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A heterogenous network selection algorithm for internet of vehicles based on comprehensive weight

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Abstract With the development of mobile communications and Internet of things (IoT), the Internet of vehicles (IoV) has become commonplace. To integrate the heterogenous IoV networks, this paper mainly explores the heterogenous network selection mechanism for the IoV. Considering the diversity of IoV networks, the authors proposed a heterogenous network selection algorithm based on comprehensive weight. Based on different service scenarios and user preferences, the proposed algorithm obtains the subjective weights of candidate networks, calculates the objective weights of judgement indices by entropy method, and combines the subjective and objective weights into a comprehensive weight. On this basis, the candidate networks were analyzed by the utility function (UF), and the optimal network was selected for access. The research results provide a reference for high-quality access to heterogenous networks.

1. 1.Introduction

With the boom of mobile and Internet technologies, the Internet of Vehicles (IoV), as one of the three major application scenarios of the fifth generation (5G) technology, has become a new industrial form that deeply integrates multiple industries, such as transportation and information. The development of mobile technology has also further promoted the advancement in wireless technologies for broadband communication and the Internet of things (IoT). Various communication technologies, namely, WiFi, BT, ZigBee, and ultra-wideband (UWB), and mobile technology help each other forward. A dazzling array of network methods have gradually permeated into the application scenarios of the IoV. However, the traditional wireless access technology cannot adapt to the growing new service types and data volume of the IoV. It is important to develop an access technology for heterogenous networks in the IoV.

The dawn of the 5G era has caused an explosion in single network bandwidth. With the diversification of the IoV application scenarios, two inevitable trends of data communication will take hold in the IoV: the coexistence and integration of heterogenous networks, and the service provision by multiple networks and operators. Therefore, communication researchers are striving to provide users with optimal network access anytime and anywhere, and satisfy the diversified user demand for high-quality access to heterogenous networks [1].

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Thanks to the rapid development of microelectronic chips, the hardware performance of vehicle intelligent terminals has been greatly improved to fully satisfy the performance demand of heterogeneous networks. The key to improving the experience of end-users lies in the optimization of the selection algorithm for the optimal network. A reasonable heterogeneous network selection algorithm could enable users to effectively access the optimal network and satisfy their quality of service (QoS) requirement and personal preferences, and also balance the network load and further improve network utilization.

2. Literature review

The burgeoning of heterogeneous networks has given rise to various network selection algorithms. These algorithms were developed with different starting points and optimization goals, such as maximizing user throughput, balancing the load between networks, improving resource utilization, and reducing blocking rate, communication cost, and resource consumption. Overall, the network selection algorithms can be divided into the following classes:

2.1. Algorithms based on received signal strength (RSS)

To a certain extent, the RSS can characterize the quality of wireless signal, laying the basis for network selection. Then, the terminal collects the RSSs from wireless networks, compares the link qualities between them, and chooses the one with the best link quality. Tucker and Alizadeh [2] set a lowest threshold for the RSS of each wireless network, such that the mobile terminal could choose the optimal network by comparing the RSS of each network with the threshold. Lee et al. and Haider et al. [3,4] improved RSS-based algorithms to solve the ping-pong effect induced by RSS fluctuations.

The RSS-based algorithms mostly predict the trend of the current RSS, so that the terminal knows the network to be accessed in advance. Despite their simple network alternatives, the RSS-based algorithms often fail to make the right choice under complex network coverage, for the RSS cannot fully reflect the quality of wireless links or demonstrate the overall performance of the network.

2.2. Algorithms based on fuzzy logic (FL) theory [5]

The integration between fuzzy logic theory and network attributes could effectively improve the accuracy and effectiveness of network selection. Hou and O'Brien [6] established a fuzzy set for each network decision attribute, defined a fuzzy inference rule base for reasoning, and evaluated the network performance through defuzzification. By fuzzy comprehensive evaluation (FCE), Radhika and Reddy [7] and Wang et al. [8] determined the relative membership of each decision attribute, evaluated the performance of each candidate network through weighted summation, and selected the optimal network based on evaluation results.

The FL-based network selection algorithms rely on linear mapping to measure attributes and establish fuzzy sets, failing to objectively describe the fuzzy user information or network state. In addition, the huge computing load impedes the application of these algorithms in the selection between heterogeneous wireless networks.

2.3. Algorithms based on utility function (UF) [9]

Inspired by the utility theory in microeconomics, the UF-based algorithms parameterize each alternative with utility function, construct a mathematical model to evaluate the performance of network selection, and derive the effective resource allocation alternative by maximizing the utility of each access network (the benefit of the user after accessing each network). Chan et al. [10] adopted the logarithmic UF solely based on the RSS. Stevens-Navarro and Wong [11] designed a UF-based algorithm in view of multiple attributes: bandwidth, safety, price, and power loss. Wang and Binet [12] developed a UF-based algorithm in the light of bandwidth, price, traffic, fault tolerance, and jitter. Zhu and McNair [13] presented a UF-based algorithm, in consideration of bandwidth, delay, and power consumption.

The UF-based network selection algorithm needs to clarify the attributes to be considered in network decision-making, and also reasonably describe the benefit and cost of each attribute. Note that the utility curve of an attribute might vary with service types.

2.4. Algorithms based on game theory (GT) [14]

The game theory is suitable for solving network selection problems in heterogeneous wireless networks, because the users in these networks share wireless resources, and different networks compete for interests. Cesana et al. [15] modeled the network selection problem as a non-cooperative game, in which each user formulated a pricing strategy as per the congestion degree in the candidate network, and selects the network access with the least cost. Niyato and Hossain [16] and Chan et al. [10] modeled the game between users as an evolutionary game, and realized the achieve access control of heterogeneous wireless networks.

The game theory-based algorithms are too complex to efficiently control the access to heterogeneous wireless networks. In addition, the game theory-based algorithms need to clearly define the game model and the equilibrium method before controlling network access.

