A Revenue-Maximizing Scheme for Radio Access Technology Selection in Heterogeneous Wireless Networks with User Profile Differentiation

Elissar Khloussy[1], Xavier Gelabert[2], and Yuming Jiang[1]

[1] Department of Telematics, NTNU, Norway
[2] Huawei Technologies Sweden AB, 16440 Kista, Sweden
{khloussy,jiang}@item.ntnu.no, xavier.gelabert@huawei.com

Abstract. In this paper, the problem of radio access technology (RAT) selection in heterogeneous wireless networks (HWNs) is tackled from an operator's perspective, with the objective of maximizing the generated revenue. Two user profiles are considered with different priority levels. An integrated 3GPP Long Term Evolution (LTE) and Wireless Fidelity (WiFi) network is considered as an example of HWN, where LTE is used mainly for the high-priority class, while a portion of its resources, defined by a load threshold, can be shared by the low-priority class. A Markovian model is defined and validated by simulation. Subsequently, the value of the load threshold for resource sharing in LTE is investigated, and an optimization problem is formulated to find the optimal threshold for which the revenue is maximized.

Keywords: Heterogeneous Wireless Networks, Resource Management, Revenue Maximization.

1 Introduction

With the tremendous evolution of wireless network technologies and the ever increasing demand from users to be always best connected, various radio access technologies (RATs) have been standardized and deployed. It has become very likely to encounter geographical areas covered by more than one RAT, each with different characteristics in terms of latency, coverage, and link capacity. By providing more connection options than a single-RAT network, a heterogeneous wireless network (HWN) offers the operator additional tuning knobs to meet the users' needs and at the same time generate higher revenues.

In this paper, we consider the scenario of a HWN that is run by a single operator and where two RATs are integrated, namely 3rd Generation Partnership Project (3GPP) Long Term Evolution (called LTE hereafter) and Wireless Fidelity (WiFi). This network scenario is rather practical and can be found from real networks. Moreover, mobile devices and smartphones supporting both technologies are now available in the market. With these factors combined, it becomes of interest to investigate mechanisms that allocate users' connections effectively, allowing an efficient utilization of the system resources.

T. Bauschert (Ed.): EUNICE 2013, LNCS 8115, pp. 66–77, 2013.

In order to take advantage of the combined features of the different coexisting RATs in a HWN, a good coordination among these RATs is required. This involves the adoption of common radio resource management (CRRM) strategies, a critical factor for the success of HWNs. Among the various CRRM functionalities [1], RAT selection is known to be most fundamental. It can be *user-centric* or *operator-centric*. Typically, a user-centric RAT selection scheme considers the user's preferences as objective, such as signal strength and access cost. An operator-centric one is oriented towards maximizing the operator's interests, e.g. the overall HWN capacity, and takes into consideration the network-related parameters such as RATs' loads and capabilities as well as the existing service types [1]. In this paper, we address an *operator-centric* RAT selection with specific objective of maximizing the operator's revenue.

A thorough analysis and classification of the recently proposed radio resource management procedures in HWNs can be found in [1, 2]. In [1], the authors provided a case study that illustrated the potential gain offered by CRRM especially in terms of capacity enhancement. In [3], a CRRM scheme that minimizes the vertical handover rate and service cost while achieving the desired quality of service (QoS) was proposed. In CRRM, RAT selection functionality has gained a particular attention in the literature. For example, Gelabert et al. provided in [4] a framework to allocate services in HWNs with the help of Markov chain. The model was used to compare and evaluate the performance of various RAT selection policies that fall into three categories: service-based, load-balancing based and multi-mode terminal driven strategies. However, the users' perceived QoS was the main focus of most of the proposed RAT selection algorithms e.g., [5–7].

