A Weighted Bipartite Graph Based Network Selection Scheme for Multi-Flows in Heterogeneous Wireless Network

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Abstract—Network selection is an important issue in the next generation of heterogeneous wireless network and well studied for individual flows. However, researches of network selection for multi-flows at network side are seldom touched upon but also important from the global view of optimizing usage of network resources. In this paper, a weighted bipartite graph based network selection scheme for multi-flows is proposed, which adopt secondary exponential smoothing method to perform network resource prediction and assign flows to networks based on Matching Degree (MD). The network selection scheme is modeled as weighted bipartite graph with objectives of maximizing Matching Degrees and access ratio as well as the constraint of guaranteeing no network overloaded. Weighted Bipartite Graph Algorithm (WBGA) is designed to achieve the goal. Simulation results show that WBGA demonstrates best performance compared to other schemes, with regard to average MD, access ratio and utilization ratio of network resources.

I. INTRODUCTION

Different access technologies will be integrated to form the next generation of heterogeneous wireless network, providing a wide range of innovative services to end users [1][2]. In this kind of network, mobile terminals will be equipped with multiple radios and able to access various wireless networks such as IEEE 802.11, 802.15, 802.16, GSM, UMTS, satellite networks and etc [3]. In order to keep mobile users in continuous communication, it is important to design a network selection scheme based on flow requirements and network status, which has become an hot research topic recently [4]∼[11].

Most existing researches on network selection schemes are user-centered, devoted to select the most appropriate network for individual flows. Among these, the scheme of Always Best Connected (ABC) [5] is widely explored. Some of these researches focus on the optimization of a single QoS requirement. For example, in [6], a utility based network selection scheme is proposed, where the price mechanism acting as a lever system guides users to select the most efficient network and controls the allocation of network resources. Similarly literature [7] takes into account power consumption in hybrid wireless networks. The lifetime of the mobile terminal is calculated based on the information of the battery, traffic class and etc. Some other researches put an emphasis on multiple QoS requirements. In [5][8], Analytical Hierarchy Process (AHP) is proposed to study the importance of various QoS requirements on flows, namely weights. And a grey relational analysis (GRA) method is designed to calculate the relational grade between network parameters and QoS requirements [5][11]. Other researches have investigated into network selection models, such as game theory model[9][10].

While user-centered network selection schemes have been well studied, network-centered selection schemes deployed on network side such as the gateway are seldom touched upon. Actually the research of network selection schemes on network side is as important as that of user-centered in next generation heterogeneous network if not more important, because of the followings. Firstly, network-side entity such as the gateway are endowed with more powerful computing capability to perform network selection for flows; Secondly, the gateway can obtain all flow information and status information of all covered networks, and then globally optimize the usage of network resources. For network-centered scheme, it is commonly seen in the gateway that multiple flows from many users in coverage are transmitting to other networks simultaneously, making a network-centered selection scheme for multi-flows necessary and different from user-centered scheme with individual flows.

Fig. 1. heterogeneous wireless network architecture
In this paper, a network selection scheme for multi-flows on network side is proposed based on weighted bipartite graph model. And the scheme can be applied in the heterogeneous wireless network architecture as shown in the Fig. 1. Firstly, due to the dynamic property of network status, a secondary exponential smoothing method is applied to perform network resource prediction for network selection. Secondly an improved network select criteria is designed and named Matching Degree (MD), which considers multiple QoS requirements and weights based on existing AHP method [5][8]. Lastly, a weighted bipartite graph model is designed to select appropriate networks for multiple flows simultaneously, with the design objectives of maximizing Matching Degrees (MD) and access ratio in a global view, and the constraint of no network overloaded.

The rest of the paper is organized as follow. In Section II, the bipartite graph model is introduced. Then in Section III, a thorough description of Weighted Bipartite Graph Algorithm (WBGA) is given. Simulation results are presented in Section IV and conclusions are drawn in Section V.

II. SYSTEM MODEL

A. System model

Network selection judgement in heterogenous wireless network is mainly based on network parameters, QoS requirements and their weights. Network parameters typically include available network resources (i.e. bandwidth), data rate, security levels, cost, energy consumption and etc. Usually they can be obtained through request-reply originated at the gateway or periodic status report from access network to the gateway. The method of periodic status report is adopted in this paper to gather network parameters. Corresponding to network parameters are QoS requirements, which have the same categories and can be obtained from core network before each connection is established. Weights are used to measure the importance of various QoS requirements to flows, and are calculated at the gateway utilizing AHP method in advance.

