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Elissar Khloussy

Doctoral thesis

NTNU

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Thesis for the Degree of
Philosophiae Doctor
Faculty of Information Technology
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Department of Information Security
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Thesis for the Degree of Philosophiae Doctor

Trondheim, May 2018

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# Abstract

Wireless networks have witnessed a great success recently. The number of users along with the traffic demands have grown exponentially. Therefore, the wireless resources of a single Radio Access Technology (RAT) might not be sufficient to meet this increase in traffic demand.

Recently, several new technologies have been standardized, which made it common to encounter geographical areas where two or more RATs have overlapping coverage, forming the so-called Heterogeneous Wireless Networks (HWNs). This gives the opportunity to exploit the pool of resources of the coexisting RATs in order to boost the capacity, and subsequently generate higher revenue. However, this requires coordination among the different RATs, known in the literature as Common Radio Resource Management (CRRM).

This work is devoted to shedding light on the importance of CRRM, and the role it can play in increasing the generated revenue in HWNs scenarios. This choice is dictated by the importance of the economic aspects for the success of the wireless services business. Moreover, this aspect has not been sufficiently addressed in the literature where the focus has been mainly on the user's perspective.

The considered system is a cellular / Wireless Local Area Network (WLAN) overlay network which can be easily found in real scenarios, and the emphasis is mainly on RAT selection which is the first involved CRRM component when a new connection request is received.

First, RAT selection schemes that prioritize the traffic with the highest contribution to the revenue are proposed, showing the impact that these schemes have on revenue as well as the Quality of Service (QoS). Additionally, the role of WLAN offloading in alleviating the traffic load from the cellular RAT is highlighted.

Second, revenue-maximizing RAT selection policies are implemented. To this end, Markov Decision Process (MDP) is used to derive the optimal policy. An investigation of MDP as a tool for modeling RAT selection problems has been conducted, including how to tune the involved parameters

in order to achieve the targeted goal.

Another aspect that is covered by this work is net neutrality, which can be seen as an additional constraint when taking RAT selection decisions. Applying net neutrality regulations involves providing equal treatment to all Internet traffic. However, it allows granting exemption to some non-Internet access traffic know as specialized services. This case has been integrated in the modeling of RAT selection policies, and the impact of net neutrality adoption on the performance of various RAT selection policies, each having different admission strategy, is shown. The results depict that, with a careful choice of the RAT selection strategy, the loss in revenue caused by applying net neutrality could be reduced.

The effect of net neutrality is then further investigated by considering different ways of bandwidth reservation for specialized services. The aim is to figure out which way of bandwidth reservation achieves better results, and to study the impact of the ratio of reserved bandwidth for specialized services on the revenue. The results indicate that it would be more beneficial to dedicate bandwidth for specialized services in the whole HWN as compared to reserving the bandwidth in cellular RAT only, as the QoS experienced by the Internet access services is less affected in the first case.

In this research work, RAT selection problem is tackled from an operator's perspective. However, both operator's and user's perspectives can be seen as complimentary. While the focus is on revenue maximization, QoS metrics are considered when comparing the studied RAT selection schemes.

# Preface

This thesis is submitted in partial fulfillment of the requirement for the degree of philosophiae doctor (PhD) at the Norwegian University of Science and Technology (NTNU). The PhD study was conducted at the Department of Information Security and Communication Technology at NTNU. Professor Yuming Jiang has been the main supervisor of this work, and Professor Geir E. Øien has been the co-supervisor.

## Acknowledgments

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# Abbreviations

| | |
|---|---|
| 3GPP | Third Generation Partnership Project |
| AP | Access Point |
| BS | Base Station |
| CRRM | Common Radio Resource Management |
| HWN | Heterogeneous Wireless Network |
| ISP | Internet Service Provider |
| LTE | Long Term Evolution |
| LTE-LAA | Long Term Evolution License-Assisted Access |
| MADM | Multiple Attribute Decision Making |
| MDP | Markov Decision Process |
| PPP | Poisson Point Process |
| QoS | Quality of Service |
| RAT | Radio Access Technology |
| RRM | Radio Resource Management |
| VHO | Vertical Handover |
| WiFi | Wireless Fidelity |
| WiMAX | Worldwide Interoperability for Microwave Access |
| WLAN | Wireless Local Area Network |
| WWAN | Wireless Wide Area Network |

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# Part I

# Introduction

# Chapter 1

# Motivation and Focus of This Thesis

## 1.1 Motivation

The wireless telecommunications sector has evolved tremendously in the past decades. Smart devices have become affordable and widely available, leading to a fast growth of number of users along with the amount of data to be transmitted. A single Radio Access Technology (RAT) might not have enough capacity to cater for this explosion of data, making the need for cooperation among co-existing RATs inevitable.

The term Heterogeneous Wireless Networks (HWNs) denotes wireless networks where two or more RATs co-exist. They have become prevalent especially with the deployment and standardization of various technologies ranging from Wireless Wide Area Networks (WWAN) and down to Wireless Local Area Network (WLAN). Some examples of these standards include Worldwide Interoperability for Microwave Access (WiMAX), 3rd Generation Partnership Project Long Term Evolution (3GPP LTE) and Wireless Fidelity (WiFi).

The evolution of wireless sector has caused the users' expectations in terms of Quality of Service (QoS) to become very high. However, it is known that the wireless resources are scarce; and with the demand for resources driven upwards [1], those demands are expected to exceed, in short period, the wireless capacity.

Moreover, the network operators are requested to follow the regulations and rules that govern the telecommunications market. One such regulation that gained lots of attention recently is net neutrality. It aims to hinder network operators from exercising any kind of traffic discrimination. Such regulations may impose additional challenges in a resource-limited environment.

Network operators are therefore facing a major challenge: how to benefit from the existence of HWNs and find solutions that optimize the usage of the available resources, in order to satisfy the customers' demands and enhance the system performance.

One way to alleviate the problem of scarcity of resources could be the expansion of the wireless capacity by adding more base stations (BS) or femto cells. However, beside the increase in cost that is incurred by such solutions, the congestion problem is not totally resolved since the entire traffic still has to go through the same core network. Moreover, this solution will lead to higher number of small-size cells, which will in turn increase the handover rates in the network [2] and incur extra complexity due to heavy interference management [3].

Another candidate solution to cope with the increasing demand for wireless resources consists of enabling the operation of LTE in unlicensed spectrum. 3GPP announced the operation of LTE license-assisted access

(LTE-LAA) as an enhancement in LTE release 13 [4]. This means that LTE-LAA and other technologies, particularly WiFi, will be sharing the same band. However, this imposes challenges in securing fair coexistence of LTE-LAA and WiFi, and in avoiding that they affect each other's performance. The adoption of appropriate channel access scheme is hence required [5, 6]. Moreover, compatible smartphones have to become available in the market. Some commercial tests have already been in place and higher bandwidth and faster speed are claimed to be reached [7, 8].

In addition to the abovementioned solutions, mechanisms that manage the utilization of the wireless resources, namely Common Radio Resource Management (CRRM), remain crucial. CRRM allows to get advantage of the pools of combined resources of the co-existing RATs in heterogeneous networks. It provides means to control the admitted traffic and its distribution in the system, allowing a better assignment of resources. When the utilization of resources is optimized, a better system performance may be achieved, and a larger number of connections may be served which is translated by larger customer base and increase in the generated revenue.

CRRM mechanisms consist of several components. One major component, which is the center of the work in this thesis, is the RAT selection. In the following section, RAT selection and its main aspects will be presented.

## 1.2 RAT Selection as Key Component for Resource Management in HWNs

In an HWN, each of the available RATs has its own internal RRM controller that is responsible for managing the resources internally. To coordinate among the coexisting RATs, an entity that operates at a higher level is needed. This is often referred to in the literature as CRRM or Joint Radio Resource Management [9, 10].

CRRM mechanisms help optimize the usage of the wireless resources and ensure a better system performance. The main components of CRRM include: RAT selection, vertical handover (VHO), and congestion control [11]. RAT selection is of particular importance, being the first functionality that is triggered upon the arrival of a new connection request. It is responsible for the decision of admission or rejection of the arriving connections, and for the selection of the appropriate RAT that the connection will be assigned to.

Taking admission decision is not straightforward; several aspects have to be taken into account by the RAT selection component during this process, such as ensuring that the selected RAT is able to satisfy the QoS

requirements of the application requesting connection, avoiding to connect to the RATs that are highly-loaded, and avoiding to assign connections to a RAT that will likely disappear shortly. This latter issue requires the RAT selection component to be able to predict the availability of the different RATs.

### 1.2.1 Importance of RAT Selection

Adopting RAT selection strategies allows to achieve several gains, which include:

1. Capacity gain: when the resources are allocated efficiently, the number of users that the system is capable to serve becomes larger.
2. Enhanced system performance: by taking into account the load of the different RATs, the RAT selection module can contribute into a more efficient load distribution and a more stable system.
3. Enhanced user satisfaction: RAT selection can be tailored to perform the admission based on the user preferences. While some users prefer to connect to the cheapest RAT, others might be more interested in connecting to the one that provides high connection speed.
4. Increase in generated revenue: By increasing the network capacity, more users may be served and hence higher revenue may be achieved.

A well-designed RAT selection policy does not only increase the resource utilization, it may also help the network operator take decisions that enhance the network performance. For instance, by studying and analyzing the performance of RAT selection strategies, the operator may identify the need to add WLAN access points (APs) at certain locations to offload part of the traffic from the cellular network.

RAT selection and the other CRRM components collaborate to enhance the system performance. Information exchange among those components is hence necessary to dictate the decision taken at each level [12].

### 1.2.2 RAT Selection Classification

The RAT selection strategies can be classified based on the way the newly-arriving traffic is treated when the network is overloaded. In other words, when the system load reaches a certain maximum value, RAT selection functionality might decide to allow or deny new connections requests, depending on the operator's strategy. Two important admission strategies can be distinguished [9]:

- User blocking admission: new calls are blocked when the consumption of system resources reaches its maximum.
- Bandwidth sharing admission: new connections are admitted and they share the bandwidth with the existing ones.

In terms of decision making, RAT selection can be classified as user-initiated or network-initiated [2]. User-initiated approaches imply that the mobile terminal selects the RAT to connect to. In this case, the user has the flexibility of selecting the network of its preference. This choice depends on different parameters such as connectivity cost, signal strength and link capacity. At the opposite, network-initiated RAT selection is performed by the network whose goal is mainly the maximization of the capacity and the enhancement of the system performance.

In user-initiated RAT selection, three main stages are to be distinguished (Figure 1.1):

- Monitoring: The user terminal monitors the available RATs and the network conditions.
- Network selection: Based on the results obtained from the monitoring phase, the user selects the RAT to connect to. The decision criteria that governs the network selection depends on the application and the user preferences. For instance, a user might decide to connect to the RAT with the lowest connectivity cost or the one with the best QoS provisioning.
- Call setup: After the selection of the candidate RAT, the call is established. In the case where the selected RAT is no more available, the one that comes next on the list is chosen.

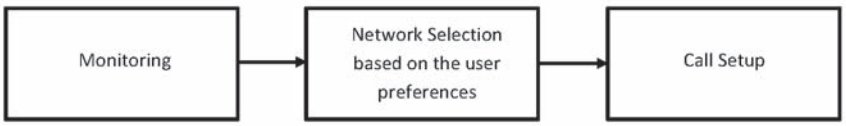



Figure 1.1: Stages of user-initiated RAT selection.

With network-initiated RAT selection, the objective is different. The decision criteria are usually network-utility-oriented such as load balancing, system capacity enhancement, or revenue maximization. With network-centric RAT selection, the involved stages are the following (Figure 1.2):

- Collecting traffic measurements: This requires the existence of network components that are assigned the task of collecting traffic measurements and other needed information.

- Decision making: The RAT selection decisions are taken transparently to the users, by adopting the decision that maximizes the network utility or by following a given allocation policy.

- Call setup: The call is allocated to the selected RAT.

Compared to network-initiated RAT selection, user-initiated approaches offer some advantages; they take into account the user preferences without incurring significant signaling load. However, user-initiated approaches suffer from a major drawback: when it is up to the users to take the RAT selection decision, they do not cooperate, which leads to a decrease in the system performance.

The RAT selection policies that are studied in this work are network-initiated with user blocking admission.

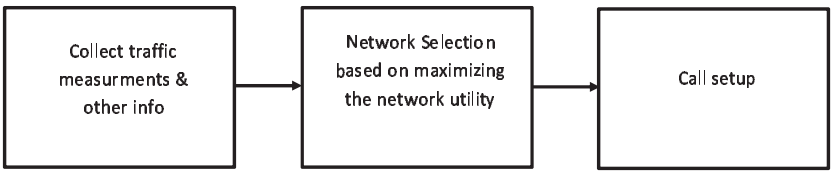



Figure 1.2: Stages of network-initiated RAT selection.

## 1.3 Research Context

The objective of this research work is to propose intelligent ways for resources allocation in HWNs that allow to maximize the revenue while taking into account the QoS requirements of the offered traffic. Finding cost-effective solutions is a major concern for network operators to help their business survive the various obstacles that are emerging, which are mainly dictated by the scarcity of wireless resources compared to the fast-increasing demands.

### 1.3.1 Adopted Scenario

In this thesis, an HWN is considered, and particularly, an overlay cellular / WLAN network that is run by a single operator. Cellular and WLAN can be seen as having complementary characteristics. While WLAN provides local coverage at a relatively low cost, the cellular network is characterized by global coverage, more suitability for mobile users, and better QoS provisioning. The network operator can benefit from this complementarity to offer better services to the users. Moreover, this network architecture is commonly found in real scenarios such as LTE / WiFi or WiMAX / WiFi overlay networks.

It is assumed that the mobile terminals are multi-mode in order to allow the users to connect to any of the available RATs. Furthermore, user profile differentiation is taken into consideration. As observed in real world, all users don't belong to the same category and their requirements and preferences may vary. Therefore, in this research work, two classes of services (or user profiles) are considered. Offering several user profiles is beneficial for both the users and the operator. On one hand, it provides more options to the users allowing them to choose the profile that suits best their needs and preferences (required QoS, suitable price,..). On the other hand, this supplies the operator with a better knowledge of the users and allows to grant different priority levels to different categories of users.

### 1.3.2 Research Questions

A survey of the existing literature shows that most research work has dealt with CRRM problem from a user's point of view, where the objective is to maximize the user's utility [13–15]. While this side is highly important, it is also interesting to tackle the problem from the operator's side. This observation initiated the main idea behind this research work which aims to prove the efficiency of CRRM, and particularly the RAT selection component, as means for revenue enhancement in HWNs.

An important aspect in the considered HWN scenario is the role that WLAN may play in alleviating the traffic load of the cellular RAT. Since WLAN is characterized by local coverage, this involves the need for an analytical model that captures the probability for a user to be under the coverage of WLAN, which will be addressed in this research work.

Another issue that might affect the revenue in wireless networks is the adoption of net neutrality regulation. Studying how to formulate RAT selection policies that are net neutrality-compliant will also be part of this research work.

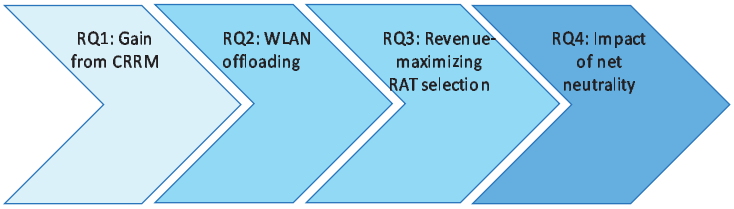



Figure 1.3: Addressed research questions.

Considering the abovementioned context, the focus of this work is narrowed to the following research questions:

- RQ1 - How much revenue may be gained by the implementation of well-designed CRRM mechanisms?
- RQ2 - How important is the WLAN offloading in HWNs scenarios?
- RQ3 - How to design RAT selection policies that allow to maximize the revenue?
- RQ4 - What is impact of net neutrality regulation on the revenue and the QoS?

Figure 1.3 illustrates the addressed research questions.

## 1.4 Thesis Outline

The present thesis consists of two parts. The first part, Part I, is composed of the following four chapters:

- Chapter 1: provides the motivation of this work. RAT selection and its importance are highlighted, the considered HWN scenario is presented, and the main research questions addressed in the present thesis are introduced.
- Chapter 2: background information on CRRM is provided. Markov chain and Markov Decision Process (MDP) as tools for modeling RAT selection are presented. An insight on pricing in wireless networks and its importance as a RRM tool is also provided in this chapter.

- Chapter 3: this chapter is devoted to presenting the contribution, by providing a summary of the published articles as well as the obtained results.
- Chapter 4: concludes the thesis. The main issues are summarized and some open problems for future research are pointed out.

Part II consists of the published articles that resulted from this research work.

# Chapter 2

# Background

In this chapter, the related background is presented. First, RAT selection and VHO are introduced as two important components of CRRM. Second, Markov chain and MDP are presented as the tools of choice for modeling RAT selection, in addition to some reflections concerning solving MDPs. Afterwards, Poisson Point Process (PPP) is introduced as a tool for spatial distribution modeling which allowed to derive a formulation of the coverage probability of WiFi. Finally, pricing and the role it can play as a resource management tool in wireless networks is highlighted, and a summary of some of the well-known pricing schemes in wireless networks is provided.

## 2.1 Radio Resource Management in Heterogeneous Wireless Networks

Radio resource management is of significant importance in resource-limited wireless networks. With the deployment of HWNs, new specifically designed CRRM components have emerged. Their role is the coordination between the co-existing RATs. Two CRRM components that gained lots of attention in the literature are presented in this section, namely RAT selection and VHO.

### 2.1.1 RAT Selection

RAT selection plays a substantial role in CRRM frameworks [9] [10]. Different approaches for RAT selection have been proposed in the literature and can be divided into the following categories:

- Load-balancing-based RAT selection: aims to balance the traffic among the existing RATs, which results in an efficient utilization of the wireless resources and a more stable system. Load balancing schemes are network-centric. Triggered at the session setup phase, load balancing schemes may be complemented by regularly checking the load in the different RATs and handing off some of the ongoing sessions to a different RAT in case the current one has become overloaded.

- Service-class-based RAT selection: where each class of service i.e. voice, video streaming, and data, is assigned to the most appropriate RAT that was designed for this kind of service. While this type of algorithms provide good QoS, it doesn't consider the load balanc-

ing issue which might arises if the traffic was not evenly distributed among the different classes of services.

- Policy-based approaches: presented in [16]. In addition to the service type, the position of the user (whether he/she is indoor or outdoor) is also accounted for as criterion for RAT selection decision.

In addition to the abovementioned categories, other RAT selection strategies, e.g. terminal-driven strategies, have been proposed in the literature [17].

### 2.1.2 Vertical Handover

Another CRRM component that has been widely studied in literature is VHO. Traditionally, VHO is performed due to mobility, when a user moves out of the coverage of the serving RAT and needs to connect to another RAT that has become available during an active session, avoiding that this session gets dropped. This kind of mobility-based handover aims to preserve QoS and is usually user-initiated.

VHO, on the other hand, can play another important role as RRM tool [18], which may be seen as a complementary functionality to RAT selection. After the admission decision has been taken by the RAT selection module at call initiation time, it is important to maintain the QoS experienced by this call, or to keep the traffic balanced among the different RATs when the network conditions change. For this purpose, when a network is detected as congested, network-motivated VHO may be initiated to re-allocate some of the calls. This helps also release resources for potential session requests that might arrive to the previously congested RAT, especially for requests coming from terminals with one network interface. Network-motivated handover allows hence a better utilization of the wireless resources.

While network-motivated RAT selection and VHO are important as CRRM tools, implementing such modules encounters several challenges. In order to select the appropriate RAT to accommodate the new or handed off calls, various information should be made available to those modules, such as the current load of all RATs, the number and type of interfaces that each mobile terminal is equipped with, and the type of application that is currently run by the users.

## 2.2 Modeling RAT Selection

RAT selection can be modeled with the help of various mathematical tools each having its own characteristics in terms of complexity, accuracy and performance. The choice of the mathematical tool is also dependent on the objective of optimization. It is therefore important to acquire knowledge of the various potential tools and choose the one that best suits the studied problem and defined objective.

In a HWN environment, numerous attributes are involved in the RAT selection process, making it difficult to have a model that captures all of them. These attributes can be:

- RAT-specific: such as bandwidth (total bandwidth of each RAT, average bandwidth a user can occupy), price charged for connecting to each RAT and current traffic load.
- application-specific: such as required QoS or required security level.
- terminal-specific: such as battery life and available network interfaces.

In the literature, the mathematical theories that are commonly used in modeling RAT selection include Markov chain and MDP, fuzzy logic, multiple attribute decision making (MADM) and game theory. A comprehensive survey on these theories can be found in [19]. Although each of these theories has its own features and functionalities, it is possible to combine several of them when modeling a RAT selection problem.

In this research work, Markov chain and MDP were the chosen tools for modeling RAT selection.

## 2.3 Preliminaries on Markov Chain and Markov Decision Process

### 2.3.1 Markov Chain

Markov chain is a stochastic process which allows the modeling of systems that satisfy the Markov properties, i.e. the future state is dependent on the current state only (memoryless system) [20]. It provides a rigid analytical tool that can be used to model RAT selection.