Very few *operator-centric approaches with the objective of maximizing the operator's revenue* can be found. In [8], a fuzzy neural-based CRRM strategy was presented. Both techno-economic cognitive mechanisms and user differentiation concepts were investigated, with the aim of guaranteeing the user satisfaction maintained at a certain target level, while also considering the network's generated revenue. However, the proposed CRRM strategy, based on a fuzzy neural network, is complex for implementation in real networks. In our early work [9], CRRM strategies based on call admission control and vertical handover were presented and compared. It was shown that a significant increase of revenue could be incurred by the adoption of CRRM policies. However, the evaluation in [9] was only based on simulation. Other admission control where decisions are taken dynamically to maximize the operator's revenue can also be found in the literature [10, 11].

In this paper, we propose a new scheme for RAT selection that is intuitive and easy to implement. In addition, the proposed approach is devised to work at a different level in the sense of providing the operator with the initial setting of an important parameter i.e., the load threshold in LTE, at the early planning phase of the system. With an appropriate setting of the load threshold, system resources can be used efficiently and the revenue be maximized. To demonstrate its use, a specific example of HWN, which is an integrated LTE/WiFi network, is considered. Also, for practical reasons, only two user profiles with different priority levels are offered and a load threshold is defined in LTE to reserve resources to the high-priority users. Importantly, an analytical model for the proposed scheme is presented and validated by simulation. In addition, we investigate the impact of the choice of the load threshold on the revenue and solve the corresponding optimization problem.

The paper is organized as follows. Sec. 2 describes the system model and the proposed RAT selection scheme. In Sec. 3, the different elements of the Markovian model are introduced. Sec. 4 presents the results obtained by the model and the simulation. In Sec. 5 we introduce and solve the optimization problem for finding the optimal threshold value, and Sec. 6 concludes the paper.

2 The System Model and User Profile-Based RAT Selection

We consider an integrated LTE/WiFi heterogeneous network. While WiFi offers broadband data transmission for a limited coverage area at low cost and simple control plane, LTE provides more efficient services and better QoS with wider coverage area, at bandwidth and cost comparable to that of the WLAN [12, 13].

In the considered scenario, a user can be either residing in an area covered by LTE only, or in a dual coverage area with a probability P_{dual}. Two user profiles C_1 and C_2 are provided. Class C_1 has higher priority than class C_2. Practically, the prioritized class C_1 targets the business sector, known to be more sensitive to the perceived QoS than the charged price. The low-priority class C_2 targets the individual users who care mainly about the access cost, and don't have strict requirements with respect to the QoS. Naturally, C_1 users get faster connection speed by paying higher connection fees as compared to users belonging to C_2 class. In terms of admission to LTE, C_1 users have a privilege in using LTE resources over C_2. For this purpose, a load threshold θ is defined as the percentage of LTE capacity that the low-priority users are allowed to share with C_1 users.

The RAT selection block, as illustrated in Fig. 1, requires mainly two types of inputs: network parameters (LTE and WiFi loads and the value of θ), and user parameters (the user's class of service, and whether the user is in a dual-coverage area or not). It generates as output the decision of admitting or blocking the arriving session, as well as the selected RAT in the case where the admission of the session is successful.

Based on the RATs characteristics and the considered user profile differentiation, we propose the following RAT selection strategy:

- When a new C_1 session arrives, it is admitted to LTE as long as LTE has enough available resources. This policy reflects the operator's willingness to offer better QoS for C_1 users whose contribution, in terms of generated revenue, is more significant than C_2 users.
- When a new C_2 session arrives, the RAT selection module tries to admit this session into WiFi first. This way, the operator benefits from WiFi capacity

