Network Select in 5G Heterogeneous Environment by M-F-U Hybrid Algorithm

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Abstract. Heterogeneous network convergence, as the current development trend of wireless communication network systems, has attracted the attention and research of many experts. In order to solve the problem of incomplete handover decision parameters and single decision algorithm in 5G heterogeneous network handover system, an M-F-U hybrid algorithm based on the multiple attribute decision making (MADM), fuzzy logic, and utility function is proposed. First, the decision parameters are divided into two parts, which are calculated by the MADM and fuzzy logic methods, the results obtained as the input of the utility function, secondly, the risk attitude coefficient is introduced into the utility function to describe the user's tolerance for switching risk, then, Then calculate the value of the comprehensive utility function, and finally, choose the optimal network scheme according to the comprehensive utility value. The simulation results show that compared with the traditional algorithm, the M-F-U algorithm can improve the handover accuracy, reduce the number of handovers, and complete the switching decision in a short time.

Keywords: 5G heterogeneous network · MADM · Fuzzy logic · Utility function · The optimal network scheme

1 Introduction

There has been an exponential growth in mobile data usage over the last 15 years (over 400 million times) that is expected to go up nearly 6-fold between 2017–2022 reaching 77 Exabyte per month by 2022 [1]. In addition to providing high data rates, it is equally important to provide reliable handover (HO) mechanisms as this directly impacts on the perceived quality of experience (QoE) for the end-user [2]. During the communication process, mobile terminals inevitably cross the cell boundaries of networks of the same structure or networks of different structures, which is more frequent in the network environment of multi-network convergence. As one of the key technologies of communication networks, handover technology has a great influence on improving the effectiveness and reliability of the entire system, and plays an important role in modern communication systems. The whole handover process is divided into three stages, namely handover discovery, handover decision and handover execution. The handover decision phase is the most important stage to solve the handover problem. Therefore, how to improve the handover decision algorithm, optimize the handover execution

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mechanism, provide the best experience for users at the lowest price, and achieve the purpose of ensuring communication quality and service requirements has important practical significance [3].

Based on the development in recent decades, domestic and foreign scholars have never stopped the research on network switching algorithms. Based on mobile behavior, literature [4] categorizes frequent handover-experience users as either fast-moving or ping-pong users. Fast-moving users are then handed over to the macro layer, and ping-pong users are managed by adjustment of handover parameters. The method that leverages device-level caching along with the capabilities of dual-mode base stations to minimize handover failures has proposed in [5]. Literature [6] combines the Analytical Hierarchy Process (AHP) technique to obtain the weight of the handover metrics and the Grey Relational Analysis (GRA) method to rank the available cells for the best handover target. References [7–9], including the above references, increase the algorithm complexity to a certain extent.

With the increase of decision parameters, different users and the types of services required by different users have different requirements for decision parameters. On the other hand, the computational complexity of their switching algorithms also greatly increases. Fuzzy algorithm can comprehensively consider many parameters, so it has been widely used in various fields. However, if a single decision parameter or a single processing method is still used to process the decision parameters [10, 11], once the decision parameters are increased, the number of fuzzy rules will increase by a geometric multiple.

Therefore, this paper proposes an M-F-U algorithm based on multi-attribute and sub-module, the algorithm divides eight parameters into several modules, each module uses different processing methods according to its characteristics. The algorithm introduces the S-type utility function into the decision-making process, use the S-type utility function to express user preferences, assist the decision-making system to make more reasonable decisions, reduce decision risks, and make decisions more scientific and effective. according to the principle of utility maximization, it provides decision-makers with the choice of the highest utility, which solves the problems of long handover time, high algorithm complexity and poor handover performance in the traditional network.

The rest of this paper is outlined as follows. In the next section, Heterogeneous network model will be discussed. the proposed M-F-U algorithm are provided in Sect. 3. Section 4 gives the simulation results and analysis. Finally, Sect. 5 concludes this paper.

2 System Model

This paper considers a common heterogeneous network model. As shown in Fig. 1, the network covers WLAN, WiMAX, 5G and LTE from inside to outside in the same area, serving as network access points for users. Users are randomly distributed in a heterogeneous network and follow a certain speed. Move in random directions.

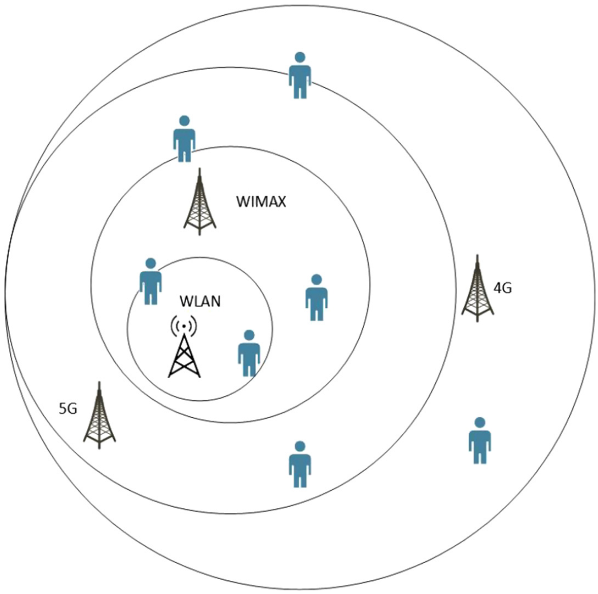


Fig. 1. Heterogeneous network model

Based on the above model, the received signal strength (RSS) of the system can be expressed as:

$$RSS_i = S_i - S_{loss} - \delta \tag{1}$$

Where S_i indicates the transmit power, δ is the shadow fading, S_{loss} is the path loss, and can be given by:

$$S_{loss} = S + 10 * n * \log(d) \tag{2}$$

Where S is the constant path loss, n stands for path loss index, and the distance between the user and the network center is d. When the user moves from the edge of the network to the other end, the moving speed is V, and the coverage radius of the network is R. According to [12], the formula for the probability of handover failure is

$$\mathrm{p}_f = \frac{2}{\pi}\left(\sin^{-1}\left(\frac{V\tau_i}{2R}\right) - \sin^{-1}(\frac{VT_1}{2R})\right)(0 \le T_1 \le \tau_i) \tag{3}$$

T_1 is the time threshold. When the residence time of the user entering the network is calculated to be greater than T_1, the handover is started, and when the user's movement time in the cell is less than the required handover delay time, considered handover failure.

When the user's movement time in the cell is less than the sum of the handover time when entering and leaving the cell, an unnecessary handover occurs. For the unnecessary handover probability, the time threshold T_2 is introduced, the probability of non-essential switching is as follows:

$$p_f = \frac{2}{\pi}\left(\sin^{-1}\left(\frac{V(\tau_i + \tau_0)}{2R}\right) - \sin^{-1}(\frac{VT_2}{2R})\right)(0 \le T_2 \le \tau_i) \quad (4)$$

Where τ_o indicates the delay in switching from the current network to other networks, the handoff delay from the other network to current network is τ_i.

3 M-F-U Algorithm

3.1 Handover Decision Process

The network selection algorithm of M-F-U is shown in Fig. 2. In the selection of parameters, the network conditions and user selection are comprehensively considered here, and some parameters are selected as switching decision indicators. According to the characteristics of the parameters, MADM and fuzzy logic inference methods are used respectively, and the final network selection depends on the value of the utility function. Before network selection, it is necessary to make a preliminary screening based on the mobile terminal speed and network load. The purpose is to eliminate the network that does not meet the standard and reduce the unnecessary switching, and shorten the calculation time of algorithm.

Screening of mobile speed, Compare the current speed of the user with the maximum movement speed. The calculation of the maximum moving speed can refer to [14]. If it is greater than the maximum mobile speed supported by the network, then remove the network from the list of candidate networks.

Network load screening, the network load reflects the usage of users in a network. If the number of network users exceeds the maximum available number of the network, this network is saturated and need to select the candidate network.

Figure 2 illustrates the specific handover decision process.

This paper abandons the method of single processing decision parameters, and divides the handover decision model into Network QoS (NQ) module, Spend Engine (SE) module, Benefit Engine (BE) module and utility function module.

The NQ model includes the calculation of received signal strength (RSS), transmission rate, delay, and packet loss. Based on the highly sensitive characteristics of the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method for data, this paper takes the TOPSIS method as the basis of judgment in NQ model. The BE and SE models include fuzzy inferences about velocity, power consumption, coverage and battery life. For SE and BE model, most of the indicators contained in it can be expressed by degree quantifier, which are processed by fuzzy reasoning. Finally, the S-type utility function is introduced to express user preferences, and the ideal network is selected according to the utility function.

