HetWN Selection Scheme Based on Bipartite Graph Multiple Matching

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Abstract. Next generation communication networks will be a heterogeneous wireless networks (HetWN) based on 5G. Studying the reasonable allocation of new traffics under the new scenario of 5G is helpful to make full use of the network resources. In this paper, we propose a HetWN selection algorithm based on bipartite graph multiple matching. Firstly, we use the AHP-GRA method to calculate the user's preference for network and the network's preference for user. After these two preferences are traded off as the weights of edges in bipartite graph, we can extend the bipartite graph to a bipartite graph network. The minimum cost maximum flow algorithm is used to obtain the optimal matching result. Simulations show that our scheme can balance the traffic dynamically. And it is a tradeoff between user side decision and network side decision.

Keywords: Heterogeneous wireless network · Bipartite graph Minimum cost and maximum flow

1 Introduction

With the development of wireless communication technology, the future mobile communication networks will not be a single well-functional networks but a heterogeneous networks in which multiple wireless access technologies coexist. The performance in different networks, such as network throughput, coverage area and minimum delay will have a huge difference. So there is no wireless access technology that can satisfy all kinds of traffic needs [1]. It can be foreseen that the next-generation wireless communication networks will be a heterogeneous network consists of 5G networks and 4G networks (LTE-A and WIMAX2). In addition, the development of smart terminal such as mobile phone makes it possible for smart network selection. The reasonable selection results should

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satisfy the QoS requirements of different traffics and network operators' interests as much as possible at the same time.

Existing HetWN selection algorithms are mainly based on 3G or 4G network background and traffic background (Session class, streaming media class, interaction class, and background class). This article extends the network types and traffic types to 5G new scenario. The related works can be roughly classified into the following categories: Analytic Hierarchy Process (AHP) and its improvements, game theory methods and other methods. Reference [2] introduces the AHP method and the bankruptcy game model. References [3–5] are improvements to AHP algorithm. The former introduces an ordered weighted average operator to improve the performance of network selection handover. Reference [4] combines Grey Relational Analysis (GRA) and AHP, this paper is an improvement based on it. The concept of fuzzy logic is used in [5,6] to make AHP judgement matrix more suitable and reasonable. In addition, game theory tool is very suitable for analyzing the problem which contains a resource competing relationships. Game theory method includes non-cooperative game and cooperative game. Reference [7] considers that all users share the total network rate and therefore establishes a non-cooperative game model for each participant (user) regarding their respective data rate. References [8,9] propose an evolutionary game model. The proposed algorithm converges faster than non-cooperative game and Q-learning algorithm. Reference [10] proposes a multi-user TOPSIS-based matching game which improves the utilization of network and reduces the network blocking rate.

The rest of paper is organized as follows: In Sect. 2, a generic heterogeneous network model is established. In addition, 5G network parameters and new traffic types that may appear in 5G new scenario are also analyzed. In Sect. 3, a bipartite graph network model is established, and a minimum cost maximum flow algorithm is used to obtain the optimal matching results. In the last section, simulation analysis is carried out.

2 System Model

We consider a HetWN environment which consists of 5G, LTE-A, and WIMAX2 based on IEEE 802.16 m, as shown in Fig. 1. In addition, we assume that parameters such as per connection rate and average delay of network will not change before the user number reaches the upper limit of network capacity, that is, the network can provide service stably when the network capacity does not reach the upper limit. This article mainly analyzes the network selection of users in zone 3. The attributes and parameters of these three networks are listed in Table 1.

We have also summarized the related works on 5G new traffics, which the Global Mobile Suppliers Association briefly outlined in 2015. The impact of user mobility and energy efficiency must be considered in 5G new scenario. This paper takes transportation traffic, industrial automation and utility traffic, health traffic, virtual reality (VR) and augmented reality (AR) traffic and smart city traffic into consideration. The QoS requirement parameters are listed in Table 2.

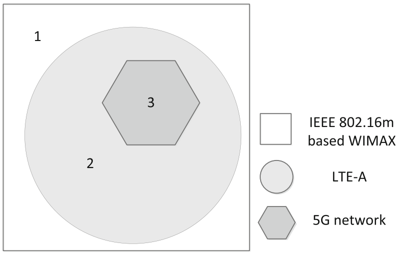


Fig. 1. The 5G heterogeneous wireless network system.