2.5. Algorithms based on multiple attribute decision-making (MADM) [17]

The MADM is a decision-making method that prepares a limited number of alternatives in advance for multiple attributes that cannot be shared or substituted for each other, and choose the best alternative out of the prepared ones [18]. During the MADM, the decision-maker makes comprehensive evaluation of each alternative by a certain method, according to the judgement matrix and attribute weights [19].

In heterogeneous networks, there are certain differences in bandwidth, packet loss rate, and delay. These factors must be considered comprehensively when selecting network access. Obviously, the MADM is applicable to network selection of heterogeneous networks. The MADM model is detailed in Table 1.

In general, the MADM model contains decision-making units (DMUs), attribute set X, alternative set S, and weight set W. Specifically, the attribute set $X = \{x_1, x_2, \ldots, x_n\}$ indicates that each alternative has n attributes; the alternative set

Table 1 The MADM model.

Alternative	Attribute			
	X_1	X_2	$\cdots$	X_n
S_1	x_{11}	x_{12}	$\cdots$	x_{1n}
S_2	x_{21}	x_{22}	$\cdots$	x_{2n}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_m	x_{m1}	x_{m2}	$\cdots$	x_{mn}
Weight	ω_1	ω_2	$\cdots$	ω_n

$S = \{s_1, s_2, ..., s_m\}$ indicates that each decision-making problem has m alternatives; $\omega_j(1 \leqslant j \leqslant n)$ is the weight of each attribute.

The judgement indices must be normalized to overcome their marked differences in unit, dimension, and magnitude. Thus, the normalized attribute value of the j-th parameter in the i-th alternative was denoted as $x_{ij}(1 \leqslant i \leqslant m, 1 \leqslant j \leqslant n)$. The higher the overall utility, the more superior the alternative. The UF can be expressed as:

$$U(S_i) = \sum_{j=1}^{n} \omega_j x_{ij}, 1 \leqslant i \leqslant m \tag{1}$$

where x_{ij} is the normalized attribute value; ω_j is the weight of attribute j; S_i is the i-th alternative.

Depending on the decision-making rules, the MADM methods can be divided into simple additive weighting (SAW), technique for order preference by similarity to ideal solution (TOPSIS), grey relational analysis (GRA) and analytic hierarchy process (AHP) [20–22].

The MADM-based network access algorithms compute the utility of each network attribute, assign a weight to each attribute, and combine the attributes by weight through a certain method. These algorithms have relatively high complexity, due to the multiple factors being considered; the correctness of network access is greatly affected by the accuracy of weight settings. Hence, an important direction of research is to consider network and user factors in a more objective manner. The advantages and disadvantages of various algorithms mentioned above are shown in Table 2.

Table 2 The advantages and disadvantages of various algorithms.

Algorithm	Advantage	Disadvantage
RSS-based	Simple	Network parameter is single and one-sided
FL-based	Don't need an exact mathematical model	Network states cannot be objectively described after fuzzy processing
UF-based	Network utility can be maximized	The utility and cost of each attribute is uncertain
GT-based	Network performances are improved	High complexity and low efficiency
MADM-based	Network attributes are comprehensively considered	High complexity

3. Algorithm design

The existing network selection algorithms face various defects, when they are applied to the IoV. In heterogeneous networks, there are certain differences in bandwidth, packet loss rate, and delay. These factors must be considered comprehensively when selecting network access. Obviously, the MADM is applicable to well dealt with these influential factors. However, the MADM algorithm based on a single decision criterion cannot comprehensively consider the subjective and objective factors. In this paper, a network selection algorithm is designed by combing subjective and objective weights into a comprehensive weight. According to different service types and user preferences, the AHP was implemented to obtain the subjective weight of each candidate selection. Then, the objective weight of each judgment index was derived through entropy method. Finally, the UF was used to sort the candidate networks, and choose the optimal network for access. Simulation results show that our algorithm achieved better performance than the traditional network selection algorithms. The performance of our algorithm is expected to further improve with the development of IoV and artificial intelligence (AI).

3.1. AHP

The AHP is a popular tool to solve complex decision-making problems. During the AHP, the nature, influencing factors, and internal relations of the problem are analyzed in details; Then, the relevant factors of the problem are decomposed into a goal layer, a criterion layer, and an alternative layer; After that, the subjective judgements are quantified objectively against a certain scale; Finally, a decision is made through qualitative and quantitative analyses.

If a user is in an area covered by multiple networks, he/she needs to consider the QoS of each network and his/her personal preferences before choosing the most suitable network to access. In this case, network selection becomes a complex MADM problem.

The AHP offers a good solution to such a problem. In general, the AHP can be broken down into the following steps: building a hierarchical model, constructing a judgement matrix, and checking the consistency of the judgement matrix.

3.1.1. Building a hierarchical model

During the application, the AHP needs to firstly divide the problem into multiple layers, and construct a hierarchical model. Generally, the hierarchical model of AHP consists of three layers: the goal layer of the optimal network on the highest level; the criterion layer of attributes in the middle; the alternative layer of candidate networks at the bottom (Fig. 1).

Generally, a complex problem requires a detailed analysis on its factor. To create a reasonable hierarchy model, the relations between the elements in the problem must be parsed as detailed and reasonable as possible, while dividing the problem into multiple layers and determining the dominating relations between the elements.