A Markov chain is characterized by a set of states $S$ with a transition probability matrix $P$ where $P_{ij}$ represents the transition probability to state

$j$ given that the current state is $i$ . $P_{ij}$ can be defined as follows [21]:

$$P_{ij} = P(S_t = j|S_{t-1} = i), i \in S, j \in S, \forall t \; S_t \in S \tag{2.1}$$

where $S_t$ is a random variable representing the state at time $t$.

Steady-state probability or equilibrium probability: The probability $P_i(t)$ that the system is in state $i$ at step $t$ converges to a limit $\pi_i$ as $t$ tends to infinity. $\pi_i$ is called the steady-state probability of the Markovian process. The steady-state probability can be computed from a set of balance equations that balance the probabilities of entering and leaving a state in equilibrium. The resulting equations to compute the steady-state probability are the following:

$$\pi_i \sum_{j \neq i} p_{ij} = \sum_{j \neq i} \pi_i p_{ji}, \; i \in S \tag{2.2}$$

In vector-matrix notation, $\pi$, the row vector with elements $\pi_i$, can be written in the form:

$$\pi = \pi P. \tag{2.3}$$

along with the normalization equation:

$$\sum_{i \in S} \pi_i = 1 \tag{2.4}$$

The solution of the set of equations defined in (2.3) is unique.

### 2.3.2 Markov Decision Process

Markov chains lack dynamism and are often used for performance analysis. MDP considers, by contrast, actions and rewards (or costs), allowing to capture the dynamism of the system. It is used for decision making under uncertainty [22].

MDP can be described as a mathematical framework that allows to model the system's dynamics when a decision maker (such as RAT selection module) applies an action to its environment and then transits from one state to another, in order to optimize the network's defined objectives.

The usage of MDP as a modeling tool brings two important gains:

- In wireless networks where the resources are limited, static decisions may lead to underutilization of resources. With the help of MDP, dynamic optimization of the network operation can be obtained. This results in significant improvement of resource utilization.

- MDP modeling allows the design of optimization problems with multiple objectives. An example of a combined objective could be the combination of revenue maximization and load balancing.

A known drawback of MDP is the computation time used to find the optimal solution which increases fast with the number of system states. However, it is possible to store the solution of an MDP model in look-up tables. This reduces significantly the time needed to find the optimal solution. Moreover, near-optimal solutions can be derived to reduce the complexity of the studied problem which results in finding sub-optimal but faster solutions [23, 24].

### Markov Decision Process Formulation

In RAT selection problems, the MDP model serves to derive the optimal RAT selection policy which maximizes a given objective function. At each decision time, defined by the arrival of a new connection request, the RAT selection module chooses an action $a$ that is available at the system's current state $s$. Subsequently, the RAT selection entity receives an immediate reward and the system evolves to a new state $s'$ according to a state transition probability $P_{ss'}(a)$. An MDP model can be uniquely identified by a tuple $(S, A, P_{ss'}(a), R, \mathcal{T})$ defined as follows [22]:

- $S$ is a finite set of feasible states. At any given time, the system's current state is $s \in S$.
- $A$ is a finite set of actions that the decision maker can take. The chosen action is based on the current state of the integrated system.
- $P_{ss'}(a)$ represents the transition probability from state $s$ to state $s'$ when action $a$ is taken.
- $R$ is the immediate reward obtained following a taken action $a$.
- $\mathcal{T}$ is the set of decision epochs. In the case of RAT selection, it is the time following the arrival of a new connection request. $\mathcal{T}$ can be finite or infinite.

The goal of MDP is to find the optimal policy $\pi$ that optimizes a certain objective function, where $\pi$ is defined as a mapping from state $s$ to action $a$:

$$\Pi = \{\pi : S \rightarrow A | \pi_s \in A_s, \forall \boldsymbol{s} \in S\} \tag{2.5}$$

where $A_s \subset A$ is the action space at state $s$.
An optimal policy is the one that, among all possible policies, maximizes

the expected utility. A fundamental result of the theory of MDP is that each MDP has an optimal policy [21].

## 2.4 Methods for Solving MDPs

A known aspect related to solving MDPs is the computational complexity. MDP problems can be solved with the help of linear programming in polynomial time. However, linear programming is a general technique and the polynomial in the theoretically-efficient algorithms are of high order in practice, making them impractical [21]. This explains the need for more efficient techniques that consider the special characteristics of MDP.

There are three classical ways to solve MDP models [25]:

- Linear programming: It consists of formulating the problem as an optimization problem with linear objective function and constraints, and finding the optimal value function.
- Successive approximations: It consists of iteratively computing a value function that approximates the optimal value $V^*$. Examples of successive approximations methods are value iteration and Q-learning.
- Direct policy search: It searches for an optimal policy in the space of policies. An example of direct policy search is the policy iteration method.

In the following, linear programming, value iteration, Q-learning, and policy iteration methods are briefly explained.

### 2.4.1 Linear Programming

To solve an MDP with the help of linear programming, an optimization problem is formulated as the maximization of the utilities. The QoS formulations are usually included as constraints in the linear program by truncating the state space to those points that satisfy the constraints. The problem can be formulated as follows:

$$\begin{aligned} &\text{maximize} && \sum_{s \in S} V(s) \\ &\text{subject to} && V(s) = r(s,a) + \gamma \sum_{s' \in S} P(s,s',a) V(s') \end{aligned} \tag{2.6}$$

where $V(s)$ is the utility of state $s$, $r(s,a)$ is the reward obtained from choosing action $a$ at state $s$, $P(s,s',a)$ is the transition probability from

state $s$ to state $s'$ when action $a$ is chosen, and $\gamma$ is a discount factor whose value is in the interval [0, 1).
The constraints in (2.6) are known as the Bellman equations [21].

### 2.4.2 Value Iteration

As mentioned earlier, value iteration is a successive approximation algorithm. It starts by computing the optimal value function assuming a one-stage horizon, then a two-stage horizon, and so on. It stops when the change of the optimal value function is less than some specified threshold $\epsilon$ [21].

The algorithm for value iteration works as follows [26]:

- Step 0: Set the utility $V^0(s) = 0$ for each state $s$, and set $k = 0$.
- Step 1: For each state $s$, compute $V^{k+1}(s)$:

$$V^{k+1}(s) = \max_{a \in A(s)} \{r(s,a) + \sum_{s' \in S} P(s,s',a)V^k(s')\}$$

- Step 2: If $(CLOSE\_ENOUGH(V^k, V^{k+1}))$ go to step 3. Otherwise, set $k = k+1$ and return to step 1. The function $CLOSE\_ENOUGH()$ is defined below.
- Step 3: For each $s \in S$, compute the stationary optimal policy:

$$\pi(s) = \arg\max_{a \in A(s)} \{r(s,a) + \gamma \sum_{s' \in S} P(s,s',a)V^k(s')\}$$

- return $\pi$

$CLOSE\_ENOUGH()$ returns true if:

$$\max_{s \in S} \left| V^{k+1}(s) - V^k(s) \right| < \epsilon,$$

and $\gamma \in [0, 1)$ is a discount factor.

### 2.4.3 Q-Learning

Reinforcement learning generates near-optimal solutions to large and complex MDPs. It offers the possibility to solve MDPs that suffer from curse of dimensionality, which makes them unsolvable, with the help of dynamic programming. Reinforcement learning requires the update of quantities in

its database known as Q-factors, which are stored for each state-action pair in the system.

A particular reinforcement learning algorithm that appears to be suitable for RAT selection is the Q-learning [27]. It is a technique for solving MDPs when the state transition probabilities are unknown.

Q-learning provides a rule to successively approximate the value function $Q(s, a)$, called as Q-function. The Q-function is updated as follows [28]:

$$Q_{t+1} = (1 - \alpha)Q_t(s_t, a_t) + \alpha[r(s_t, a_t) + \gamma V^*(s_{t+1})]$$

where $\alpha \in (0, 1]$ is the learning rate. It indicates the extent to which the newly acquired information will override the old values,
$\gamma \in (0, 1]$ is a discount factor,
$r(s_t, a_t)$ is the one-step reward when applying action $a_t$ from state $s_t$,
and $V^*(s_{t+1})$ denotes the value function that maximizes the Q-function at state $s_{t+1}$ over all actions $a$.

The optimal policy is therefore computed as:

$$Q_t^*(s_t, a) = \max_{a \in A(s)} Q_t(s_t, a).$$

### 2.4.4 Policy Iteration

The policy iteration method performs a search among the finite group of possible policies for the MDP in order to find the optimal one in a finite number of steps. The algorithm of policy iteration works as follows [29]:

- Step 0: An arbitrary policy $\pi$ is chosen by selecting a random action for each state.
- Step 1 - Value determination:
  While not done:
  - Given the current policy $\pi$, the utility (value function) $V_\pi$ is computed for all states. This can be achieved by solving the following system of linear equations:

    $$V_\pi(s) = r(s, \pi(s)) + \gamma \sum_{s' \in S} p(s, s', \pi(s))V_\pi(s')$$

    where $r(s, \pi(s))$ and $p(s, s', \pi(s))$ denote respectively the reward and the transition probability to state $s'$ from the current state $s$, given that policy $\pi$ is chosen, and $\gamma \in (0, 1]$ is a discount factor.
  - update the state utilities.

– for each $s \in S$, compute $\widetilde{\pi}$ as follows:

$$\widetilde{\pi}(s) = \arg\max_{a \in A(s)} \{r(s,a) + \gamma \sum_{s' \in S} p(s,s',a) V_{\pi}(s')\}$$

- Step 2 - Policy improvement: if $\widetilde{\pi} = \pi$, the algorithm is stopped with $\pi_{opt} = \pi$, otherwise, go to step 1.

### 2.4.5 Reflections on the Methods for Solving MDPs

Linear programming is a general method that does not capture the MDP specifics. However, it offers the advantage of performing the optimization over several constraints. Dynamic programming methods, i.e. value iteration and policy iteration, are standard algorithms for solving MDPs. These methods are model-based, which means they require a priori knowledge of the state transitions probabilities and rewards. However, when the number of states increases, the problem of curse of dimensionality emerges. Reinforcement learning, on the other hand, remains applicable even when state space becomes computationally intractable, but the solutions they generate are near-optimal.

Value iteration method has two weaknesses: (1) it can take a long time to converge in some situations even when the underlying policy is not changing, and (2) it works by computing the value of each state in order to find the optimal policy, instead for searching for the optimal policy directly.

The policy iteration, on the other hand, starts with a random policy, computes each state's utility given that policy, and then selects a new optimal policy.

There isn't currently a standard agreement over which algorithm is better (policy iteration or value iteration). For small MDPs, policy iteration is often very fast and converges with very few iterations. However, for MDPs with large state spaces, value iteration may be preferred. For this reason, in practice, value iteration seems to be used more often than policy iteration, and it is therefore the method of choice in this research work for solving MDP problems.

## 2.5 Poisson Point Process for Spatial Distribution Modeling

When addressing RAT selection in integrated cellular / WLAN networks, the need for modeling the spatial distribution of the cellular BSs, WLAN

APs, as well as the users arises. This can be realized with the help of a spatial point process such as PPP. This latter has been used extensively for modeling unplanned networks [30] which is typically the case of WLAN APs' deployment.

The HWN adopted in this work can be seen as a 2-tier network, where tier-1 is the cellular RAT and tier-2 is the WLAN. In addition, the positions of BSs (resp. APs) belonging to tier-k can be modeled according to a homogeneous PPP, $\phi^{(k)}$, with intensity $\lambda^{(k)}$, where $\lambda^{(k)}$ is defined as the number of BSs (resp. APs) per area unit, and $k \in \{1, 2\}$.

Similarly, the users are considered scattered in the plane according to a homogeneous PPP, $\phi^{(u)}$, with intensity $\lambda^{(u)}$ users per area unit, independently of $\phi^{(k)}$.

In this research work, the use of PPP allowed to derive a simple formulation for the coverage probability of WLAN. First, it is assumed that each AP covers a circular area of known radius $R$, i.e. the transmission of each AP can be received clearly by users residing at a distance not exceeding $R$. Second, the interference from neighboring APs is considered negligible. Hence, a typical user is said to be under the coverage of WLAN if the distance $r$ separating this user from the nearest AP is less than $R$. Therefore, the probability that a user is under WLAN coverage is equivalent to the cumulative distribution function of $r$, namely $\mathbb{P}[r < R]$.

Without loss of generality, the typical user is considered to be located at the origin of the plane under consideration [30]. Then, knowing that the null probability of a 2D Poisson process in an area $Z$ is $exp(-\lambda Z)$ [31], $\mathbb{P}[r > R]$ becomes:

$$\mathbb{P}[r > R] = \mathbb{P}[\phi^{(2)} \cap b(0, R) = 0] = e^{-\pi\lambda^{(2)}R^2} \tag{2.7}$$

where $b(0, R)$ is the Euclidean ball of radius $R$ centered at origin.

Hence, the coverage probability of tier-2 (i.e. WLAN), $P_{c,2}$, can be formulated as:

$$P_{c,2} = \mathbb{P}[r < R] = 1 - \mathbb{P}[r > R] = 1 - e^{-\pi\lambda^{(2)}R^2} \tag{2.8}$$

## 2.6 Pricing in Wireless Networks

Affected by the evolution of the wireless technologies, pricing the wireless services took different shapes throughout the years. While in the early stage, flat pricing (i.e. users are charged a fixed fee periodically irrespective of their consumption) was the most common [32], this pricing strategy is no longer viable with the current conditions [33], and more sophisticated

pricing schemes need to be devised taking into account the disproportion between the users' demands and the available wireless resources.

When setting pricing policies, the network operator is interested in offering competitive prices in order to increase its customers' base. However, this must not come at the expense of network stability and system performance.

In addition to its known economical role, pricing the wireless services has gained attention recently as tool for RRM. In fact, the applied pricing scheme dictates the user's behavior, thus affecting the load and the performance of the network [34, 35]. For instance, if the prices are too high, this might lead to a decrease in the customers' base, while setting very low prices will likely lead to capacity issues as the the number of customers will tend to increase fast. Moreover, offering large data allowance drives higher the volume of data consumed per user.

Various solutions have been proposed in the literature, where pricing has been used as tool to solve RRM problems from an economic point of view [36]. And with the exponential increase in data demand, the network operators started to resort to pricing to alleviate the network congestion [33, 37]. Their goal is to find effective pricing policies that help control the traffic load, allow to offer satisfactory QoS to the users, and achieve the targeted profit.

### 2.6.1 Aspects of a Pricing Scheme

When devising a pricing scheme, cost recovery and profit realization should indeed be considered. In addition, other aspects are important and must be taken into account by the network operator. These aspects include:

- The user's willingness to pay: It represents the amount of money that a user is willing to pay for a certain volume of consumed data and at certain QoS guarantees.

- The structure of the pricing scheme: A user always prefers to purchase services at prices that are easy to interpret [38], and where it is easy to predict the total amount to pay without hidden or unexpected expenses [39]. Complicated pricing schemes can have repellent impact on users especially when other providers are offering simple pricing plans.

- Computation and implementation complexity: The lower the implementation complexity of a pricing scheme is, the more practical it becomes.

- Acquisition of network usage information: Some pricing schemes, e.g. congestion-based schemes (introduced in Section 2.6.2), require to continually receive information regarding the load of the network. This information is a required parameter to calculate an updated value of the price. This kind of information exchange not only increases the implementation complexity of the pricing scheme, but also causes additional traffic load to the network.

### 2.6.2 Common Pricing Schemes in Wireless Networks

Various pricing schemes have been proposed in the literature, which can be categorized under static and dynamic schemes [32].

#### Static Pricing

This category includes the pricing schemes for which the price is pre-decided and is not dependent on other parameters such as the network load.

1. Flat rate pricing:
   With flat rate pricing, the charged price is fixed, irrespective of the bandwidth usage. The user pays a subscription fee over a given period (for example monthly) and can use as much data as he/she wants during the paid period. Several variations can be found under the flat pricing category. The simplest form is the unlimited data plan where no cap on the usage exists. Other variations try to give the users some incentive to monitor the amount of bandwidth usage by setting a cap (maximum data usage) beyond which a penalty is imposed to the user. An example of penalty can be in the form of charging the user proportionally to the excess usage by changing from flat to usage-based pricing. A penalty could also involve throttling the speed to a minimal one for the remaining time of the actual period.

   The operators offer often a variety of flat rate plans, each defined by a fixed price and a usage cap, and the user can choose the plan that is the most suitable for his/her usage and needs.

   Flat pricing is no doubt the simplest to implement by the operator and encourages the customers to use the network by offering predictable monthly fees. However, flat pricing can affect negatively the system performance especially when no cap is set. On the other hand, heavy users will receive greater benefit than customers with low usage, which creates market segmentation. It would also become difficult to define

a fair price for resources when the peak load costs are mainly driven by heavy users [32].

2. Two-tier pricing:
   With two-tier pricing, the provider offers price points for several data usage options. For example, a user is charged a fixed price $p_1$ if his consumption is below a threshold $th_1$, and a fixed price $p_2$ for a consumption that exceeds $th_1$.

   Two-tier pricing provides economical incentive to users to keep their data consumption at a low level, hence leading to a less congested network. It offers higher granularity and also better revenue than flat and volume-based pricing [40]. However, the values of the different parameters have to be selected carefully. For instance, if $p_2$ is relatively low, then the user's behavior will be similar to that of flat pricing.

3. Usage-based pricing:
   With usage-based pricing, also known as volume-based pricing, the user is charged a certain price respective to the data usage. As mentioned above, usage-based is often combined with flat rate pricing when the amount of consumed data exceeds the defined cap.

In addition to the pricing schemes mentioned above, other schemes can also be found under the static pricing category such as pricing that is based on QoS classes (Paris metro pricing, token pricing, priority pricing), pricing that are bound by negotiated contracts, application-based and time-of-day. The reader may refer to [32] for a detailed description of each of these schemes.

### Dynamic Pricing

Dynamic pricing, also known as congestion pricing, is based on the idea of dynamically changing the price depending on the current load of the network. It is a promising solution that uses economics to tackle the congestion problem. By offering lower prices in periods of low network load, the users will be encouraged to shift their usage to off-peak periods [41]. Hence, dynamic pricing promotes efficient use of the wireless resources by influencing users' behaviors and reshaping the traffic (Figure 2.1). The following four sub-categories can be found under dynamic pricing: Raffle-based, Real-time congestion, Auction-based and Day-ahead time-dependent [32].

1. Raffle-based pricing:
   With raffle-based pricing, the day is divided into peak and off-peak

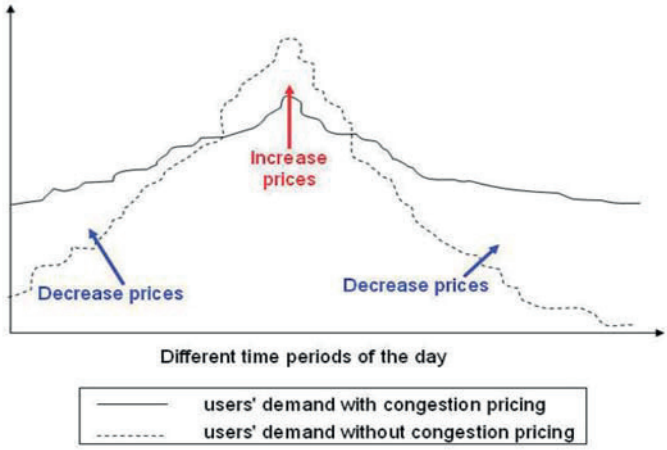



Figure 2.1: Effect of congestion pricing on shifting the user's demand [42].

periods. A probabilistic incentive in form of lottery is offered to encourage the users to shift their network usage to off-peak periods. The reward amount is proportional to the users' contribution in reducing the traffic load in peak periods.

While this form of pricing tries to motivate the time-shift of usage, it suffers from uncertainty of the reward. As a consequence, the users might not get enough incentive to shift their demand to off-peak periods.

2. Real-time congestion pricing:
   With real-time congestion pricing, the network announces the prices based on the actual level of congestion. The response from the users is used subsequently to compute the new prices.

3. Auction-based pricing:
   Auction-based pricing implies that users declare how much they are willing to pay for each packet. The network operator selects a certain amount of received packets to be admitted. The lowest admitted bid or "cost of congestion" is the amount charged for all users. This type of pricing requires the existence of automated agents at the users' terminals that are able to make bids and receive the updated price.

4. Day-ahead time-dependent pricing:
   As its name implies, day-ahead pricing suggests to inform the users

about the projected prices one day in advance. The traffic is monitored daily and compared to a baseline traffic trace. The variation in traffic volume is used to compute the prices for the next day.

Day-ahead pricing offers an advantage over raffle-based pricing in a sense that the users have advance knowledge over the prices that they will get charged. On the other hand, the price computation is based on the traffic of the day before and does not reflect the exact congestion of the current traffic.

When dynamic pricing is applied, the users get incentive to delay a certain amount of traffic to periods when prices get lower. Therefore, the network usage during peak hours will decrease and this leads to an alleviation of the congestion problem. Consequently, a better QoS may be provided to the users and the generated revenues may increase.

However, the implementation of dynamic pricing involves new system requirements and modeling challenges. Moreover, whether the users will accept or not this kind of pricing is to be considered. While in real world static pricing are still dominating as pricing plans, some variants of congestion-based pricing have started to be adopted or are under trial [32].