- *Transport traffic: There are multiple wireless applications that require low latency such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and various intelligent transportation systems. They need a lower latency than the existing LTE networks can provide. For example, the expected delay for anti-collision system is 5* ms*, and the reliability is 99.999%.*
- *Industrial automation and utility traffic: Wireless sensors in industrial automation and robotics usually require secure, ultra-reliable communications and must have a low power consumption. In the public utilities, for example, many countries are developing smart grids. The low latency is necessary to protect power grid.*
- *Health traffic: The concept of mobile health applications has been developed for many years, such as personal health records and fitness data, wearable activity tracking and smart phone-based applications. In addition, mobile services can provide remote diagnosis for nursing staff.*
- *VR and AR traffic: VR and AR require a large amount of data. When the head show and other displayers are wirelessly connected, they must support low latency and high reliable data transmission.*
- *Smart city traffic: There are many applications of smart city in multiple fields as traffic, public management and others.*

3 Multiple Matching Algorithm Based on Bipartite Graph Networks

3.1 Bipartite Graph Networks Model

Assuming that there are M users and N alternative access networks in area 3 as shown in Fig. 1, denoted as $X = \{x_1, x_2, \ldots x_m\}$, $Y = \{y_1, y_2, \ldots y_n\}$, respectively ($N = 3$ in this paper). User i's preference for all access networks is denoted as $\theta(x_i)$. $\varphi(y_j)$ is the preference of access network j to all users. Therefore, the network selection model can be simplified as a bipartite graph model. The weight of edge in bipartite graph indicates the degree of matching between user and network. The weight matrix U is written as follows:

$$U = \begin{pmatrix} U(\theta(x_{11}), \varphi(y_{11})) & U(\theta(x_{12}), \varphi(y_{21})) & \cdots & U(\theta(x_{1n}), \varphi(y_{n1})) \\ U(\theta(x_{21}), \varphi(y_{12})) & U(\theta(x_{22}), \varphi(y_{22})) & \cdots & U(\theta(x_{2n}), \varphi(y_{n2})) \\ \vdots & \vdots & \ddots & \vdots \\ U(\theta(x_{m1}), \varphi(y_{1m})) & U(\theta(x_{m2}), \varphi(y_{2m})) & \cdots & U(\theta(x_{mn}), \varphi(y_{nm})) \end{pmatrix}_{M \times N} \tag{1}$$

Where U is a utility function about user-network preferences and network-user preferences.

This paper selects the minimum cost maximum flow algorithm to solve the bipartite graph multiple matching problem. The bipartite graph is firstly extended to a network as shown in Fig. 2. An aggregation node t and a source node s is added at the network side and user side, respectively. Each edge includes 2 elements. The former means the capacity of each edge, while the latter means the price of this edge. The edge capacity of source node to each user and users to networks are set to 1. The edge capacity of each network to aggregation node is the upper limit of each network's capacity. Only the edges between the users and networks have a price. This price depends on the remaining capacity of network. As the remaining capacity decreases, the price rises. The price of other edges are 0.

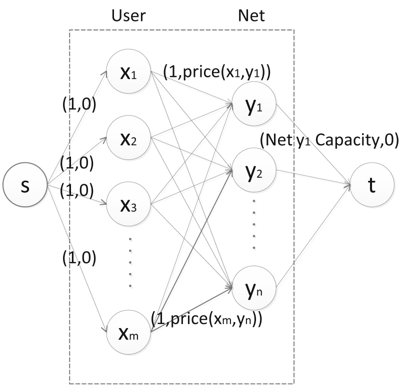


Fig. 2. Expanded bipartite graph networks.

3.2 Weight Decision of Bipartite Graph Using AHP and GRA

The weight of bipartite is determined by the utility function which consists of 2 preferences as described above. The price should be inversely proportional to weight in each corresponding edge. The greater the weight, the smaller the corresponding price. The user's preference for network mainly depends on user's traffic type, and the network always prefers to the user who can provide the highest price, so all networks have the same preference for each user.

The throughput per connection(1), average network delay(2), network supported mobility(3), network packet loss rate(4), network jitter(5), network energy efficiency(6) and price(7) are considered as the network parameters and different traffic's QoS requirement parameters. These 2 preferences are firstly calculated by AHP and then correlated by GRA.

Step 1: Parameter normalization. The parameters in Table 1 can be divided into two categories, namely the profit type (the bigger the better) and the cost type (the smaller the better). For users, profitable parameters include the throughput per link and network supported mobility, while the rest are cost-type parameters. For networks, all parameters are cost type except the user available payment. The normalization of profit types and cost types are as written as follows respectively:

$$a_{ij} = \frac{b_{ij} - \min_i b_{ij}}{\max_i b_{ij} - \min_i b_{ij}} \tag{2}$$

$$a_{ij} = \frac{\max_i b_{ij} - b_{ij}}{\max_i b_{ij} - \min_i b_{ij}} \tag{3}$$

b_{ij} is the original parameter in Table 1, a_{ij} is the normalized one.