3.1.2. Constructing the judgement matrix

Once the hierarchical model is established, the subordination relations between upper and lower layers were developed

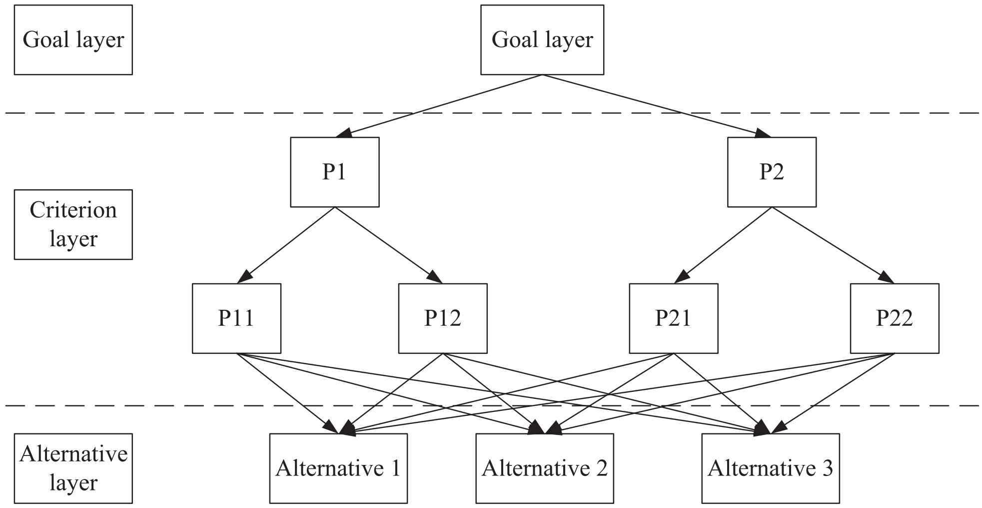

Fig. 1 The hierarchical model.

clearly. Next, the judgement matrix should be created to determine the relations between attributes on the same layer, and evaluate the importance of each of them. The judgement matrix can be generally expressed as:

$$B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1N} \\ b_{21} & b_{22} & \cdots & b_{2N} \\ \cdots & \cdots & b_{mn} & \cdots \\ b_{N1} & b_{N2} & \cdots & b_{NN} \end{bmatrix} = \begin{bmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_N \\ w_2/w_1 & w_2/w_2 & \cdots & w_2/w_N \\ \cdots & \cdots & w_m/w_n & \cdots \\ w_N/w_1 & w_N/w_2 & \cdots & w_N/w_N \end{bmatrix} \tag{2}$$

where b_{mn} is the relative importance between the m-th and n-th elements; w_m and w_n are the weights of the m-th and n-th elements, respectively.

3.1.3. Calculating relative importance

The relative importance of each attribute can be solved by the judgement matrix. The common methods for weight calculation include least squares (LS), logarithmic LS, and eigenvalue method. Here, the eigenvalue method is adopted:

$$Aw = \lambda_{\max} w \tag{3}$$

where $\lambda_{\max}$ is the maximum characteristic root of judgement matrix A; w is the eigenvector. The weight vectors can be obtained by normalization.

3.1.4. Consistency check

Due to the subjectivity of decision-makers and complexity of the problem, the judgement matrix might not be reasonable. Therefore, the consistency of the matrix needs to be checked by the consistency index (CI). The consistency ratio (CR) can be obtained by:

$$CR = CI/RI \tag{4}$$

If the order degree of the judgement matrix is known, then the random consistency index (RI) can be determined (Table 3).

The CI value can be obtained by:

$$CI = (\lambda_{\max} - N)/(N - 1) \tag{5}$$

If $CR > 0.1$, then the judgement matrix is unacceptable, and the corresponding service types and user requirements should be adjusted. Otherwise, the subjective weight $W = [\,w_1 \quad w_2 \quad \cdots \quad w_N\,]^T$ can be obtained from the non-zero vector corresponding to the largest eigenvalue $\lambda_{\max}$.

3.2. Entropy method

In information theory, the amount of information mainly measures the degree of system order. Therefore, the two signs have equal absolute values, but opposite signs. By this property, the information entropy of each evaluation index can be computed by entropy method, using the original information of each alternative. If the parameter changes greatly through the adjustment, then the information volume is negatively correlated with information entropy. Thus, a small information volume indicates the information has a large utility, and the parameter has a large weight. Otherwise, the parameter has a small weight. Capable of reflecting the difference between attributes, information entropy can be used to compute the weight of each attribute.

3.2.1. Calculation of information entropy

In an MADM problem, there are m alternatives and n evaluation attributes. The original evaluation matrix can be expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{6}$$

where x_{ij} is the parameter value of the j-th phase attribute of the i-th alternative. Normalizing the parameter value, weight p_{ij} can be obtained. Then, the entropy of the j-th attribute can be solved by:

$$E(j) = -K \sum_{j=1}^{n} p_{ij} \ln p_{ij}, p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{7}$$

Table 3 The values of RI.

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

where K is a constant.

3.2.2. Calculation of attribute difference

The difference coefficient G(j) reflects the importance of an attribute in the judgement. If the attribute difference is large, the attribute will have a small entropy, and a large role in the judgement. In this case, the attribute is highly important. Otherwise, the attribute is not important.

$$G(j) = 1 - E(j) \tag{8}$$

3.2.3. Calculation of weight vector

Normalizing G(j), the weight of each attribute can be obtained by:

$$w_j^o = \frac{G(j)}{\sum_{j=1}^{n} G(j)} \tag{9}$$

Personal preferences of users are different when choosing a network, so the network factors considered will be different. Users usually require an optimal network to deliver their applications, but the optimal network is not absolute due to individual needs. Therefore, there are many factors to be considered when users choose a network. An AHP can solve this complex problem by subdividing the hierarchy. This paper divides the first criterion layer based on user preference and the second criterion layer based on service type by AHP (Fig. 2).

The first criterion layer based on user preference is mainly composed of QoS level, network cost and network available load. This paper mainly divides user preferences into two categories. One type of user needs high quality network QoS to delivery their traffic, and this type of user gives priority to network QoS. In the case of QoS priority, the importance of the three parameters in descending order is: QoS level, network available load, and cost. The other kind of users pursue the low cost of network, so the network QoS requirements are not high. In the case of cost priority, the importance of the three parameters in descending order is: cost, QoS level, network available load. After ranking the importance of each attribute, the comparison decision matrix as shown in Tables 4 and 5 can be constructed. Because the construction of the comparison decision matrix has the subjectivity of the decision-maker in this paper, the values can be modified appropriately according to the specific situation.

