A Novel MAD-Based Network Selection Algorithm for Heterogeneous Networks

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Abstract—**Next generation wireless network (NGWN) is expected to integrate different radio access technologies (RATs) and to support user services with different quality-of-service (QoS) requirements. In the overlapped area of various RATs, the problem of optimally selecting the access network has to be considered. However, the heterogeneity and incompatibility of different wireless access technologies, and the variety of user services pose challenges to guarantee the users' QoS. In this paper, we stress the problem of network selection in heterogeneously integrated networks, and propose a novel multiple attribute decision (MAD)-based network selection algorithm. In addition to network current states and user requirements, user long-term handoff information between various access networks, which can be modeled based on hidden Markov model (HMM), is taken into account in designing the optimal network selection scheme. Numerical results show that the proposed algorithm can offers the better call block rate and achieves the balanced load status compared to the original MAD-based network selection algorithm.**

Keywords-Heterogeneous wireless networks; network selection; multiple attribute decision; hidden Markov model

I. INTRODUCTION

In next generation wireless network (NGWN), different radio access technologies (RATs) will be heterogeneously integrated to support user services with different quality-of-service (QoS) requirements. However, the heterogeneity of access network technologies and the diversity of user applications pose new challenges on network selection scheme, i.e., choosing the optimal candidate network for accessing in the overlapping coverage area of various access networks.

In recent years, some research works have been conducted on optimal network selection problem [1] and various network selection algorithms have been designed based on cost function [2], fuzzy theory [3], Game theory and multi-attribute decision (MAD) [4], etc. To design a MAD-based vertical handoff algorithm, the factors affecting the performance of vertical handoff are chosen as the decision factors. By assigning each factor a suitable weight reflecting the significance of the corresponding parameter on the handoff performance, the performance of each candidate target network can be evaluated and the one with the best performance will be chosen as the handoff destination network. Comparing to other methods, MAD-based algorithm offers desired performance for multiple network and user factors affecting the performance of network selection are jointly considered.

In [5], the authors propose a hierarchy multiple attribute decision with possibilities (HMADP) method based network selection scheme, which jointly considers the parameters including access delay, delay jitter and packet loss rate in evaluating the performance of candidate networks. Reference [6] presents a novel multi-attribute vertical handoff algorithm for heterogeneous wireless networks which achieves seamless mobility while maximizing end-users' satisfaction. Two modules are designed to estimate the necessity of handoff and to select the target network.

Previous MAD-based network selection algorithms mainly consider current network state information and user preference, based on which the network selection decision is made. However, as instantaneous state information cannot reflect network and user long-term status sufficiently due to the variation of network status and user requirements, the resulted decision may not be optimal in a relatively long time. Thus it is highly desired to jointly consider network/user history information and current state in making network selection decision.

In this paper, a novel MAD-based network selection algorithm is proposed for a heterogeneously integrated network. In addition to network current states and user requirements, user long-term handoff information between various access networks which is modeled based on hidden Markov model (HMM), is taken into account in designing the optimal network selection scheme.

The rest of this paper is organized as follows. In Section II, user handoff probability modeling based on HMM is proposed. A novel MAD-based network selection scheme is presented in Section III. In Section IV, simulation results are presented. Finally, the conclusions are drawn in Section V.

II. HMM-BASED USER HANDOFF INFORMATION MODELING

In this paper, we consider a heterogeneously integrated network consisting of multiple access networks. Users in the network are allowed to choose the optimal access network or perform handoff from one network to another network.

Assuming the status of each access network can be characterized by various network attribute parameters. For each user, the access preference can be characterized by user service requirement parameters. Further assuming for certain previous time instances, the status of access networks, user requirements on network attribute parameters and user decisions for network switching can be obtained from the network management center, in this section, based on these history information, the probability of user switching between various access networks can be calculated based on HMM.