Step 2: Construct the judgement matrix using the 1–9 ranking scheme.

Step 3: Calculation the network parameter's weight through judgement matrix C.

$$W_i = \prod_{j=1}^{np} c_{ij} (i = 1, 2, ...np) \tag{4}$$

$$\bar{W}_i = \sqrt[np]{W_i} \tag{5}$$

$$weight_i = \frac{\bar{W}_i}{\sum\limits_{i=1}^{np} \bar{W}_i} \tag{6}$$

$Weight = (weight_1, weight_2, \ldots weight_{np})$ is the parameter weight which decides the network selection results. np is the number of attribute parameters.

Step 4. Consistency test. The consistency index and average random consistency index are denoted as C_I and R_I, respectively. The check will pass if $C_I < 0.1$.

Step 5. Calculation of network selection weight. Simple additive weighting (SAW) scheme is used to decide the network's weight.

Step 6. Calculation of grey relational matrix. ρ (usually equals to 0.5.) is the correlation coefficient and a_{0j} is the optimal reference sequence.

Algorithm 1 Network Optimal Selection Algorithm Based on Bipartite Graph

Initialization:

1: There are M users and N alternative access networks. User's traffic is randomly distributed.
2: The price and capacity information for each edge in this bipartite graph network.
3: **while** 1 **do**
4: Randomly select the minimum value in P.
5: If the minimum value is P_{ij}, then allocate user i to network j and update P and edge capacity.
6: If the edge capacity is 0, then delete the edge between user i and network j. $P_{ij} = nan$.
7: If all users have been assigned, break out.
8: **end while**

Output:

9: Output the matching results.

$$R = \frac{\min_i \min_j |a_{0j} - a_{ij}| + \rho \max_i \max_j |a_{0j} - a_{ij}|}{|a_{0j} - a_{ij}| + \rho \max_i \max_j |a_{0j} - a_{ij}|} \tag{7}$$

Step 7. Calculation of correlation network's weight. Finally, according to the correlation matrix R obtained by GRA and network's weight obtained by AHP, the preferences of users with different types of traffic for all networks are obtained as:

$$\theta = R \cdot F^T \tag{8}$$

Similarly, we can also get the network's preference for users (φ).

Step 8. Calculation of utility function and price of edge in bipartite graph network. The utility function consists of 2 preferences. And a compromise factor is set to combine these 2 preferences which is denoted as α. The price can be calculated by the following formula:

$$P_{ij} = \frac{1}{\alpha\theta(x_{ij}) + (1-\alpha)\varphi(y_{ji})} + (\max_i \max_j P_{ij} - \min_i \min_j P_{ij})(NC_j - RC_j)^\gamma \tag{9}$$

NC_j is the network j's capacity and RC_j is its remaining capacity. γ is a number between 1 and 2.

3.3 Proposed Heterogeneous Wireless Networks Selection Algorithm

In this paper, the minimum cost maximum flow algorithm is used to solve this optimal matching problem. Firstly, the price and capacity of each edge is initialized by the analysis we have talked above. Then we find out all the paths from s to t. The average cost per path is equal to the total cost divided by the maximum capacity in this path. Since the capacity of edge connected to s is 1,

P_{ij} is the average cost per path. Then we find out the minimum value in P. If there are multiple paths with same price at the same time, randomly selection should be taken to ensure the fairness. After the user has been assigned to the corresponding network, the capacity and price of each edge in this bipartite graph networks will update. The edge will be deleted if its capacity is 0. The loop is ended until all users have been assigned. The specific algorithm refers to the Algorithm 1.

4 Simulation Results

In this simulation, we mainly study a NetWn which consists of 3 wireless network: 5G, LTE-A and WIMAX2 based on IEEE 802.16m. There are many users randomly distributed in area 3 as shown in Fig. 1. The network's parameters and traffic QoS requirement parameters are listed in Tables 1 and 2. The total user number is 20 to 500. The capacity of each network is set to 400. Due to the randomness of user traffic, we used 1000 Monte Carlo simulations per cycle.

Table 1. The attribute parameters of 5G, LTE-A and WIMAX2 network.