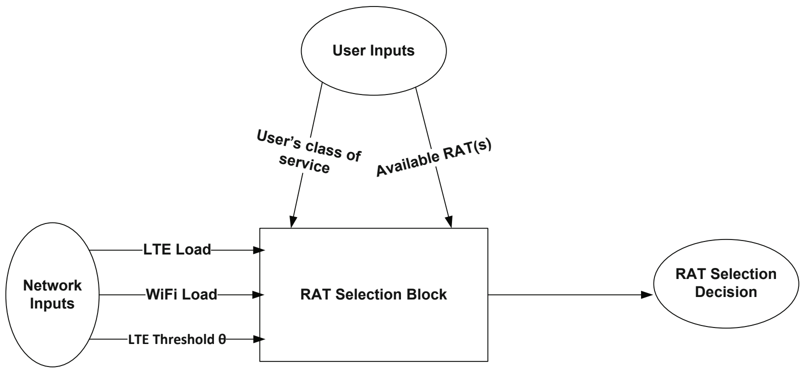
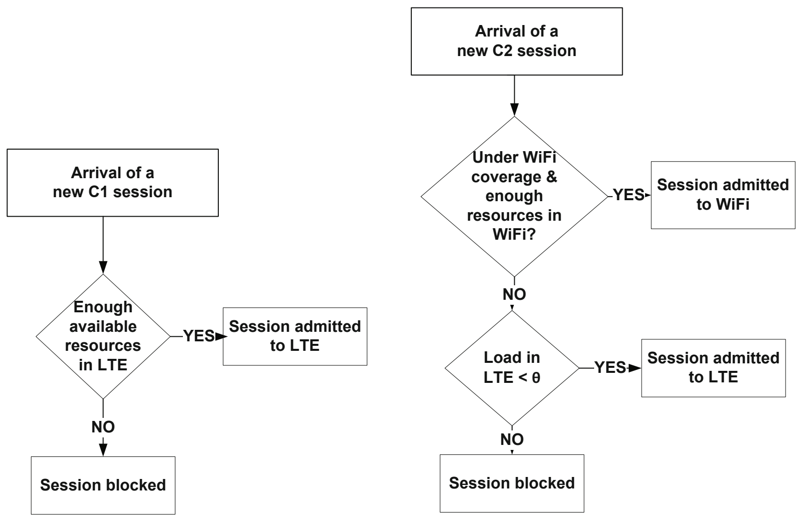


Fig. 1. RAT selection block

to accommodate sessions belonging to the low-priority profile, keeping more resources in LTE available for C_1 class. In the case where the admission of the new C_2 session to WiFi is not possible (user out of WiFi coverage or WiFi is overloaded), and with traffic load in LTE below the threshold θ, the RAT selection module allows the admission of the new C_2 session to LTE.

– When the load in LTE exceeds θ, only C_1 sessions are admitted.



(a) Arrival of C_1 session. (b) Arrival of C_2 session.

Fig. 2. Algorithm for RAT selection

Corresponding to the above strategy, Fig. 2 illustrates the RAT selection algorithm. Note that though the proposed RAT selection scheme gives higher priority to C_1 class in using LTE, it also tries to keep the QoS of C_2 class from degrading drastically. This is realized by not allowing C_1 users to compete with C_2 users in using WiFi resources, even when LTE is overloaded.

3 The Analysis

The considered scenario can be modeled by the means of a 3D Markov chain. Each state $S(i, j, k)$ represents a state of the network in which i sessions of class C_1, and j sessions of class C_2 are being served in LTE, and k sessions of class C_2 are being served in WiFi.

The transition from one state to another is initiated upon the arrival/departure of a C_1 or C_2 session to/from any of the two RATs. We assume the traffic generated in both classes C_1 and C_2 to be inelastic, and arriving according to Poisson processes with rates λ_1 and λ_2 respectively. As for the session holding times, they follow exponential distributions with mean values $1/\mu_1$ and $1/\mu_2$ for classes C_1 and C_2 respectively. We would like to stress that, at the session level, these assumptions are rather realistic [14].

3.1 The Set of Feasible States

In the proposed scenario, we assume a fixed total bandwidth for each of the RATs, namely C_{lte} and C_{wifi} for LTE and WiFi respectively, each being partitioned into a fixed set of basic bandwidth units (bbu) as in, e.g. [15, 16].