After the consistency test of the two decision matrices, the consistency index CR = 0.0048 < 0.1, indicating that the two matrices meet the consistency requirements, and the construction is reasonable. Then, the normalized weight of each attribute is obtained in Table 6.

With the rapid development of communication and network technologies, the IoV is no longer a simple data transmission network. Instead, the network is developing into an integrated entertainment network, containing various multimedia information, such as images, data, and voices.

The diverse applications raise varied QoS requirements. In general, the QoS is measured by bandwidth, delay, delay jitter, and packet loss rate. Here, four mainstream 3rd Generation Partnership Project (3GPP) services are discussed, including session service, streaming media service, interactive service, and background service.

Different services have great differences in their characteristic requirements for network QoS, so bandwidth, packet loss rate, delay and jitter have a great impact on network QoS. Therefore, this paper selects them as the attribute parameters of network QoS to construct the second criterion layer.

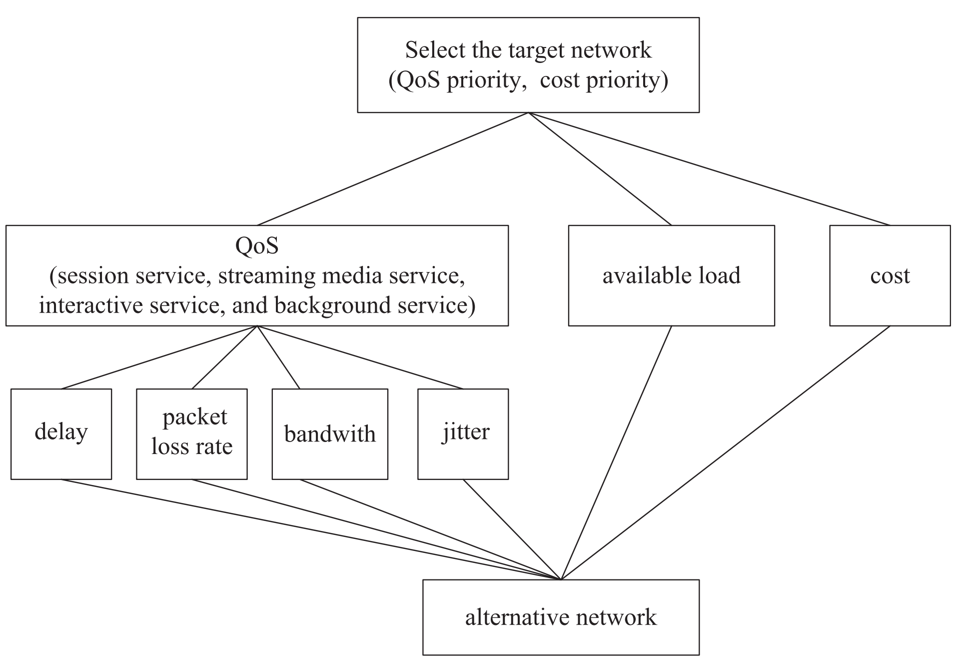

Fig. 2 Hierarchical network model.

Table 4 Decision matrix under QoS priority.

QoS priority	QoS	Cost	Available load
QoS	1	5	2.5
cost	1/5	1	1/2.5
available load	1/2.5	2.5	1

Table 5 Decision matrix under cost priority.

Cost priority	QoS	Cost	Available load
QoS	1	1/2.5	2.5
cost	2.5	1	5
available load	1/2.5	1/5	1

Table 6 The index weights of the first criterion layer under different circumstances.

	QoS	cost	available load
QoS priority	0.6186	0.1149	0.2665
cost priority	0.2665	0.6186	0.1149

Table 7 The weights of QoS parameters under different service types.

Category	Weight				Consistency index
	bandwidth	Packet loss rate	Delay	jitter	
conversation	0.0474	0.1123	0.4321	0.4181	0.0076
Streaming media	0.4936	0.2980	0.0565	0.1691	0.0304
interactive	0.1364	0.4091	0.4091	0.0455	0
background	0.2646	0.6260	0.0533	0.0597	0.0121

Through the above process, the network selection problem was decomposed, and each attribute was given a subjective weight through AHP (Table 7). The weights thus obtained carry the subjective arbitrariness of the decision-maker.

3.3. Calculation of objective weights

As mentioned in the entropy method above, the objective weights can be obtained through the entropy method. However, before that, the judgement indices must be normalized to unify their different dimensions. Suppose there are n parameters and m alternatives. Then, the original judgement matrix can be expressed as:

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & \cdots & x'_{1n} \\ x'_{21} & x'_{22} & \cdots & x'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x'_{m1} & x'_{m2} & \cdots & x'_{mn} \end{bmatrix} \tag{10}$$

Generally, judgment indices can be divided into two categories: benefit indices that should be maximized, such as bandwidth and network available load, and cost indices that should be minimized, such as packet loss rate, delay, jitter, and communication cost. The benefit indices means the normalized value should be positively related to the x_{ij}, which can be normalized by:

$$s_{ij} = \frac{x_{ij}}{\max(x_j) + \min(x_j)}, \quad 1 \leqslant i \leqslant m, 1 \leqslant j \leqslant n \tag{11}$$

By contrast, the cost indices can be respectively normalized by:

$$s_{ij} = 1 - \frac{x'_{ij}}{\max(x'_j) + \min(x'_j)}, \quad 1 \leqslant i \leqslant m, 1 \leqslant j \leqslant n \tag{12}$$

where $\max(x'_j)$ and $\min(x'_j)$ are the maximum and minimum of the j-th judgement index in each alternative, respectively; s_{ij} is the normalized attribute value of x'_{ij}.

3.4. Calculation of comprehensive weight

The subjective weight obtained by AHP and the objective weight obtained by entropy method were further combined into the final comprehensive weight. In this way, the network load can be well balanced by paying attention to the subjective factors and objective factors. The subjective factors include the user preference in network selection, as considered in AHP; the objective factors include the QoS of each alternative.

