The QoE-oriented Heterogeneous Network Selection Based on Fuzzy AHP Methodology

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***Abstract*—The next generation of wireless communication will be characterized by heterogeneity. One of the challenges arisen is access selection among various radio access technologies. Meanwhile, the quality of experience (QoE) of user is becoming one of the most concerned topics. Analytic Hierarchy Process (AHP) has been popularly used in network selection, while this method is usually imprecise because consistency index in AHP does not accurately indicate users' perception. In order to deal with this problem as well as optimize the system performance, an effective fuzzy Analytic Hierarchy Process scheme for network selection is proposed in this paper, which takes the multiple criterions of quality of experience (QoE) into consideration. By introducing the fuzzy consistency, the performance of the proposed scheme is consistent with user preferences and experiences. The fuzzy AHP derives relative weights from consistent fuzzy comparison matrices, which eliminates both additional consistency test and modification for the comparison matrix. Simulation results are analyzed in aspects of *session quality*, *availability* and *instantaneity*, and it is indicated that the proposed scheme outperforms the traditional AHP method and load balancing oriented method.**

Keywords- QoE; heterogeneous; network selection; fuzzy AHP; consistency

I. INTRODUCTION

Motivated by the ever-increasing demand for wireless communications, the past few years has witnessed rapid development of varies of wireless networks. It is widely accepted that heterogeneity will be a prominent feature of the next-generation wireless system.

While heterogeneous networks bring multi-access benefit, new challenges also emerge as how to achieve orderly and efficient cooperation across heterogeneous radio networks. Furthermore, the mobile multimedia services are expected as the most promising killer-applications for the next generation wireless systems. As the prime criterion for quality evaluation of multimedia applications, quality of experience (QoE) becomes important to network (service) providers in order to reduce user churn and maintain, and it has been well studied in both the academia and industrial community [1-3]. For QoE, it comprises all elements of an end user's perception of using a service or product. QoE not only covers end-to-end Quality of Service (QoS) parameters such as coverage, throughput, delay, jitter, bit error rate (BER) and so on, but also contains user preference criterions such as cost, mean of score (MOS), mobility, etc. Therefore, an essential issue in heterogeneous radio environments is how to select the most appropriate network according to QoE evaluations including user preference, network capability and service characteristics.

Analytic hierarchy process (AHP) has been applied in many fields, such as network selection and satisfaction evaluation [4]. The relative importance of factors and sub-factors with respect to their parents are estimated through pair-wise comparison based on human's knowledge and experiences. In spite of its popularity, the method is often criticized for its inability to precisely represent human perception, the main reason for this imprecision lies in the *inconsistent* comparison matrices. As a result, AHP requires additional test of comparison matrix's consistency to avoid the violation of common sense that "A is more important than B, B is more important than C, however C is more important than A". However, problems still exist due to the fact that consistency index in AHP is not accurately consistent with user preference.

This paper proposes a fuzzy AHP (FAHP) scheme for network selection based on QoE evaluation in heterogeneous scenarios. In order to deal with the problem mentioned above and effectively capture the ambiguity in user requirements, fuzzy complementary matrix and fuzzy consistent matrix are introduced to relax the consistency requirement in conventional AHP. Then relative weights are deduced based on FAHP theory without consistency test and modification to the judgment matrix. According to [5], several key quality indicators (KQIs) are chosen in this paper to reflect the degree of QoE, including *availability*, *session quality*, and *instantaneity*. Meanwhile, a number of key performance indicators (KPIs) are account for each KQI as its subcategories. Therefore, the FAHP procedure will be implemented in double-layer assessments, and then gives performance ranking of all the networks.

The rest of the paper is organized as follows. The system model and framework for the proposed network selection is studied in Section II. The detail process of FAHP is presented in Section III. A scenario in heterogeneous networks and simulation results are shown in Section IV. Finally, the conclusion is given in Section V.

II. SYSTEM MODEL AND FRAMEWORK

In the typical scenario of heterogeneous radio system, several radio access technologies (RATs) are deployed and different RATs may overlap with each other. These networks are diverse in capabilities of data rates, mobility, coverage, charging mechanisms, etc. For the mobile user, all

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available networks are denoted as the set $\Omega = \{\text{AN}_1, \text{AN}_2, \cdots \text{AN}_K\}$. A network is available means that the pilot or beacon of the network can be detected and recognized by the user.