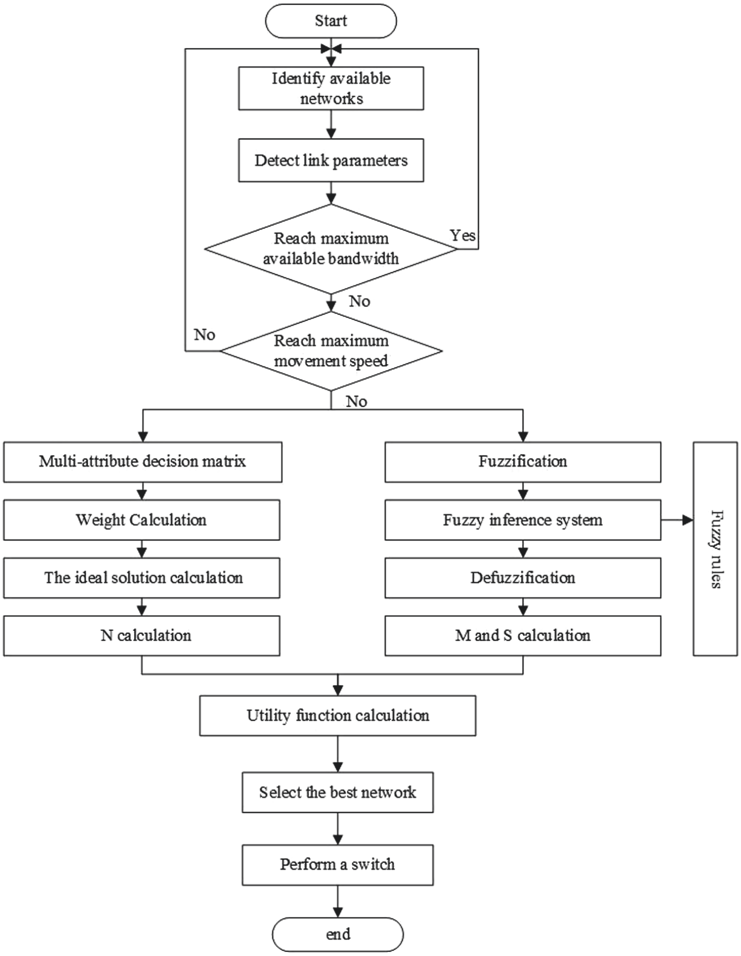


Fig. 2. Improved handover decision process

3.2 NQ Module

Consider the HetNets where the user is located with m available network alternatives, and n network parameters are selected. The candidate network set can be expressed as $S = \{S_1, S_2, \ldots, S_m\}$, $\mathrm{G} = \{\mathrm{G}_1, \mathrm{G}_2, \ldots, \mathrm{G}_n\}$ is the decision parameter set, The NQ module can be formulated as a multi-attribute decision matrix A as follows

$$A = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1j} & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2j} & d_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ d_{i1} & d_{i2} & \cdots & d_{ij} & d_{in} \\ d_{m1} & d_{m2} & \cdots & d_{mj} & d_{mn} \end{bmatrix} \tag{5}$$

Where d_{ij} indicates the value of the decision parameter j in the network candidate network i.

Due to the difference in measurement methods between different parameters, normalization is essential. For benefit parameter, the normalization formula is as follows:

$$\mathrm{E} = \frac{a_i - a_{\min}}{a_{\max} - a_{\min}} \tag{6}$$

For spend parameter, the normalized formula is

$$\mathrm{E} = \frac{a_{\max} - a_i}{a_{\max} - a_{\min}} \tag{7}$$

The value range of the attribute obtained by this normalization method is range from 0 to 1, which can also reflect the performance of the attribute value to a certain extent.

Then, the standardized multi-attribute decision-making matrix B can be expressed as:

$$B = \begin{bmatrix} \mathrm{b}_{11} & b_{12} & \cdots & b_{1j} & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2j} & b_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ b_{i1} & b_{i2} & \cdots & b_{ij} & b_{in} \\ b_{m1} & b_{m2} & \cdots & b_{mj} & b_{mn} \end{bmatrix} \tag{8}$$

The value from matrix B is the Normalized value.

Determine the weight values of different decision parameters. According to the preference of QoS performance under different service types, the weight relations can be expressed as:

$$\mathrm{W}_i = \frac{\left(\prod_{j=1}^{n} b_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n} (\prod_{j=1}^{n} b_{ij})^{\frac{1}{n}}} \tag{9}$$

Thus, the set of network parameter is given by $\mathrm{W} = \{\mathrm{w}_1, \mathrm{w}_2 \ldots, \mathrm{w}_N\}$.

After obtaining the weight of each handover decision parameter, the consistency test should be carried out on the decision matrix C. As shown in Table 1, the consistency ratio (CR) is calculated regarding the value of the random consistency index (RI). If CR < 0.1, the inconsistency of the matrix is within the allowable range, and the weight W derived from the matrix is available.

Table 1. RI values

N	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The standard decision matrix $C = (C_{ij})_{mn}$ with weights is expressed as:

$$C = \begin{bmatrix} \omega_1 b_{11} & \omega_2 b_{12} & \cdots & \omega_i b_{1j} & \omega_m b_{1n} \\ \omega_1 b_{21} & \omega_2 b_{22} & \cdots & \omega_i b_{2j} & \omega_m b_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \omega_1 b_{i1} & \omega_2 b_{i2} & \cdots & \omega_i b_{ij} & \omega_m b_{in} \\ \omega_1 b_{m1} & \omega_2 b_{m2} & \cdots & \omega_i b_{mj} & \omega_m b_{mn} \end{bmatrix} \tag{10}$$

In the standard weighted decision matrix $C_{ij} = \omega_j b_{ij}$, the positive ideal solution C^+ and negative ideal solution C^- of matrix C can be calculated by the following formula:

$$C_j^+ = \max\{\omega_j b_{ij} | i = 1,2,\cdots,m\} = b_j^+ \omega_j \tag{11}$$

$$C_j^- = \min\{\omega_j b_{ij} | i = 1,2,\cdots,m\} = b_j^- \omega_j \tag{12}$$

Where b_j^+ in it is the optimal value of column j in the matrix B, b_j^- is the worst value of column of the matrix B, they can be expressed as:

$$b_j^+ = \max\{b_{ij} | i = 1,2,\cdots,m\} \tag{13}$$

$$b_j^- = \min\{b_{ij} | i = 1,2,\cdots,m\} \tag{14}$$

Referring to (13) and (14), the final positive ideal solution and negative ideal solution can be calculated according (11) (12) as follows:

$$C^+ = \left(b_1^+ \omega_1, b_2^+ \omega_2, \cdots, b_n^+ \omega_n\right) \tag{15}$$

$$C^- = \left(b_1^- \omega_1, b_2^- \omega_2, \cdots, b_n^- \omega_n\right) \tag{16}$$