A. Normalized Network Attribute Matrix Modeling

To evaluate and compare the performance of various access networks in a unified framework, the attribute parameters of the networks should be normalized. Let $b_{mn}^{0,t}$ indicates that the *n*th attribute parameter of the *m*th network at the time instance *t,* $1 \le m \le M$,$1 \le n \le N$ **,**$1 \le t \le T$, where *M* denotes the number of access networks, *N* denotes the number of attribute parameters of the networks, *T* denotes the number of observation time instances. Assuming $b_{mn}^{\min} \le b_{mn}^{0,t} \le b_{mn}^{\max}$, where $b_{mn}^{\min}$ and $b_{mn}^{\max}$ indicate respectively the minimum and maximum value of the *n*th attribute parameter of the *m*th network. For convenience, we divide the range of $b_{mn}^{0,t}$ into (l_{mn}-1) segments, where l_{mn} is a constant, indicating that the number of states of the *n*th attribute of the *m*th network. Introducing b_{mni}^{scale}, $1 \le i \le l_{mn}$, such that $b_{mn}^{\min} = b_{mn1}^{scale} \le b_{mn2}^{scale} \le \cdots \le b_{mnl_{mn}}^{scale} = b_{mn}^{\max}$. If $b_{mni}^{\text{scale}} \le b_{mn}^{0,t} \le b_{mn(i+1)}^{\text{scale}}$, then approximating $b_{mn}^{0,t}$ as b_{mn}^{t} , which is the middle value of b_{mni}^{scale} and $b_{mn(i+1)}^{scale}$, i.e.,

$$b_{mn}^{t} = \frac{b_{mni}^{\text{scale}} + b_{mn(i+1)}^{\text{scale}}}{2} \tag{1}$$

To obtain the normalized network attribute parameters, the parameter b_{mn}^{t} should be normalized over different networks and among all the attribute parameters inside one network, as described in the following:

1) Normalizing over Different Networks

Denoting $b_{n}^{t,\max} = \max_{m}(b_{mn}^{t})$, $b_{n}^{t,\min} = \min_{m}(b_{mn}^{t})$, $1 \le m \le M$, and classifying network attribute parameters as revenue parameters, which are positively proportional to network selection performance, such as available network bandwidth, received signal strength (RSS), etc., and cost parameters, which are negatively proportional to network selection performance, such as connection delay, packet loss rate, etc., the normalization approach for revenue parameters, can be chosen as:

$$t_{mn}^{t} = \frac{b_{mn}^{t}}{b_{n}^{t,\min} + b_{n}^{t,\max}} ,1 \le m \le M ,1 \le n \le N ,1 \le t \le T \tag{2}$$

Similarly, the normalization approach for cost parameters, can be chosen:

$$t_{mn}^{t} = 1 - \frac{b_{mn}^{t}}{b_{n}^{t,\min} + b_{n}^{t,\max}} ,1 \le m \le M ,1 \le n \le N ,1 \le t \le T \tag{3}$$

2) Normalizing over Various Attribute Parameters inside One Network

Normalizing t_{mn}^{t} over all the attribute parameters of the *m*th network, we obtain:

$$r_{mn}^{t} = \frac{t_{mn}^{t}}{\sum_{n=1}^{N} t_{mn}^{t}} ,1 \le m \le M ,1 \le n \le N ,1 \le t \le T \tag{4}$$

Thus, the normalized attribute parameter matrix $R^{t} = [r_{mn}^{t}]_{M \times N}$ can be obtained.

B. User Handoff Probobility

To characterize user requirements on network attribute paramters, let u_{sn}^{t} denote the normalized demand factor of the *s*th user at time *t* for the *n*th service-sensitive parameter, $1 \le t \le T$,$1 \le s \le S$,$1 \le n \le N$, where *S* is the total number of sample users. Denoting $u_{s}^{t} = \left[u_{s1}^{t} \quad u_{s2}^{t} \quad \cdots \quad u_{sN}^{t} \right]$ as the service requirement vector of the *s*th user at the time instance *t*, $\sum_{n=1}^{N} u_{sn}^{t} = 1$, $0 \le u_{sn}^{t} \le 1$. Based on MAD theory, the observational probability of the *s*th user in the *m*th network can be expressed as [7][8]:

$$p_{sm}^{t} = \sum_{n=1}^{N} u_{sn}^{t} r_{mn}^{t} \quad 1 \le t \le T, 1 \le s \le S, 1 \le m \le M \tag{5}$$

Denoting $a_{m_1 m_2}$ as the probability that one user switches from the m_1 network to the m_2 network, $1 \le m_1, m_2 \le M$, the transition probability matrix of network states can be expressed as $A = [a_{m_1 m_2}]$, let π_m denote the probability that users select the *m*th network at the initial stage of network selection, $\pi = [\pi_m]_{1 \times M}$ represents the initial state matrix of each network. Based on p_{sm}^{t} and system initial parameters A_0 and π_0, the forward probability α_{sm}^{t} and consequent probability β_{sm}^{t} that the *s*th user selects the *m*th network probabilities at time instance *t* can be calculated, $1 \le t \le T$, $1 \le s \le S$,$1 \le m \le M$, and $a_{m_1 m_2}$ can be calculated, $1 \le m_1, m_2 \le M$. The detail process can be described as follows:

a. Given *M*，*N*， R^{t} , and set $A = A_0$ ， $\pi = \pi_0$ ， *s*=1.