As shown in Figure 1, the resource assessment is decomposed into hierarchical levels. Several typical KQIs are considered to comprehensively to reveal the QoE of service in AN_k, $k = 1, 2, \cdots, K$. One KQI provides a specific aspect of the service performance. Meanwhile different KPIs are listed as sub-factors with respect to the upper layer KQIs.

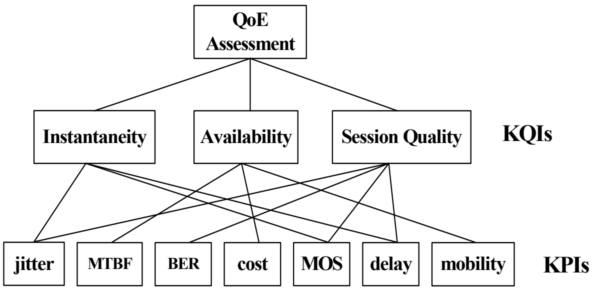

Figure 1. The hierarchy of resource assessment

A. KQIs and KPIs

Session Quality, *Availability* and *Instantaneity* are considered as the three typical KQIs in this paper. Each KQI is described as follows [5].

- **Session Quality—**It represents the collective effect of performances that mainly concern with the definition of the service. A common metric of session quality is the Mean Opinion Score (MOS). Besides, objective performance indicators are also included: delay, BER and jitter. Thus the degree of session quality is achieved by a composite of objective and subjective parameters.
- **Availability—**The service availability is expressed as a percentage of time during which the service is available and the customer has the ability to use the service. It relates to the maintainability performance during the service and the charge cost of the service. Mean time between failure (MTBF) is used as a important metric for multimedia service quality. Besides, cost-effectiveness and mobility are also considered.
- **Instantaneity—**It refers to the punctuality performance of the service. The more prompt service delivery is, the high grade of instantaneity is, especially for real time services. The instantaneity assessment should include MOS, delay and jitter.

B. Framework of network selection

Figure 2 shows the block diagrams of network selection based on QoE evaluation. The whole FAHP system is divided into three parts: sub-category estimator, weights estimator and overall-category estimator, all of which coordinate with each other to give the ranking of network alternatives.

Suppose that QoE assessment is decomposed into N aspects. Then for, $\mathbf{G}_i^k = (g_{i1}^k, g_{i2}^k, \cdots g_{iN_i}^k)$, $i = 1, 2 \cdots N$ denotes the KPI vector that the candidate AN_k is to be judged upon, where N_i KPIs are taken into account for the ith KQI. All the three parts of network selection are introduced based on AN_k as follows.

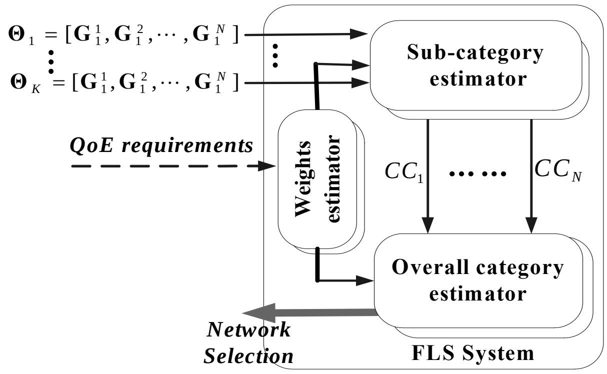

Figure 2. The block diagrams of network selection

Weights estimator is used to deduce the relative weights of KPIs and KQIs based on FAHP theory. According to user preferences described in QoE requirements, the relative weights of KPIs for ith KQI are deduced and denoted by a weight vector $W_i = (w_1, w_2, \cdots, w_{N_i})$. While $\boldsymbol{\alpha}_i = (\alpha_1, \alpha_2, \cdots, \alpha_N)$ stands for relative weights of different KQIs. The KQI weights and KPI weights are then distributed to overall-category estimator and sub-category estimator, respectively.