Then, the distance of each value in the standard weighted decision matrix C to the positive ideal solution and the negative ideal solution, which can be expressed by the sum of squares of errors:

$$d^+ = \sum_{j=1}^{n} \left(C_{ij} - C_j^+\right)^2 = \sum_{j=1}^{n} \omega_j^2 \left(b_{ij} - b_j^+\right)^2, i = 1, 2, \cdots, m \tag{17}$$

$$d^- = \sum_{j=1}^{n} \left(C_{ij} - C_j^-\right)^2 = \sum_{j=1}^{n} \omega_j^2 \left(b_{ij} - b_j^-\right)^2, i = 1, 2, \cdots, m \tag{18}$$

According to (17) and (18), Calculate the relative proximity to the ideal solution. the final output $N_{(\mathrm{value})}$ is calculated as follows:

$$N = \frac{\mathrm{d}_i^-}{d_i^+ + \mathrm{d}_i^-}, (0 \le N \le 1) \tag{19}$$

As NQ module output, $N_{(\mathrm{value})}$ determines the network performance.

3.3 BE and SE Modules

For SE modules, two input variables (Velocity and Power consumption) are assigned as its inputs and $S_{(\mathrm{value})}$ as its output using the FIS Editor. which is shown in Fig. 3. In Fig. 3, the $V_{(\mathrm{value})}$ is defined within the range of 0 to 50 km/h, where the range of $P_{(\mathrm{value})}$ is defined from 0 to 3700 W and $M_{(\mathrm{value})}$ is from 0 to 1. Three fuzzy membership functions (L, M, and H) with trapezoidal shapes are used to indicate each of the input variables. While, in the case of output variable, three fuzzy membership functions (L, M, and H) with triangular shape. Since, there are two variables or two fuzzy sets at the input of SE modules, and each of them has three FMFs, need $3^2 = 9$ fuzzy rules to specify the behavior of the mentioned fuzzy engine.

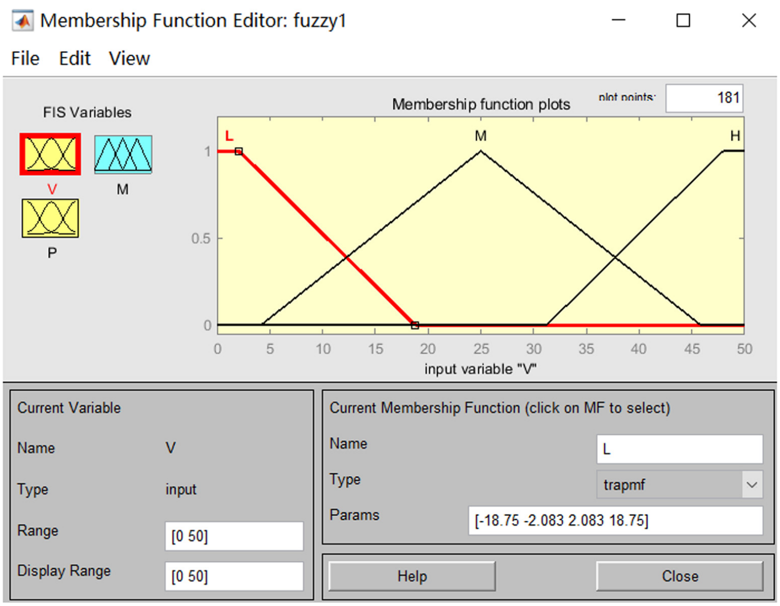


Fig. 3. The membership function editor of SE module

The applied rules in this fuzzy engine are listed in Table 2, where indicate the changes of $S_{(value)}$ or output fuzzy membership functions with different values of input fuzzy membership functions.

Table 2. SE module fuzzy rules

Number	Velocity	Power consumption	Output
1	Low	Low	High
2	Low	Medium	Medium
⋮	⋮	⋮	⋮
9	High	High	Low

Then, performing the defuzzification process, convert the aggregated fuzzified data back into crisp value by applying centroid method, which can be given by:

$$S = \frac{\int \tilde{\mathrm{SE}}(x) \cdot x dx}{\int \tilde{\mathrm{SE}}(x) dx} \tag{20}$$

Where x is a continuously changing quantity in the value range of the fuzzy set, represents the membership function of fuzzy sets, the $S_{(value)}$ is the final output value of the SE module.