b. Calculating α_{sm}^{t} and β_{sm}^{t} [9][10]:

According to HMM theory, we obtain:

$$\alpha_{sm_1}^{t} = \pi_{m_1} p_{sm_1}^{1} \qquad 1 \le \mathrm{m}_1 \le M \tag{6}$$

$$\alpha_{sm_1}^{t+1} = \left[\sum_{m_2=1}^{M} \alpha_{sm_2}^{t} a_{m_2 m_1} \right] p_{sm_1}^{t+1} \qquad t = 1,2,...,T-1, 1 \le m_1, m_2 \le M \tag{7}$$

$$\beta_{sm_1}^{T} = 1 \qquad 1 \le m_1 \le M \tag{8}$$

$$\beta_{sm_1}^t = \sum_{m_2=1}^{M} a_{m_1 m_2} \beta_{sm_2}^{t+1} p_{sm_1}^{t+1} \quad 1 \le m_1 \le M \,, \quad t = T-1, T-2, \ldots, 1 \quad (9)$$

$$\gamma_{sm_1}^t = \left[\frac{\alpha_{sm_1}^t \beta_{sm_1}^t}{\sum_{m_1=1}^{M} \alpha_{sm_1}^t \beta_{sm_1}^t} \right] \quad 1 \le t \le T \,, 1 \le m_1, m_2 \le M \quad (10)$$

$$\varepsilon_{sm_1 m_2}^t = \frac{\alpha_{sm_1}^t a_{m_1 m_2} \beta_{sm_2}^{t+1} p_{sm_2}^{t+1}}{\sum_{m_1=1}^{M} \sum_{m_2=1}^{M} \alpha_{sm_1}^t a_{m_1 m_2} \beta_{sm_2}^{t+1} p_{sm_2}^{t+1}} \quad 1 \le t \le T-1, 1 \le m_1, m_2 \le M \quad (11)$$

Based on $\gamma_{sm_1}^t$ and $\varepsilon_{sm_1 m_2}^t$, the initial probability of the mth network and the transition probability between the m_1 th network and the m_2 th network can be obtained:

$$\pi_{m_1} = \gamma_{sm_1}^1 \quad 1 \le m_1 \le M \quad (12)$$

$$a_{m_1 m_2} = \frac{\sum_{t=1}^{t=T-1} \varepsilon_{sm_1 m_2}^t}{\sum_{t=1}^{t=T-1} \gamma_{sm_2}^t} \quad 1 \le m_1, m_2 \le M \quad (13)$$

c. The conditional probability of observation sequence vector $p(\mathrm{U}_s \mid \lambda)$ can be calculated as:

$$p(U_s \mid \lambda) = \sum_{m=1}^{M} \alpha_{sm}^T \qquad 1 \le m \le M \quad (14)$$

Given the convergence threshold δ, the convergence criterion can be defined as:

$$\log p(\mathrm{U}_s \mid \lambda) - \log p(\mathrm{U}_s \mid \lambda_0) < \delta \quad (15)$$

If the condition in (15) meets, then the algorithm terminates, otherwise, check if $s<S$, set $\lambda_0 = \lambda$, $s=s+1$, go back to step b, otherwise, the algorithm fails.

III. Proposed Network Selection Algorithm

Based on the probabilities of user handoff between various systems obtained from previous time instances from 1, 2 to T-1, user network selection strategy at time T can be obtained as follows.

Given normalized network attribute matrix R^T and service requirement vector u_s^T of the sth user at the Tth time instance, user observational probability can be calculated as:

$$p_{sm}^T = \sum_{n=1}^{N} u_{sn}^T r_{sn}^T \quad (16)$$

Applying the method of Viterbi decoding algorithm, and jointly considering user historic information, $a_{m_1 m_2}$, $1 \le m_1, m_2 \le M$, the optimal network m_2^* at t=T can be obtained as:

$$m_2^* = \arg\max_{1 \le m_2 \le \mathrm{M}} [a_{m_1 m_2} p_{sm_2}^T] \quad (17)$$

IV. Numerical Results

In this section, the performance of the proposed MAD-based network selection algorithm is examined based on numerical simulation. As an example, a heterogeneously integrated network with universal mobile telecommunications system (UMTS) and wireless local area network (WLAN) is considered. Assuming UMTS covers the entire area while WLAN only covers hot areas, multi-mode user terminals in the overlapped area select the access network based on the proposed MAD network selection algorithm and the original multi-attribute network selection algorithm based on (5), respectively. The performance of both algorithms will be evaluated.