All KPI measures of each KQI are collected in the **sub-category estimator**. Meanwhile the desirable KPI measures and weights are obtained from QoE requirements. Fuzzy rating of each aspect is represented by a *closeness coefficient* based on the **TOPSIS** (Technique for Order Preference by Similarity to Ideal Solution). According to the concept of **TOPSIS**, the positive ideal solution (PIS) and the negative ideal solution (NIS) will be defined as $\mathbf{G}_i^+$ and $\mathbf{G}_i^-$, respectively [6]. Then the sub-category estimator calculates the distance of each alternative from PIS and NIS, which are denoted as d^+ and d^- respectively. In this paper, the distances are defined as (1) based on vector norms, since it can be proved that the vector norms satisfy the monotonic property required by TOPSIS method.

$$\begin{cases} d_{ik}^+ = \left\| \mathbf{G}_i^k - \mathbf{G}_i^+ \right\| = \left[\sum_{m=1}^{N_i} {w_m}^2 (g_{im}^k - g_{im}^+)^2 \right]^{1/2} \\ d_{ik}^- = \left\| \mathbf{G}_i^k - \mathbf{G}_i^- \right\| = \left[\sum_{m=1}^{N_i} {w_m}^2 (g_{im}^k - g_{im}^-)^2 \right]^{1/2} \end{cases} \tag{1}$$

Then the closeness coefficient for the *i*th aspect is defined as (2):

$$CC_i^k = \frac{d_{ik}^-}{d_{ik}^- + d_{ik}^+} \tag{2}$$

Overall-category estimator is designed to aggregate the estimation of all aspects to get the whole rank of available networks. The aggregated coefficient is defined as a *Grade of Service Index* (*GSI*)

$$GSI_k = \sum_{i=1}^{N} \alpha_i^k \cdot CC_i^k \tag{3}$$

where CC_i^k is the output of sub-category estimator for the *i*th KQI evaluation. It is worth pointing out that both KPI weights and KQI weights derived from Fuzzy AHP satisfy the consistency requirement, which will be discussed in the Section III. Therefore, according to the *GSI*, the candidate networks will be ranked and the best one can be selected.

III. DESIGN OF FUZZY AHP

To relax the consistency requirement in conventional AHP, fuzzy consistent matrix is introduced, which is well consistent with user's perception and meanwhile can capture the ambiguity in user requirements.

A. Basic concepts

Definition 2.1. [7] For the fuzzy matrix $\mathbf{R} = (r_{mn})_{N \times N}$, if $r_{mn} + r_{nm} = 1$ for any integer *m and n*, then $\mathbf{R}$ is a fuzzy complementary matrix.

Definition 2.2. [7] For the fuzzy complementary matrix $\mathbf{R} = (r_{mn})_{N \times N}$, if $r_{mn} = r_{mk} - r_{nk} + 0.5$ for any integer *m*, *n*, *k* given at random, then $\mathbf{R}$ is a fuzzy consistent matrix.

For a given user, the element r_{mn} is a fuzzy membership in that criterion *m* is more important than criterion *n* according to their contribution to the upper layer criterions. When one criterion compares to itself, it is expressed as $r_{mm} = 0.5$. According to definition 2.2, the inherent consistency of fuzzy consistent matrices can be proved by Theorem 1.

Theorem 1**:** For any fuzzy consistent matrix $\mathbf{R}$ described in definition 2.2, $\mathbf{R}$ satisfies the consistency requirement by user perception. Suppose *m* is more important than *n*, and *n* is more important than *k*, then *m* is more important than *k*.

Proof**:** For different criterions *m*, *n*, *k*, if *m* is more important than *n*, and *n* is more important than *k*, then we have $r_{mn} > 0.5$ and $r_{nk} > 0.5$. According to definition 2.2, $r_{mn} = r_{mk} - r_{nk} + 0.5$, then $r_{mk} = r_{mn} + r_{nk} - 0.5 > 0.5$. Hence**,** it is true that *m* is more important than *k*, which is consistent with user's common sense of consistency.

B. Fuzzy AHP process

Step 1: Construct pair-wise comparison matrices

It is required that the comparison matrices constructed is fuzzy consistent. As shown in Table I, comparison matrices can be obtained from pair-wise comparison, which is conducted similarly as the nine-point scale used in AHP.

TABLE I. FUZZY PAIR-WISE COMPARISON

Quantitative value	Fuzzy language
0.5	*A* is equally important as *B.*
0.6	*A* is a little important than *B.*
0.7	*A* is more important than *B.*
0.8	*A* is strongly important over *B.*
0.9	*A* is absolutely important over *B.*
0.1~0.4	If the quantitative value is *x* when *B* compares to *A*, then it is 1-*x* when *A* compares to *B.*

For KPI level, the consistent matrix is denoted as (4).

$$\mathbf{P} = (p_{mn})_{N \times N} \tag{4}$$

Step 2: Calculate relative weights

Relative importance of each criterion is derived from consistent matrices. Since element p_{mn} in $\mathbf{P}$ is the result of importance comparison between sub-factors *m* and *n*, p_{mn} is supposed to be a function of w_m and w_n. The following theorem gives the detailed function expression.