A state of the network is called feasible if each of its dimensions does not exceed the limit defined by the RATs capacities. Let I, J and K denote the maximum values of i, j and k that can be accommodated by the system. Since C_1 class has the priority in using LTE up to the totality of its resources, and so does C_2 in WiFi, The values of I and K can be defined as: $I = \left\lfloor \frac{C_{lte}}{b_1} \right\rfloor$, and $K = \left\lfloor \frac{C_{wifi}}{b_2} \right\rfloor$, where b_i is the number of bbu required for a C_i session, and $\lfloor x \rfloor$ is the largest integer not greater than x. Here, we highlight that while the main interest of network operators is to increase their revenue, it is also critical that the QoS level remains acceptable, which can be ensured with properly chosen b_i. There are various techniques for calculating b_i, and a promising technique is *effective bandwidth* [17], but this is out of the scope of the present paper. Here we assume b_i is given.

As for J, it can be expressed as the minimum of two quantities, namely the maximum number of C_2 sessions allowed to be in LTE assuming that no C_1 sessions are being served in the system, and the number of C_2 sessions that can be admitted to LTE after serving the i ongoing C_1 sessions. Hence, J can be defined as follows:

$$J(i) = min(\left\lfloor \theta \frac{C_{lte}}{b_2} \right\rfloor, \left\lfloor \frac{C_{lte} - b_1 \cdot i}{b_2} \right\rfloor). \tag{1}$$

Hence, the set of feasible states in the proposed system can be written as:

$$S = \{S(i, j, k) |\, 0 \leq i \leq I\,,\, 0 \leq j \leq J(i), 0 \leq k \leq K\}. \tag{2}$$

Table 1. Transition rates from generic state $S(i, j, k)$

To State	Rate	Condition
$S(i+1, j, k)$	λ_1	$i < I$
$S(i-1, j, k)$	$i.\mu_1$	$i > 0$
$S(i, j, k+1)$	$\lambda_2.P_{dual}$	$k < K$
$S(i, j, k-1)$	$k.\mu_2$	$k > 0$
$S(i, j+1, k)$	$\lambda_2.(1 - P_{dual})$	$j < J(i) \wedge k < K$
	λ_2	$j < J(i) \wedge k = K$
$S(i, j-1, k)$	$j.\mu_2$	$j > 0$

3.2 State Transitions

Having defined the set of feasible states, we need to specify the transitions between the different states in order to build the transition rate matrix **Q**. The transition rates from a given state $S(i, j, k)$ to any of its neighboring states are provided in Table 1. After creating **Q** matrix, the next step is to find the stationary probability vector. This can be obtained with the help of numerical methods, and specifically we use the Successive Overrelaxation Method (SOR) [18]. The steady state probability allows us to derive the needed performance metrics as shown in the following subsection.

3.3 Performance Metrics

Average Number of Sessions. The average number of sessions admitted in the system for both classes is defined as follows:

$$E[x] = \sum_{S(i,j,k) \in S} x \cdot P_{(i,j,k)} \ , x \in \{i, j, k\} \,. \tag{3}$$

where $E[x]$ is the average value of x, and $P_{(i,j,k)}$ is the steady state probability for the state $S(i, j, k)$.

Blocking Probability. By (3), the average number of users is found, which also represents the carried traffic in the system. This latter can be computed as the portion of the offered traffic A ($A = \lambda/\mu$) that has been admitted successfully to the system as follows:

$$E[x] = A_\gamma \cdot (1 - P_{b,\gamma}), \gamma \in \{1, 2\} \,. \tag{4}$$

where $P_{b,\gamma}$ is the blocking probability of class C_γ, $x = i$ for $\gamma = 1$, and $x = j + k$ (with $E[j + k] = E[j] + E[k]$) for $\gamma = 2$. Therefore, the blocking probability of class C_γ is computed as:

$$P_{b,\gamma} = 1 - \frac{E[x]}{A_\gamma}, \gamma \in \{1, 2\} \,. \tag{5}$$

Table 2. System Parameters

Parameter	Symbol	Value
Capacity of LTE	C_{lte}	10
Capacity of WiFi	C_{wifi}	5
Number of bbu required per C_1 session	b_1	2
Number of bbu required per C_2 session	b_2	1
Throughput per bbu in LTE	r_{lte}	1Mbps
Throughput per bbu in WiFi	r_{wifi}	1Mbps
Arrival rate of C_1 class	λ_1	$1/60\,s^{-1}$
Arrival rate of C_2 class	λ_2	$1/30\,s^{-1}$
Session holding time of C_1 class	$1/\mu_1$	200 s
Session holding time of C_2 class	$1/\mu_2$	150 s
Dual coverage probability	P_{dual}	0.6