# Chapter 3

# Publications and Contributions

Throughout this research work, the major target has been to find efficient ways of resources assigning in HWNs in order to help the network operators maximize their revenue. The QoS metrics are accounted for when evaluating the performance of the proposed solutions. The research results are presented in five publications which are attached in Chapter A to Chapter E.

First, the enhancement realized by RAT selection and VHO in terms of revenue is investigated and compared to the case where the assignment of network resources is done arbitrarily (Publication A). Then the focus is shifted to RAT selection by proposing a scheme that prioritizes the traffic with the highest contribution to revenue (Publication B).

Afterwards, the problem is generalized by deriving the optimal RAT selection scheme with the help of MDP. Moreover, the role that WLAN can play as an extension to the cellular RAT is investigated (Publication C). Then, an additional constraint is considered, namely net neutrality. Publication D highlights the net neutrality aspect and its impact on the revenue and QoS in wireless networks. And finally, in Publication E, revenue-maximizing RAT selection policies are studied with net neutrality integration.

The author of the thesis played an active role in the research and in writing those publications under the supervision of Prof. Yuming Jiang. Anna N. Kim contributed in the discussions and identification of the problem addressed in Publication A. Jie Xu contributed in the discussions and provided the simulation code that was further adapted and used to draw the results presented in publication A. Xavier Gelabert contributed in Markov chain modeling, the discussions around the studied topic and the interpretation of the results in the work presented in Publications B and C.

Each of the abovementioned publications has been subject to international peer-reviewing. Publications A, B and D are published in conference proceedings, while Publication C and E are published in journals.

In the following, a brief summary of the included publications is presented along with the main contributions.

## 3.1 List of Publications Included in This Thesis

### 3.1.1 Publication A

- Elissar Khloussy, Jie Xu, Anna N. Kim and Yuming Jiang; Maximizing Network Revenue through Resource Management in Heterogeneous Wireless Networks; 16th IEEE Symposium on Computers and

Communications (ISCC), Kerkyra, Greece, June 28-July 1, 2011.

### Summary of the Paper

This paper studies the impact of CRRM in an overlay WiMAX/WiFi environment. Two CRRM components are considered, namely admission control and VHO. A multi-service environment is proposed in which real-time applications are prioritized over the elastic applications. Real-time applications are admitted to WiMAX solely for the QoS guarantees that WiMAX provides. The objective is to find mechanisms for distributing the elastic traffic between WiMAX and WiFi in order to maximize the profit.

The problem is formulated as an optimization problem. To compute the revenue generated in the studied scenario, a volume-based billing scheme is applied, inspired from the one suggested in [43]. The obtained revenue as well as some quality of experience metrics are presented. The simulation results prove that the network revenue is significantly increased when CRRM is applied. The increase in revenue obtained with VHO is shown to be slightly higher than the one obtained through admission control. However, since the gap in revenue between the two cases is insignificant, it is concluded that admission control is preferred over VHO. The small sacrifice in revenue is compensated by the avoidance of the overhead that the VHO process introduces in practice.

### Contributions

This paper establishes a starting point for this thesis and the contributions can be summarized as follows:

- It highlights the improvement in terms of revenue that can be realized when CRRM schemes are implemented, compared to the case where the traffic admission is random.

- The problem of managing the resources is tackled from a provider's viewpoint, unlike most of the work in the literature where this kind of research problems is addressed from a user's perspective. This also applies to the other publications included in this thesis.

- The pricing in WiMAX and WiFi is integrated into the optimization problem and different billing schemes are adopted for streaming and elastic applications.

### 3.1.2 Publication B

- Elissar Khloussy, Xavier Gelabert and Yuming Jiang; A Revenue-Maximizing Scheme for Radio Access Technology Selection in Heterogeneous Wireless Networks with User Profile Differentiation; Lecture Notes in Computer Science, Vol. 8115, pp. 66 - 77, Springer, 2013. (Proceedings of 19th EUNICE/IFIP WG 6.6 International Workshop on Advances in Communication Networking, Chemnitz, Germany, August 28 - 30, Chemnitz, Germany, 2013.)

#### Summary of the Paper

The focus of this paper is on RAT selection and how it may contribute to maximizing the revenue in HWNs. Considering a multi-service network, an algorithm for traffic distribution among the two available RATs, namely LTE and WiFi, is proposed. Specifically, two types of service or user profiles, $C_1$ and $C_2$, are considered where $C_1$ is granted priority in using LTE which is characterized by its global coverage and QoS guarantees. In exchange, $C_1$ is charged higher connection fees than $C_2$.

$C_1$ targets the business sector known to be more sensitive to the QoS than to the charged fees, while $C_2$ targets the individuals who prefer cheap connections and can tolerate some degradation in the perceived QoS.

To reflect the different priority levels granted to each of the traffic profiles, a load threshold $\theta$ in LTE is introduced. $\theta$ is defined as the percentage of LTE capacity that the low-priority traffic is allowed to occupy and share with $C_1$ traffic.

The proposed RAT selection algorithm tries first to allocate the incoming $C_2$ traffic to WiFi which is considered as an extension network to LTE. In the case where this admission is not possible (user is not under the coverage of WiFi or WiFi does not have available resources) then $C_2$ traffic may be admitted to LTE as long as the load in this latter is below $\theta$. The proposed scheme does not allow $C_1$ traffic to compete with $C_2$ traffic in using WiFi resources to keep the QoS perceived by $C_2$ traffic at an acceptable level.

The system is modeled with the help of a 3-dimensional Markov chain. The analytical model is then validated by simulation and a good matching between the model and the simulation is proven.

The last part of the paper is dedicated to revenue maximization with focus on the threshold $\theta$ as a key parameter. The goal is to find, for each combination of the offered traffic loads of $C_1$ and $C_2$, the optimal value of $\theta$ for which the revenue is maximized, while keeping the blocking probability for class $i$ below a predefined threshold $\beta_i$, $i \in \{1, 2\}$.

Finding the optimal value of $\theta$ is important for the network operator. Through acquiring advance knowledge regarding the usage patterns of the network (expected offered load of the different user profiles), the network operator may adjust the value of $\theta$ accordingly, and a better usage of the network resources as well as higher revenue may be secured.

#### Contributions

The main contributions of this paper are the following:

- It gives insight into the importance of CRRM and how a good usage of the network resources may lead to enhanced results (revenue in our case).
- An analytical model for the proposed RAT selection scheme is derived and validated.
- The provided analysis may help the network operator make design decisions that allow to increase the profit.

### 3.1.3 Publication C

- Elissar Khloussy, Xavier Gelabert and Yuming Jiang; Investigation on MDP-Based Radio Access Technology Selection in Heterogeneous Wireless Networks; Computer Networks, 2015 Nov 14;91:57-67.

#### Summary of the Paper

This paper adds several dimensions to the problem proposed in paper B. The same multi-service network architecture with two types of user profiles is considered. However, this time the dynamism of the system is captured, and the optimal RAT selection policy which maximizes the revenue is derived with the help of MDP. The problem is generalized by allowing both traffic classes to be served by cellular or WLAN, with the possibility of handover between the two RATs for the low-priority traffic.

In addition to addressing the main RAT selection problem, other related sub-problems are also tackled, namely modeling the coverage probability of WLAN, and a further investigation of the choice of the weights in the MDP framework and its impact on the obtained results. Since both traffic classes could be admitted to any of the RATs, a 4-dimensional Markov chain serves to model the proposed RAT selection scheme.

#### Contributions

The main contributions of this paper can be summarized as follows:

- Investigation of the MDP-based approach for RAT selection with the objective of maximizing the revenue.
- Investigation of the choice of the weights in the MDP framework and how this may affect the obtained results.
- Deriving an analytical model for the coverage probability of WLAN with the help of PPP.
- The performance of the MDP-based RAT selection scheme is evaluated and compared to the performance of two other static RAT selection schemes.
- The importance of traffic offloading to WLAN is also highlighted.

### 3.1.4 Publication D

- Elissar Khloussy and Yuming Jiang; The Impact of Net Neutrality on Revenue and Quality of Service in Wireless Networks; 15th IEEE Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, USA, Jan 12 - 15, 2018.

#### Summary of the Paper

In Paper D, the integration of net neutrality and RAT selection is addressed. Net neutrality regulation calls for equal treatment of Internet traffic, and allows to grant exemption to some non-Internet access traffic that requires high transmission quality, known as specialized services (SS). The aim of this paper is to give insight into the impact that net neutrality has on both the revenue and the QoS. To this end, a comparison of the performance of four net neutral RAT selection policies, having different traffic admission strategies (LTE-first or WLAN-first), with and without privilege to SS traffic, is conducted.

The results obtained by the four net neutral policies are compared to those realized by the non-net neutral revenue-maximizing policy that was introduced in Paper C. Markov chain and MDP are used to model the studied policies. The traffic is divided into two classes: SS traffic and Internet Access Services (IAS) traffic and the performance of the policies in terms of revenue, social benefit and blocking probability is analyzed. In

addition, the impact of the ratio of the reserved capacity for SS traffic on the revenue and blocking probability is explored.

The obtained results underline that, applying net neutrality would lead to a decrease in the generated revenue, however this decrease may be reduced by the proper choice of the net neutral RAT selection policies. Hence, in order to support net neutrality and at the same time maximize the revenue, the Internet service provider has to carefully choose/design the proper RAT selection policy.

The results obtained in this paper are preliminary, and are meant to give insight into the consequences that may occur when net neutrality regulations are implemented. While far from exhaustive, they shed light on further study along this direction.

#### Contributions

The main contributions of this paper are:

- An important problem, namely net neutrality integration with RAT selection policies, is addressed.
- It highlights that, with the proper choice of RAT selection policy, the negative effect on the revenue incurred by the introduction of net neutrality may be mitigated.
- The importance of the right choice of the proportion of reserved bandwidth for SS traffic is also highlighted.

### 3.1.5 Publication E

- Elissar Khloussy and Yuming Jiang; Revenue-Maximizing Radio Access Technology Selection with Net Neutrality Compliance in Heterogeneous Wireless Networks; Wireless Communications and Mobile Computing journal, 2018.

#### Summary of the Paper

This paper addresses the problem of deriving revenue-maximizing RAT selection policies that are net neutrality-compliant. The objective is to answer the following question: how the bandwidth reservation for SS traffic would be made in a way that allows to maximize the revenue while in compliance with net neutrality, and how the choice of the ratio of reserved bandwidth would affect the revenue?

Two scenarios for bandwidth reservation for SS traffic are proposed, namely capacity reservation in LTE only, and reservation across the whole HWN. The two variants of RAT selection policies are modeled with the help of MDP. The results obtained are compared to those of a revenue-maximizing policy that does not account for net neutrality (introduced in paper C). It is shown that reserving resources in the whole HWN may be more beneficial as it guarantees better social benefit than the other variant, as well as lower blocking probability for IAS traffic, at the expense of a marginal loss in the generated revenue.

#### Contributions

The main contributions of this paper are:

- Investigation of MDP-based approach for RAT selection with net neutrality compliance, and with revenue maximization as objective.
- Two variants of bandwidth reservation for SS traffic are proposed.
- The impact of the ratio of reserved capacity for SS traffic on the achieved revenue is investigated with both variants of the RAT selection policy.
- For the use of the results in this paper, an Internet service provider, given its traffic condition, could do similar numerical investigation to find out how much capacity it could reserve for SS traffic to maximize the revenue.

## 3.2 Publication not Included

### 3.2.1 Publication F

In addition to the publications mentioned above, the author of the thesis also contributed to the following research paper, which does not take part of this work:

- Jie Xu, Yuming Jiang, Andrew Perkins, and Elissar Khloussy; Multiservice Load Balancing in a Heterogeneous Network with Vertical Handover; Proceedings of the 1st European Teletraffic Seminar, 2011 Sep.

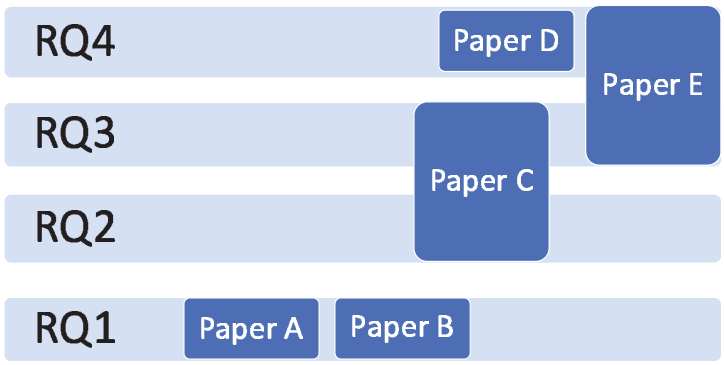



Figure 3.1: Included publications and relationship to the research questions.

#### Summary of the Paper

In this paper, load balancing mechanisms are investigated in an overlay WiMAX/WiFi network through vertical handover. System performance of the HWN in which elastic applications share network capacity with streaming applications is studied.

All traffic is assumed to arrive to WiMAX in the first place. Streaming applications are given strict preemptive priority over elastic applications in WiMAX. Then, based on the expected finish time (in WiMAX and WLAN), handing off certain elastic applications to WLAN is conducted, either on their arrivals or during their service. Two different handover mechanisms are studied. The first one selects the file with maximum remaining size to be handed off to WLAN, at the opposite to the second one which performs the handover for files with minimum remaining size.

The results indicate that the selection of files with minimum remaining size outperforms the other mechanism at the cost of significant increase in the number of handovers. A closer analysis of the simulation results also indicate that both the load balancing granularity and integration of elastic and streaming applications in WiMAX determine the performance of the whole system.

## 3.3 Summary of Publications and Contributions

While working on the different publications that resulted from this research work, the aim has been to provide answers to the research questions listed in Section 1.3.2. In most of them, and particularly Papers A and B, the gain

in revenue resulting from implementing CRRM mechanisms is highlighted, which answers RQ1. Moreover, the role that WLAN can play in mitigating the traffic load of cellular RAT is highlighted in Paper C, providing an answer to RQ2. In Papers C and E, optimal RAT selection policies that aim to maximize the revenue are derived and MDP is used to this end, thus answering RQ3. And finally, net neutrality is accounted for as additional constraint in Papers D and E, and the impact of integrating net neutrality regulation on the revenue and the QoS has been addressed, providing answer to RQ4.

The relationship of the publications to the different research questions is illustrated in Figure 3.1.

The results obtained throughout this research effort allow to build some knowledge that may help the network operator gain higher revenue; knowing how to intelligently manage the wireless resources and how to tune certain system parameters may have significant impact on both the achieved revenue and the QoS.

# Chapter 4

# Conclusion

With the fast evolution of wireless communication, network operators are forced to find innovative solutions to cater for the massive increase of data traffic. Several approaches may be considered to face this challenge such as expanding the network capacity through the addition of femto cells or acquiring additional spectrum. Another promising solution that emerged recently is the LTE-LAA, which is subject to tests by different providers. However, these approaches alone may not be sufficient.

HWNs offer several advantages that help face this explosion in data demand. When two or more RATs co-exist, additional wireless resources become available. To get benefit from this heterogeneity, cooperation among the coexisting RATs is required. This can be realized through CRRM which helps establish a communication and coordination among the different RATs in order to accomplish the performance goals.

CRRM is composed of several components that include RAT selection, vertical handover, and congestion management. RAT selection is a fundamental CRRM functionality which intervenes at call setup and corresponds to the selection of the initial RAT to serve the newly arriving request. The selection of the appropriate RAT is governed by several criteria such as QoS requirements, user preferences and policies, link quality, and traffic load. Despite the advantages that CRRM offers in terms of enhancing the system performance, the implementation of CRRM strategies is not trivial and imposes many challenges.

Another means that is proved to be an important tool for resource management is pricing. The network operators have started to resort to different forms of pricing in order to provide incentive to the users to adjust their usage in a way that alleviates the congestion especially in peak hours. Pricing is a crucial issue and is now subject to intensive research. Dynamic pricing has started to emerge and some dynamic plans have already been implemented. This opens another direction in managing the congestion and handling the fast-growing demands.

The objective of this research work is to shed light on the importance of CRRM, and particularly RAT selection, and the significant gains that may be achieved by implementing CRRM functionalities in HWNs. The problem is addressed from a network operator's viewpoint, and revenue-maximizing RAT selection schemes are derived. Under this main objective, several research problems have been covered, namely investigating MDP as tool for modeling RAT selection policies, and defining a model that captures the coverage probability of WLAN.

Furthermore, the integration of net neutrality within RAT selection frameworks is tackled. Specifically, the impact of net neutrality on the revenue and QoS in HWNs scenarios is highlighted. Moreover, granting exemption to specialized services that net neutrality allows is addressed

and solutions for bandwidth reservation for specialized services in HWNs are proposed and evaluated.

Wireless technologies are in continuous evolution, and the growth in bandwidth demand is driven upwards at the same time. Whether or not any of the upcoming technologies will be able to meet the capacity demands is hard to predict. But until then, heterogeneous networks, if well managed, seem to offer promising solutions that allow to boost the capacity, and subsequently increase the generated revenue.

This research work covers an area of growing interest. The results obtained thus far are encouraging, and it is therefore interesting to continue in the same direction. Some issues that are left for future study include:

- Combining more than one CRRM component, investigating the interaction between them, and the impact of this integration on the revenue and the system performance.
- Exploring other mathematical theories such as MADM and game theory, and the insight they might provide which could not be captured with MDP.
- Further investigation of the impact of net neutrality on the generated revenue, and exploring the possibility of deriving closed-form expression for the obtained solution, i.e. expressing the revenue as an explicit function of the adopted net neutrality approach and the involved parameters.

# References


[1] Cisco visual networking index: Forecast and methodology, 2016-2021. *https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/complete-white-paper-c11-481360.pdf*. 2017 Jun.

[2] Trestian R, Ormond O, Muntean GM. Game theory-based network selection: Solutions and challenges. *IEEE Communications surveys & tutorials*. 2012 Oct;14(4):1212-31.

[3] Andreev S, Gerasimenko M, Galinina O, Koucheryavy Y, Himayat N, Yeh SP, Talwar S. Intelligent access network selection in converged multi-radio heterogeneous networks. *IEEE wireless communications*. 2014 Dec;21(6):86-96.

[4] 3GPP News. Evolution of LTE in Release 13. 2015. *http://www.3gpp.org/news-events/3gpp-news/1628-rel13*.

[5] Kwon HJ, Jeon J, Bhorkar A, Ye Q, Harada H, Jiang Y, Liu L, Nagata S, Ng BL, Novlan T, Oh J. Licensed-assisted access to unlicensed spectrum in LTE release 13. *IEEE Communications Magazine*. 2017 Feb;55(2):201-7.

[6] Chen B, Chen J, Gao Y, Zhang J. Coexistence of LTE-LAA and Wi-Fi on 5 GHz with corresponding deployment scenarios: A survey. *IEEE Communications Surveys & Tutorials*. 2017 Jan 1;19(1):7-32.

[7] Ericsson. Reaching gigabit milestones with Ericsson. *https://www.ericsson.com/en/news/2017/8/reaching-gigabit-milestones-with-ericsson*. 2017 Aug 7.

[8] T-Mobile. T-Mobile completes nation's first live commercial network test of license assisted access (LAA). *https://newsroom.t-mobile.com/news-and-blogs/lte-u.htm*. 2017 Jun 26.

[9] da Silva AP, Cardoso LS, de Sousa Jr VA, Cavalcanti FR. Common radio resource management for multiaccess wireless networks. *Optimizing Wireless Communication Systems*. 2009 Jul 31:233-65.

[10] Gelabert X, Sallent O, Pérez-Romero J, Agustí R. Performance evaluation of radio access selection strategies in constrained multi-access/multi-service wireless networks. *Computer Networks*. 2011 Jan 7;55(1):173-92.

[11] Gelabert Doran X. Contribution to radio resource and spectrum management strategies in wireless access networks: a Markov modeling approach (Doctoral dissertation, Universitat Politècnica de Catalunya). 2010

[12] El Helou M. Radio access technology selection in heterogeneous wireless networks (Doctoral dissertation, Université Rennes 1). 2014

[13] Niyato D, Hossain E. Dynamics of network selection in heterogeneous wireless networks: An evolutionary game approach. *IEEE transactions on vehicular technology*. 2009 May;58(4):2008-17.

[14] Sgora A, Vergados DD, Chatzimisios P. An access network selection algorithm for heterogeneous wireless environments. *Computers and Communications (ISCC), 2010 IEEE Symposium on*. 2010 Jun 22 (pp. 890-892).

[15] Falowo OE, Chan HA. RAT selection for multiple calls in heterogeneous wireless networks using modified topsis group decision making technique. *Personal Indoor and Mobile Radio Communications (PIMRC), 2011 IEEE 22nd International Symposium on*. 2011 Sep 11 (pp. 1371-1375).

[16] Pérez-Romero J, Sallent O, Agustí R. Policy-based initial RAT selection algorithms in heterogeneous networks. *Proceedings of the 7th IFIP International Conference on Mobile and Wireless Communication Networks (MWCN'05)*. Marrakech, Morocco 2005 Sep 19.

[17] Gelabert X, Pérez-Romero J, Sallent O, Agustí R. A Markovian approach to radio access technology selection in heterogeneous multi-access/multiservice wireless networks. *IEEE Transactions on Mobile Computing*. 2008 Oct;7(10):1257-70.