Theorem 2**:** $\mathbf{P} = (p_{mn})_{N \times N}$ is a fuzzy complementary matrix. Then $\mathbf{P}$ is a fuzzy consistent matrix if and only if $\exists\, W = (w_1, w_2, \cdots w_N)^{\mathrm{T}} \in R_+^N$, $\sum_{m=1}^{N} w_m = 1$.

$$st: \quad p_{mn} = \frac{1}{\theta} \ln \frac{w_m}{w_n} + 0.5 \tag{5}$$

where $1 \le m, n \le N$, and $\theta > 0$ is an adjustable parameter.

Proof**:** On one hand, if $\mathbf{P}$ is a fuzzy consistent matrix, then the KPI weight can be defined as

$$w_m = \frac{\exp(\frac{\theta}{N} \sum_{n=1}^{N} p_{mn})}{\sum_{m=1}^{N} \exp(\frac{\theta}{N} \sum_{n=1}^{N} p_{mn})} \tag{6}$$

Since $\sum_{m=1}^{M} w_m = 1$, by the definition of fuzzy consistent matrix

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$$\begin{aligned}\frac{1}{\theta}\ln\frac{w_m}{w_n} &= \frac{1}{N}\sum_{l=1}^{N}p_{ml} - \frac{1}{N}\sum_{l=1}^{N}p_{nl} \\ &= \frac{1}{N}N(p_{mn}-0.5) = p_{mn}-0.5\end{aligned} \tag{7}$$

Therefore, the equation (4) is satisfied.

On the other hand, if the equation (4) is true, that is, for $\forall m, n, k \in 1, 2, \cdots N$,

$$\begin{aligned}p_{mn} &= \frac{1}{\theta}\ln\frac{w_m}{w_n} + 0.5 = (\frac{1}{\theta}\ln\frac{w_m}{w_k} + 0.5) \\ &- (\frac{1}{\theta}\ln\frac{w_n}{w_k} + 0.5) + 0.5 = p_{mk} - p_{nk} + 0.5\end{aligned} \tag{8}$$

Obviously, $\mathbf{P} = (p_{mn})_{N\times N}$ is a fuzzy consistent matrix. Hereby, the poof is completed, and the weights can be constructed as (6). Moreover, this method to construct the weights is not occasional, instead it is reasonable according to Theorem 3.

***Theorem 3*:** For any fuzzy complementary matrix $\mathbf{P} = (p_{mn})_{N\times N}$, assume that the weight vector can be calculated by solving the following constraint programming problem

$$\begin{cases}\min\ f = \sum_{m=1}^{N}\sum_{n=1}^{N}(\frac{1}{\theta}\ln\frac{w_m}{w_n} + 0.5 - p_{mn})^2 \\ s.t. \sum_{m=1}^{N}w_m = 1,\ w_m > 0,\ m = 1, 2, \cdots, N\end{cases} \tag{9}$$

where $\theta > 1$ .Then the solution is

$$w_m(\theta, \mathbf{P}) = \exp(\frac{\theta}{N}\sum_{n=1}^{N}p_{mn}) \Big/ \sum_{m=1}^{N}\exp(\frac{\theta}{N}\sum_{n=1}^{N}p_{mn}) \tag{10}$$

***Proof*:** Firstly, according to the MSE (Mean Squared Error) principle, it is reasonable to form the constraint programming problem based on Theorem 2. Considering the *Lagrange* multiplier method, problem (9) can be transformed into (10), where $\lambda \geq 0$.

$$\min\ L(w,\lambda) = \sum_{m=1}^{N}\sum_{n=1}^{N}(\frac{1}{\theta}\ln\frac{w_m}{w_n} + 0.5 - p_{mn})^2 + \lambda(\sum_{m=1}^{N}w_m - 1) \tag{11}$$

In order to get the optimal solution, assume that $\frac{\partial L(w,\lambda)}{\partial w_m} = 0$, then we have

$$2\sum_{m=1}^{N}\left[\sum_{n=1}^{N}(\frac{1}{\theta}\ln\frac{w_m}{w_n} + 0.5 - p_{mn}) + \lambda w_m\right] = 0 \tag{12}$$