Throughput. The throughput of a certain class of service is the product of its carried traffic by the throughput of the total allocated bbu for this class in the serving RAT. Hence, the throughput for service class C_γ can be defined as:

$$Th_\gamma = \sum_\alpha E[x] \cdot b_\gamma \cdot r_\alpha \ , \gamma \in \{1, 2\} \, . \tag{6}$$

where: r_α is the throughput (in Mbps) per bbu of RAT α, $x = i$ for $\gamma = 1$, $x = j$ for $(\gamma = 2 \wedge \alpha = \text{LTE})$, and $x = k$ for $(\gamma = 2 \wedge \alpha = \text{WiFi})$.

4 Validating the Analysis

To validate the analytical model, a system-level simulation has been conducted in Matlab. The simulation was run for 5000 time units, and the same simulation repeated 100 times to get its average performance. The applied RAT selection policy in simulation follows the state feasibility conditions imposed for the Markov model. For ease of presentation, we used the settings in Table 2 to analyze the performance of the proposed RAT selection policy. The analysis may be further extended for other more realistic settings. The results are plotted in Fig. 3 and Fig. 4, with the 95% confidence intervals provided. the results show a good matching between the model and the simulation, proving the validity of our proposed Markovian model.

Fig. 3 depicts the blocking probabilities for classes C_1 and C_2, considering different values of θ, ranging from 0 i.e., no C_2 sessions can be admitted to LTE, to 1 where the whole capacity of LTE can be shared by traffic of both classes. It is shown that, when the admission to LTE is restricted to C_1 class solely, the low-priority class suffers from extremely high blocking probability. This is a consequence of the limited coverage and smaller capacity of WiFi as compared to LTE. Therefore, denying the access of C_2 sessions to LTE decreases their probability of being admitted to the system. However, when the admission of C_2 class to LTE is allowed, through an increase of the value of θ, the blocking probability

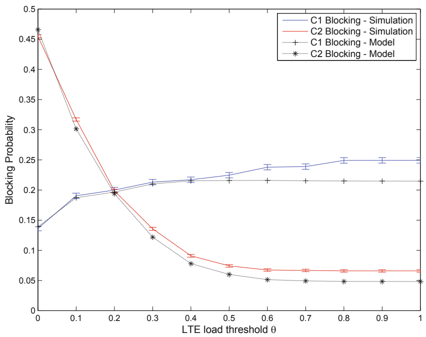


Fig. 3. C_1 and C_2 blocking probabilities for different values of θ

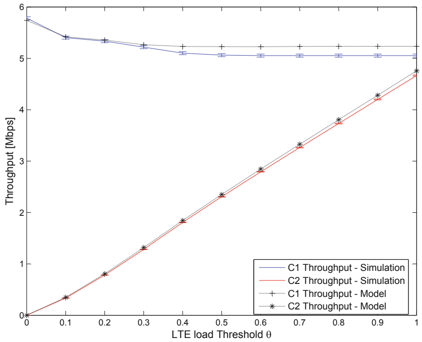


Fig. 4. C_1 and C_2 throughput variations for different values of θ

of C_2 class drops fast, leading to an enhancement of the QoS perceived by the low-priority users. On the other hand, the blocking probability of class C_1 is not severely affected by the admission of C_2 sessions to LTE.

Another performance metric is depicted in Fig. 4, namely the throughput. With the increase of the value of θ, the throughput of C_2 sessions increases fast. This is directly related to the decrease of the blocking probability of C_2 class in similar conditions as discussed earlier. Also, even when C_2 sessions are allowed to share the entire capacity of LTE, this does not cause a dramatical decrease of the throughput of C_1 sessions, which are granted the double number of bbu per session as compared to C_2 class.