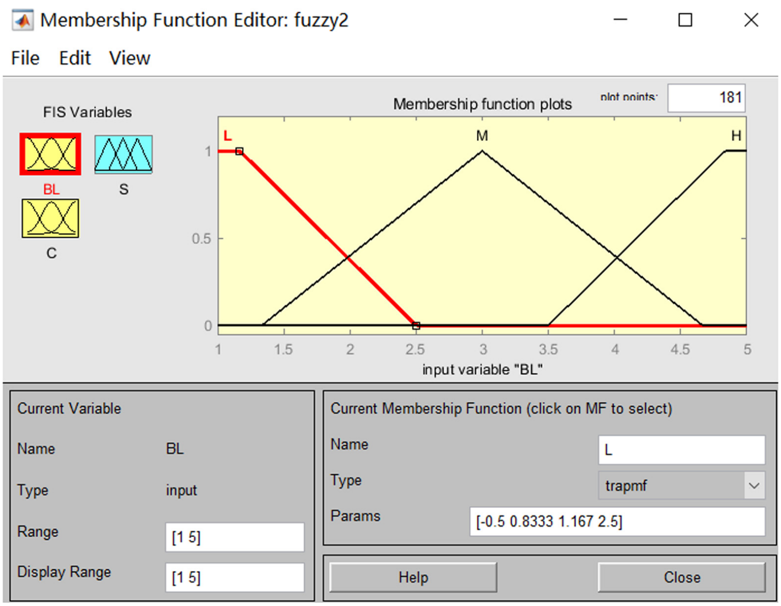


Fig. 4. The membership function editor of BE module

Similarly, two input variables (Battery Life and Coverage) are assigned as its inputs and $B_{(\text{value})}$ as its output using the FIS Editor. which is shown in Fig. 4. In Fig. 4, the $BL_{(\text{value})}$ is defined within the range of 1 to 5 day, where the range of $C_{(\text{value})}$ is defined from 0 to 2000 m and $B_{(\text{value})}$ is from 0 to 1. Three fuzzy membership functions (L, M, and H) with trapezoidal shapes are used to indicate each of the input variables. While, in the case of output variable, three fuzzy membership functions (L, M, and H) with triangular shape. Since, there are two variables or two fuzzy sets at the input of BE modules, and each of them has three FMFs, it needs $3^2 = 9$ fuzzy rules to specify the behavior of the mentioned fuzzy engine.

The applied rules in this fuzzy engine are listed in Table 3, where indicate the changes of $B_{(\text{value})}$ or output fuzzy membership functions with different values of input fuzzy membership functions.

Table 3. BE module fuzzy rules

Number	Battery life	Coverage	Output
1	Low	Low	Low
2	Low	Medium	Low
⋮	⋮	⋮	⋮
9	High	High	High

Then, performing the defuzzification process, convert the aggregated fuzzified data back into crisp value by applying centroid method, which can be given by

$$B = \frac{\int \tilde{\mathrm{B}}\mathrm{E}(y) \cdot y dy}{\int \tilde{\mathrm{B}}\mathrm{E}(y) dy} \tag{21}$$

Where y is a continuously changing quantity in the value range of the fuzzy set. The $B_{(\text{value})}$ is the final output value of the BE module.

3.4 S-Type Utility Function Module

Since the utility function allows user to express their preference for each standard involved in the decision-making process by determining the degree of satisfaction, which In line with the problem of network selection. This paper uses the utility function as the criterion for evaluating degree of satisfaction. Three input variables (M(value), S (value), and B(value)) are assigned as the inputs of utility function. The multi-attribute decision steps under the S-type utility function are as follows:

Consider $\theta = (\theta_1, \theta_2, \cdots, \theta_l)$ is the network's risk state set, such as handover failed, unnecessary handover, etc. P_{t} express as the probability of risk occurs which satisfies $0 \le P_t \le 1$, the evaluation information of the status θ_t of each attribute in the network is $\left(\mu_{ij}^t, \sigma_{ij}^t\right)$, a fuzzy number. Thus, the risk state matrix can be express as:

$$D_1 = \left(\mu_{ij}^1, \sigma_{ij}^1\right)_{m\times n}, D_2 = \left(\mu_{ij}^2, \sigma_{ij}^2\right)_{m\times n}, \cdots, D_l = \left(\mu_{ij}^l, \sigma_{ij}^l\right)_{m\times n} \tag{22}$$

Step 1: Change the risk state decision matrix into scoring function matrix, $\left(\mu_{ij}^t, \sigma_{ij}^t\right)$ can be convert to real number S_{ij}^t as follow:

$$S_{ij} = \frac{\exp(\mu(x) - \sigma(x))}{\pi(x) + 1} \tag{23}$$

Where $\mu(x)$, $\sigma(x)$, and $\pi(x) = 1 - \mu(x) - \sigma(x)$ expressed as membership, non-membership, and hesitation for fuzzy sets of evaluation information, respectively. The scoring function is given by:

$$S_1 = \left(s_{ij}^1\right)_{m\times n}, S_2 = \left(s_{ij}^2\right)_{m\times n}, \cdots, S_l = \left(s_{ij}^l\right)_{m\times n} \tag{24}$$

In the process of switching decisions, the decision system has corresponding expected values for each attribute. This expected value can be used as a reference point for system decision-making, and the reference point reflects user preferences well. When the attribute value is higher than the reference point of the decision system for this attribute, it will be regarded as a loss to the user, and the higher the reference point, the greater the loss. Conversely, when the attribute value is lower than the reference point of the decision system for the attribute, the user will consider it to be profitable, and the lower the reference point, the greater the value of the income.

Step 2: To calculate the value matrix, this article takes the mean as a reference point and calculates the utility value of each attribute in the network to obtain the value matrix:

$$U = \left(u_{ij}\right)_{m\times n} = \sum_{t=1}^{l} \omega(P_t) u\left(s_{ij}^t\right) \tag{25}$$

Where $u\left(s_{ij}^t\right)$ indicates the value function which reflect the subjective utility value of the decision system, the formula is expressed as:

$$u\left(s_{ij}^t\right) = \begin{cases} \left(s_{ij}^t - \bar{s}_j^t\right)^\alpha & s_{ij}^t \ge \bar{s}_j^t \\ -\theta\left(\bar{s}_j^t - s_{ij}^t\right)^\beta & s_{ij}^t \le \bar{s}_j^t \end{cases} \tag{26}$$

Where α, β indicate the risk attitude coefficient which satisfies $0 < \alpha, \beta < 1$, as the increase of α and β indicate that the degree of risk that users can take, and θ show the loss avoidance coefficient. Research shows that the decision results are basically consistent with the empirical data when $\alpha = \beta = 0.88, \theta = 2.25$ [13].