![Network Selection Model for Multi-Flows](image)

Fig. 2 is an example of how network-centered selection schemes can be implemented. The modules of Network Parameter Collector and QoS Requirement Collector are used to collect parameters as illustrated in above paragraph. Decision center functions as the key module of the system to execute WBGA network selection algorithm which is the main contribution of this paper. Rule Generator module works to provide critical input parameters to Decision Center such as weights, the smoothing index $\alpha$ (depicted in next subsection B), and etc. Execution module performs actual operations of link layer handover, context transmission, and IP layer handover on the basis of network selection results. Monitor module takes observation on the execution of actual selection results to provide feedback to Rule Generator so as to adjust input parameters and optimize network selection algorithm.

B. Network Resource Prediction

As mentioned above, network resources (i.e. bandwidth) are periodically collected in the module of Network Parameter Collector. However, because access network is changing rapidly, and there are non-negligible signaling transmission delay from the moment network status is collected to the moment handover is actually performed based on network selection results, the collected network resource values become overdue and invalid for network selection. Therefore, to adapt to the rapid changing network, an exponential smoothing method for network resource prediction is introduced as follows.

Let's take the network resource prediction for one network as an example. Suppose network resources are collected periodically at the gateway with time interval $\Delta T$, and the value at time $t$ is depicted as $r(t)$. Then resource values collected for this network within the latest time period $L \ast \Delta T$ can be depicted as the follows:

$$R_t = \{r(t-(L-1)\Delta T),...,r(t-\Delta T),r(t)\}$$  \hspace{1cm} (1)

The smoothing index is defined as $\alpha$ with a value range of $[0,1]$. Now we are doing the first exponential smoothing to generate $R_t^{(1)} = \{r_{(1)}(t-(L-1)\Delta T),...,r_{(1)}(t)\}$ as follows:

$$r_{(1)}^{(1)}(t-(L-1)\Delta T) = r(t-(L-1)\Delta T)$$

$$r_{(1)}^{(1)}(t-(L-2)\Delta T) = \alpha r(t-(L-2)\Delta T) + (1-\alpha)r_{(1)}^{(1)}(t-(L-1)\Delta T)$$

$$r_{(1)}^{(1)}(t-(L-3)\Delta T) = \alpha r(t-(L-3)\Delta T) + (1-\alpha)r_{(1)}^{(1)}(t-(L-2)\Delta T)$$

$$\vdots$$

$$r_{(1)}^{(1)}(t) = \alpha r(t) + (1-\alpha)r_{(1)}^{(1)}(t-\Delta T)$$  \hspace{1cm} (2)

Similarly a secondary exponential smoothing is applied to generate $R_t^{(2)} = \{r_{(2)}^{(2)}(t-(L-1)\Delta T),...,r_{(2)}^{(2)}(t)\}$. Then the intercept and slope at time $t$ are calculated respectively based on $r_{(1)}^{(1)}(t)$ and $r_{(2)}^{(2)}(t)$:

$$\begin{cases} a_t = 2r_{(1)}^{(1)}(t) - r_{(2)}^{(2)}(t) \\ b_t = \frac{\alpha}{1-\alpha}(r_{(1)}^{(1)}(t) - r_{(2)}^{(2)}(t)) \end{cases}$$  \hspace{1cm} (3)

Suppose the prediction time interval is $\beta \Delta T$. Then the network resource at time $\beta \Delta T$ can be calculated by:

$$r(t+\beta \Delta T) = a_t + \beta \Delta T b_t$$  \hspace{1cm} (4)

Note here $L$, $\alpha$, $\beta$ are generated by Rule Generator module mentioned above. Resources of all covered networks are adjusted utilizing the same method, which will be used as the actual input of network selection algorithm.

C. MD Calculation

For each flow, the criteria to select the most appropriate network from its candidates is its Matching Degrees (MD) with candidate networks. In this paper, MD is designed to be calculated from QoS requirements and network parameters.
Let’s take MD calculation between one flow and one candidate network as an example. Flow QoS requirements are defined as a vector \( Q = \{q_1, q_2, ..., q_k\} \) and network parameters for one network are defined as a vector \( P = \{p_1, p_2, ..., p_k\} \) (suppose there are \( k \) kinds of parameters). Similarity \( s \) between each pair of QoS requirement and network parameter is proposed and calculated as follows:

\[
s_i = \begin{cases} 
\frac{q_i - p_i}{|q_i - p_i|}, & 0 \leq p_i \leq 2q_i, \\
0, & p_i > 2q_i, \\
\end{cases} \quad 1 \leq i \leq k
\]  

(5)

So the closer QoS requirement and network parameter are, the larger \( s \) is. The similarity vector is denoted as \( S = \{s_1, s_2, ..., s_k\} \). The weights to measure the importance of various QoS requirements are generated according to existing AHP method and depicted as \( W = \{w_1, w_2, ..., w_k\} \). Then MD between this flow and one candidate network is calculated as vector inner product of \( W \) and \( S \) with a range of \([0, 1]\):

\[
MD = W^T S = \sum_{i=1}^{k} w_i s_i 
\]  

(6)

Note that network resource is not included here in network parameters used to calculate MD. Instead it is just used for judging whether the network is overloaded or not. Using above method, Matching Degrees between all flows and corresponding candidate networks are calculated for WBGA algorithm.