5 Revenue Maximization

In the previous sections, a RAT selection strategy in HWNs with profile differentiation has been proposed, and several performance metrics have been derived with the help of a Markovian model. According to the proposed scenario, the number of users that can be admitted to LTE is directly related to the value of the load threshold θ. Therefore, the parameter θ plays a key role in determining the revenue generated in the overall system, and any variation of its value can cause an increase or decrease of the operator's profit. In this section, we aim to find the optimal value of θ that leads to maximizing the network revenue, while guaranteeing that the user's perceived QoS in terms of blocking probability stays below a predefined threshold β.

Let R_1 and R_2 denote the prices that users pay for C_1 and C_2 connections respectively, with $R_1 > R_2$. A simple way to formulate the operator's average revenue is:

$$Avg\_Rev = R_1 \cdot E[i] + R_2 \cdot (E[j] + E[k]) \tag{7}$$

where the detailed expressions of $E[i]$, $E[j]$ and $E[k]$ are given by (3) with $x = i$, $x = j$ and $x = k$ respectively.

The optimization problem for revenue maximization can be formulated as:

$$\begin{aligned} \underset{\theta}{\text{maximize}} \quad & Avg\_Rev \\ \text{subject to} \quad & \theta \in S_\theta \\ & P_{b,i} \leq \beta_i \ , i \in \{1, 2\} \, . \end{aligned} \tag{8}$$

where S_θ is the set of values of θ chosen as: $S_\theta = \{0, 0.1, 0.15, 0.2, .., 1\}$.

The admission of C_2 sessions to LTE is dependent on the value of θ. For each combination of values of the offered traffic loads A_1 and A_2 of C_1 and C_2 respectively, we intend to find the optimal threshold θ^* that solves the optimization problem in (8). For this purpose, we use Algorithm 1.

Algorithm 1. Algorithm for finding the optimal threshold θ^*

```
Input: A_1, A_2
Output: θ*, Avg_Rev*
Initialize: sol ← 0 , Avg_Rev* ← 0
for all θ in S_θ do
   Find P_b,1, P_b,2, Avg_Rev
   if (P_b,1 ≤ β_1) ∧ (P_b,2 ≤ β_2) then
      sol ← 1
      if Avg_Rev > Avg_Rev* then
         Avg_Rev* ← Avg_Rev
         θ* ← θ
      end if
   end if
end for
if sol=1 {a solution has been found} then
   Return θ*, Avg_Rev*
end if
```

As shown in Algorithm 1, to find θ^* for some given values of the offered load traffic of C_1 and C_2 profiles, we first start with the smallest value of θ (i.e. $\theta = 0$), and keep increasing it until we find the value that provides a feasible solution for the considered optimization problem. Once found, we keep increasing the value of θ to check if highest revenue could be achieved without violating the blocking probability constraints. If there are more than one value of θ that ensure the same highest revenue, we have interest in choosing the smallest θ^*, as it corresponds to a smaller blocking probability for the high-priority class.

Fig. 5 depicts the selected values of θ^* for different traffic loads of C_1 and C_2 classes. It shows that, for small values of A_1, C_2 class can share up to 60% of C_{LTE}. When A_1 increases, the value of θ^* decreases, and it becomes less likely to find a θ^* that solves the optimization problem.