Where $\omega(p)$ is a monotonically increasing probability weight function which reflects the overestimation or underestimation of risk events as follow:

$$\omega(P) = \begin{cases} \frac{P^{\chi}}{(P^{\chi} + (1-P^{\chi})^{\chi})^{1/\chi}} & s_{ij}^{t} \geq \bar{s}_{j}^{t} \\ \frac{P^{\delta}}{\left(P^{\delta} + (1-P^{\delta})^{\delta}\right)^{1/\delta}} & s_{ij}^{t} \geq \bar{s}_{j}^{t} \end{cases} \tag{27}$$

Where P is the objective probability of risk occurrence, the coefficient of risk-return attitude and the coefficient of risk-loss attitude can be express as χ and δ, which satisfies $0 < \chi, \delta < 1$, and usually set to $\chi = 0.61, \delta = 0.72$.

Step 3: Calculate the attribute weights $G = \{M, S, B\}$ with square root method.

Step 4: Calculate the comprehensive utility value. The greater the comprehensive utility value, the better the network scheme. The final formula given by:

$$u_i = 10 \sum_{j=1}^{n} G_j \cdot \omega_j \cdot \mu_{ij}, i = 1, 2, \cdots, m \tag{28}$$

If the utility value of the candidate network is almost the same as the utility value of the original network, it indicates that the user has the same preference for the two networks, and in this case, the handover is not performed. If the value of the original network's comprehensive utility function is the largest of all available networks, the user prefers to maintain the original network service without being forced by external factors.

4 Simulation and Analysis

In this section, we evaluate the performance of the proposed heterogeneous network handover algorithm in a heterogeneous network environment with multi-network convergence by MATLAB simulation platform. The simulation scenario of the heterogeneous network consists of 5G, LTE, WiMAX, and WLAN, the cell radius of 5G base stations (BS) is set to 500 m, the cell radius of LTE is 1000 m, WIMAX is 300 m, and WLAN is 75 m (Table 4).

Table 4. Network-side handover parameters

Access network	RSS (dBm)	Transmission rate (Mbit/s)	Delay (ms)	Drop rate (%)
5G	−95 ~ −20	200	20	0.015
LTE	−95 ~ −20	50	100	0.04
WiMAX	−95 ~ −20	55	100	0.04
WLAN	−95 ~ −20	1000	25	0.025

The 5G network base station is taken as the origin coordinate, and the rest available networks are randomly distributed with reference to 5G base stations. By consulting the existing network parameter standards in the literature, the simulation parameters are set as Table 5.

According to (6) and (7), normalizing RSS, transmission rate, delay, and drop rate. The final result is as follows:

Table 5. Normalized network side handover parameters

Access network	RSS (dBm)	Transmission rate (Mbit/s)	Delay (ms)	Drop rate (%)
5G	0.853	0.728	0.679	0.15
LTE	0.744	0.384	1	0.4
WiMAX	0.702	0.421	1	0.4
WLAN	0.54	1	0.623	0.25

Then, the output of NQ module is calculated according to the formula from (8) to (19), and the final $N_{(\text{value})}$ is

$$N = \{0.6834, 0.5514, 0.5411, 0.6003\}$$

Where the $N_{(\text{values})}$ are stored in the order of 5G, LTE, WiMAX, and WLAN.

The parameters in the SE and BE modules undergo the process of fuzzification, fuzzy reasoning, and defuzzification, $S_{(\text{values})}$, $B_{(\text{values})}$ are given by

$$S = \{0.4967, 0.1343, 0.3574, 0.5260\}$$

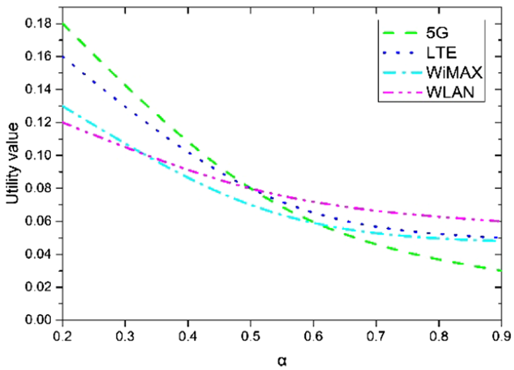
$$B = \{0.4610, 0.6194, 0.5053, 0.4769\}$$

Then, $N_{(\text{values})}$, $S_{(\text{values})}$, $B_{(\text{values})}$ are assigned as the input of the comprehensive utility function, the output of the utility function is the evaluated result, and the final obtained utility function values are sorted as follows:

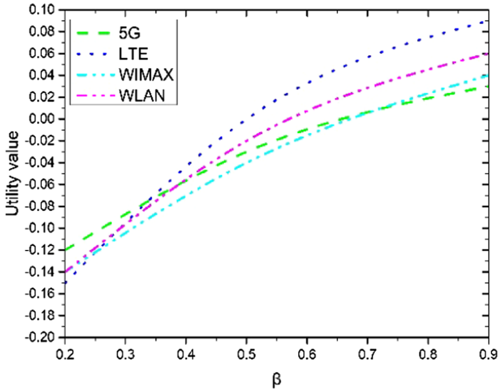
$$u_i = \{0.0335,\ 0.013,\ 0.0149,\ 0.0205\}$$

From the simulation results, under the comprehensive consideration of network quality and user preferences, network users' preference for 5G is higher than that of other traditional networks, followed by WLAN, which is also the development trend of future communication networks.