It is proved that for any fuzzy consistent matrix, the sum of all its element equals to $N^2/2$, and $\sum_{m=1}^{N}w_m = 1$. Therefore,

$$\sum_{m=1}^{N}\sum_{n=1}^{N}(\frac{1}{\theta}\ln\frac{w_m}{w_n} + 0.5 - p_{mn}) = 0 \tag{13}$$

Obviously, $\lambda = 0$. Hence, the solution can be calculated from (14).

$$\begin{cases}\sum_{n=1}^{N}(\frac{1}{\theta}\ln\frac{w_m}{w_n} + 0.5 - p_{mn}) = 0 \\ \sum_{m=1}^{N}w_m = 1\end{cases} \tag{14}$$

Then (10) has been satisfied.

Step 3: Closeness coefficient calculation

When all *N*-aspect measures are collected in the sub-category estimator, the fuzzy rating of each aspect is represented by a closeness coefficient based on the TOPSIS. Before calculating the closeness coefficient, the input measures need to be normalized in two situations, larger-the-better and smaller-the-better. For $\mathbf{G}_i^k = (g_{i1}^k, g_{i2}^k, \cdots g_{iN_i}^k)$, it is normalized as (15).

$$\begin{cases}\tilde{g}_{i1}^k = \min\left\{1, \frac{g_{i1}^k}{g_{i1}^*}\right\}, \text{for larger-the-better} \\ \tilde{g}_{i1}^k = \min\left\{1, \frac{g_{i1}^*}{g_{i1}^k}\right\}, \text{for smaller-the-better}\end{cases} \tag{15}$$

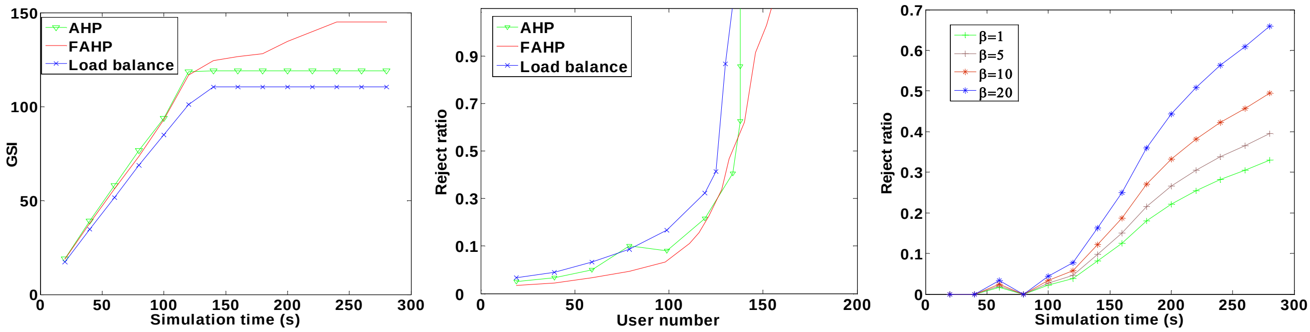
where $\mathbf{G}_i^* = (g_{i1}^*, g_{i2}^*, \cdots g_{iN_i}^*)$ is the desirable KPI vector. Then, for all *i*, *j*, $0 \leq g_{ij}^k \leq 1$. Meanwhile, PIS and NIS can be defined as $\mathbf{G}_i^+ = (1, 1, \cdots 1)$ and $\mathbf{G}_i^- = (0, 0, \cdots 0)$.

According to the concept of TOPSIS, the closeness coefficient for each aspect is calculated as (1-2) based on relative weights.

Step 4: Overall estimation and decision making

Similar to the sub-category estimation, both pair-wise comparison and relative weights construction are necessary in KQI-level estimation. With respect to different user, KQI preference may totally different. As to the KQI *comparison matrices*, it is denoted as $\mathbf{Q} = (q_{mn})_{N\times N}$, where q_{mn} describes the fuzzy membership in that the user is more care about criterion *m* than *n*. Based on comparison matrices, weights of different KQIs are obtained as $\alpha_m(\beta, \mathbf{Q})$ according to (10). The GSI value of each network is obtained through (3). Referring to the performance ranking of all the networks, the best network is selected.