Network parameters	5G	LTE-A	WIMAX2 (Low mobility)	WIMAX2 (High mobility)
Throughput per connection (Gbps)	1	0.1	1	0.1
Network average latency (ms)	1	10	10	10
Network supported mobility (km/h)	500	350	6	120
Network packet lost (%)	0.001	0.003	0.002	0.002
Jitter (ms)	1	3	2	2
Energy Efficiency (1e-7 J/bit)	1	100	200	200
Price ($)	5	3	4	4

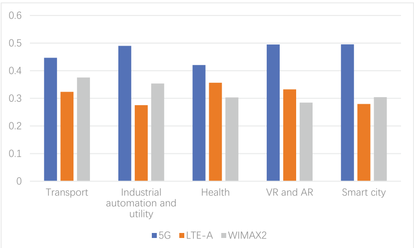
Due to the user in different moving conditions, the network parameters of WIMAX2 change a lot. So this paper considers the performance of WIMAX2 in low mobility scenario and high mobility scenario respectively. Figure 3 shows the weight of network selection under different traffics. Figure 4 shows the ratio of users which select different networks to the total number of users. In Fig. 4, the number of users who choose 5G network is the most. Because 5G network can provide the best service so that most of traffics are more suitable to choose 5G. With the total user number decreases, the ratio of user who selects 5G is increasing. With the total number of user increases, the result of network selection tends to be balanced, which shows that theproposed algorithm has the

Table 2. The required QoS attribute parameters of 5G new traffics.

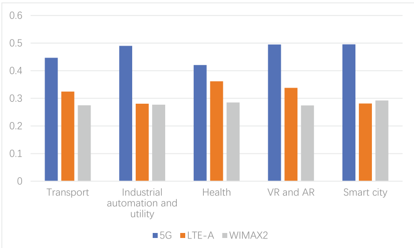
QoS requirement attributes	Transport	Industrial automation and utility	Health	VR&AR	Smart city
Throughput per connection (Gbps)	0.0001	0.0001	0.05	0.5	0.05
Network average latency (ms)	5	10	10	1	50
Network supported mobility (km/h)	350	1	1	6	60
Network packet lost (%)	0.001	0.003	0.002	0.002	0.004
Jitter (ms)	1	3	3	2	5
Energy Efficiency (1e-7 J/bit)	300	10	200	500	500
Price ($)	10	7	12	10	5

function of balancing the traffic load while reasonably allocating services. This is due to an update of price in bipartite graph network.

The effect of compromise factor α on network selection results is shown in Fig. 5. When $\alpha = 0$, the network selection only considers the network's preference for user. Due to the prices of 3 networks are not much different, the proportion of users who choose different networks is not much different. When the compromise factor is 1, the network selection only considers the user's preference for network, which is the case in [4].



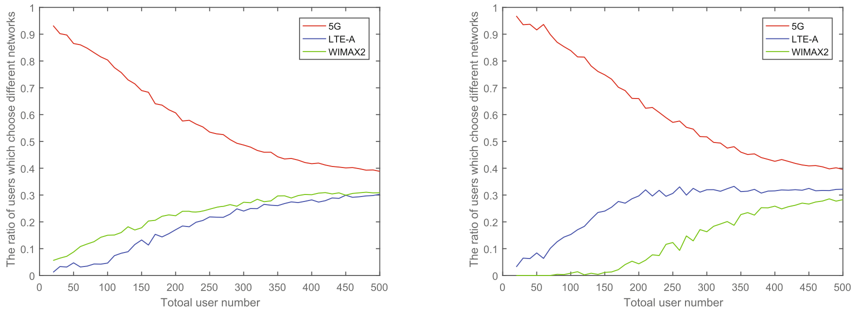
(a) WIMAX2 with low mobility



(b) WIMAX2 with high mobility

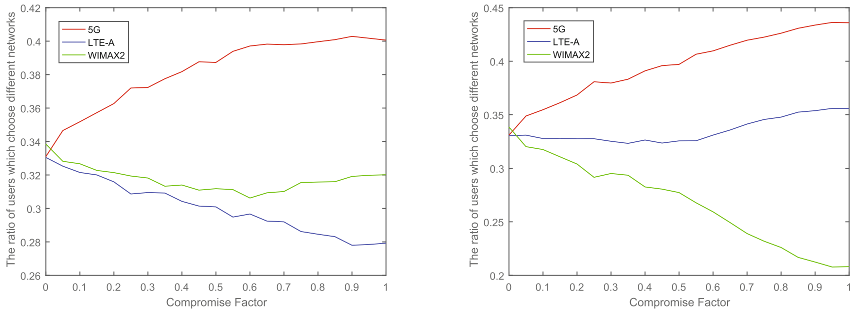
Fig. 3. The weight of network selection.