D. Weighted Bipartite Graph Model

As introduced before, the gateway has to perform network selection for many flows simultaneously. The network selection scheme for multi-flows can be modeled as a weighted bipartite graph (Fig. 3). Assume that there are \( m \) flows and \( n \) networks. Each flow can choose from a sub-set of networks, and the link connecting each flow to each of its candidate networks is associated with MD (i.e. link weight) calculated in subsection C. Each flow has its requirement for network resources (depicted as \( req \) below), and each network has limited resources (depicted as \( res \) below) to accept flows.

![Fig. 3. Initial Status](image)

![Fig. 4. Results of Network Selection](image)

As shown in the following formulated, the design objectives of network selection are to maximize in a global view flows’ Matching Degrees and access rate with the constraint of no network overloaded, the second part is to maximize access rate from the global perspective of all flows. Each flow can be accepted by network (then \( s = 1 \)) or refused due to limited network resources (then \( s = 0 \)). The design objectives can be formulated as:

\[
\begin{align*}
\text{Max} & \sum_{i=1}^{m} MD_i \\
\text{Max} & \left( \sum_{i=1}^{m} s_i \right) / m, s_i = 1 \forall 0 \\
\end{align*}
\]  

(7)

and constraint condition can be formulated as:

\[
st : res_j - \sum_{i=1}^{m} req_i \geq 0, j = 1, 2, ..., n
\]  

(8)

where \( res_j \) is the available resources of network \( j \) and \( \sum_{i=1}^{m} req_i \) denotes the summation of resource requirements of all flows that have selected network \( j \). In order to achieve the goals, an efficient algorithm is proposed in the next section.

III. WBGA Algorithm Description

In this section, we are going to present Weighted Bipartite Graph Algorithm (WBGA) for multi-flows which is implemented at Decision Center to achieve the objectives with constraint illustrated above. The notations used in WBGA are described in Table I. Notations from 1 to 6 are input parameters of WBGA, and other notations are used in the middle or as final results of WGBA.

**Table I**

<table>
<thead>
<tr>
<th>Notations used in WBGA algorithm</th>
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<tbody>
<tr>
<td>1 FLOW</td>
</tr>
<tr>
<td>2 NET</td>
</tr>
<tr>
<td>3 MDSet</td>
</tr>
<tr>
<td>4 REQ</td>
</tr>
<tr>
<td>5 RES</td>
</tr>
<tr>
<td>6 MDthresh</td>
</tr>
<tr>
<td>7 SEL</td>
</tr>
<tr>
<td>8 LBlock</td>
</tr>
<tr>
<td>9 LBEver</td>
</tr>
</tbody>
</table>

And the pseudo code of this algorithm is presented in Algorithm 1 with detailed explanations as follows. Firstly parameters are initialized such as sets of flows, networks, network resources, requirement of flows, etc (from Line 2 to Line 7). Note that network resources are obtained from Network Parameter Collector module and adjusted using exponential smoothing method in Section II (Line 4). In Line 5, the set of MDSet is calculated based on MD calculation in Section II. Next is the first phase of WBGA algorithm (Line 9 to 11). In this phase, all flows are assigned to the optimum network, namely flow’s candidate network associated with the maximum MD. Doubtlessly, this assignment might cause some networks overloaded. So in second phase (Line 13 to 22), we examine each overloaded network, and redirect attached flows to the next optimum network based on the minimum MD decreasing criteria. It means that the flows with minimum difference between current selected network and the next optimum network will be removed from overloaded network (Line 15 and 17). If the removing flow is acceptable for target network, update the information of original network and new bearer network (Line 22). Otherwise, the flow will be stored in the list of LBlock (Line 20).