Let $W_1 = (w_1, w_2, \cdots, w_n)^T$ and $W_2 = (w'_1, w'_2, \cdots, w'_n)^T$ be the subjective weight obtained by AHP and the objective weight obtained by entropy method, respectively. Then, the final comprehensive weight $W = (\omega_1, \omega_2, \cdots, \omega_n)^T$ can be calculated by:

$$\omega_j = \alpha \cdot w_j + (1-\alpha) \cdot w'_j, j = 1, 2, \cdots n \tag{13}$$

$$W = \alpha \cdot W_1 + (1-\alpha) \cdot W_2 \tag{14}$$

where α is the proportion of subjective and objective weights in the comprehensive weight. If $\alpha = 0$, the objective weight is the comprehensive weight; if $\alpha = 1$, the subjective weight is the comprehensive weight. Here, the α value is set to 0.5.

After obtaining the comprehensive weight, the optimal network could be selected by utility calculation. The alternative with the highest utility will be chosen for access. Let $R = (r_{ij})_{m\times n}$ be the judgement matrix with normalized network parameters. Then, the utility of each network can be solved by:

$$Utility = [u_1, u_2, \cdots, u_m]^T = R \cdot W^T \tag{15}$$

$$u_i = \sum_j r_{ij} \cdot \omega_j, i = 1, 2, \cdots m; j = 1, 2, \cdots n \tag{16}$$

Finally, the network with the highest utility is chosen as the network to be accessed, that is:

$$u_{best} = \operatorname{argmax}(u_i), \quad 1 \leqslant i \leqslant m \tag{17}$$

4. Simulation analysis

In recent years, the cellular vehicle-to-everything (C-V2X) communications has received much attention and is develop-

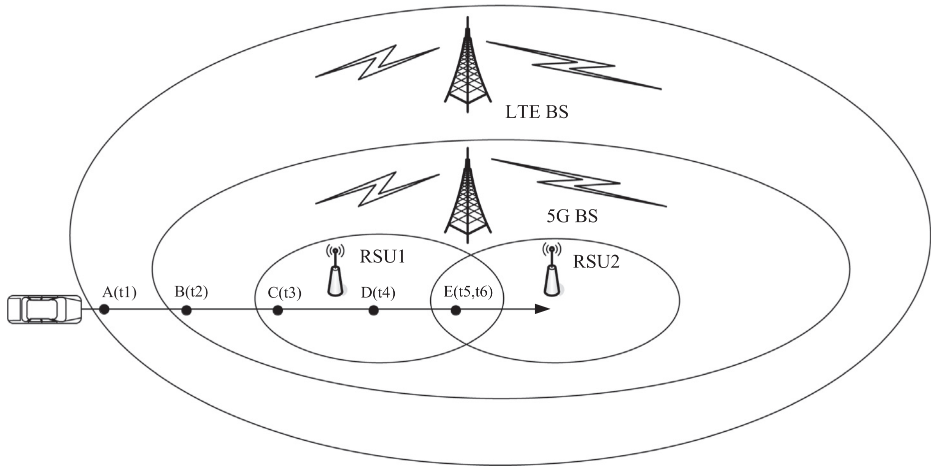

Fig. 3 The simulation environment of Scenario 1.

ing as an important part of 5G. The current C-V2X standard mainly referring to Long Term Evolution V2X (LTE-V2X) provides a wider signal coverage range and supports large-scale data transmission. However, with the continuous increase of vehicular user density and vehicular network data volume, the authorized spectrum of C-V2X communication is difficult to fully meet the demand of massive data transmission. For the delay tolerant service, the traditional network application data can be transmitted through the road-side unit (RSU) based on the unauthorized spectrum, thus reducing the load of the cellular network.

Two simulation scenarios were set up to verify the effectiveness and load balancing of our algorithm: In Scenario 1, a single user requests for different network services in a region covered by multiple networks; In Scenario 2, multiple users successively access the network in a region covered by multiple networks.

4.1. Scenario 1

As shown in Fig. 3, a user requests for different network businesses as it moves from point A to point D in a region covered by four heterogenous networks:), 5G, LTE, RSU1 and RSU2. The initial parameters of each network are shown in Table 8, and the values are represented to reflect the characteristics of different networks [23].

In the simulation environment of Fig. 2, the system initially defaulted to the QoS priority mode. At time t1, the user arrived at point A, and made a video call on a mobile terminal; at time t2, the user arrived at point B, and remained in the call; at time t3, the user arrived at point C, and sent an email on a mobile terminal; at time t4, the user browsed the web on a mobile terminal; at time t5, the user arrived at point E, and paid to view an online video on a mobile terminal; at time t6, the user switched to the cost priority mode, in view of the cost. Fig. 4 presents the workflow of our algorithm in Scenario 1. Table 9 shows the utility of each network though Formula (15) at each time. Fig. 5 displays the simulation results.

Time t1: The user made a video call at point A. The service belongs to a conversational service. Since point A is only covered by the LTE, the user unconditionally selected this network.

Time t2: The user arrived at point B, and the conversational service continued. But point B is both covered by 5G and LTE, our network selection algorithm was thus initiated. The system initially defaulted to the QoS priority mode, and obtained that the LTE had a higher utility than 5G. Thus, the network selection was not changed. Since video call is a conversational service requiring short delay, low delay jitter, and small bandwidth, the choice of the LTE with low delay and jitter meets the actual needs of the user.

Time t3: The user sent an email at point C. At this time, the user fell in the coverage of 5G, LTE, and RSU1. Our algorithm shows that the utility of RSU1 was higher than that of the other two networks. Email is a background service with a slack requirement on delay and jitter, but a strict requirement on reliability. Thus, it meets the user needs to choose RSU1, which has a limited packet loss rate and a large bandwidth.