Figure 6 shows the average price of access network which is equal to the total system price divided by total system throughput in high mobility scenario. It also shows that our scheme is a tradeoff between AHP-GRA network selection at user side and network side. In addition, we propose a modified random network selection scheme: If the traffic can only be carried by 5G, then only the 5G network is selected, otherwise it is randomly allocated to these 3 networks. Simulation shows that our scheme has a lower average price than modified random selection scheme.



(a) WIMAX2 with low mobility (b) WIMAX2 with high mobility

Fig. 4. Matching results ($\alpha = 0.5$,$\gamma = 1.4$).



(a) WIMAX2 with low mobility (b) WIMAX2 with high mobility

Fig. 5. Effect of compromise factor on matching results ($\gamma = 1.4$, user number is 500).

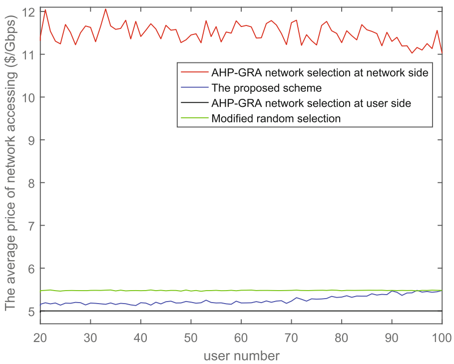


Fig. 6. The average price of networks with different schemes ($\gamma = 1.4$).

5 Conclusion

In this paper, we have proposed a heterogeneous network selection scheme based on bipartite graph. First of all, we have analyzed the system model and 5G new traffics, which makes it easy for us to calculate the following problems. By designing a price function consists of user to network preference and network to user preference, we have set up a bipartite graph network model. After using minimum cost and maximum flow algorithm, the matching results were carried out. Simulation results showed that our scheme could balance the traffics into different networks dynamically. That is, some 5G traffics could be carried by 4G networks when there are too many users in one area. And our scheme was also a tradeoff between users and networks.

References

1. Sgora, A., Vergados, D.D., Chatzimisios, P.: An access network selection algorithm for heterogeneous wireless environments. In: The IEEE symposium on Computers and Communications, pp. 890–892. Riccione, Italy, 22 June 2010
2. Liu, B., Tian, H., Wang, B.: AHP and game theory based approach for network selection in heterogeneous wireless networks. In: 2014 IEEE 11th Annual IEEE Consumer Communications and Networking Conference (CCNC), pp. 501–506. Las Vegas, USA, 10 Jan 2014
3. Preethi, G.A., Chandrasekar, C.: A network selection algorithm based on AHP-OWA methods. In: 6th Joint IFIP Wireless and Mobile Networking Conference (WMNC), pp. 1–4. Dubai, United Arab Emirates, 23 April 2013
4. Zhang, P., Zhou, W., Xie, B., Song, J.: A novel network selection mechanism in an integrated WLAN and UMTS environment using AHP and modified GRA. In: 2010 2nd IEEE International Conference on Networking Infrastructure and Digital Content, pp. 1–6. Beijing, China, 24 Sept 2010
5. Goyal, R.K., Kaushal, S.: Effect of utility based functions on fuzzy-AHP based network selection in heterogeneous wireless networks. In: 2015 2nd International Conference on Recent Advance in Engineering and Computational Sciences (RAECS), pp. 1–5. Chandigarh, India, 21 Dec 2015
6. Brajkovic, E., Sjekavica, T., Volaric, T.: Optimal wireless network selection following students online habits using fuzzy AHP and TOPSIS methods. In: 2015 International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 397–402. Dubrovnik, Croatia, 24 Aug 2015
7. Cui, Y., Xu, Y., Xu, R., Sha, X.: A heterogenous wireless network selection algorithm based on non-cooperative game theory. In: 2011 6th International ICST Conference Communications and Networking in China (CHINACOM), pp. 720–724. Harbin, China, 17 Aug 2011
8. Niyato, Dusit, Hossain, Ekram: Dynamics of network selection in heterogeneous wireless networks: an evolutionary game approach. IEEE Trans. Veh. Technol. **58**(4), 2008–2017 (2009)

9. Zhu, K., Niyato, D., Wang, P.: Network selection in heterogeneous wireless networks: evolution with incomplete information. In: 2010 IEEE Wireless Communications and Networking Conference, pp. 1–6. Sydney, NSW, Australia, 18 April 2010
10. Xiulan, Yu., Zeng, Cheng: Matching game network selection algorithm based on TOPSIS. J. Chongqing Univ. Post Telecommun. (Natural Science Edition) **28**(4), 451–455 (2016)