[18] Taha AE, Hassanein HS, Mouftah HT. Vertical handoffs as a radio resource management tool. *Computer Communications*. 2008 Mar 25;31(5):950-61.

[19] Wang L, Kuo GS. Mathematical modeling for network selection in heterogeneous wireless networks-A tutorial. *IEEE Communications Surveys & Tutorials*. 2013 Mar;15(1):271-92.

[20] Stewart WJ. Probability, Markov chains, queues, and simulation: The mathematical basis of performance modeling. Princeton University Press; 2009 Jul 26.

[21] Oza N. Markov decision problems. Department of computer science, Berkeley University. 1995.

[22] Puterman ML. Markov decision processes: Discrete stochastic dynamic programming. John Wiley & Sons; 2014 Aug 28.

[23] Chen H, Cheng CC, Chung WH, Yeh HH. A reduced dimension MDP-based call admission control scheme for next generation telecommunications. *Wireless Communications and Mobile Computing Conference (IWCMC), 2012 8th International*. 2012 Aug 27 (pp. 984-989).

[24] Li L, Littman ML. Lazy approximation for solving continuous finite-horizon MDPs. *AAAI*. 2005 Jul 9 (Vol. 5, pp. 1175-1180).

[25] Csáji BC. Introduction to Markov decision processes. *Signals & Systems Colloquium. The University of Melbourne: Department of Electrical and Electronic Engineering*. 2010.

[26] Stevens-Navarro E, Lin Y, Wong VW. An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks. *IEEE Transactions on Vehicular Technology*. 2008 Mar;57(2):1243-54.

[27] Senouci SM, Beylot AL, Pujolle G. A dynamic Q-learning-based call admission control for multimedia cellular networks. *Proceedings of the 3rd IEEE International Conference in Mobile and Wireless Communication Networks, MWCN2001, Recife, Brazil*. 2001 Aug (pp. 37-43).

[28] Littman ML, Szepesvári C. A generalized reinforcement-learning model: Convergence and applications. *ICML*. 1996 Jul 3 (pp. 310-318).

[29] Khawam K, Ibrahim M, Tohme S. Centralised multi-class Access Control in a WiMAX-UMTS hybrid network. *Personal Indoor and Mobile Radio Communications (PIMRC), 2010 IEEE 21st International Symposium on*. 2010 Sep 26 (pp. 1265-1270).

[30] Jo HS, Sang YJ, Xia P, Andrews JG. Heterogeneous cellular networks with flexible cell association: A comprehensive downlink SINR analysis. *IEEE Transactions on Wireless Communications*. 2012 Oct;11(10):3484-95.

[31] Andrews JG, Baccelli F, Ganti RK. A new tractable model for cellular coverage. *Communication, Control, and Computing (Allerton), 2010 48th Annual Allerton Conference on* 2010 Sep 29 (pp. 1204-1211).

[32] Sen S, Joe-Wong C, Ha S, Chiang M. A survey of smart data pricing: Past proposals, current plans, and future trends. *ACM Computing Surveys (CSUR)*. 2013 Nov 1;46(2):15.

[33] Sen S, Joe-Wong C, Ha S, Chiang M. Incentivizing time-shifting of data: A survey of time-dependent pricing for Internet access. *IEEE Communications Magazine*. 2012 Nov;50(11).

[34] Joe-Wong C, Ha S, Sen S, Chiang M. Do mobile data plans affect usage? results from a pricing trial with ISP customers. *International Conference on Passive and Active Network Measurement*. 2015 Mar 19 (pp. 96-108). Springer, Cham.

[35] Ericsson. Traffic and Market report. White paper, 2013 Aug.

[36] Zhang L, Wu W, Wang D. Time dependent pricing in wireless data networks: Flat-rate vs. usage-based schemes. *INFOCOM, 2014 Proceedings IEEE 2014*. Apr 27 (pp. 700-708).

[37] Hou J, Yang J, Papavassiliou S. Integration of pricing with call admission control to meet QoS requirements in cellular networks. *IEEE Transactions on Parallel and Distributed Systems*. 2002 Sep;13(9):898-910.

[38] Hosein P. Pricing for QoS-based wireless data services and its impact on radio resource management. *GLOBECOM Workshops (GC Wkshps), 2010 IEEE 2010*. Dec 6 (pp. 539-544).

[39] Roberts JW. Internet traffic, QoS, and pricing. *Proceedings of the IEEE*. 2004 Sep;92(9):1389-99.

[40] Lee J, Yi Y, Chong S, Jin Y. Economics of WiFi offloading: Trading delay for cellular capacity. *IEEE Transactions on Wireless Communications*. 2014 Mar;13(3):1540-54.

[41] Ha S, Sen S, Joe-Wong C, Im Y, Chiang M. TUBE: Time-dependent pricing for mobile data. *ACM SIGCOMM Computer Communication Review*. 2012 Sep 24;42(4):247-58.

[42] Al-Manthari B, Nasser N, Hassanein H. Congestion pricing in wireless cellular networks. *IEEE Communications Surveys & Tutorials*. 2011 Jul;13(3):358-71.

[43] Belghith A, Nuaymi L, Maillé P. Pricing of differentiated-QoS services WiMAX networks. *Global Telecommunications Conference, 2008. IEEE GLOBECOM*. 2008 Nov 30 (pp. 1-6).

# Part II

# Included Publications

# Appendix A

# Publication A

Elissar Khloussy, Jie Xu, Anna N. Kim and Yuming Jiang; Maximizing Network Revenue through Resource Management in Heterogeneous Wireless Networks; 16th IEEE Symposium on Computers and Communications (ISCC), Kerkyra, Greece, June 28-July 1, 2011.

**Abstract** Several radio access technologies are now likely to coexist in the same area, and form the so-called heterogeneous wireless networks. In this paper, we study the coordination between WiMAX and WiFi through radio resource management in order to maximize the network operator's revenue. Two solutions for the optimization problem, in which vertical handover and admission control are invoked, are suggested and compared. The simulation results indicate that, through our methods, the network revenue could be greatly increased without seriously degrading the user experience in terms of call-average throughput.

**Keywords**
*heterogeneous networks, radio resource management, revenue, WiMAX, WiFi.*

## A.1 Introduction

In next generation networks, it is more likely to witness the coexistence of several technologies (e.g. GSM, WiFi and WiMAX) within the same area. Because each of these technologies has its own characteristics, such as coverage, cost and data rates, their coexistence can be beneficial for both users and network operators. On one hand, it gives the users the choice of getting connected to their preferred network. This choice is usually dependent on both the cost and the Quality of Service (QoS) that the users' application requires. While on the other hand, this coexistence helps the network operators increase their revenue and provide a better service to the users. However, management of resources in such networks becomes challenging and coordination between the different Radio Access Technologies (RAT) becomes necessary in order to accomplish the overall performance goal.

The objective of our work is to efficiently allocate resources in heterogeneous wireless networks. This topic is broad and can be viewed from different angles depending on who is interested in the outcome of the network design (either the user or the network operator). In the current work, we focus on the network operator's perspective by studying how the operator's revenues can be maximized through Radio Resource Management (RRM) in heterogeneous network, particularly in a WiMAX/WiFi integrated network. The problem, as viewed from the user's perspective, will be the subject of a future work.

In the literature, many research papers and articles dealing with resource management in integrated wireless networks can be found. Authors of [2] reviewed recent joint call admission control algorithms and classified them based on the approach adopted for the selection of the most appropriate RAT. Call admission control is studied thoroughly but independently from any other RRM scheme. In [3], the authors proposed two preemption-based call admission control schemes for real-time and non-real-time traffic in integrated heterogeneous mobile and wireless networks. Their main goal was to satisfy the QoS requirements for the different types of traffic by taking advantages of the service features of heterogeneous networks and the moving nature of mobile users. Vertical handover as RRM and how it increases the network performance was studied in [4]. The goal was to improve the system throughput through access selection and load sharing. A cost and a profit functions were associated to each handoff and the mobile selects the network with the highest profit function. J. Kim in [5] focused on load balancing in heterogeneous networks. A marginal cost function was proposed to determine how to transit user traffic among networks. This allowed for appropriate assignment of new traffic and redistribution of existing traffic, and hence the traffic load of the entire network system could

be balanced.

Less work has been conducted to study the network's revenue maximization. In [6], a gametheoretic model was presented to study the case of competing profit-maximizing providers that offer resources on-demand to the users. I. Chen et al. analyzed in [7] the integration of pricing with admission control in order to maximize the revenues generated without sacrificing the QoS constraints in a single network that handles multiclass traffic.

In this study, we consider the maximization of the operator's revenues (profit) in heterogeneous networks through RRM. The particular case of a WiMAX/WiFi network is studied in which streaming applications are prioritized over elastic applications because of the stringent QoS they require, and can only be hosted in WiMAX. Elastic applications arrive first to WiMAX, and then the network decides whether and when a vertical handover to WiFi has to be performed. This decision is based on the maximization of our objective function. The optimization problem is formulated, and two solutions are proposed. The first solution, a Handover solution, finds the optimal file size to be served in WiMAX, and then triggers a handover of the remaining size of the file to WiFi. The second solution, called Admission Control solution, dispatches the files to WiFi on their arrivals, if the revenues they are expected to generate in WiFi are higher than their revenues in WiMAX. We compare the performance of the two mechanisms along with a Random Admission scheme by simulation. The results indicate that our two proposed solutions lead to considerably higher revenues without serious degradation of the user satisfaction.

The paper is organized as follows. In Section A.2, we elaborate on the system model, Section A.3 describes the adopted billing schemes for WiMAX and WiFi. Section A.4 introduces the optimization problem and suggests two solutions. In Section A.5, the simulation details are provided, and the results are analyzed and discussed, before concluding in Section A.6.

## A.2 System Model

WiMAX and WiFi are two RATs having different characteristics that in some cases can be complementary. While the former provides wider coverage (up to 50 Kilometers [8]) with bandwidths that are somewhat higher and better QoS guarantees, the latter is widely deployed and offers cheaper prices. Fig. A.1 depicts the considered scenario. WiMAX and WiFi coexist in the same area. Within the coverage of one WiMAX base station, there exist several WLAN access points. Users that reside in a commonly

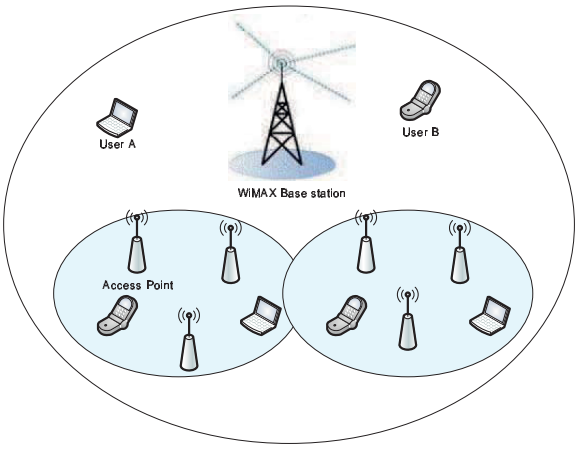



Figure A.1: A WiMAX / WiFi heterogeneous network.

covered area can connect to any of the RATs. Users A and B can connect only to WiMAX as their locations are not covered by any of the existing WLAN access points. It is worth mentioning that, for the users to be able to exploit this combination, their mobile terminals should have connection interfaces to both WiFi and WiMAX.

The network operators can benefit from this type of integrated networks to offer better service to their subscribers and at the same time increase their revenue. This can be realized by the means of an efficient resource management mechanism. This resource management includes admission control, vertical handover, congestion control, and inter-system scheduling [1] which will be described shortly hereby. Admission control is triggered when a new call arrives. Its role is the selection of the network that is more appropriate to handle the candidate call depending on the considered objective function. Vertical handover is the process by which an ongoing call is transferred from one network to the other. It can be either user-initiated or network-initiated in a sense that the decision of switching to another radio access network can be taken by the user or forced by the network. Only network-initiated handover will be considered in this study. Congestion control tries to balance the load between the integrated networks and is generally triggered by load measurements that have to be conducted periodically. And finally, the inter-system scheduling that assigns different packets to different RATs.

In this study, we consider the case of a heterogeneous WiFi/WiMAX network that is owned by one network operator, with two types of calls being offered: video calls (divided into Normal quality and High quality video calls) and file transfer calls. Both types of calls arrive to WiMAX

in the first place. Video streaming calls can be processed in WiMAX only, because of the QoS they require. let $C_{wimax}$ represent the total capacity of WiMAX, and $N$ the number of ongoing streaming calls of which: $N_{norm}$ is the number of normal-quality video applications requiring bandwidth $C_v$ each, and $N_{high}$ is the number of high-quality video calls requiring additional bandwidth $C_{extra}$. Thus, $N = N_{norm} + N_{high}$ and the bandwidth occupied by all ongoing video calls is $C_{videos} = N \cdot C_v + N_{high} \cdot C_{extra}$. Therefore, we can still admit new video calls to the system as long as the condition $C_{videos} \leq C_{wimax}$ is valid. When the admission of a new video call violates the latter condition, this call is immediately blocked.

On the other hand, the arrival of a file transfer call does not affect the streaming calls which are granted higher priority. Upon the arrival of a new file transfer call, it will be admitted to WiMAX where it can be totally served, partially served and then handed off to WiFi, or it might be directed and served entirely in WiFi. File transfer calls, share, in WiMAX, the remaining free bandwidth without affecting the capacity reserved by the prioritized streaming calls. While in WiFi, all ongoing file transfer calls share the entire WiFi bandwidth.

In this considered scenario, we assume that the network has all needed information regarding the overall system performance. This allows the operator to perform the network optimization, provided that the service fee is not a critical factor to the end-user. To satisfy the mentioned condition, the parameters in the adopted billing scheme have to be chosen in a way to keep the user's willingness to pay at a relatively high level.

Hence, our task is to find mechanisms for distributing the file transfer calls between WiMAX and WiFi that allows the network operator to realize the highest achievable profits. This requires to have predefined billing schemes for the services provided in each of the RATs.

## A.3 Billing Schemes

In this section, we introduce the billing schemes that will be adopted in this study for both WiMAX and WiFi networks.

### A.3.1 Billing Schemes in WiMAX

As stated earlier, WiMAX can host video streaming calls as well as file transfer calls. Let us consider the following parameters:

- WiMAX has in total $R_{tot}$ OFDM symbols.

- Video calls have minimum guaranteed rate $R_{min}$
- Video calls can request extra rate $R_{extra}$ that will incur additional price to be paid by the user.
- File transfer calls share the remaining unused bandwidth after video calls have been served.

The billing schemes for WiMAX, which are inspired by [9], can be described as follows:

### Video streaming

Video streamers will be charged a fixed price for the minimum rate $R_{min}$. Then, if they require an additional extra rate $R_{extra}$, a floating price is added. Pricing $P_v(r)$ for this class of service can be formulated as:

$$P_v(r) = V_1 \cdot R_{min} + V_2 \cdot R_{extra} \tag{A.1}$$

Where:

- $r$: is the reserved rate.
- $V_1$: is the fixed price charged for the minimum rate $R_{min}$.
- $V_2$: is the price charged for the additional rate $R_{extra}$.

$V_2$ can be formulated as:

$$V_2 = \frac{K}{R_{tot} - R_{min}} \tag{A.2}$$

Where:

- $K$: is a pricing constant fixed by the operator.

### File transfer calls

File sharing has no QoS guarantees in WiMAX. Their pricing will be an increasing function of the reserved OFDM symbols up to a maximum value $S_{max}$. When the reserved symbols exceed $S_{max}$, a fixed price will then be charged. Hence, the price for file transfer calls $P_f(s)$ can be formulated as follows:

$$P_f(s) = \begin{cases} \gamma \cdot (\frac{-s^2}{S_{max}} + 2s) & \text{if } s \leq S_{max} \\ \gamma \cdot S_{max} & \text{otherwise} \end{cases} \tag{A.3}$$

Where:

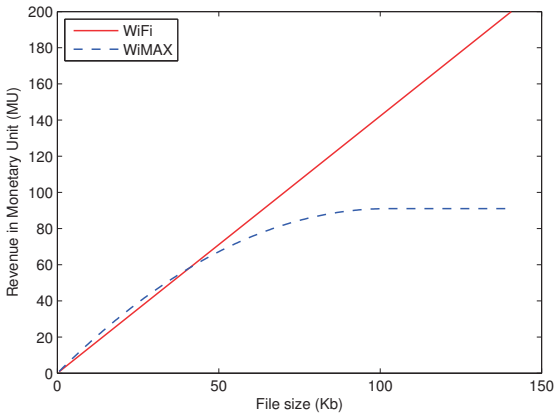



Figure A.2: Comparison of revenues generated by file transfer calls in WiMAX and WiFi.

- $s$: is the number of reserved symbols.
- $\gamma$: is a constant coefficient in monetary unit (MU) per reserved symbol.

### A.3.2 Billing Schemes in WiFi

As mentioned earlier, WiFi will host only file transfer calls, and offers cheaper connection price in comparison to WiMAX. A fixed price per reserved symbol will be considered. Pricing charged in WiFi $P_w(s)$ becomes:

$$P_w(s) = \omega \cdot s \tag{A.4}$$

Where:

- $\omega$: is the price per reserved symbol $s$ in WiFi.

Fig. A.2 shows the revenues in WiMAX and WiFi as a function of the file size. The curve of WiFi revenues remains below WiMAX revenues' curve up to a certain value of the file size, above which it becomes more profitable to serve the file in WiFi. This value of file size depends on the choice of the values of the different pricing parameters. Fig. A.2 is based on the values used in our simulation code and detailed in Subsection A.5.1.

## A.4 Optimization Formulation

### A.4.1 Optimization Problem

The objective of our optimization problem is the maximization of the total network revenue. The solution of this problem consists of finding the best distribution of the file transfer calls between WiMAX and WiFi that contributes to the highest revenue. Since video calls are served with preemptive priority in WiMAX, the revenue generated by serving video calls is the same with different distribution mechanisms for file transfer calls. Therefore, we only need to consider the revenue generated by serving file transfer calls, which can be formulated as:

$$Rev_{tot}(x) = Rev_{wimax}(x) + Rev_{wifi}(FileSize - x) \tag{A.5}$$

Where:

- $Rev_{tot}(x)$ denotes the total revenue generated by serving a file transfer call of initial size $FileSize$ of which $x$ is processed in WiMAX and the remaining size $(FileSize - x)$ is processed in WiFi.

We first calculate the optimal value of $x$, denoted as $x_{opt}$, without considering the practical limits. In other words, the file in WiMAX can be switched to WiFi in any time epoch.

By plugging the billing schemes into Eq. (A.5), we can get the revenue generated by a file transfer call as function of its size. Two cases can be distinguished:

The first one is the case where $x$ requires less than $S_{max}$ OFDM symbols to be processed in WiMAX; in this case, the first part of Eq. (A.3) applies for $Rev_{wimax}$, and hence $Rev_{tot}$ becomes:

$$\begin{aligned} Rev_{tot}(x) &= \gamma \cdot \left(\frac{-x^2}{(bps_{wimax})^2 \cdot S_{max}}\right) + \frac{2 \cdot x}{bps_{wimax}}) \\ &+ \omega \cdot \frac{(FileSize - x)}{bps_{wifi}} \end{aligned} \tag{A.6}$$

Where:

- $bps_{wimax}$: is the number of bits per symbol in WiMAX.
- $bps_{wifi}$: is the number of bits per symbol in WiFi.

Subsequently, by calculating the derivative of $Rev_{tot}$ in respect to $x$ we can find the value of $x_{opt}$:

$$\frac{dRev_{tot}}{dx} = \frac{-2 \cdot \gamma \cdot x}{(bps_{wimax})^2 \cdot S_{max}} + \frac{2 \cdot \gamma}{bps_{wimax}} - \frac{\omega}{bps_{wifi}} \tag{A.7}$$

The optimal size to be served in WiMAX $x_{opt}$ is then the value of $x$ for which $\frac{dRev_{tot}}{dx}$ is equal to zero:

$$x_{opt} = bps_{wimax} \cdot S_{max}(1 - \frac{bps_{wimax}}{bps_{wifi}} \frac{\omega}{2 \cdot \gamma}) \tag{A.8}$$

The second case is for $x$ requiring more than $S_{max}$ OFDM symbols; by applying the second part of Eq. (A.3), $Rev_{tot}$ becomes:

$$Rev_{tot}(x) = \frac{\gamma \cdot S_{max}}{bps_{wimax}} + \omega \cdot (\frac{(FileSize - x)}{bps_{wifi}}) \tag{A.9}$$

In this case, $\frac{dRev_{tot}}{dx}$ is always negative, which means that $Rev_{tot}(x)$ is a decreasing function.

Based on the cases studied above, $x$ should not exceed $(S_{max} \cdot bps_{wimax})$ bits in order to ensure a maximization of the network's revenue.

### A.4.2 Proposed Solutions

Different solutions for our optimization problem i.e. maximizing $Rev_{tot}(x)$ can be defined according to the constraint on the value of $x$.