Time t4: The user browsed the web at point D. As an interactive service, web browsing raises certain requirements for delay and bit error rate. Since the network coverage was the same, 5G boasted the highest utility. It is reasonable to choose

Table 8 The initial parameters of each network.

Parameters	Bandwidth	Packet loss rate	Delay	Jitter	Tariff	Available load
LTE	10	0.05	14	7	3	80
5G	18	0.04	10	11	15	70
RSU1	25	0.03	20	18	1	65
RSU2	19	0.06	21	14	1.1	70

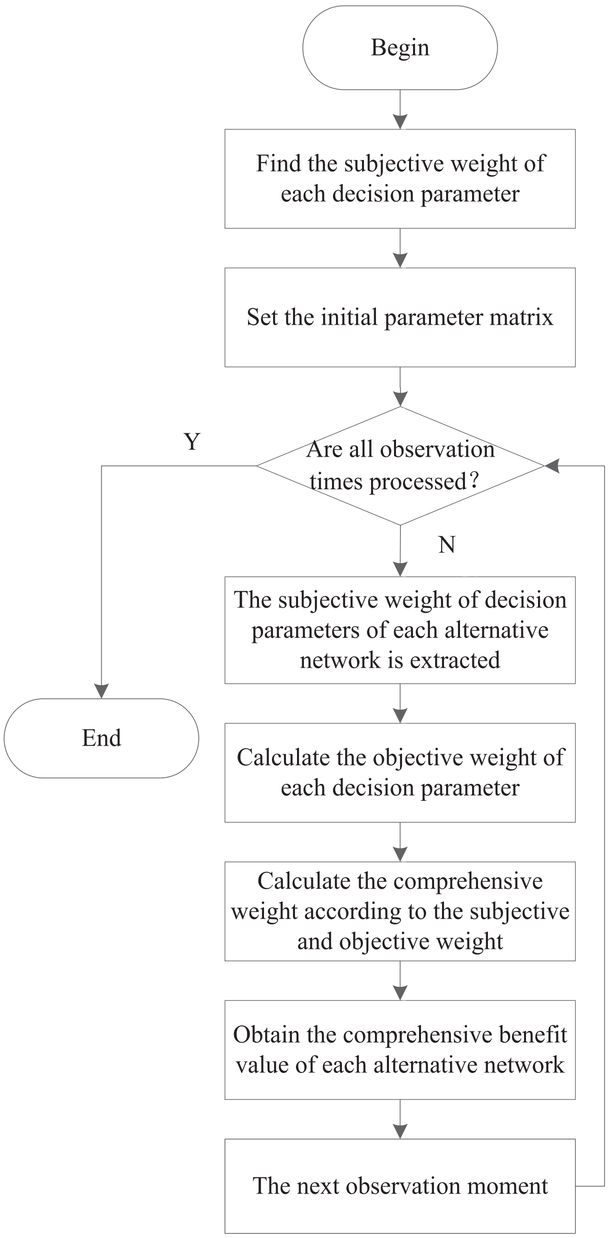

Fig. 4 The workflow of our algorithm in Scenario 1.

5G, thanks to its better overall performance in network delay and packet loss rate.

Time t5: The user arrived at point E, which is within the coverage of the four networks: 5G, LTE, RSU1, and RSU2. At this time, the user paid to view an online video. This

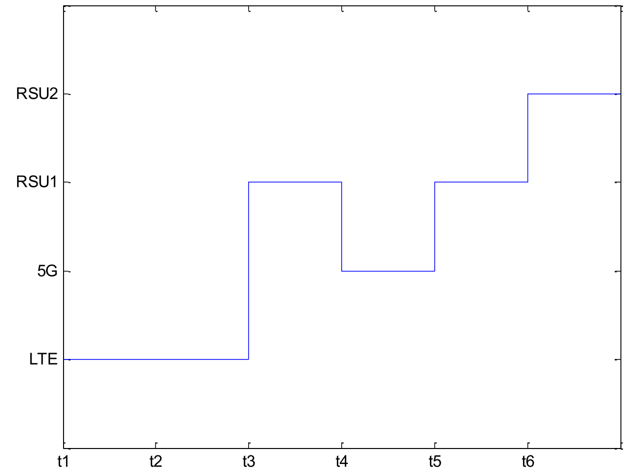

Fig. 5 The simulation results of Scenario 1.

streaming media service requires a large bandwidth, but a low timeliness. Therefore, it meets the user needs to choose RSU1, which has the highest overall utility.

Time t6: The user still stayed at point E, and the requested the same service. However, he/she became aware of the high cost of long-term use of this service, and switched to the cost priority mode. In this case, RSU2, with the highest overall utility, meets the requirements of the minimum cost.

The above simulation results confirm that our algorithm can fully consider the demand features of the service requested by the user, and flexibly selects the optimal network for the user, allowing the user to satisfy his/her real needs in a heterogeneous network environment.

4.2. Scenario 2

In the preceding subsection, our algorithm was proved effectiveness. To further verify its load balancing ability against the AHP, Scenario 2 was designed, in which multiple users entered the region covered by all four heterogenous networks (i.e., 5G, LTE, RSU1, and RSU2), and initiated service requests. Suppose there was a total of 200 users, each network was idle at the start, and the system defaulted to QoS priority mode. For comparison, each network was assumed to have the ability to access up to 100 users. Fig. 6 illustrates the simulation environment of Scenario 2. Table 10 lists the initial parameters of each network. Fig. 6 presents the workflow of our algorithm in Scenario 2.