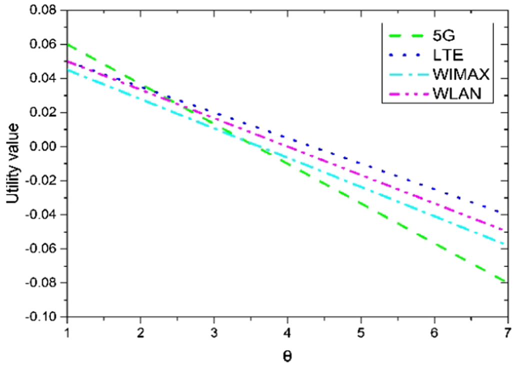
Considering that different users have different preferences for network attributes, the difference of α, β and θ have an impact on the optimal network scheme, this section conducts a sensitivity analysis on the value parameter (α, β or θ) that reflects the user's risk attitude. As the values of the parameters are different, the change trend of the comprehensive utility value is shown in Fig. 5.



(a) Trend of utility value with α



(b) Trend of utility value with β



(c) Trend of utility value with θ

Fig. 5. Trend of utility value

As shown in Fig. 5(a), when α is increased to 0.5, the 5G network is no longer the optimal network scheme. As the user's risk tolerance increases, the utility value curve of the income area is flatter, indicating that the user is more biased risk. As shown in Fig. 5(b), when β is increased to 0.36, the LTE network becomes the best choice. For the increased risk tolerance of the loss area, the smoother the utility curve of the loss area, indicating that users also prefer risk. As shown in Fig. 5 (c), as the value of θ becomes larger, users are more sensitive to losses, indicating that users will be more conservative when facing risks. Therefore, as the value of and decreases and the value increases, users are more inclined to avoid risks.

In order to further evaluate the performance of the algorithm proposed in this paper, the M-F-U algorithm is compared with the traditional RSS-based handover algorithm and fuzzy algorithm. Consider that the network users are randomly distributed in the coverage area of networks. The performance comparison is shown in the following figure:

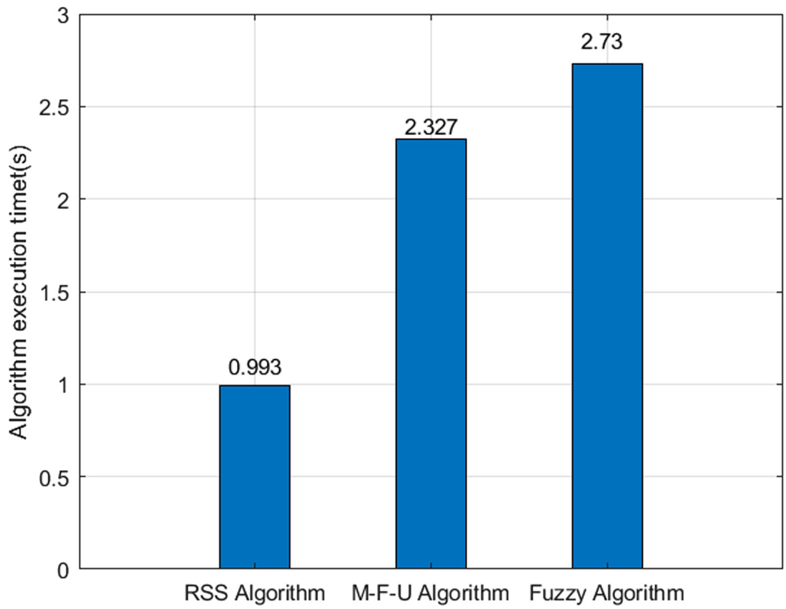


Fig. 6. Comparison of algorithm execution time

Figure 6 is a comparison of the execution time of algorithms based on the RSS algorithm, M-F-U algorithm, and fuzzy algorithm. It can be seen that due to the single handover decision parameter, the RSS-based handover decision algorithm has the shortest execution time, while under the condition that the same number of decision parameters, the M-F-U algorithm has a performance advantage of about 0.4 s in execution time compared with the single fuzzy logic algorithm.