In general, the domain of values of $x$ can be expressed as follows:

$$x \begin{cases} = 0 & \text{File totally served in WiFi} \\ \in \ ]0, FileSize[ & \text{File partially served in WiMAX} \\ = FileSize & \text{File totally served in WiMAX} \end{cases}$$

Two solutions are proposed in this study:

#### Handover solution

This solution considers that the file can be totally served in WiMAX, or partially served in WiMAX and then handed off to WiFi. In this case, the optimization problem becomes:

$$\begin{aligned} \underset{x}{\text{maximize}} \quad & Rev_{tot}(x) \\ \text{subject to} \quad & 0 < x_i \leq FileSize_i, \ i = 1, \ldots, m. \end{aligned}$$

Where:

- $m$ represents the number of ongoing file transfer calls in WiMAX.

The aim of the Handover scheme is to solve the optimization problem described above. The size to be served in WiMAX $x$ can be obtained, according to this approach, as follows:

$$x = \begin{cases} FileSize & \text{if } FileSize \leq x_{opt} \\ x_{opt} & \text{otherwise} \end{cases}$$

Upon the arrival of a new file transfer call, it is first admitted into WiMAX. Subsequently, a handover test is performed to decide whether and when this file has to be handed off to WiFi:

- The optimal size to be served in WiMAX ($x_{opt}$) is calculated according to (A.8).
- The size of the file is compared to $x_{opt}$.
- In the case where the file size is less or equal than $x_{opt}$, the file is then entirely processed in WiMAX and no handover to WLAN is triggered.
- Otherwise, $x_{opt}$ is served in WiMAX, before handing off the remaining size to WiFi.

### Admission control solution

The admission control solution considers that a file will be either entirely served in WiMAX or in WiFi. This can be translated by the following problem formulation:

$$\begin{aligned} \underset{x}{\text{maximize}} \quad & Rev_{tot}(x) \\ \text{subject to} \quad & x_i = 0 \; or \; x_i = FileSize_i, \; i = 1, \ldots, m. \end{aligned}$$

According to this approach, the revenue gained by the admission of a file transfer call of size $FileSize$ is:

$$Rev_{tot} = \max(Rev_{wimax}(FileSize), Rev_{wifi}(FileSize))$$

where $Rev_{wimax}$ and $Rev_{wifi}$ are obtained by (A.3) and (A.4) respectively. In this scheme, the selection of the candidate RAT to host a newly arriving elastic application is performed through comparing the expected revenues in WiMAX and WiFi and then admitting the call into the RAT with higher generated revenue.

In other words, this scheme suggests that, an admitted file transfer call is directed and totally served in WiFi only in the case where the revenue it can generate in WiFi is expected to be higher than its revenue in WiMAX.

Table A.1: Simulation parameters

| | |
|---|---|
| WiMAX capacity in the WLAN area | 7.0 Mbps |
| Bits per symbol in WiMAX | 576 |
| Bits per symbol in WiFi | 144 |
| Bandwidth for normal quality video | 500 kbps |
| Bandwidth for high quality video | 800 kbps |
| Percentage of high quality video calls | 20 % |
| Average file size | 0.0646 Mb |
| Average video length | 150.0 s |

## A.5 Simulation

The simulation was conducted in Matlab. The values of the different parameters are shown in Table A.1. For elastic applications, bounded Pareto distribution is adopted to represent a heavy-tailed distribution for file sizes, with shape parameter of value 1.1, while an exponential distribution is considered for the arrival intervals of real-time applications as well as for the arrival intervals of elastic applications.

In order to evaluate the performance of our two initially proposed solutions, a third scheme, called Random Access scheme, is also simulated. With this scheme, the distribution of elastic applications is performed according to the proportion of the remaining free capacity in WiMAX (after streaming calls have been served) to the capacity of WiFi, without any considerations on the revenue. Hence, in this case, elastic applications are more likely to be moved and served in WiFi when the load of video traffic in WiMAX increases.

### A.5.1 Numerical Values

Different parameters are involved in the billing schemes, namely $\gamma$, $\omega$, $S_{max}$, $V_1$, and $K$. The choice of the values of these parameters is critical as they affect directly the revenue. These parameters were investigated in [9], and we are particularly interested in the values that contribute in increasing the network revenue:

- $\gamma$: It was demonstrated that the symbol price for best effort calls has to be less than 0.9 MU / symbol beyond which the revenue starts

to decrease (the user satisfaction decreases). Hence, we adopted the value of 0.5 for $\gamma$.

- $\omega$: Due to the non QoS guarantee, the symbol price in WiFi should be significantly lower than that in WiMAX. We chose the value of 0.2 MU/symbol for $\omega$.

- $S_{max}$: $S_{max}$ was given the value of 182.04 that corresponds to a file of size 0.1Mb.

- $V_1$ and $K$: Considering that the price per symbol for video calls has to be higher than that of a file transfer call in WiMAX, we assigned the value 0.9 to $V_1$. For $K$, we adopted the value 10 as in [9].

### A.5.2 Discussion

In addition to the generated revenues, two common performance metrics are considered in comparing the studied approaches, namely the average file service time and the throughput represented by time-average throughput and call-average throughput (explained in [10]). The value variations of the considered parameters are studied according to $\rho_{video}$, which represents the load of the video traffic with respect to the capacity of WiMAX.

#### Revenues

Fig. A.3 depicts the revenues generated by all three proposed solutions without taking into account the revenues from real-time traffic that has no effect on the comparison results. The Handover solution provides higher revenues than the Admission Control scheme and they both considerably outperform the Random Access scheme. With Random Access, the generated revenue increases with the increasing load of streaming calls in WiMAX. This is due to the higher probability of distributing files to WLAN, which results in increasing the revenue. We conclude that the Handover solution proposes a 'relaxation' on the constraint on the size $x$ to be served in WiMAX, by considering continuous values for $x$, and forms an upper bound to the Admission Control solution in which $x$ can be assigned only one of two values, i.e. it can be either equal to zero or equal to the total size of the file ($FileSize$). However, it can be seen that the revenue gap between Handover and Admission Control is not very significant. Therefore, Admission Control should be preferred in this case since normally Handover introduces much more overheads in practice.

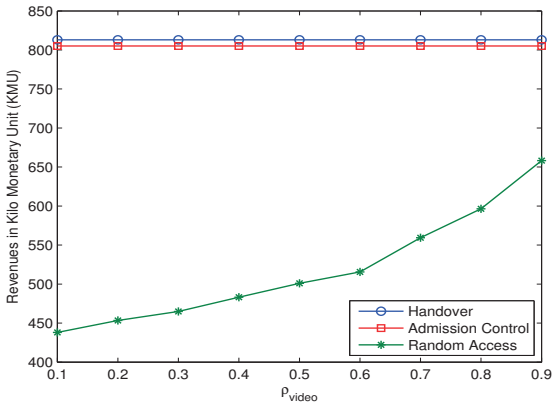



Figure A.3: Revenues generated as function of the offered video load.

### Average file service time

With the increase of the offered load of video traffic, the average file service time for all three cases increases fast (Fig. A.4), particularly when the value of this offered load surpasses 0.6. This is due to the fact that, when the number of video calls served in WiMAX increases, file transfer calls processed in WiMAX will suffer from low available capacity because of the priority granted to video calls. While the service degradation in the Random Access solution is more tolerable, the Handover solution performs the worst. The reason can be related to the cost of the handover process. Finally, the performance of the Admission Control solution is worse than the Random Access because it admits large files in WiFi network where they can provide higher revenues. However, these files get smaller bandwidth and consequently a slower service.

### Throughput

The third metric adopted for the comparison of the performance of the three studied schemes is the throughput. The results show that the throughput decreases with the increase of the offered video load (Fig. A.5 and Fig. A.6). This decrease in throughput is directly related to the increase in the file average service time metric. In terms of call-average throughput, all three solutions perform roughly the same. Whereas, we notice that the decay is slower for time-average throughput because this latter depends solely on the system throughput. This explains as well the gap in time-average throughput of Random Admission solution with the two other schemes.

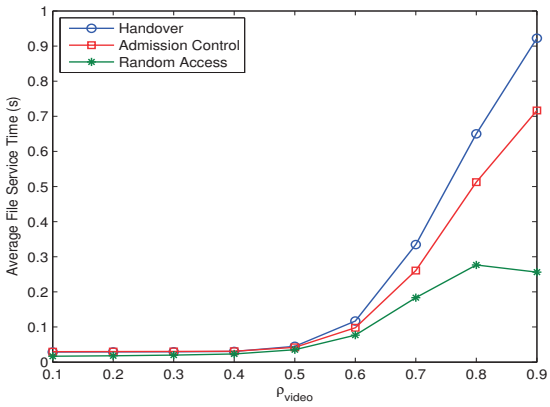



Figure A.4: File service time as function of the offered video load.

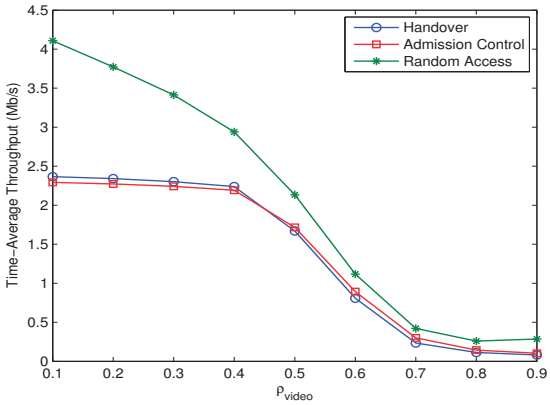



Figure A.5: Time-average throughput as function of the offered video load.

However, this gap becomes negligible when the offered video load increases because, at this stage, the whole capacity of WiMAX is reserved for video calls, leaving only small space to serve the elastic traffic.

As a conclusion on the performance evaluation of the Handover and Admission Control schemes, we can say that, although according to traditional QoS metric, like average service time and time-average throughput, our proposed schemes perform worse compared with Random Access, however, and according to call-average throughput, which is believed to be the most proper metric with respect to Quality of Experience (QoE), our schemes perform very close.

We could not compare the results found in the current work to some

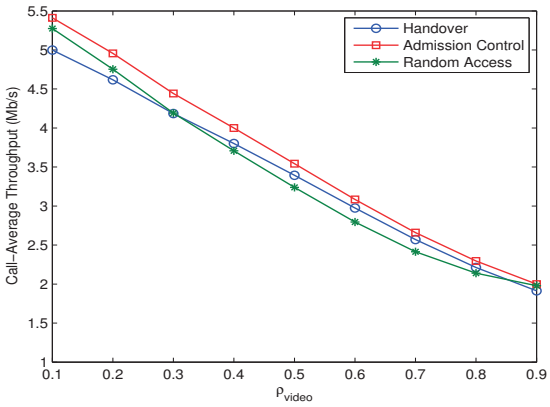



Figure A.6: Call-average throughput as function of the offered video load.

other results. The reason is that, in the literature, the problem of maximizing the operator's revenues was mostly studied in single networks scenarios. In the future, it would be interesting to compare our results to those emerging from different billing schemes and draw some conclusions in this direction.

## A.6 Conclusion and Future Work

This paper studies the maximization of the network operator's revenue through RRM in heterogeneous networks. The particular case of a WiFi / WiMAX integrated network is chosen. Two schemes are proposed and compared. Simulation results show that, by adopting RRM, higher profits can be achieved as compared to the case where no resource management scheme is adopted and the admission control is performed randomly. Moreover, in terms of QoE, the performance of our proposed methods is relatively close to that of the Random Access scheme.

This paper does not cover all aspects of the studied problem. Other RRM schemes have to be investigated in the future. Also, adding a third class of services for voice calls, as well as comparing the results for different values of pricing parameters could enhance the present work.

# References


[1] da Silva AP, Cardoso LS, de Sousa Jr VA, Cavalcanti FR. Common radio resource management for multiaccess wireless networks. *Optimizing Wireless Communication Systems*. 2009 Jul 31:233-65.

[2] Falowo OE, Chan HA. Joint call admission control algorithms: Requirements, approaches, and design considerations. *Computer Communications*. 2008 Apr 18;31(6):1200-17.

[3] Shen W, Zeng Q. Resource allocation schemes in integrated heterogeneous wireless and mobile networks. *Journal of Networks*. 2007 Sep;2(5):78-86.

[4] Liu X, Li VO, Zhang P. Joint radio resource management through vertical handoffs in 4G networks. *Global Telecommunications Conference, 2006. GLOBECOM'06*. IEEE 2006 Nov 27 (pp. 1-5).

[5] Kim JH. Design of common resource management and network simulator in heterogeneous radio access network environment. *Journal of Network and Systems Management*. 2009 Jun 1;17(1-2):137-56.

[6] Roggendorf M, Beltran F. A heuristic approach to revenue maximization in a competitive bandwidth-on-demand wireless market. *Bandwidth on Demand, 2006 1st IEEE International Workshop on*. 2006 Nov 27 (pp. 4-11).

[7] Chen R, Yilmaz O, Yen IL. Admission control algorithms for revenue optimization with QoS guarantees in mobile wireless networks. *Wireless Personal Communications*. 2006 Aug 1;38(3):357-76.

[8] Ma L, Jia D. The competition and cooperation of WiMAX, WLAN and 3G. *Mobile Technology, Applications and Systems, 2005 2nd International Conference on*. 2005 (pp. 1-5).

[9] Belghith A, Nuaymi L, Maillé P. Pricing of differentiated-QoS services WiMAX Networks. *Global Telecommunications Conference, 2008. IEEE GLOBECOM 2008*. IEEE 2008 Nov 30 (pp. 1-6).

[10] Xu J, Jiang Y, Perkis A, Khloussy E. Multi-service load balancing in a heterogeneous network with vertical handover. *Proceedings of the 1st European Teletraffic Seminar* . 2011 Sep.

# Appendix B

# Publication B

Elissar Khloussy, Xavier Gelabert and Yuming Jiang; A Revenue-Maximizing Scheme for Radio Access Technology Selection in Heterogeneous Wireless Networks with User Profile Differentiation; Lecture Notes in Computer Science, Vol. 8115, pp. 66 - 77, Springer, 2013. (Proceedings of 19th EUNICE/IFIP WG 6.6 International Workshop on Advances in Communication Networking, Chemnitz, Germany, August 28 - 30, Chemnitz, Germany, 2013.)

**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.*

## B.1 Introduction

With the tremendous evolution of wireless network technologies and the 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.

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 network utility, e.g. the overall HWN capacity, and takes into consideration the network-related parameters such as the RATs' loads and capabilities as well as the existing service types [1]. In this paper, we address an *operator-centric* RAT selection with the 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 to be 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 can 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. B.2 describes the system model and the proposed RAT selection scheme. In Sec. B.3, the different elements of the Markovian model are introduced. Sec. B.4 presents the results obtained by the model and the simulation. In Sec. B.5 we introduce and solve the optimization problem for finding the optimal threshold value, and Sec. B.6 concludes the paper.

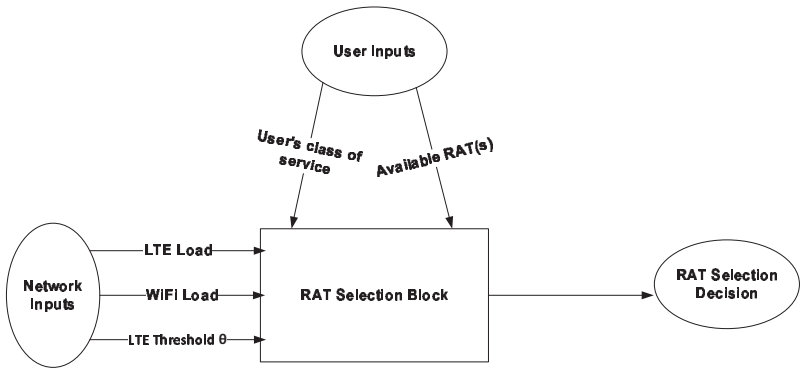



Figure B.1: RAT selection block.

## B.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].

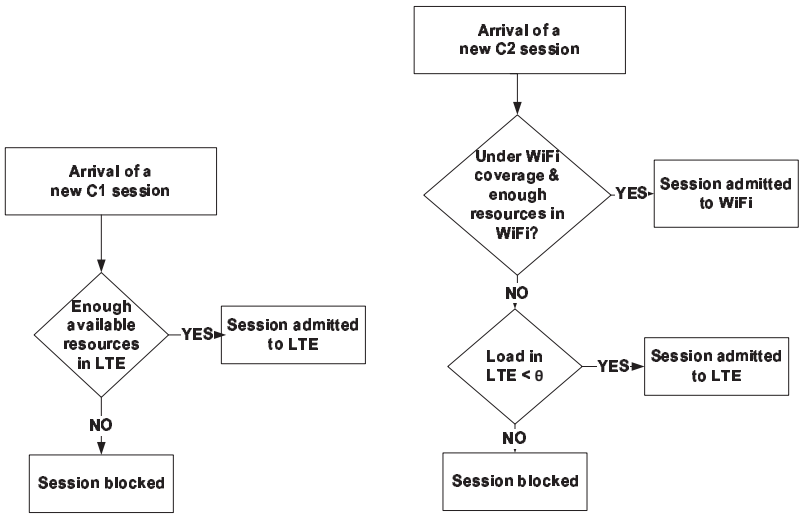
In the considered scenario, a user can be either residing in an area covered by LTE only, or in a dual coverage area with a probability $P_{dual}$. Two user profiles $C_1$ and $C_2$ are provided. Class $C_1$ has higher priority than class $C_2$. Practically, the prioritized class $C_1$ targets the business 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 $\theta$ 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. B.1, requires mainly two types of inputs: network parameters (LTE and WiFi loads and the value of $\theta$), 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 session admission is successful.

Based on the RATs characteristics and the considered user profile dif-

ferentiation, 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 the capacity of WiFi 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 $\theta$, the RAT selection module allows the admission of the new $C_2$ session to LTE.
- When the load in LTE exceeds $\theta$, only $C_1$ sessions are allowed to be admitted to LTE.




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

Figure B.2: Algorithm for RAT selection.

Fig. B.2 illustrates the proposed 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.

## B.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 $\lambda_1$ and $\lambda_2$ 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].

### B.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:

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

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

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

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

| To State | Rate | Condition |
|---|---|---|
| $S(i+1, j, k)$ | $\lambda_1$ | $i < I$ |
| $S(i-1, j, k)$ | $i.\mu_1$ | $i > 0$ |
| $S(i, j, k+1)$ | $\lambda_2.P_{dual}$ | $k < K$ |
| $S(i, j, k-1)$ | $k.\mu_2$ | $k > 0$ |
| $S(i, j+1, k)$ | $\lambda_2.(1 - P_{dual})$ | $j < J(i) \wedge k < K$ |
| | $\lambda_2$ | $j < J(i) \wedge k = K$ |
| $S(i, j-1, k)$ | $j.\mu_2$ | $j > 0$ |

### B.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 $\mathbf{Q}$. The transition rates from a given state $S(i, j, k)$ to any of its neighboring states are provided in Table B.1. After creating $\mathbf{Q}$ 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.

### B.3.3 Performance Metrics

#### Average number of sessions

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

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

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 (B.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:

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

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

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

**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 $C_\gamma$ can be defined as:

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

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

## B.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 B.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. B.3 and Fig. B.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. B.3 depicts the blocking probabilities for classes $C_1$ and $C_2$, considering different values of $\theta$, 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 $\theta$, the blocking probability of $C_2$ class

Table B.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 | $\lambda_1$ | $1/60\ s^{-1}$ |
| Arrival rate of $C_2$ class | $\lambda_2$ | $1/30\ s^{-1}$ |
| 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 |

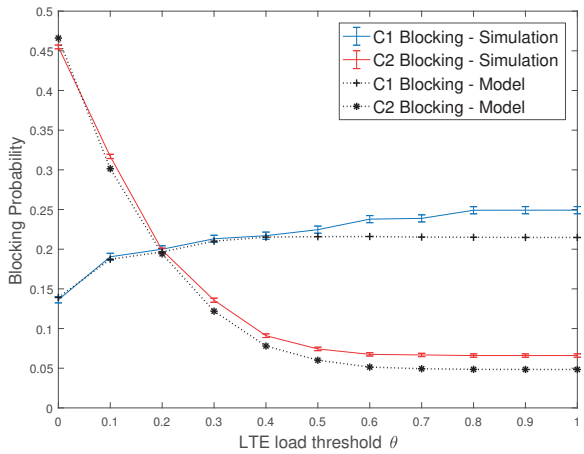



Figure B.3: $C_1$ and $C_2$ blocking probabilities for different values of $\theta$.

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. B.4, namely the throughput. With the increase of the value of $\theta$, 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.

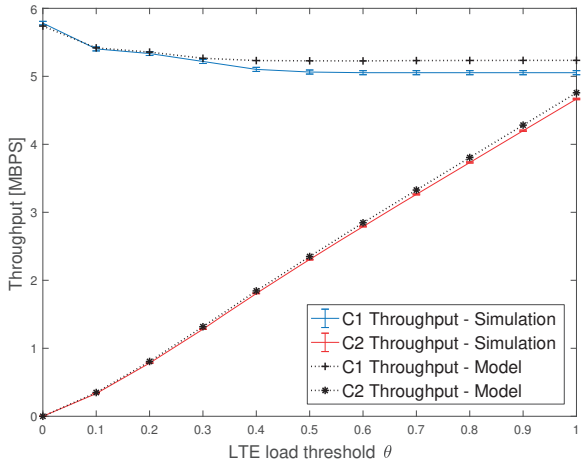



Figure B.4: $C_1$ and $C_2$ throughput variations for different values of $\theta$.