The next phase of network selection for multi-flows is to reassign flows stored in LBlock to proper network (from Line 24 to Line 35) to maximize resource utilization and access ratio. For each entry in LBlock, Line 26 judges whether it has next optimum network to be chosen. If not, it will be
Algorithm 1 Weighted Bipartite Graph Algorithm
1: // Initialize parameters;
2: Generate sets of FLOW, NET;
3: Generate set of REQ from QoS Requirement Collector module;
4: Generate set of RES from Network Parameter Collector module and adjust using exponential smoothing method;
5: Calculate MDSel based on MD Calculation;
6: Initialize set of SEL to be an array of zeros;
7: Generate MD\_thresh from Rule Generator;
8: /*ist phase: Select the optimum network;
9: for each flow, in FLOW do
10: \(sel_i = \) the optimum network with maximum MD associated with this flow; denote \(sel_i\) as \(k\);
11: \(res_k = res_k - req\);
12: /2nd phase: Flow adjustment for overloaded network;
13: for each \(sel_j\) in NET do
14: if \(res_j < 0\) then
15: Make an ascending sort list of those flows that have selected network \(j\) based on MD difference between flow \(k\)’s current network and next optimum network;
16: while list ≠ ∅ and \(res_j < 0\) do
17: Pick the next flow \(k\) in sort list, denote flow \(k\)'s next optimum network as \(l\); \(res_l = res_j + req\); if \(res_l - req_k < 0\) then
18: Put flow \(k\) in blocked list LBlock; 
19: else
20: \(res_k = l; res_l = res_l - req\);
21: /3rd phase: Reassignment of flows in blocked list
22: while LBlock ≠ ∅ do
23: Pick up the next flow \(i\) in LBlock;
24: if flow \(i\) has no next candidate network then
25: remove flow \(i\) from LBlock and put it into LBEver;
26: Continue;
27: else
28: Move to flow \(i\)'s next optimum network and denote as \(l\);
29: if \(res_l - req < 0\) then
30: put flow \(i\) at the tail of LBlock;
31: else
32: remove flow \(i\) from LBlock;
33: \(sel_i = k; res_l = res_l - req\);
34: /4th phase: Minute adjustment
35: for each flow \(i\) in FLOW do
36: if \(sel_i = 0\) or \(MD_{sel_i} \geq MD_{thresh}\) then
37: \(i++; \)Continue; // then no adjustment
38: for flow \(j > i\) in FLOW do
39: \(MD_{j_{sel}} \geq MD_{thresh}\) and \(MD_{sel_i} \geq MD_{thresh}\) and \(res_{sel_i} - req_i \geq 0\) and \(res_{sel_i} - req_j \geq 0\) and \(MD_{sel_i} + MD_{j_{sel}} < MD_{sel_i} + MD_{j_{sel}}\) then
40: \(sel_i = sel_j; sel_j = sel_i;\)
41: \(res_{sel_i} = res_{sel_i} - req_i; res_{sel_j} = res_{sel_j} - req_j;\)

removed from LBlock because it can not be accepted by any of existing networks and will be put in list LBEver (Line 27).

Otherwise, new bearer network will be evaluated whether it has sufficient network resources to accept the flow (Line 31).

If there is sufficient network resource, information associated with this flow and target network will be updated (Line 34 and 35). If not, the flow will be put back into LBlock, waiting for next adjusting round (Line 32).

The last phase of network selection is named minute adjustment phase (Line 37 to 43) to further increase total MDs. Line 38 searches for flow i whose MD with target network is lower than MD\_thresh. Then from Line 40 to 43, we look for exchangeable flow j and then exchange the target networks for flow i and j. Flow j is deemed to be exchangeable with flow i only if when exchanged, flow i and j both have satisfactory MD, the new target networks have sufficient resources, and meanwhile new summation of MDs of flow i and j are enlarged (Line 41).

When WBGA algorithm converges, flows’selected networks are stored in SEL, and blocked flows are stored in list LBEver.