Finding the optimal threshold has an important impact on the generated revenue. This can be deduced from Fig. 6 that depicts the revenue of the network for arbitrary load thresholds compared to the revenue achieved with the optimal

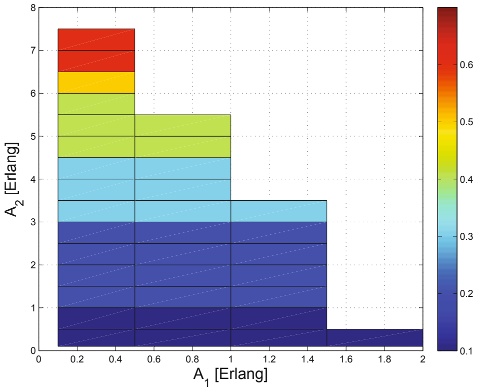


Fig. 5. Optimal threshold value for $\beta_1 = 5\%$ and $\beta_2 = 10\%$

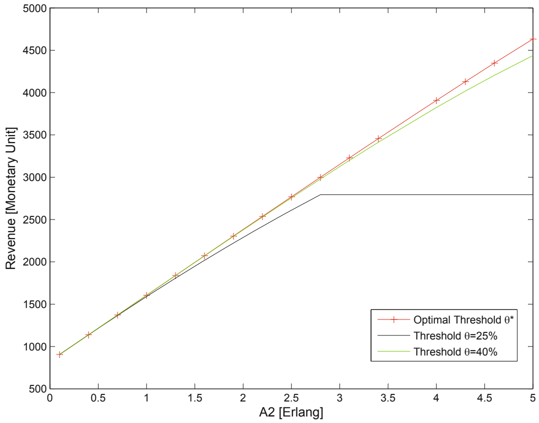


Fig. 6. Revenue for arbitrary and optimal load thresholds, $A_1 = 0.8$ Erlang

threshold, for an offered traffic $A_1 = 0.8$ of class C_1. Fig. 6 clearly shows that the optimal threshold always achieves the highest revenue.

When the offered traffic for C_2 is low, e.g. $A_2 = 1.5$, an arbitrary threshold of 25% or 40% provide the same revenue as θ^*. However, for a load traffic of C_2 profile exceeding the value of 3, a threshold of 25% is no more sufficient. It leads to significantly lower achieved revenue than the optimal threshold, because it cannot satisfy the QoS constraint for C_2 profile. This choice of the threshold results in blocking C_2 sessions, and hence deprives the operator from the profit that could be achieved from the potential admittance of the blocked C_2 sessions if a proper choice of the load threshold was initially made. These results are indeed consistent with the ones given by Fig. 5. Similarly, when choosing the value of 40% for the LTE load threshold, less revenue could be achieved due to blocking of C_2 sessions when the traffic load of this latter is high. The blocking probabilities $P_{b,1}$ and $P_{b,2}$ for the same values of θ are presented in Table 3. For

Table 3. Values of $P_{b,1}$ and $P_{b,2}$, $A_1 = 0.8$ Erlang

		$\theta = 25\%$	$\theta = 40\%$	θ^*
$A_2 = 1.1$	$P_{b,1}$	0.33 %	0.36 %	0.31 %
	$P_{b,2}$	2.2 %	0.77 %	2.52 %
$A_2 = 3.1$	$P_{b,1}$	0.55 %	0.99 %	0.99 %
	$P_{b,2}$	**11.3 %**	1.52 %	1.52 %
$A_2 = 4.1$	$P_{b,1}$	0.61 %	1.34 %	1.30 %
	$P_{b,2}$	**16 %**	3.44 %	3.7 %

targeted blocking probabilities $\beta_1 = 5\%$ and $\beta_2 = 10\%$, a choice of threshold of 25% will cause unacceptable blocking probabilities for C_2 class when the load of this latter exceeds the value of 3. Therefore, the network operator has interest in knowing, based on a pre-assessment of the users' load and profiles, the optimal setting of the load threshold in LTE that allows the maximum number of users to be admitted to the system and leads to the highest achievable revenue.

6 Conclusion

In this paper, we present an algorithm for RAT selection in HWNs where different user profiles are supported, with the objective of enhancing the system capacity and maximizing the network operator's revenue, without degrading the QoS. An LTE/WiFi heterogeneous network is chosen as a representative of HWN, and a load threshold in LTE is defined to reserve resources for the high-priority user profile. Sessions of low-priority are preferably admitted to WiFi, unless the user was not in a dual-coverage area or WiFi was overloaded. In these latter cases, LTE's load is considered to decide on whether to admit the low-priority session to LTE or reject it. A 3-D Markov model is defined to study and analyze the proposed RAT selection scheme that is further validated by simulation. Then, an optimization problem is presented, and a solution is provided in order to find the optimal load threshold that ensures the highest achievable revenue, while satisfying the blocking probability constraints. Finally, the importance of defining the optimal value of the load threshold is highlighted.