A. HMM-Based User Handoff Probability Modeling

To perform the proposed MAD network selection algorithm, the probability of user handoff should be modeled.

In the simulation, assuming system states are characterized by parameters including available system bandwidth, access delay, packet loss, delay jitter and cost. Based on different combination of these parameters, the states can be categorized into four cases, as shown in Table I. Further assuming two user service types, i.e., voice service and data service are supported. As voice service is relatively sensitive to connection delay and delay jitter, the service requirement vector is chosen as [0, 0.5, 0, 0.4, 0.1], data service is more sensitive to network bandwidth and packet loss, thus, the service requirement vector is chosen as [0.5, 0, 0.4, 0, 0.1].

Choosing the number of user samples as 300, the service type of each user is randomly chosen from data service and voice service. For each user, the observational probability can be calculated according to (5). Assuming the initial state of networks is $\pi = [0.5, 0.5]$, the network transition probability can be obtained based on (6)-(13) iteratively. Choosing the convergence threshold as $\delta = 1 \times 10^{-3}$, the modeling process is completed when the convergence condition is satisfied. Fig. 1 shows the variation of conditional probability is described for each iteration. It can be seen from the Figure that when the number of the iterations is larger than 170, the probability difference becomes less than the given threshold $\delta = 1 \times 10^{-3}$, indicating the modeling process has become converged.

Table I An Example of Network Status

	Networks	System Bandwidth	Access Delay	Packet Loss	Delay Jitter	Cost
Case 1	UMTS	0.5	40	70	25	0.6
	WLAN	1.6	140	20	50	0.05
Case 2	UMTS	0.5	40	70	25	0.6
	WLAN	0.4	200	180	100	0.05
Case 3	UMTS	0.12	50	80	60	0.6
	WLAN	1.6	140	20	50	0.05
Case 4	UMTS	0.12	50	80	60	0.6
	WLAN	0.4	200	180	100	0.05

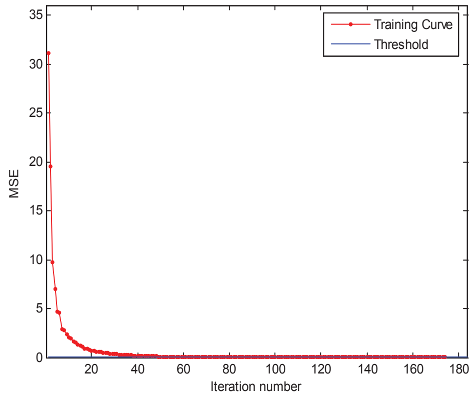

Figure 1. MSE versus iteration numbers

B. Network Selection Performance Evaluation

In this subsection, the performance of both proposed MAD network selection algorithm and the original MAD-based network selection algorithm will be evaluated and compared. To applying the proposed MAD-based network selection algorithm, user observational probability at particular time instance is calculated, then combined with user handoff probabilities, the network selection decision can be made based on (17), and the optimal access network can be chosen. On the other hand, to apply the original MAD-based network selection algorithm, user observational probabilities are calculated, the candidate access network corresponding to the larger user observational probability will be chosen as the optimal access network. Assuming the arrival time of user calls meets Poisson distribution, and the duration of user calls is of exponential distribution.

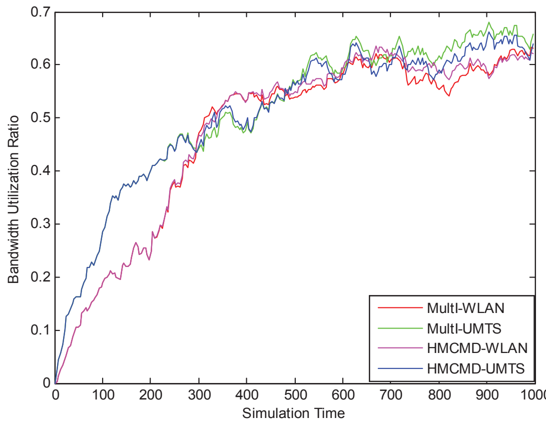

Figure 2. System bandwidth utilization ratio (user number =250)