IV. SIMULATION

In this section, numerical simulation results are discussed to evaluate the performance of WBGA. Three additional network selection schemes are constructed based on existing single-flow schemes and simulated for comparison. They are Basic Bipartite Graph Algorithm (BBGA), Data Rate Prioritized Algorithm (DRPA) and Energy Prioritized Algorithm (EPA). BBGA are based on optimal matching rule with bipartite graph, i.e. kuhn-Munkres algorithm [12], targeting at maximizing flow ‘s Matching Degree with bearer network. DRPA and EPA extend existing single flow selection method in literature [6][7] to multi-flows, adopting date rate and energy consumption respectively as the objective of utility function. In this paper, three experiments are performed firstly to evaluate respectively average MD, access ratio, and utilization ratio of network resources. Then the last experiment demonstrates the running process of WBGA algorithm.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>NETWORK PARAMETERS</th>
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<tbody>
<tr>
<td>Net type</td>
<td>Data rate (kbps)</td>
</tr>
<tr>
<td>Type0</td>
<td>800~1000</td>
</tr>
<tr>
<td>Type1</td>
<td>79~82</td>
</tr>
<tr>
<td>Type2</td>
<td>1100~1125</td>
</tr>
<tr>
<td>Type3</td>
<td>300~400</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>FLOWS QoS REQUIREMENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow type</td>
<td>Date Rate (kbps)</td>
</tr>
<tr>
<td>Type0</td>
<td>700~9000</td>
</tr>
<tr>
<td></td>
<td>0.4~0.6</td>
</tr>
<tr>
<td>Type1</td>
<td>50~100</td>
</tr>
<tr>
<td></td>
<td>0.2~0.3</td>
</tr>
<tr>
<td>Type2</td>
<td>1000~1200</td>
</tr>
<tr>
<td></td>
<td>0.1~0.2</td>
</tr>
<tr>
<td>Type3</td>
<td>100~700</td>
</tr>
<tr>
<td></td>
<td>0.25</td>
</tr>
</tbody>
</table>

TABLE II and TABLE III list network parameters and QoS requirements respectively used in the simulation. In TABLE II, four kinds of networks are introduced with varying capabilities and characteristics. Type0 networks are featured with high security levels. Correspondingly TABLE III enumerates four
kinds of flow QoS requirements and respective weights. In the simulation, all networks are endowed with limited resources. That is in the first three experiments, about 100 flows can be accommodated and in the last experiment, about 10 flows can be accommodated.

![Fig. 5. Average Matching Degree](image)

![Fig. 6. Access ratio](image)

![Fig. 7. Utilization of resource](image)

In Fig. 5, the average MD for all flows is evaluated. Note that MD of blocked flows is counted as zero and in DRPA and EPA MD of successfully accessed flows is counted as 1. We can observe that both WBGA and BBGA can achieve higher average MD because maximizing MD is a design objective of these two algorithms. With the number of flows increasing, networks are over-burdened and more flows are blocked, causing average MD decreasing.

Fig. 6 shows access ratio against number of flows. It is seen that WBGA and BBGA show much higher access ratio than DRPA and EPA because the latter two algorithms are considering single criteria to select any satisfactory network instead of selecting the best matching network from the perspective of making full usage of network resources. When the number of flows is less than 100 (networks can tolerate 100 flows), WBGA achieves almost 100 percent access ratio, which demonstrates WBGA ’s ability in maximizing access ratio. However for BBGA, the access ratio decreases sharply when number of flows exceeds 20, because BBGA takes no further action to handle blocked flows.

In Fig. 7, we observe the utilization ratio of network resources, which shows similarity with Fig. 6 in comparison between these four algorithms. With number of flows increasing, utilization ratio of network resources is growing for all four algorithms. When the number of flows reaches 100, WBGA is approaching 100 percent in utilization ratio of network resources because WBGA is using every bit of network resources in design objective.

Fig. 8 shows the running process of WBGA with number of flows setting to 10, 15, 20, 25 respectively. Y-axis represents MD summation of all flows while X-axis represents sampling time during the running process of WBGA. The red line with constant MD summation values presents the ideal situation in which networks are endowed with unlimited resources and each flow is selecting the optimal network. In Fig. 8, all four blue lines display similar trends, which corresponds to the four phases of the algorithm. The initial point indicates the end of the first phase of WBGA that each flow is selecting the optimal network with maximum MD. The decreasing trend before the first turning point illustrates the 2nd phase of WBGA that all flows causing network overloaded are redirected or put into blocked flow list. The 3rd phase of WBGA reassigns blocking flows, making summation of MD increase to turning point 2. Then during the minute phase of WBGA, summation of MD is increasing to the converge point (i.e. results). From Fig. 8, we can also see with the growth of flow numbers, more flows are blocked and gaps of MD summation with comparison to ideal summation value are enlarged.

**V. CONCLUSIONS**

This paper proposes a weighted bipartite graph based network selection scheme for multi-flows in next generation heterogeneous wireless networks. In this scheme, a secondary exponential smoothing method is applied to predict network resources which are then used in WBGA algorithm. And an improved MD calculation method is introduced to work as the network selection criteria for individual flows. Then a weighted bipartite graph model is designed with the objectives of maximizing MD summation and access ratio, and the constraint of no network overloaded. The implementation of WGBA algorithm is presented and simulation is carried out to evaluate its performance with comparison to three additional network selection schemes. Simulation results demonstrate that WGBA achieves best performance in its objectives including high Matching Degree, access ratio, and utilization ratio of network resources.

**REFERENCES**