## B.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 $\theta$. Therefore, the parameter $\theta$ 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 $\theta$ 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 $\beta$.

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:

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

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

The optimization problem for revenue maximization can be formulated as:

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

where $S_\theta$ is the set of values of $\theta$ chosen as: $S_\theta = \{0, 0.1, 0.15, 0.2, .., 1\}$, and $P_{b,i}$ is the blocking probability of class $C_i$, $i \in \{1, 2\}$.

The admission of $C_2$ sessions to LTE is dependent on the value of $\theta$. 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 $\theta^*$ that solves the optimization problem in (B.8). For this purpose, we use Algorithm 1.

**Algorithm 1** Algorithm for finding the optimal threshold $\theta^*$.

```
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 $\theta^*$ for some given values of the offered load traffic of $C_1$ and $C_2$ profiles, we first start with the smallest value of $\theta$ (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 $\theta$ to check if highest revenue could be achieved without violating the blocking probability constraints. If there are more than one value of $\theta$ that ensure the same highest revenue, we have interest in choosing the smallest $\theta^*$, as it corresponds to a smaller blocking probability for the high-priority class.

Fig. B.5 depicts the selected values of $\theta^*$ 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 $\theta^*$ decreases, and it becomes less likely to find a $\theta^*$ that solves the optimization problem.

Finding the optimal threshold has an important impact on the generated revenue. This can be deduced from Fig. B.6 that depicts the revenue of the network for arbitrary load thresholds compared to the revenue achieved with the optimal threshold, for an offered traffic $A_1 = 0.8$ of class $C_1$. Fig.

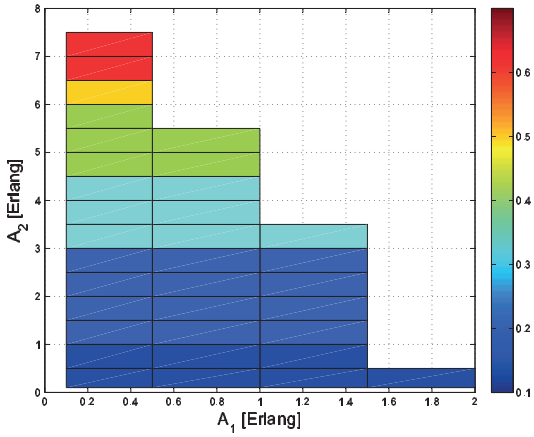



Figure B.5: Optimal threshold value for $\beta_1 = 5\%$ and $\beta_2 = 10\%$.

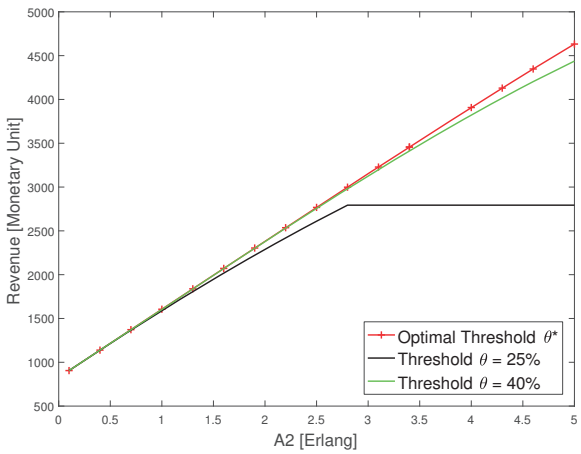



Figure B.6: Revenue for arbitrary and optimal load thresholds, $A_1 = 0.8$ Erlang.

B.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 $\theta^*$. 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 have been be achieved

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

| | | $\theta = 25\%$ | $\theta = 40\%$ | $\theta^*$ |
|---|---|---|---|---|
| $A_2 = 1.1$ | $P_{b,1}$ | 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 % |

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. B.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 $\theta$ are presented in Table B.3. For 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.

## B.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 3D 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 AP, Cardoso LS, de Sousa Jr VA, Cavalcanti FR. Common radio resource management for multiaccess wireless networks. *Optimizing Wireless Communication Systems*. 2009 Jul 31:233-65.

[2] Piamrat K, Ksentini A, Bonnin JM, Viho C. Radio resource management in emerging heterogeneous wireless networks. *Computer Communications*. 2011 Jun 15;34(9):1066-76.

[3] Hasib A, Fapojuwo AO. Analysis of common radio resource management scheme for end-to-end QoS support in multiservice heterogeneous wireless networks. *IEEE Transactions on Vehicular Technology*. 2008 Jul;57(4):2426-39.

[4] Gelabert X, Pérez-Romero J, Sallent O, Agustí R. A Markovian approach to radio access technology selection in heterogeneous multiaccess/multiservice wireless networks. *IEEE Transactions on Mobile Computing*. 2008 Oct;7(10):1257-70.

[5] Song W, Jiang H, Zhuang W, Shen X. Resource management for QoS support in cellular/WLAN interworking. *IEEE Network Magazine*. 2005 Sep;19(5):12-8.

[6] Niyato D, Hossain E. A nonCooperative game-theoretic framework for radio resource management in 4G heterogeneous wireless access networks. *IEEE Transactions on Mobile Computing*. 2008 Mar;7(3):332-45.

[7] Falowo OE, Zeadally S, Chan HA. Dynamic pricing for load-balancing in user-centric joint call admission control of next-generation wireless networks. *International Journal of Communication Systems*. 2010 Mar 1;23(3):335-68.

[8] Giupponi L, Agustí R, Pérez-Romero J, Sallent O. An economic-driven joint radio resource management with user profile differentiation in a

beyond 3G cognitive network. *Global Telecommunications Conference, 2006. GLOBECOM'06*. IEEE 2006 Nov 27 (pp. 1-5).

[9] Khloussy E, Xu J, Kim AN, Jiang Y. Maximizing network revenue through resource management in heterogeneous wireless networks. *Computers and Communications (ISCC), 2011 IEEE Symposium on*. 2011 Jun 28 (pp. 365-370).

[10] Yu F, Krishnamurthy V. Optimal joint session admission control in integrated WLAN and CDMA cellular networks with vertical handoff. *IEEE Transactions on Mobile Computing*. 2007 Jan;6(1).

[11] Chen H, Cheng CC, Yeh HH. Guard-channel-based incremental and dynamic optimization on call admission control for next-generation QoS-aware heterogeneous systems. *IEEE Transactions on Vehicular Technology*. 2008 Sep;57(5):3064-82.

[12] Kim DK, Griffith D, Golmie N. A new call admission control scheme for heterogeneous wireless networks. *IEEE Transactions on Wireless Communications*. 2010 Oct;9(10):3000-5.

[13] The 3rd generation partnership project. *http://www.3gpp.org/lte-advanced*

[14] Bonald T, Roberts JW. Internet and the Erlang formula. *ACM SIGCOMM Computer Communication Review*. 2012 Jan 16;42(1):23-30.

[15] Falowo OE, Chan HA. Multiple-RAT selection for reducing call blocking/dropping probability in cooperative heterogeneous wireless networks. *EURASIP Journal on Wireless Communications and Networking*. 2012 Dec 1;2012(1):221.

[16] Nasser N, Hassanein H. Dynamic threshold-based call admission framework for prioritized multimedia traffic in wireless cellular networks. *Global Telecommunications Conference, 2004. GLOBECOM'04*. IEEE 2004 Nov (Vol. 2, pp. 644-649).

[17] Kelly F. Notes on effective bandwidths in stochastic networks: Theory and applications. Royal Statistical Society Lecture Notes Series, 4. Oxford University Press, (1996).

[18] Stewart WJ. Probability, Markov chains, queues and simulation. Princeton University Press. 2009 Jul 26.

# Appendix C

# Publication C

Elissar Khloussy, Xavier Gelabert and Yuming Jiang; Investigation on MDP-Based Radio Access Technology Selection in Heterogeneous Wireless Networks; Computer Networks. 2015 Nov 14;91:57-67.

**Abstract** The new generation of wireless networks is characterized by heterogeneity i.e. the coexistence of two or more Radio Access Technologies (RAT) in the same geographical area. While this coexistence of RATs offers various advantages, it also imposes many challenges for the network operator, whose aim is to maximize the generated revenue while satisfying the customers' increasing demands. One important mechanism in Heterogeneous Wireless Networks (HWN) is the RAT selection. It is normally triggered when a new call arrives, and provides the decision on whether the call can be admitted or not, and by which RAT it has to be served. Different approaches can be used to tackle the problem of RAT selection in HWNs. In this paper, we study Markov Decision Process (MDP)-based RAT selection in a cellular / WLAN heterogeneous network where the maximization of the revenue is considered as objective. An optimal RAT selection policy is therefore derived. The performance of the optimal scheme is evaluated in comparison with two other policies, namely Cellular-First policy and Load Balancing policy.

**Keywords**
*radio access technology (RAT) selection, Markov decision processes (MDPs), heterogeneous wireless networks, Poisson Point Process.*

## C.1 Introduction

The new generation of wireless networks is characterized by heterogeneity where two or more Radio Access Technologies (RATs) coexist in the same geographical area. The coexisting RATs may have different, but often complementary characteristics in terms of coverage, latency and link capacity. This trend of multiplicity of RATs is also expected to be dominating in the future for the many advantages it offers. These advantages include, among others, multiple connectivity options, and an expansion of the coverage at a relatively low structure cost [2]. However, this imposes additional challenges for the operator especially in finding means of coordination among the coexisting RATs.

Getting full advantage of the combined features of the deployed RATs is crucial for the network operator. On one hand, this can be explained by the fast increase of demands from users with high Quality of Service (QoS) requirements, coupled with the proliferation of bandwidth-hungry applications widely available on smart phones, and electronic devices. On the other hand, the wireless resources are very scarce as compared to the growing demands. Therefore, the operator has interest in making the best utilization of all available resources to increase the capacity of the network and meet, as much as possible, the users' expectations and demands.

Heterogeneous Wireless Networks (HWN) provide many opportunities for capacity improvement. Considering the case of a cellular / WLAN overlay network, WLAN can play an important role in alleviating some of the problems encountered by the cellular network in terms of congestion and coverage (WLAN offloading [3]). By deploying access points (APs) in specific targeted areas such as cell edges, and hotspots, considerable amount of traffic can be carried by the WLAN [4], thus increasing the network capacity.

Cellular and WLAN have complementary characteristics. On one hand, broadband cellular networks such as 3GPP Long Term Evolution (LTE) can implement quite complex resource management schemes, more efficient QoS and wider coverage than WLAN. On the other hand, WLAN is characterized by its cheap deployment and access costs, small coverage and limited QoS guarantees. A network operator can, through an efficient management of the joint pool of resources of both RATs, take advantage of their combined features to increase the overall system performance and consequently generate higher profit.

Managing resources in HWNs involves setting up policies that regulate the amount and type of traffic served by each of the RATs. These regulations may vary depending on whether the adopted scheme is user-centric or operator-centric. For instance, considering the user's perspective, the

objective is usually to guarantee the best achievable QoS such as low delay and blocking probabilities or high throughput. The operator, however, would be more interested in maximizing the network's capacity in order to accommodate the maximum number of users and increase the generated revenue.

A well known key mechanism for resource management in HWNs scenarios is RAT selection. It consists of taking a decision, at each arrival of a new call request, on whether to accept this call or not, and the RAT to which it can be admitted. A well-designed RAT selection policy allows a better assignment of the traffic to the available access networks, increasing the number of sessions that the system can accommodate.

Different approaches can be used to tackle the RAT selection problem in HWNs. In the present work, we investigate Markov Decision Process (MDP)-based RAT selection with the objective of maximizing the operator's revenue. Different user profiles with their respective QoS requirements and charged prices are considered, and a preferential treatment is provided to the profile that is charged higher fees. Moreover, the spatial distribution of the base stations (BSs) and APs (for the cellular and WLAN respectively), and that of the users in the HWN are taken into account in modeling the traffic.

The main contributions of this paper can be summarized as follows:

(1) Investigation of the MDP-based approach for RAT selection, with focus on revenue maximization as objective.

(2) Considering the operator's policy of granting different levels of priority to the different classes of service, the reflection of this policy by tuning the parameters of the MDP model is discussed.

(3) The coverage probability of WLAN is analytically modeled with the help of Poisson Point Process (PPP).

(4) The spatial distribution of the users is also captured with PPP.

(5) Evaluation of the performance of the MDP-based RAT selection with comparison to two other static RAT selection schemes.

(6) Highlight on the role of WLAN in traffic offloading and improving the perceived QoS.

The remaining of the paper consists of the following parts: Section C.2 presents the motivation and related work in the literature. Section C.3 describes the system model. In Section C.4, the components of the MDP problem are presented. Section C.5 discusses the revenue maximization

problem. Section C.6 presents and analyzes the obtained results. Finally, we conclude this study in Section C.7.

## C.2 Motivation and Related Work

Broadband cellular networks, despite their great promises, might not be able to meet the expected increase in demands of data traffic in the near future [5]. This incites the network operators to be in perpetual search for solutions that alleviate the problem of increasing traffic load, and WLAN has been considered as one appealing candidate to complement the cellular network. For example, WiFi offloading is of great importance for the different advantages it provides, namely the usage of unlicensed spectrum, being a well-established technology, and more importantly all new smart phones, and electronic devices planned for 4G have the features of WiFi radio embedded, a trend that is likely to continue for 5G as well.

In order for the network operator to benefit from the WLAN capacity to alleviate the load of cellular network, a strategy for the distribution of traffic among the two RATs is needed. This can be partly realized through the implementation of an efficient RAT selection mechanism. While different approaches can be used in dealing with RAT selection problem, MDP is a good candidate for this optimization owing to its appealing properties.

MDP can be defined as a Markov chain with the addition of an action model and a performance criterion. It has been widely applied in various areas such as ecology, economics, and network routing [6]. In the case of RAT selection problems, MDP is also an intuitive stochastic control approach. Even though MDP suffers from a dimensionality problem when the number of states in the MDP is increased to represent a large number of connections, some approaches have been suggested in the literature (such as in [7]) where approximation solutions are provided. One other example can be found in [8] where a reduced dimension MDP-based call admission control scheme has been proposed. The results in [8] show a great reduction in the complexity of the original MDP model, making it practical and cost-effective for implementation in HWNs. We believe, with such solutions, the effectiveness and the promising results of MDP-based schemes can be exploited by the network operators. Nevertheless, in this paper, our focus is on investigating the effectiveness of using MDP to maximize revenue generation in HWNs. For this reason, we shall only consider the original MDP, leaving its simplification to future study.

In the literature, several RAT selection policies have been proposed. In [6], a threshold-based framework for call admission control has been provided and different objective functions have been proposed and inves-

tigated. In [9], the authors proposed a heuristic RAT selection scheme in co-located wireless networks which aims to enhance the user's QoS in terms of minimizing the call blocking probability. In [18], a stochastic process algebra is used to build a framework for network selection strategies in 3G-WLAN networks. Different strategies are evaluated, namely general non-deterministic strategies (random strategy and relative received signal strength (RRSS)-based strategy), WLAN-first and service-based. The considered performance measures (average throughput, handover rates and RAT blocking probability) which aim to compare the performance of the different schemes, take into account the user's and the network operator's perspectives. However, no specific objective function is considered. Few RAT selection schemes have been proposed with the aim of maximizing the operator's revenue such as [10] and [11]. However, the adopted pricing scheme is not taken into consideration. Pricing is a very important factor, and has a direct impact on the network's generated revenue.

An important aspect in cellular / WLAN HWNs scenarios is the spatial distribution of BSs, APs and users. Some of the proposed RAT selection schemes in the literature took the users and BSs' distribution into account such as [12] and [13]. However this has been done through a decomposition of the cell into rings and sectors, and by considering users belonging to the same zone to be having the same geometrical property. None of the mentioned work has included an analytical model for the spatial distribution of the APs and the users.

## C.3 System Model

### C.3.1 Network Architecture

We consider the case of a cellular / WLAN overlay network such as, for example, in [14]. A typical example that can be met nowadays is an LTE / WiFi heterogeneous network. The traffic arrivals to the different base stations are independently distributed. Hence, and without loss of generality, we can shift our focus to a single cell $C_{targ}$ that corresponds to the coverage area of one cellular BS. The cellular RAT has global coverage, overlaying the WLAN i.e. within the coverage of the considered BS there exists one or more WLAN AP(s).

In the studied system, we consider two user profiles or classes, namely class 1 and class 2 with different priority levels. Class 1 traffic, which is charged higher price, is granted higher priority. It targets mainly the business sector' users who have strict requirements on QoS, and are less

sensitive to the charged prices. Class 2 traffic has normal priority and targets individual users who prefer to pay low monthly fees and can tolerate some degradation of their perceived QoS. All users belonging to the same profile are charged identically.

The role of the MDP-based RAT selection scheme is to find the optimal distribution of the traffic among the existing RATs which leads to the maximization of the objective function (the revenue in our case).

### C.3.2 Spatial Distribution

Because of the overlay nature of our studied HWN scenario, a connection request might occur either in an area that is covered by the cellular RAT only, or in a dual coverage area. In the latter case, the call can be admitted to the cellular or the WLAN depending on the decision provided by the RAT selection policy. Here arises the need for getting knowledge regarding the spatial distribution of the three players in this scenario, namely the BSs, APs, and the users. The considered network architecture can be seen as a 2-tier heterogeneous network, where tier-1 is the cellular and tier-2 is the WLAN RAT. A spatial point process, such as PPP provides a concise and tractable model for HWNs, by offering a statistical modeling for the spatial distribution of users and base stations of each tier. In fact, PPP model has been used extensively for modeling unplanned networks [15] which is typically the case of WLAN APs' deployment. In our considered scenario, the different aspects of the PPP model can be described as follows:

- The positions of BSs / APs belonging to tier-k are modeled according to a homogeneous PPP $\phi^{(k)}$ with intensity $\lambda^{(k)}$, where $\lambda^{(k)}$ is defined as the number of BSs / APs per area unit, and $k \in \{1, 2\}$ with $k = 1$ refers to the cellular RAT and $k = 2$ refers to the WLAN.

- Users are also scattered in the plane according to an homogeneous PPP $\phi^{(u)}$ with intensity $\lambda^{(u)}$ users per area unit, independently of $\phi^{(k)}$.

Through PPP modeling, different metrics can be captured. In the following, we derive (1) the probability for a user to be under tier-k's coverage, and (2) the traffic arrival rates.

#### Coverage probability

The cellular system has global coverage i.e. all users in the considered HWN fall under the coverage of the cellular RAT. Therefore, the coverage probability of cellular is $P_{c,1} = 1$.

As for the coverage probability of WLAN, it can be derived with the help of PPP as follows. First, we assume that each AP covers a circular area of known radius $R$, i.e. the transmission of each AP can be received clearly by users residing at a distance not exceeding $R$. Second, the interference from neighboring APs is considered negligible. Hence, a typical user is said to be under the coverage of WLAN if the distance $r$ separating this user from the nearest AP is less than $R$. Therefore, the probability that a user is under the coverage of WLAN is equivalent to the cumulative distribution function of $r$, namely $\mathbb{P}[r < R]$. Without loss of generality, we consider that the typical user is located at the origin of the plane under consideration [15]. Then, knowing that the null probability of a 2D Poisson process in an area $Z$ is $exp(-\lambda Z)$ [16], we can derive the coverage probability of the WLAN $P_{c,2}$ as follows:

$$\mathbb{P}[r > R] = \mathbb{P}[\phi^{(2)} \cap b(0, R) = 0] = e^{-\pi\lambda^{(2)}R^2} \tag{C.1}$$

where $b(0, R)$ is the Euclidean ball of radius $R$ centered at origin. Hence, the coverage probability of tier-2 is given by:

$$P_{c,2} = \mathbb{P}[r < R] = 1 - \mathbb{P}[r > R] = 1 - e^{-\pi\lambda^{(2)}R^2} \tag{C.2}$$

### Traffic arrivals and holding times

Having two user profiles generating traffic to the system, we define $\psi$ as the ratio of class 2 users to the total number of users, and $(1 - \psi)$ that of class 1 users to the total number of users residing in the system. And with the assumption that users of class $i$, $i \in \{1, 2\}$ generate traffic following a Poisson distribution with average $\sigma_i$ calls/second, the traffic arrival rates $\lambda_1$ and $\lambda_2$ of classes 1 and 2 respectively can be easily derived as follows:

$$\lambda_1 = \sigma_1(1 - \psi)\lambda^{(u)}|C_{targ}| \text{ arrivals/second} \tag{C.3}$$

$$\lambda_2 = \sigma_2\psi\lambda^{(u)}|C_{targ}| \text{ arrivals/second} \tag{C.4}$$

where $|C_{targ}|$ is the area of the targeted cell $C_{targ}$ (in area unit).

As for the call holding time for class $i$, traffic of both classes is assumed to be inelastic, i.e. the average duration of the service is independent of the allocated number of channels, and following exponential distribution with mean $1/\mu_i, i \in \{1, 2\}$.

## C.4 Markov Decision Process Formulation

An MDP model is provided to derive the optimal RAT selection policy which maximizes our objective function. This model can be uniquely iden-

tified by five components: the state space, decision epochs, action space, state dynamics and the reward function. We define each of these components in the following subsections.

### C.4.1 State Space

The state space represents the number of ongoing sessions in the HWN i.e. the number of class 1 sessions being served in the cellular RAT, number of class 1 sessions being served in the WLAN, and similarly, number of class 2 sessions being served in cellular and those in WLAN. For ease of representation in MDP, we model the problem with one particular AP in WLAN that we call the targeted AP. Hence, a 4D-MDP serves to build our model. On the other hand, we assume a fixed total capacity for both RATs, each being partitioned into a fixed number of basic bandwidth units (bbu) as in, e.g. [14, 17, 19]. This implies that a limited number of sessions can be served simultaneously by each RAT. The total capacities of the cellular and the WLAN RATs can be defined as integers that we denote by $C_1$ and $C_2$ respectively. Any new arriving call that cannot be granted its required amount of bbu is blocked. Thus, by restricting the number of ongoing connections in the system, the delivered QoS can be maintained at a certain target level. Considering that each session of class $i$ requires $b_i$ bbu, we can define the following row vectors:

- State vector of the cellular RAT:
  $\boldsymbol{s_1} = [n_{1,1}, n_{1,2}] \in \mathbb{Z}_+^2$

- State vector of the WLAN:
  $\boldsymbol{s_2} = [n_{2,1}, n_{2,2}] \in \mathbb{Z}_+^2$

- State vector of the system:
  $\boldsymbol{s} = [s_1, s_2] = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}]$

Where:
$n_{j,i}$ denotes the number of sessions of class $i$ in RAT $j$
$\mathbb{Z}_+$ represents the set of non-negative integer numbers. Hence, the state space $S$ of the system, which is the set of all feasible states where the QoS conditions in both RATs are not violated, becomes:

$$\begin{aligned} S = \big\{ &\boldsymbol{s} = [s_1, s_2] = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}] \in \mathbb{Z}_+^4, \\ &n_{1,1} \cdot b_1 + n_{1,2} \cdot b_2 \leq C_1, n_{2,1} \cdot b_1 + n_{2,2} \cdot b_2 \leq C_2 \big\} \end{aligned} \tag{C.5}$$

### C.4.2 Decision Epochs and Actions

At each arrival of a class $i$ session request, $i \in \{1, 2\}$, the RAT selection policy makes a decision on the admission of the new session. A decision epoch occurs at each new session request. It is defined as the time following immediately an arrival event. As for the events of call completion, they do not require any decision to be taken by the system.

The action taken following each decision epoch can be defined as a vector $\boldsymbol{a} = [a_1, a_2]$ where $a_i$ denotes the action resulting from the arrival of a class $i$ session. A decision can be either to admit the arriving session to cellular RAT, admit it to WLAN or block it. $a_i$ can be defined as follows:

$$a_i = \begin{cases} -1, & \text{if the session is admitted to cellular.} \\ 1, & \text{if the session is admitted to WLAN.} \\ 0, & \text{if the session is blocked.} \end{cases}$$

The action space of the MDP is defined as the set of vectors $\boldsymbol{a}$ as follows:

$$A = \{\boldsymbol{a} = [a_1, a_2], a_1 \in \{-1, 0, 1\}, a_2 \in \{-1, 0, 1\}\} \tag{C.6}$$

However, for a given state $\boldsymbol{s} \in S$, the decision should always lead to a state $\boldsymbol{s'}$ that is also in $S$. Moreover, when the system is in state (0,0,0,0), the action (0,0) should be avoided in order for the system to keep evolving. Hence, for a given state $\boldsymbol{s} = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}] \in S$, the state action space $A_s \subset A$ is given by:

$$\begin{aligned} A_s = \{&\boldsymbol{a} \in A : a_i \neq -1 \text{ if } [s_1 + e_i^u, s_2] \notin S, \\ &a_i \neq 1 \text{ if } [s_1, s_2 + e_i^u] \notin S, \\ &a_i = 0 \text{ if } [s_1 + e_i^u, s_2] \notin S \text{ and } [s_1, s_2 + e_i^u] \notin S, \\ &a \neq (0, 0) \text{ if } s = (0, 0, 0, 0)\} \end{aligned} \tag{C.7}$$

Where $e_i^u \in \{0, 1\}^I$, is a row vector of zeros except for the $i^{th}$ element which is equal to 1, ($I$ being the number of traffic classes, $I = 2$). $s_1 + e_i^u$ corresponds to an increase of the sessions of the $i^{th}$ class by 1 in the cellular RAT. $s_2 + e_i^u$ corresponds to an increase of the sessions of the $i^{th}$ class by 1 in the WLAN.

The admission of a class 1 session, to either cellular RAT or WLAN, might involve the vertical handover of one or more class 2 sessions. This handover can be performed from cellular to WLAN or vice versa.

### C.4.3 State Dynamics

The state dynamics of the MDP are defined by two parameters, namely the expected sojourn time and the transition probabilities.

### Expected sojourn time

The sojourn time $\tau(s, a)$ is defined as the expected time for the system to stay in state $\boldsymbol{s} \in S$ given that action $\boldsymbol{a} \in A_s$ is chosen, until a new state is entered. The sojourn time is used to compute the transition probabilities for a continuous-time MDP, and its value can be expressed [6, 10] as follows:

$$\tau(s, a) = \left\{ \sum_{i=1}^{2} \lambda_i |a_i| + \sum_{i=1}^{2} \sum_{j=1}^{2} n_{j,i} \mu_i \right\}^{-1} \tag{C.8}$$

Where $\lambda_i$ is the arrival rate for class $i$ traffic, $i \in \{1, 2\}$, defined by (C.3) and (C.4) for $i = 1$ and $i = 2$ respectively, and $1/\mu_i$ is the mean value of the call holding time of class $i$.

### Transition probabilities

Let $P_{ss'}(a)$ denote the transition probability from state $\boldsymbol{s} = [s_1, s_2] \in S$ to state $\boldsymbol{s'} \in S$, $\boldsymbol{s} \neq \boldsymbol{s'}$, provided that action $\boldsymbol{a} \in A_s$ is chosen. $P_{ss'}(\boldsymbol{a})$ can thus be written as:

$$P_{ss'}(\boldsymbol{a}) =$$

$$\begin{cases} \lambda_1 \delta(-a_1) \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} + e_1^u, \boldsymbol{s_2}]. \\ \lambda_1 \delta(-a_1) \tau(\boldsymbol{s}, \boldsymbol{a}) h, & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} + e_1^u - n_{h,2} \cdot e_2^u, \boldsymbol{s_2} + n_{h,2} \cdot e_2^u]. \\ \lambda_2 \delta(-a_2) \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} + e_2^u, \boldsymbol{s_2}]. \\ \lambda_1 P_{c,2}^* \delta(a_1) \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} + e_1^u]. \\ \lambda_1 P_{c,2}^* \delta(a_1) \tau(\boldsymbol{s}, \boldsymbol{a}) h, & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} + n_{h,2} \cdot e_2^u, \boldsymbol{s_2} + e_1^u - n_{h,2} \cdot e_2^u]. \\ \lambda_2 P_{c,2}^* \delta(a_2) \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} + e_2^u]. \\ \mu_1 n_{1,1} \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} - e_1^u, \boldsymbol{s_2}] \ . \\ \mu_2 n_{1,2} \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} - e_2^u, \boldsymbol{s_2}]. \\ \mu_1 n_{2,1} \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} - e_1^u]. \\ \mu_2 n_{2,2} \tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} - e_2^u]. \\ 0, & \text{otherwise.} \end{cases} \tag{C.9}$$

Where:
$P_{c,2}^*$ is the coverage probability of the targeted AP: $P_{c,2}^* = \frac{P_{c,2}}{|C_{targ}| \lambda^{(2)}}$,
$n_{h,2}$ represents the number of class 2 sessions that were handed off from one RAT to another to free resources for the newly admitted class 1 session, $0 \leq n_{h,2} \leq \lceil \frac{b_1}{b_2} \rceil$ , and $\lceil x \rceil$ is the smallest integer greater than x,
$h$ is a variable that takes 1 as value if a vertical handover was performed,

and 0 otherwise,
and $\delta(x)$ is a function defined as:

$$\begin{cases} 0, & \text{if } x \leq 0 \\ 1, & \text{if } x > 0 \end{cases}$$

### C.4.4 Policy and Reward Function

For each state $\boldsymbol{s} = [s_1, s_2] \in S$, an action $\boldsymbol{a} \in A_s$ is chosen according to a policy $\pi_s \in \Pi$, where $\Pi$ is a set of admissible policies defined as:

$$\Pi = \{\pi : S \rightarrow A | \pi_s \in A_s, \forall \boldsymbol{s} \in S\} \tag{C.10}$$

The reward function for choosing action $\boldsymbol{a} \in A_s$, when the system is in state $\boldsymbol{s} \in S$ can be defined as follows:

$$\begin{aligned} r(\boldsymbol{s}, \boldsymbol{a}) = w_{1,1} \cdot \delta(-a_1) - k_{c,w} \cdot n_{h,2} \cdot h \\ + w_{2,1} \cdot \delta(a_1) - k_{w,c} \cdot n_{h,2} \cdot h \\ + w_{1,2} \cdot \delta(-a_2) + w_{2,2} \cdot \delta(a_2) \end{aligned} \tag{C.11}$$

where:
$w_{j,i} \in \mathbb{R}_+$ is the weight associated with the admission of a class $i$ session into RAT $j$, $\mathbb{R}_+$ being the set of non-negative real numbers,
$k_{c,w}$ is the cost associated for handing off a class 2 session from the cellular network to WLAN,
and $k_{w,c}$ is the cost associated for handing off a class 2 session from WLAN to the cellular network.
The first two lines in (C.11) show that the gain obtained from the admission of a class 1 session to the cellular network (resp. WLAN) is computed as the weight associated to this admission minus the cost incurred by the eventual handover of class 2 sessions. This reflects the fact that the handover is not favorable unless the gain obtained is the highest achievable gain among all possible solutions. However, the admission of a class 2 session, being a low-priority traffic, does not invoke any kind of handover.

By solving the MDP, an optimal policy $\pi^*$ that maximizes the reward function can be found. The values of the weights and the handover costs in the reward function (C.11) have to be defined based on the objective that the operator wants to maximize. The RAT selection module will, based on the optimal policy provided by the MDP, decides on the admission or rejection for every arriving session as explained in Fig. C.1.
A summary of the notations used in the paper is presented in Table C.1.

Table C.1: Table of notations.

| Symbol | Description |
|---|---|
| $\lvert C_{targ}\rvert$ | Coverage area of the targeted base station in the cellular RAT |
| $\phi^{(k)}$ | Poisson Point Process distribution of RAT $k$ |
| $\phi^{(u)}$ | Poisson Point Process distribution of users |
| $R$ | Radius of the circular area covered by an AP |
| $r$ | Distance separating a typical user from the nearest AP |
| $\lambda^{(k)}$ | Number of BS / AP per unit area of RAT $k$ |
| $\lambda^{(u)}$ | Number of camping users per unit area |
| $\lambda_i$ | The arrival rate of class $i$ |
| $p_{c,k}$ | Coverage probability of RAT $k$ |
| $\psi$ | Ratio of class 2 users to the total number of users |
| $\sigma_i$ | The average number of calls per second generated by a class $i$ user |
| $1/\mu_i$ | The average call holding time of class $i$ |
| $C_k$ | Capacity (number of channels) of RAT $k$ |
| $b_i$ | Number of bbu required to serve a class $i$ user |
| $n_{j,i}$ | number of sessions of class $i$ in RAT $j$ |
| $\boldsymbol{s_k}$ | The state vector of RAT $k$ |
| $\boldsymbol{s}$ | The state vector of the system |
| $S$ | The state space of the system |
| $a_i$ | The action resulting from the arrival of a class $i$ session |
| $\boldsymbol{a}$ | Vector representing the action taken following a decision epoch |
| $A$ | The action space of the MDP |
| $A_s$ | The action space of state $\boldsymbol{s}$ |
| $\tau(s,a)$ | Expected sojourn time in state $\boldsymbol{s}$ when action $\boldsymbol{a}$ is chosen |
| $P_{ss'}(\boldsymbol{a})$ | Transition probability from state $\boldsymbol{s}$ to state $\boldsymbol{s'}$ when action $\boldsymbol{a}$ is chosen |
| $P^*_{c,2}$ | Coverage probability of the targeted AP |
| $n_{h,2}$ | Number of class 2 sessions that were handed off from one RAT to another |
| $h$ | A variable that designates if a vertical handover was performed or not for class 2 traffic |
| $\pi_s$ | Policy chosen at state $\boldsymbol{s}$ |
| $\Pi$ | Set of admissible policies |
| $r(\boldsymbol{s},\boldsymbol{a})$ | Reward function for state $\boldsymbol{s}$ when action $\boldsymbol{a}$ is chosen |
| $w_{j,i}$ | Weight associated for admitting a class $i$ session in RAT $j$ |
| $\pi^*$ | Optimal RAT selection policy |
| $Pr_i$ | Price charged for user of class i |
| $Rev$ | The revenue or charges collected from the admission of class 1 and class 2 sessions |
| $\rho_i$ | Traffic load of class $i$ |
| $k_{c,w}$ | Cost associated to the handoff of a class 2 session from cellular to WLAN |
| $k_{w,c}$ | Cost associated to the handoff of a class 2 session from WLAN to cellular |

## C.5 Pricing Scheme and Revenue Maximization Problem

Pricing of services is highly important, and has a substantial impact on user satisfaction and operator revenue. Various pricing schemes have been proposed and studied in the literature. These schemes include flat-pricing, volume-based, and dynamic pricing. A comprehensive survey on pricing practices and their predominance in different parts of the world can be found in [20].

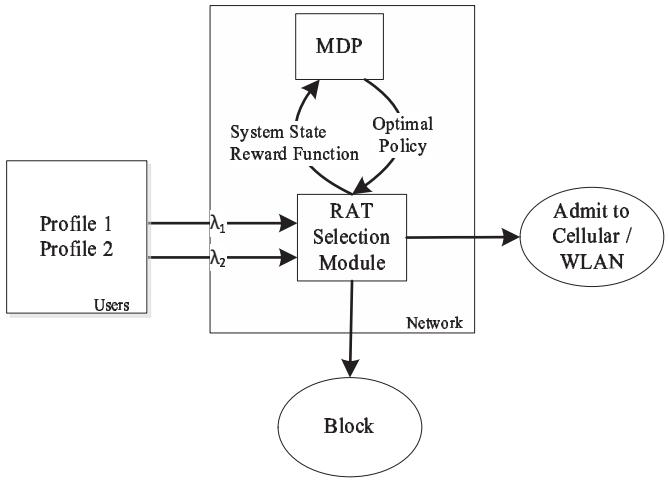



Figure C.1: RAT selection module.

Pricing and revenue are tightly related. The term revenue, as used in this paper, indicates the charges collected from the subscribers in monetary unit (MU). It is function of the charged prices and the number of subscribers belonging to the different offered profiles. In our studied scenario, we try to maximize the network's income by prioritizing the admission of class 1 users to the system, for their higher contribution in the generated revenue. This can be reflected by the appropriate choice of the weights in the reward function (C.11).

The weights are important system parameters that affect the decisions taken by the admission controller, and different combinations of weights may lead to different optimal policies $\pi^*$. By varying the values of these weights, the network operator can shape the admitted traffic, in order to reach a specific goal, such as balancing the traffic load, increasing the generated revenue, or it could be a combination of more than one objective.

## C.6 Numerical Results

In this section, the performance of the optimal MDP-based RAT selection scheme is analyzed. To solve the MDP problem and find the optimal policy, we used the relative value iteration algorithm from the MDP toolbox (developed by [21]). The system parameters used in our analysis are depicted in Table C.2. A higher value was assigned to $k_{c,w}$ than that of $k_{w,c}$ because the handover to WLAN comes at a higher risk due to the local coverage of

this latter. We also assume hereby that the price $Pr_i$, charged for class $i$, is chosen as: $Pr_1 = 2 \cdot Pr_2$.

Table C.2: System parameters.

| Parameter | Symbol | Value |
|---|---|---|
| Cellular Capacity | $C_1$ | 30 bbu |
| WLAN Capacity | $C_2$ | 5 bbu |
| Number of bbu required per class 1 session | $b_1$ | 2 bbu |
| Number of bbu required per class 2 session | $b_2$ | 1 bbu |
| Traffic intensity of class 1 ($\lambda_1/\mu_1$) | $\rho_1$ | 2 to 14 Erlang (E) |
| Traffic intensity of class 2 ($\lambda_2/\mu_2$) | $\rho_2$ | 6 E |
| Average Session holding time for class 1 | $1/\mu_1$ | 200 s |
| Average Session holding time for class 2 | $1/\mu_2$ | 150 s |
| Cost of handoff of class 2 session from cellular to WLAN | $k_{c,w}$ | 0.5 |
| Cost of handoff of class 2 session from WLAN to cellular | $k_{w,c}$ | 0.3 |

### C.6.1 Performance Evaluation

The aim of the MDP-based scheme is to find the optimal policy for RAT selection that maximizes the defined objective function. We analyze the performance of this Optimal scheme by comparing it to the performance of two static policies which we model with the help of Markov chain.

The first scheme is the Cellular-First scheme which works as follows: All arriving traffic is admitted to the cellular RAT as long as this latter has available resources. When the cellular network becomes overloaded, class 2 traffic is sent to WLAN while class 1 traffic is admitted to the cellular network if it was possible to free the needed resources by handing off a part of class 2 traffic to WLAN. In case the handover was not possible, the traffic is sent to WLAN if this latter has enough resources, and blocked otherwise.