In Fig. 2, system bandwidth utilization ratios of UMTS and WLAN obtained from applying both proposed and original MAD-based algorithms is plotted. It can be seen from the figure when the systems reaches relatively stable status, i.e., the simulation time being larger than 400, the difference of system bandwidth utilization ratios obtained from the proposed MAD-based algorithm is smaller than that from original MAD-based algorithm, indicating the load balance between two networks can be achieved from the proposed MAD algorithm, this is because besides current network status and user service requirement, the proposed algorithm also considers user long-term handoff information in selecting the optimal access network.

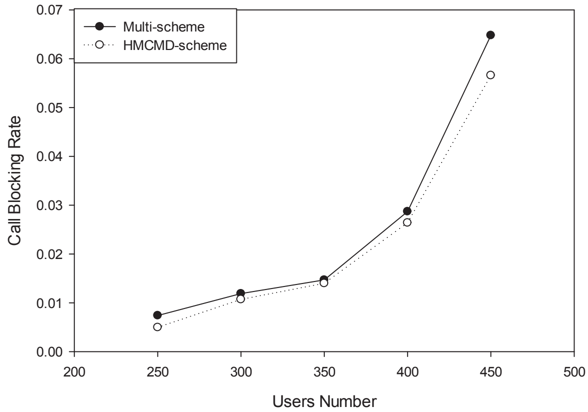

Figure 3. User call blocking rate

In Fig. 3, user call blocking rate of the integrated network versus user numbers obtained from both the proposed and original MAD algorithms is plotted. It can be seen from the figure that user call blocking probability increases with the increase of user numbers. Comparing to original MAD based algorithm, the proposed algorithm offers smaller call blocking probability.

V. CONCLUSIONS

In this paper, the problem of network selection in heterogeneous wireless networks is considered and a novel MAD-based access network selection algorithm is proposed. Through evaluating user handoff information based on network and user historic information, the optimal network selection algorithm which combines network current information, user service requirement and network/user historic information can be achieved. Numerical results show that the proposed algorithm offers better call block rate and achieves balanced load status compared to the original MAD-based network selection algorithm.

REFERENCES

[1] H. Tabrizi, G. Farhadi, J. Cioffi, "A learning-based network selection method in heterogeneous wireless systems," 2011 IEEE Global Telecommunications Conference (GLOBECOM 2011), pp.1-5, Dec. 5-9, 2011.

[2] I. Malanchini, M. Cesana, N. Gatti, "Network selection and resource allocation games for wireless access networks," IEEE Transactions on Mobile Computing, no. 99, 2012.

[3] S. J. Wu, C. T. Wu, J. Y. Chang, "Fuzzy-based self-interactive multi-objective evolution optimization for reverse engineering of biological networks," IEEE Transactions on Fuzzy Systems, vol. 20, no. 5, pp. 865-882, Oct. 2012.

[4] P. TalebiFard, V. Leung, "A dynamic context-aware access network selection for handover in heterogeneous network environments," 2011

IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp.385-390, April 10-15, 2011.

[5] H. Y. Cui, Q. J. Yan, Y. L. Cai, Y. Gao, L. Wu, "Heterogeneous network selection using a novel multi- attribute decision method," Communications and Networking in China, 2008 (ChinaCom 2008), pp.153-157, Aug. 25-27, 2008.

[6] L. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," Proceedings of the IEEE, vol. 77, no. 2, pp.257-286, Feb. 1989.

[7] L. C. Zhang, H. Zou, F. C. Yang, "Multi-attribute group decision making-based decentralized web service selection," 2010 International Conference on Service Sciences (ICSS), pp. 82-87, May 13-14, 2010.

[8] S. J. Yang, W. C. Tseng, "Utilizing weighted rating of multiple attributes scheme to enhance handoff efficiency in heterogeneous wireless networks," 2011 International Conference on Wireless Communications and Signal Processing (WCSP 2011), pp.1-6, Nov. 9-11, 2011.

[9] M. Gollery, Tahoe Informatics, Incline Village, Nevada, USA, Handbook of Hidden Markov Models in Bioinformatics, June 12, 2008 by Chapman and Hall/CRC.

[10] L. Moss, Example of the Baum-Welch Algorithm, Q520, Spring 2008.