As shown in Fig. 7, the initial parameter matrix and the maximum number of user accesses must be set in advanced before our algorithm chooses the business type. If the number

Table 9 The utility of each network at each time.

	t2	t3	t4	t5	t6
LTE	0.8529	0.8195	0.8062	0.8268	0.6009
5G	0.7791	0.8788	0.8469	0.9185	0.7528
RSU1	0	0.8845	0.8185	0.9390	0.8058
RSU 2	0	0	0	0.9163	0.8355

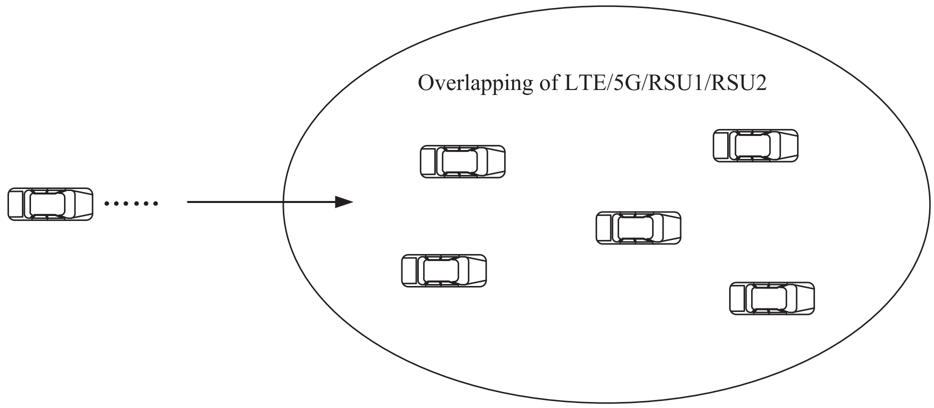

Fig. 6 The simulation environment of Scenario 2.

Table 10 The initial parameters of each network.

Parameters	Bandwidth	Packet loss rate	Delay	Jitter	Tariff	Available load
LTE	8	0.04	18	5	3	100
5G	13	0.03	12	11	6	100
RSU1	25	0.04	25	18	2.5	100
RSU 2	15	0.05	23	14	1.3	100

of user accesses is smaller than the maximum number, the comprehensive weight will be calculated, and the network resources will be updated. This process repeats until all users are accessed to the network. Then, the relevant figures will be plotted.

Fig. 8 shows the simulation results on conversational service in Scenario 2. It can be seen that, at the start, the early users chose the LTE, which is suitable for conversational service. As a result, the available load of the LTE in both AHP and our algorithm declined sharply. With the growing number of accessed users, the available load of the LTE in either algorithm declined at a slower rate, especially when there were 40 accessed users. The main reason is that the two algorithms initiated other networks for the service, so as to balance the network load. Comparatively, our algorithm had better performance than the AHP in service offload, and in load balancing.

The significant advantage of our algorithm over the AHP comes from the entropy weight method in the calculation of comprehensive weight. As mentioned before, the entropy can well reflect the change magnitude of system parameters. As shown in Figs. 9 and 10, when there were fewer than 40 accessed users, the entropy weight of available load surged up, primarily because of the fact that early users chose the LTE over the other networks. As a result, the loads of different networks became more imbalanced, pushing up the entropy weight of available load. The expansion in the entropy weight further increases the proportion of available load in comprehensive weight. When there were more than 40 accessed users, the growth margin of the entropy weight of available load slowed down significantly. This is because available load plays a much greater role in the judgement of network access, facilitating the service offload by other networks. In return, the entropy weight of available load changed at a much slower rate, indicating the falling load difference between networks. When the number of accessed users reached 140, the entropy weight basically remained the same, suggesting that the networks reached a balanced state.

To institutively display their difference in load balancing, the AHP and our algorithm were compared by the number of users in each network under a simulation environment of 200 users. As shown in Fig. 11, the users were distributed more evenly across the networks under our algorithm than under the AHP; the service offload ability of each network under our algorithm was better than that under the AHP.

5. Conclusions

This paper presents a selection algorithm for heterogenous IoV networks. Firstly, a hierarchical model was established for network selection based on the AHP, according to user preferences and service types. By this model, the subject weight of each attribute was obtained. Then, the objective weight of each attribute was calculated by entropy method. After that, the subjective and objective weights were combined into a compre-

