dependent on the number of chosen networks.

Limitations and complexity analysis

Computational Overhead: The integration of FAHP and fuzzy logic increases computational complexity compared to traditional MADM-based selection methods. The pairwise comparison process in FAHP, combined with fuzzification and defuzzification, results in an $O(n^2)$ time complexity, where n is the number of network attributes considered.

Real-Time Adaptability: High-speed mobility scenarios (such as vehicle networks) may contribute delay in decision-making, compromising real-time responsiveness, even though the model dynamically adapts to user preferences.

Scalability Issues: The suggested approach could need optimization strategies (such machine learning-based adaptive decision-making) to effectively manage large-scale situations in dense network settings with numerous heterogeneous networks.

Energy Consumption: The algorithm's frequent examination of network characteristics may result in increased power consumption, which is problematic for mobile devices with limited battery life.

Conclusion

This paper presents algorithmic approaches that effectively support user preferences and service characteristics in diverse wireless networks. By integrating utility theory, fuzzy logic, and multi-attribute decision-making into a cohesive framework, the proposed algorithm enables users to select networks that align with their specific needs. In this Proposed Model, fuzzy logic, FAHP, and MADM are used in an integrated framework to propose a unique user-centric method to network selection in diverse wireless settings. Our Proposed, in contrast to conventional algorithms, adjusts to the network circumstances as well as the demands of the individual user, leading to enhanced network usage and greater than before user satisfaction. The results show extraordinary gains in the effectiveness of network selection and the capacity to sustain reliable connections, especially when there are several overlapping networks. The framework comprises five distinct calculation modules: user preference value, network variable weight, network attribute score, candidate network total score, and overall candidate network score. Each module operates independently but contributes to an overall improved network selection process. The results obtained indicate that the algorithm not only maximizes user gains but also minimizes unnecessary network transfers, enhancing user satisfaction and experience. However, the framework does have limitations. For instance, it may not account for real-time changes in network conditions or user preferences, potentially affecting decision accuracy. Additionally, the reliance on historical data may limit the algorithm's adaptability in dynamic environments. Future research should focus on enhancing the framework's adaptability to real-time network conditions and incorporating machine learning techniques to refine user preference modelling. Exploring the integration of additional parameters, such as network security and user context, could also improve the algorithm's efficacy, ensuring it meets the evolving demands of heterogeneous wireless networks.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on request.

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S. Dinesh Krishnan: Conceptualization, methodology design, and initial manuscript drafting. A. Daniel: Data analysis, simulation setup, and validation of results. S. Ayyasamy: Literature review, related work structuring, and contribution to the introduction. Balamurugan Balusamy: Technical supervision, critical review, and manuscript refinement. Shitharth Selvarajan: Experiment design, data collection, and computational implementation. Taher Al-Shehari: Model evaluation, comparison with existing approaches, and results interpretation. Nasser A. Alsadhan: Final manuscript review, revisions, and funding acquisition. All authors contributed equally to this work. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Human/animal involvement
We declare that no human or animal involvement is associated with this project.

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