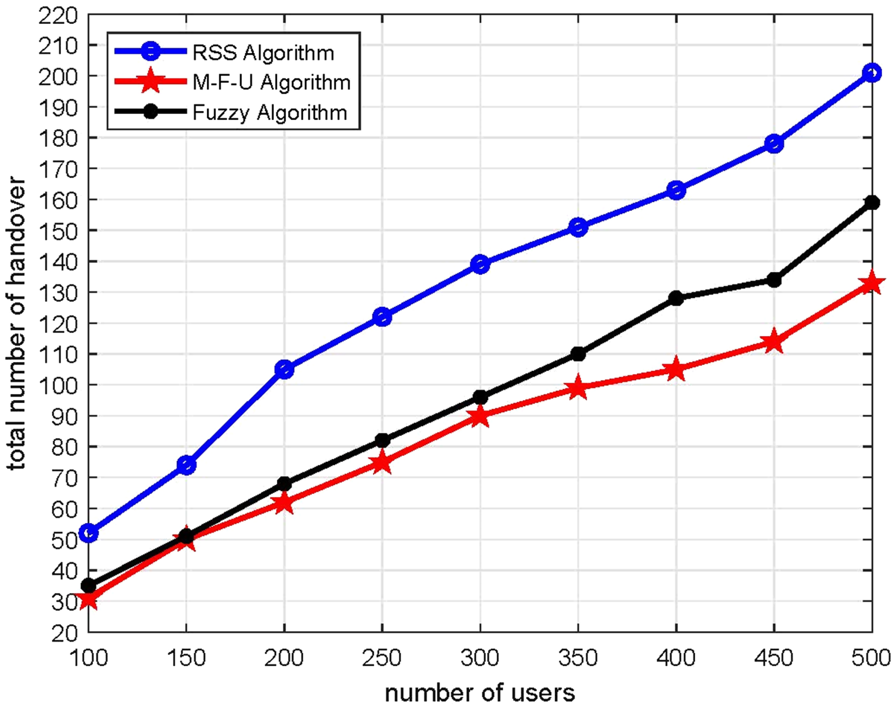


Fig. 7. Total handover times

In Fig. 7, When the number of users is different, It can be seen that the difference between the handover time of the MFU algorithm and the fuzzy algorithm is small when the number of users is about 300. Infer that in the case of the same decision model and the same decision parameters, processing complexity is almost equivalent. As the number of users increases in a certain range, the calculation of a single fuzzy algorithm will increase exponentially. The results show that the M-F-U algorithm can effectively reduce the number of handovers and improve the accuracy of handover.

5 Conclusions

In this paper, a hybrid algorithm based on traditional multi-attribute decision algorithm is proposed. The algorithm balances the weight of the network and the user. In the evaluation of the network, the value of the S-type utility function is introduced into the decision-making process. The S-type utility function is used to express user preferences, which assists the decision-making system to make more reasonable decisions and reduce decision risk, so decision-making can be more scientific and effective. Compared with the traditional handover algorithm, the M-F-U algorithm takes a more comprehensive consideration of the parameters, effectively reducing the total number of handover and shortening the execution time of the algorithm.

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References

1. Cisco: Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update 2017–2022. Cisco. White Paper, San Jose, CA, USA (2019)
2. Tayyab, M., Gelabert, X., Jantti, R.: A survey on handover management: from LTE to NR. IEEE Access **7**, 118907–118930 (2019)
3. IMT-2020 (5G) Program: White paper on 5G Concept (2015)
4. Hasan, M.M., Kwon, S., Oh, S.: Frequent-handover mitigation in ultra-dense heterogeneous networks. IEEE Trans. Veh. Technol. **68**, 1035–1040 (2019)
5. Semiari, O., Saad, W., Bennis, M., Maham, B.: Caching meets millimeter wave communications for enhanced mobility management in 5G networks. IEEE Trans. Wireless Commun. **17**, 779–793 (2018)
6. Alhabo, M., Zhang, L.: GRA-based handover for dense small cells heterogeneous networks. IET Commun. **13**(13), 1928–1935 (2019)
7. Alhabo, M., Zhang, L.: Unnecessary handover minimization in two-tier heterogeneous networks. In: 13th Wireless On-demand Network systems and Services Conference, Jackson Hole, Wyoming, pp. 160–164. IEEE (2017)
8. Barmpounakis, S., Kaloxylos, A., Spapis, P., et al.: Context-aware, user-driven, network-controlled RAT selection for 5G networks. Comput. Netw. **113**(11), 124–147 (2017)
9. Calabuig, D., Barmpounakis, S., Gimenez, S., et al.: Resource and mobility management in the network layer of 5G cellular ultra-dense networks. IEEE Commun. Mag. **55**(6), 162–169 (2017)
10. Thumthawatworn, T., Tillapart, P., Santiprabhob, P.: Adaptive multi-fuzzy engines for handover decision in heterogeneous wireless networks. Wireless Pers. Commun. **93**(4), 1005–1026 (2017). https://doi.org/10.1007/s11277-017-3963-3
11. Zineb, A.B., Ayadi, M., Tabbane, S.: Fuzzy MADM based vertical handover algorithm for enhancing network performances. In: 23rd International Conference on Software, Telecommunications and Computer Networks (SoftCOM), SplitSupetar, Croatia, pp. 153–159. IEEE (2015)
12. Almosbahi, R., Elalem, M.: Optimization of coverage and handover for heterogeneous networks. Int. J. Adv. Res. **3**(3), 213–219 (2019)
13. Zhang: Research on Cell Handover Algorithm under UDN. Chongqing University of Posts and Telecommunications (2017)
14. Tversky, K.A.: Prospect theory: an analysis of decision under risk. Econometrica **47**(2), 263–291 (1979)