It is worth mentioning that both θ and β are adjustable, which reveal the user's degree of attention on the relative importance. Assuming that $\alpha_m(\beta) > \alpha_n(\beta)$, then it is



(a) System revenue

(b) Reject ratio with total user number increases

(c) Reject ratio vs. adjustable parameter β

Figure 3. Simulation results

obvious that $\frac{\alpha_m(\beta)}{\alpha_n(\beta)}$ is a monotonically increasing function of β . For $\lim_{\beta \to 0} \left[\frac{\alpha_m(\beta)}{\alpha_n(\beta)} \right] = 1$, it means that when β becomes smaller, it blurs the difference in relative importance. For $\lim_{\beta \to 0} \left[\frac{\alpha_m(\beta)}{\alpha_n(\beta)} \right] = \infty$, it extremely emphasizes the difference in relative importance.

IV. Simulation And Results Analysis

A. *Simulation scenario*

Four wireless access networks are considered: WiMAX, WCDMA, $WLAN_1$, and $WLAN_2$. The pilots or the beacons of all reachable networks are transmitted periodically. Therefore, measurements criterions listed in Figure 1 can be always obtained by FAHP system for decision making. The subjective MOS value is calculated based on the *R*–factor model defined in [8]. MTBF can be deduced from system reliability model using basic reliability equations [9]. In the implementation scenario, three types of services are considered for simulation: VoIP, FTP and video, with Poisson arrival rates $\lambda = 0.6, 0.5, 0.6$ respectively. In order to check the scheme's performance under heavy load, it is assumed that the serving rate (or the departure rate) of the system is smaller than arrival rate, which are $\mu = 0.4, 0.3, 0.4$ for VoIP, FTP and video, respectively.

Besides, two other schemes are given as comparisons to evaluate the performance of the proposed FAHP scheme, which are named as *AHP* scheme and *load balance* scheme, respectively. Load balance is a technique to distribute workload evenly across different RATs. In the simulation, load balance is realized by utilizing the network with the lightest load. Therefore this scheme improves global resource utilization by reducing regional congestion.

B. *Simulation results and further study*

Figure 3(a) shows the total revenue of the heterogeneous system in terms of GSI. The revenue upper bound achieved by load balance scheme is about 112. The AHP has a better performance with GSI upper bound at about 120, another considerable gain is achieved by the new proposed scheme, which has an upper bound at about 145, and the improvement becomes more obvious with increasing of arrival users. Compared to the previous two algorithms, FAHP expands network assessment from currently single layer to double layers. More importantly, fuzzy consistency concept is included in FAHP, which helps overcome the weakness of AHP in consistency and therefore makes reasonable decisions. Hence, the new proposed mechanism can find out the actual most appropriate network according to user-specific QoE requirements. Although AHP scheme takes multi-criterions into consideration, it is imprecise because consistency index in AHP does not accurately indicate user's perception. Consequently, system revenue degrades due to the mismatch between network capability and user services.

As indicated in Figure 3(b), the proposed scheme has the lowest reject ratio. Especially when the system is in heavy load situation, FAHP proves robustness due to its well "understanding" of the network situation. Therefore, the proposed scheme has a considerable gain of user number at the same level of reject ratio, especially when the system bears a heavy load.

In Figure 3(c), it depicts the comparison of reject ratio when using different parameter β . As analysis given in Section III, when $\beta = 1$, the difference in relative importance is blurred. Therefore, network selection is executed passively and user service will not be rejected easily. The larger β is chosen, the user is more sensitive to the relative importance of all factors.

Therefore, different strategies are implemented by choosing different θ and β. Under different circumstances they are adjust to upgrade the overall revenue. When there exists a network connection for the user, then a passive access strategy is adopted to avoid unnecessary vertical handoff. That means small θ and β are chosen to make the user less sensitive to relative importance of factors. Then, vertical handoff is not worth, since the potential revenue improvement may not be able to compensate the cost caused by traffic handoff. The detail of this point will be studied in near future.

V. CONCLUTION

In this paper, an effective network selection scheme considering multiple QoE criterions is proposed to meet the challenges of multimedia applied in heterogeneous radio environments. For the sake of QoE evaluation, this scheme decomposes heterogeneous resource evaluation into multidimensional aspects, which are represented by KQIs. Meanwhile several KPIs are taken into account for each KQI, including both objective and subjective criterions. Then a fuzzy AHP system is designed for QoE reasoning and then gives performance ranking of all the network alternatives. Numerical results show that the proposed scheme outperforms the conventional AHP scheme and the load balance scheme.

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