References

1. Da Silva, A.P., et al.: Common Radio Resource Management for Multiaccess Wireless Networks. In: Cavalcanti, F., Andersson, S. (eds.) Optimizing Wireless Communication Systems, pp. 233–265. Springer (2009)
2. Piamrat, K., et al.: Radio Resource Management in Emerging Heterogeneous Wireless Networks. Computer Communications 34, 1066–1076 (2011)
3. Hasib, A., Fapojuwo, A.: Analysis of Common Radio Resource Management Scheme for End-to-End QoS Support in Multiservice Heterogeneous Wireless Networks. IEEE Trans. Vehic. Tech. 57, 2426–2439 (2008)

4. Gelabert, X., et al.: A Markovian Approach to Radio Access Technology Selection in Heterogeneous Multiaccess/Multiservice Wireless Networks. IEEE Trans. Mobile Comput. 7, 1257–1270 (2008)
5. Song, W., et al.: Resource Management for QoS Support in Cellular/WLAN Interworking. IEEE Network Magazine 19, 12–18 (2005)
6. Niyato, D., Hossain, E.: A NonCooperative Game-Theoretic Framework for Radio Resource Management in 4G Heterogeneous Wireless Access Networks. IEEE Trans. Mobile Comput. 7, 332–345 (2008)
7. Falowo, O.E., et al.: Dynamic Pricing for Load-Balancing in User-Centric Joint Call Admission Control of Next-Generation Wireless Networks. Int'l. J. Comm. Syst. 23, 335–368 (2010)
8. Giupponi, L., et al.: An Economic-Driven Joint Radio Resource Management with User Profile Differentiation in a Beyond 3G Cognitive Network. In: IEEE Globecom (2006)
9. Khloussy, E., et al.: Maximizing Network Revenue Through Resource Management in Heterogeneous Wireless Networks. IEEE Symp. Comp. and Comm. (2011)
10. Yu, F., Krishnamurthy, V.: Optimal Joint Session Admission Control in Integrated WLAN and CDMA Cellular Networks with Vertical Handoff. IEEE Trans. Mobile Comput. 6, 126–139 (2007)
11. Chen, H., et al.: Guard-Channel-Based Incremental and Dynamic Optimization on Call Admission Control for Next-Generation QoS-Aware Heterogeneous Systems. IEEE Trans. Veh. Tech. 57, 3064–3082 (2008)
12. Kim, D.K., et al.: A New Call Admission Control Scheme for Heterogeneous Wireless Networks. IEEE Trans. Wirel. Comm. 9, 3000–3005 (2010)
13. The 3rd Generation Partnership Project, `http://www.3gpp.org/lte-advanced`
14. Bonald, T., Roberts, J.W.: Internet and the Erlang formula. ACM SIGCOMM Comput. Commun. Rev. 42, 23–30 (2012)
15. Falowo, O.E., Chan, H.A.: Multiple-RAT Selection for Reducing Call Blocking/Dropping Probability in Cooperative Heterogeneous Wireless Networks. J. on Wirel. Comm. and Netw. (2012)
16. Nasser, N., Hassanein, H.: Dynamic Threshold-Based Call Admission Framework for Prioritized Multimedia Traffic in Wireless Cellular Networks. Globecom 2, 644–649 (2004)
17. Kelly, F.: Notes on effective bandwidths in Stochastic Networks: Theory and Applications, Royal Statistical Society. Lecture Notes Series, vol. 4. Oxford University Press (1996)
18. Stewart, W.J.: Probability, Markov Chains, Queues and Simulation (2009)