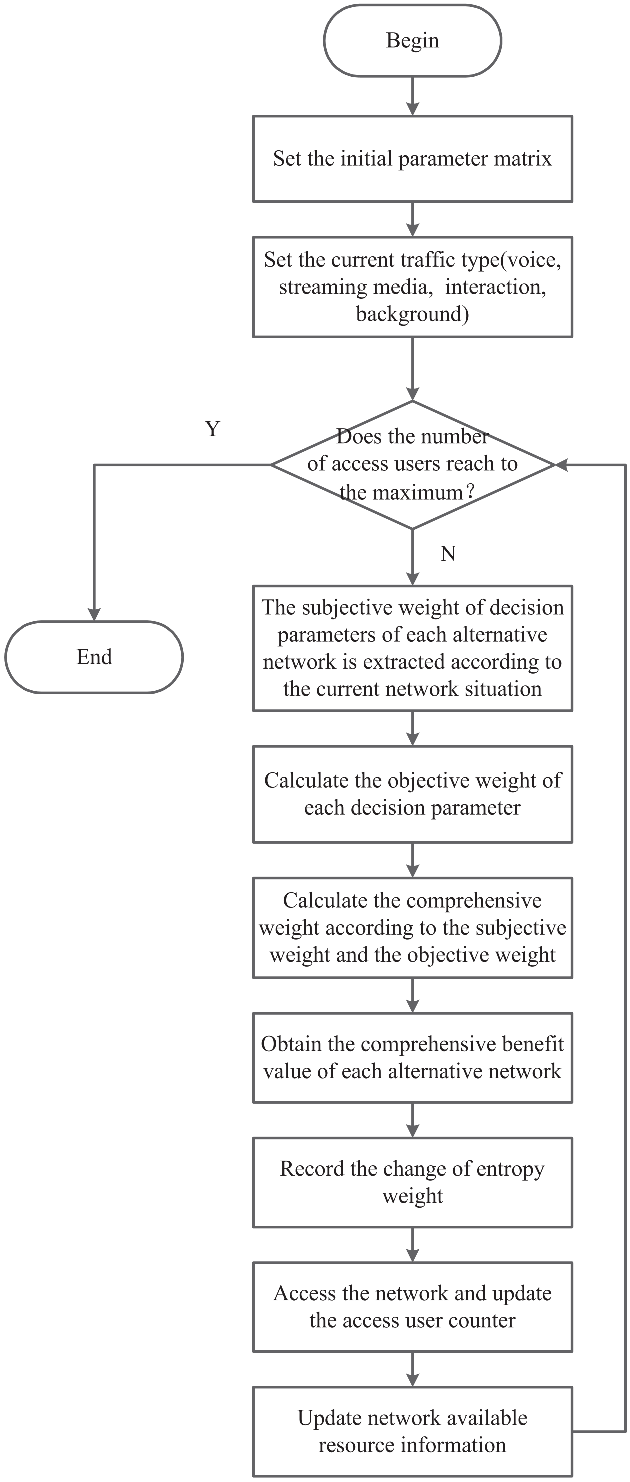

Fig. 7 The workflow of our algorithm in Scenario 2.

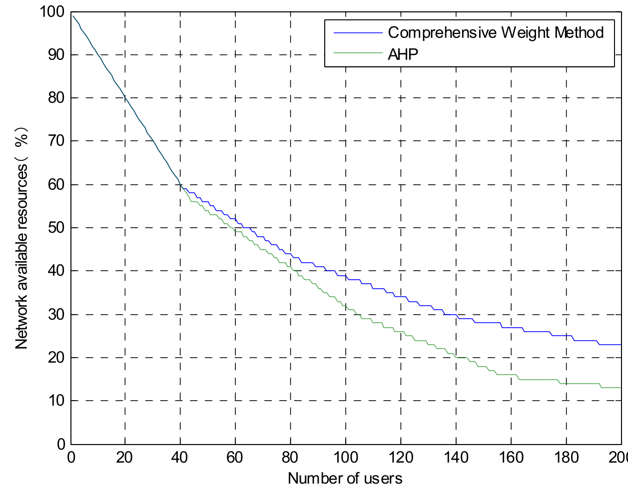

Fig. 8 The available load of the LTE.

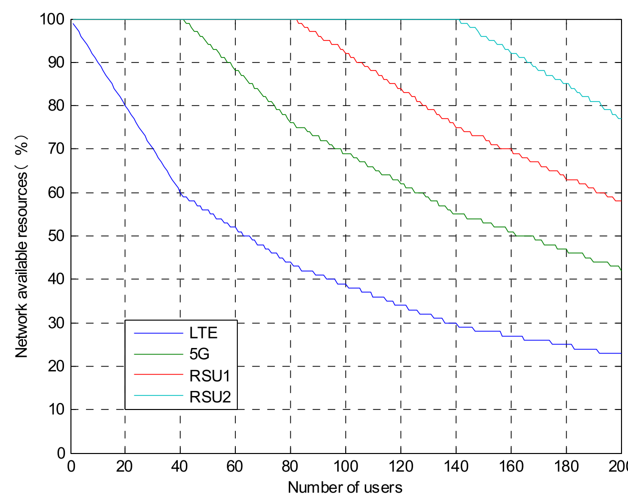

Fig. 9 The available loads of networks.

hensive weight, and the best network was selected by the final overall utility. Finally, two scenarios were designed to verify the effectiveness and load balancing ability of our algorithm, respectively. The simulation results show that our algorithm can choose the reasonable network to access to meet the diverse needs and experience of users in the heterogeneous network environment according to different service needs, user preferences, and network environments. In addition, when the network load increases, the traffic can be offloaded to other networks immediately to achieve better load balance. In

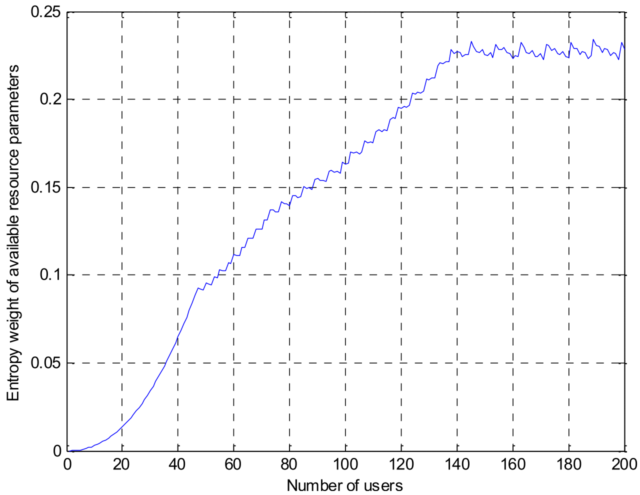

Fig. 10 The entropy weights of available loads.

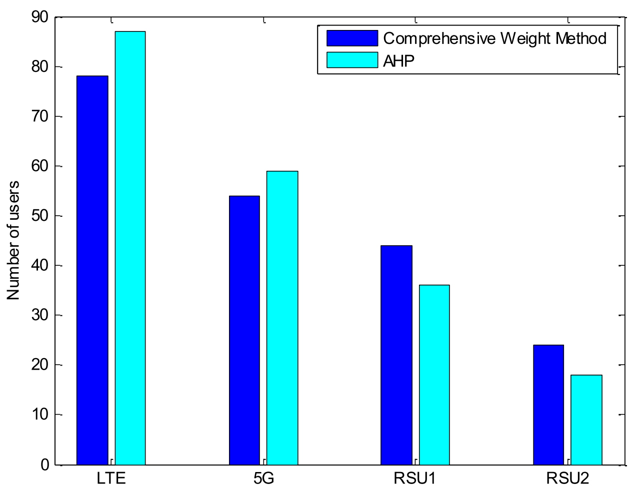

Fig. 11 The number of users in each network.

future, the influence of subjective and objective weights on network performance can be further studied, and more complex system-level simulation can be carried out for the simulation scene.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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