The second scheme, called Load Balancing policy, as suggested in [22], works as follows: When a session arrives, it is admitted to the RAT where its admission results in the minimum load (the load of a RAT being the ratio of occupied channels over the total available channels). In the case where the admission of the session results in same load for all existing RATs,

the policy selects randomly the RAT to accommodate the newly arriving session.

### C.6.2 Performance Metrics

The following performance metrics were chosen to compare the abovementioned schemes.

#### Average revenue

The average revenue (in MU) depends on the charged prices as well as the average number of sessions that the system can admit for each of the user profiles. It can be computed as:

$$E[Rev] = Pr_1 \cdot E[n_{1,1} + n_{2,1}] + Pr_2 \cdot E[n_{1,2} + n_{2,2}]$$

#### Blocking probability

A class $i$ session is blocked, in general, when none of the two RATs has free $b_i$ bbus available, or when the session is initiated out of the coverage of the WLAN and the cellular RAT has no enough free resources to accommodate it. In the case of Optimal and Cellular-First, where handover of class 2 traffic is allowed, the computation of the blocking probability of class 1 takes also into account whether a vertical handover of class 2 session(s) makes the admission of class 1 traffic to a congested network possible or not.

### C.6.3 Results

The values of the considered performance metrics for the Optimal RAT selection scheme, as well as for the Cellular-First and Load Balancing schemes are depicted in Fig. C.2, C.3, and C.4. These values are for load of class 1 traffic $\rho_1$ varying from 2 to 14 Erlang (E), load of class 2 traffic $\rho_2 = 6$ E, and for coverage probability of the targeted AP $P^*_{c,2} = 0.6$.

The values of the weights in the reward function are chosen as follows: $w_{1,1} = 2$, $w_{1,2} = 1$, $w_{2,1} = 2$ and $w_{2,2} = 1$, where a higher weight is assigned for the admission of class 1 traffic, reflecting the higher priority granted to this latter.

Among the three studied policies, the Optimal policy provides the highest revenue (Fig.C.2). The Optimal policy is hence able to find the optimal traffic distribution that can generate the highest profit among the compared

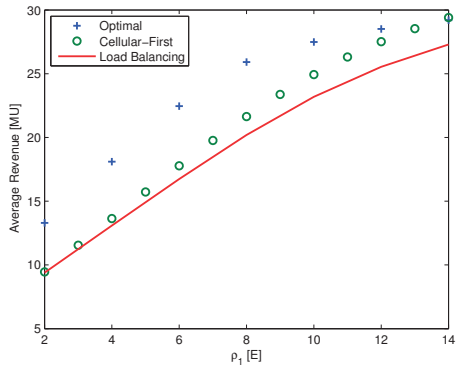



Figure C.2: Average revenue [MU].

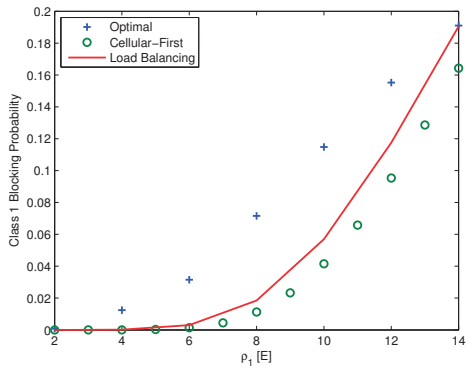



Figure C.3: Class 1 blocking probability.

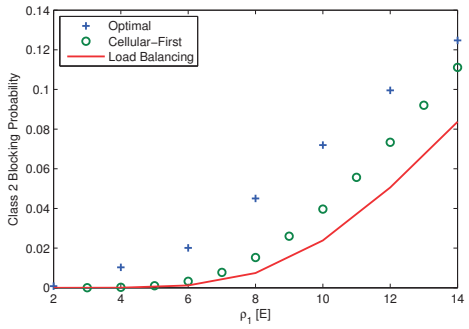



Figure C.4: Class 2 blocking probability.

policies. Cellular-First policy achieves lower revenue than the Optimal policy, but is able to outperform the Load Balancing policy, which is due to the fact that admitting to cellular RAT first will take better benefit from the large capacity and global coverage of this network, while WLAN is used only as extension to the cellular RAT when this is needed.

In terms of blocking probabilities, the results show that the Load Balancing policy achieves the lowest blocking probabilities for class 2 traffic. This is because this policy does not provide privileges to class 1 traffic over class 2 traffic. The blocking probabilities obtained through the Optimal policy are higher than the two other policies. This can be explained by the choice of the weights that is revenue-based only and does not account for the difference in the QoS of the two networks. Assigning equal weights for the admission of a class $i$ session to both cellular RAT and WLAN means that the Optimal policy will not differentiate between the different grades of QoS that an admitted session might undergo in the different RATs.

For an operator, whose interest is to maximize the profit generated from its HWN, the RAT selection policy provided by MDP is a good candidate. Not only it guarantees the highest profit, but it also keeps the QoS at a comparable level to the ones obtained with the Load Balancing and Cellular-First schemes.

### C.6.4 Effect of the Weights

The decisions taken by the Optimal policy are directly affected by the values of the weights ($w_{1,1}, w_{1,2}, w_{2,1}$ and $w_{2,2}$) in the reward function. It is therefore important to have a good insight into the choice of these weights. For this purpose, we experiment hereby with different combinations of weights values and analyze their impact on the average revenue. Nine sets of weights were selected for this comparison as shown in Table C.3. For ease of illustration, we assign the value of 2 to $Pr_1$ and 1 to $Pr_2$. The weights $w_{j,i}$ in the nine defined sets were chosen in a way that a weight for the admission of a class $i$ session varies between 0 and $Pr_i$, which is an intuitive choice having the maximization of revenue as our objective. However, $w_{1,1}$ was fixed to $Pr_1$ to reflect the higher priority granted to class 1 traffic to be admitted to cellular RAT where a better QoS can be offered.

First, we examine the revenue obtained by the different sets of weights for a varying traffic load of class 1, and for load of class 2 $\rho_2 = 6$ E (Fig. C.5). The plots show how the achieved revenue can vary with the chosen set of weights. Among all sets, set 9 performed the worst. This is obviously due to the fact that, the weights for admission to WLAN for class 1 and class 2 are set to zero meaning that the MDP will favor the admission of both traffic to the Cellular RAT, and the benefit from the capacity of WLAN is minimal.

The highest revenue was obtained from set 2 when the load of the system was relatively low ($\rho_1 < 12$). However, when the load increases, set 1 outperforms set 2. This can be explained as follows: when the traffic is low compared to the system capacity, it is more beneficial to assign lower value for $w_{2,1}$ (such as in set 2) which is translated by a lower admission of class 1 traffic to WLAN, while the cellular RAT has enough capacity to accommodate the incoming traffic. On the other hand, when the system is overloaded, the capacity of cellular RAT will not be enough to serve the traffic, and admitting more traffic to WLAN would result in an increase of the system capacity and, consequently, a higher revenue can be achieved.

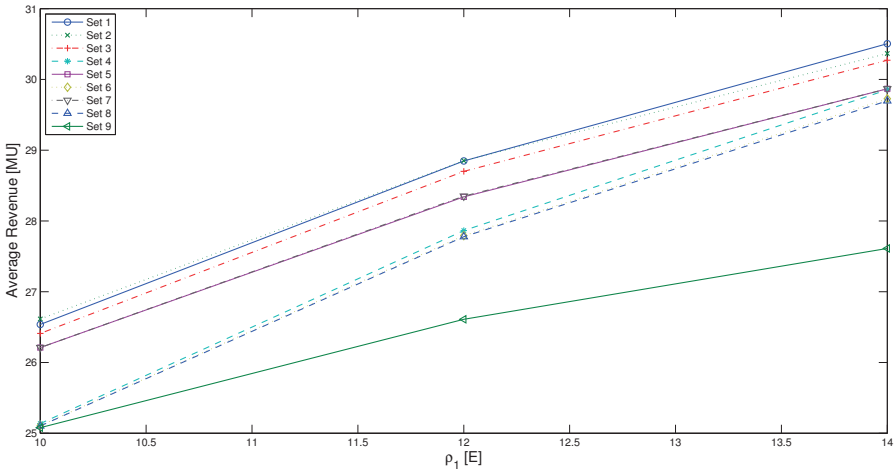



Figure C.5: Revenue obtained for varying traffic load.

Table C.3: The different selected sets of weights.

| Sets | $w_{1,1}$ | $w_{2,1}$ | $w_{1,2}$ | $w_{2,2}$ |
|---|---|---|---|---|
| Set 1 | 2 | 2 | 1 | 1 |
| Set 2 | 2 | 1 | 1 | 1 |
| Set 3 | 2 | 0 | 1 | 1 |
| Set 4 | 2 | 2 | 0 | 1 |
| Set 5 | 2 | 2 | 1 | 0 |
| Set 6 | 2 | 1 | 0 | 1 |
| Set 7 | 2 | 1 | 1 | 0 |
| Set 8 | 2 | 0 | 0 | 1 |
| Set 9 | 2 | 0 | 1 | 0 |

Due to the heterogeneous nature of the traffic, we also compared the revenue achieved by the nine sets of weights for different values of traffic mix ($\rho_1 + \rho_2$), namely (1) low traffic mix and (2) high traffic mix. In Fig. C.6, the revenue is depicted for a low value of traffic mix ($\rho_1 + \rho_2$=10). When class 2 traffic is dominating, i.e. $\frac{\rho_1}{\rho_1+\rho_2}$ is low, the performance of

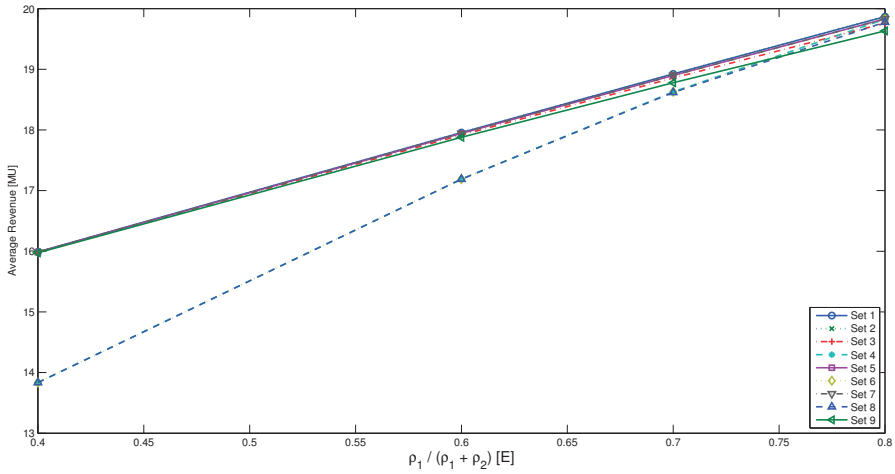



Figure C.6: Revenue obtained by the different sets of weights for traffic mix $\rho_1 + \rho_2 = 10$ E.

all sets of weights is very close except for set 6 and set 8 (plot of set 6 overlaps with that of set 8 in Fig. C.6). This is because these two sets favor the admission of class 2 sessions to WLAN. However, when class 1 traffic dominates i.e. $\frac{\rho_1}{\rho_1+\rho_2} > 0.6$, the weights for the admission of class 2 traffic become less important, and therefore the revenue obtained from sets 6 and 8 becomes closer to that of the other sets of weights.

The revenues obtained from the different sets of weights for a high traffic mix ($\rho_1 + \rho_2$ =20) are depicted in Fig. C.7. In this case, we see a clearer differentiation of the revenues obtained from the different weights, and the highest revenue is obtained by set 1, which complies with the results deduced from Fig. C.5.

The results obtained hereby showed that the set of weights that provides the maximum revenue varies with the traffic load and traffic mix. The network operator can therefore, based on an a priori knowledge of the traffic distribution and patterns, use the appropriate set of weights in order to maximize the gained profit.

### C.6.5 Effect of the Coverage Probability of WLAN

In Subsection C.6.3, we evaluated the performance of the MDP-based RAT selection scheme along with two other policies, for the same value of the coverage probability of WLAN. Because of its importance, we try hereby

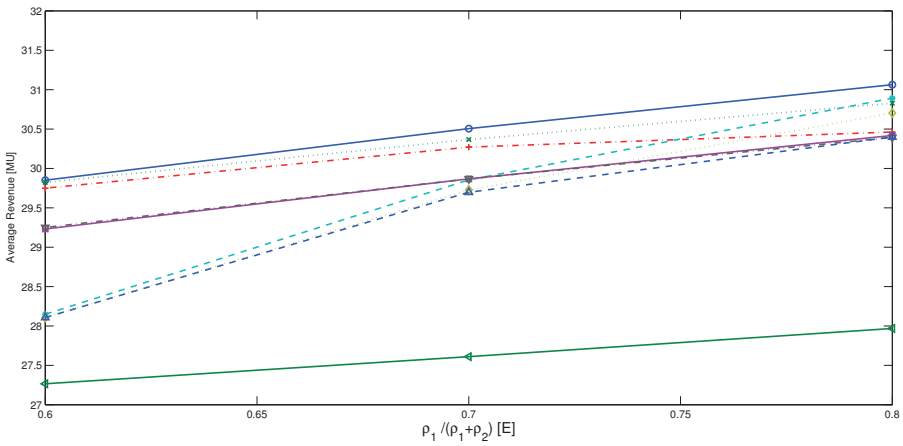



Figure C.7: Revenue obtained by the different sets of weights for traffic mix $\rho_1 + \rho_2 = 20$ E.

to further investigate this parameter. Two values of the WLAN coverage probability are considered, namely $P^*_{c,2} = 0.6$ and $P^*_{c,2} = 0.3$, and the results provided by the MDP-based RAT selection policy for these two values are shown in Fig. C.8, C.9 and C.10, where $\rho_1$ varies from 2 to 14 E, and $\rho_2$ is fixed to 6 E. In terms of revenue, it is shown that, due to a loss in the WLAN resources, it is not possible to achieve the same revenue as when WLAN has wider coverage (Fig. C.8). Similarly, a negative effect on the blocking probability for both classes of services can be noticed (Fig. C.9 and C.10). When the WLAN has very low coverage, it is no more capable of alleviating the load of cellular RAT which becomes congested faster. Therefore, the role that WLAN can play in increasing the capacity of the cellular network is important, allowing the system to serve a larger number of users. A wider coverage of the WLAN results not only in higher generated revenue but also in a better QoS for both class 1 and class 2 traffic.

## C.7 Conclusion

RAT selection strategies are key components in heterogeneous wireless systems, where more than one RAT coexist, and multiple user profiles are supported each having different QoS requirements. In this paper, we study the performance of MDP-based RAT selection in a cellular / WLAN heterogeneous network, with the objective of maximizing the revenue of the overall system. For performance evaluation, we compared the Optimal pol-

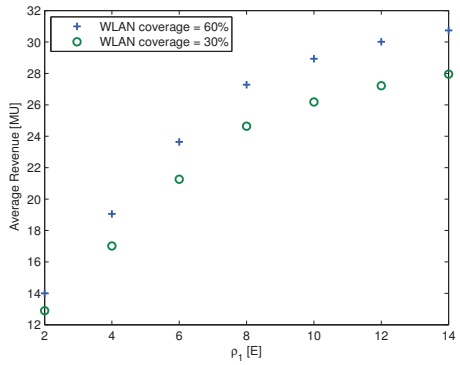



Figure C.8: Average revenue [MU].

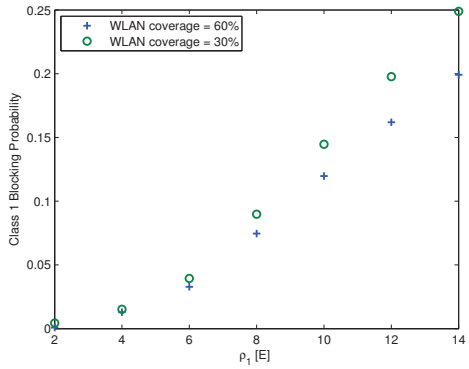



Figure C.9: Class 1 blocking probability.

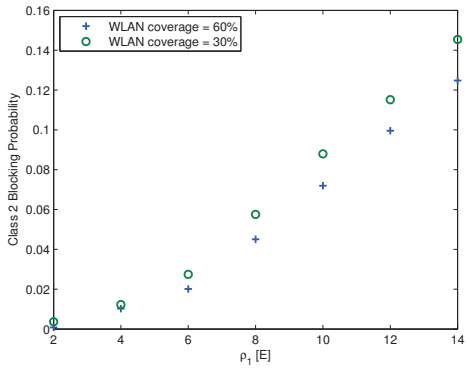



Figure C.10: Class 2 blocking probability.

icy derived from MDP to two other RAT selection policies: Cellular-First and Load Balancing. The results show that, even though the MDP-based Optimal scheme makes a negative effect on the blocking probabilities, it achieves the highest revenue among all policies. In addition, to better understand and provide insights into the MDP-based scheme, the impact of the weights in the MDP objective function has been investigated for different traffic loads and traffic mix values. Finally, the importance of the role that WLAN plays in offloading the cellular RAT is highlighted.

# References


[1] da Silva AP, Cardoso LS, de Sousa Jr VA, Cavalcanti FR. Common radio resource management for multiaccess wireless networks. *Optimizing Wireless Communication Systems*. 2009 Jul 31:233-65.

[2] Yeh SP, Talwar S, Wu G, Himayat N, Johnsson K. Capacity and coverage enhancement in heterogeneous networks. *IEEE Wireless Communications*. 2011 Jun;18(3).

[3] 3GPP TS 23.261. IP flow mobility and seamless Wireless Local Area Network (WLAN) offload. 2010.

[4] Lee K, Lee J, Yi Y, Rhee I, Chong S. Mobile data offloading: How much can WiFi deliver? *Proceedings of the 6th International Conference ACM.*. 2010 Nov 30 (p. 26).

[5] Cisco. Visual networking index: Global mobile data traffic forecast update, 2012-2017. *http://www.cisco.com/en/US/solutions/collateral/ns341/ns525/ns537 /ns705 /ns827/white_paper_c11-520862.pdf/*. 2013.

[6] Chen H, Cheng CC, Yeh HH. Guard-channel-based incremental and dynamic optimization on call admission control for next-generation QoS-aware heterogeneous systems. *IEEE Transactions on Vehicular Technology*. 2008 Sep;57(5):3064-82.

[7] Li L, Littman ML. Lazy approximation for solving continuous finite-horizon MDPs. *AAAI*. 2005 Jul 9 (Vol. 5, pp. 1175-1180).

[8] Chen H, Cheng CC, Chung WH, Yeh HH. A reduced dimension MDP-based call admission control scheme for next generation telecommunications. *Wireless Communications and Mobile Computing Conference (IWCMC), 2012 8th International*. 2012 Aug 27 (pp. 984-989).

[9] Falowo OE, Chan HA. Heuristic RAT selection policy to minimize call blocking probability in next generation wireless networks. *Wireless Communications and Mobile Computing*. 2010 Feb 1;10(2):214-29.

[10] Kumar D, Altman E, Kelif JM. Globally optimal user-network association in an 802.11 WLAN & 3G UMTS hybrid cell. *Managing Traffic Performance in Converged Networks*. 2007 (pp. 1173-1187). Springer, Berlin, Heidelberg.

[11] Yu F, Krishnamurthy V. Optimal joint session admission control in integrated WLAN and CDMA cellular networks with vertical handoff. *IEEE Transactions on Mobile Computing*. 2007 Jan;6(1).

[12] Coupechoux M, Kelif JM, Godlewski P. SMDP approach for JRRM analysis in heterogeneous networks. *Wireless Conference, 2008. EW 2008. 14th European*. 2008 Jun 22 (pp. 1-7).

[13] Khawam K, Ibrahim M, Tohme S. Centralised multi-class access control in a WiMAX-UMTS hybrid network. *Personal Indoor and Mobile Radio Communications (PIMRC), 2010 IEEE 21st International Symposium on*. 2010 Sep 26 (pp. 1265-1270). 1265–1270.

[14] Stevens-Navarro E, Lin Y, Wong VW. An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks. *Vehicular Technology, IEEE Transactions on*. 2008 Mar;57(2):1243-54.

[15] Jo HS, Sang YJ, Xia P, Andrews JG. Heterogeneous cellular networks with flexible cell association: A comprehensive downlink SINR analysis. *Wireless Communications, IEEE Transactions on*. 2012 Oct;11(10):3484-95.

[16] Andrews JG, Baccelli F, Ganti RK. A new tractable model for cellular coverage. *Communication, Control, and Computing (Allerton), 2010 48th Annual Allerton Conference on*. 2010, pp. 1204–1211.

[17] Falowo OE, Chan HA. Multiple-RAT selection for reducing call blocking/dropping probability in cooperative heterogeneous wireless networks. *EURASIP Journal on Wireless Communications and Networking*. 2012 Dec 1;2012(1):221.

[18] Wang H, Laurenson DI, Hillston J. A general performance evaluation framework for network selection strategies in 3G-WLAN interworking networks. *Mobile Computing, IEEE Transactions on*. 2013 May;12(5):868-84.

[19] Wang Y, Pedersen KI, Mogensen PE, Sørensen TB. Carrier load balancing methods with bursty traffic for LTE-Advanced systems. *Personal, Indoor and Mobile Radio Communications, 2009 IEEE 20th International Symposium on*. 2009 Sep 13 (pp. 22-26).

[20] Sen S, Joe-Wong C, Ha S, Chiang M. Pricing data: A look at past proposals, current plans, and future trends. CoRR, abs/1201.4197. 2012 Jan 3.

[21] Chades I, Chapron G, Cros MJ, Garcia F, Sabbadin R. MDPtoolbox: a multi-platform toolbox to solve stochastic dynamic programming problems. Ecography 37:916-920.

[22] Gelabert X, Sallent O, Pérez-Romero J, Agustí R. Performance evaluation of radio access selection strategies in constrained multi-access/multi-service wireless networks. *Computer Networks*. 2011 Jan 7;55(1):173-92.

# Appendix D

# Publication D

Elissar Khloussy and Yuming Jiang; The Impact of Net Neutrality on Revenue and Quality of Service in Wireless Networks; 15th IEEE Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, USA, Jan 12 - 15, 2018

**Abstract** The net neutrality principle, also known as Open Internet, states that users should have equal access to all Internet content and that Internet Service Providers (ISPs) should not practice differentiated treatment on any of the Internet traffic. While net neutrality aims to restrain any kind of discrimination, it also provides exemption for a certain category of Internet traffic known as specialized services (SS), by allowing the ISP to dedicate part of the resources for the latter. In this work, we shed light on this particular case by comparing five Radio Access Technology (RAT) selection policies in heterogeneous wireless networks where SS traffic and Internet access services (IAS) traffic are carried. The studied policies include a non-net-neutral revenue-maximizing policy used as reference policy, and four other net-neutral policies with and without exemption to SS traffic. The results show that, even though, as expected, integrating net neutrality regulation within RAT selection policies can lead to a decrease in the generated revenue, a properly designed net-neutral policy will not only be able to reduce this decrease in revenue but also can maintain a similar level of social benefit in terms of the number of users admitted to the system.

**Keywords**

*net neutrality, radio access technology (RAT) selection, wireless networks.*

## D.1 Introduction

The net neutrality debate has gained lots of attention over the past decade. The main idea behind net neutrality principle is that Internet Service Providers (ISPs) should treat all Internet traffic equally regardless of the content, application, device, sender or receiver. Although the net neutrality debate has targeted, at the beginning, the wired public Internet, it is clear that it will address the wireless networks as well. Opponents to wireless net neutrality argue that the characteristics of wired and wireless networks differ in many aspects and that the challenges faced by wireless networks are greater compared to the ones faced by wired connectivity. Such challenges are mainly due to the wireless medium; they include signal attenuation, interference, and handovers, among others [8]. Therefore, what applies to wired networks might not necessarily apply to wireless ones. However, considering that a significant fraction of Internet traffic is being sent over wireless connectivity, we believe that the applied regulations have to be quite similar in both wired and wireless networks.

Net neutrality principle allows the ISP to grant exemption to some non-Internet access services that require high transmission quality, known as specialized services (SS) [2]. Some examples of SS include VoLTE, linear broadcasting IPTV, and real-time health services [15]. The ISP can dedicate a certain amount of bandwidth to SS to secure that those services receive the required Quality of Service (QoS). However, this should not lead to a degradation of the QoS experienced by the Internet access services (IAS) traffic.

In a previous work [9], we studied revenue-maximizing Radio Access Technology (RAT) selection in a Long Term Evolution (LTE) / Wireless Fidelity (WiFi) Heterogeneous Wireless Network (HWN). The traffic with the highest contribution to the revenue was granted higher priority in getting access to the network and in being served in LTE, at the expense of blocking or handing over the low-priority traffic. This way of traffic handling allows to maximize the revenue but it indeed violates net neutrality regulations, due to the fact that the low-priority traffic is treated with some kind of discrimination [14].

RAT selection is an important radio resource management component that helps tackle the problem of scarcity of wireless resources in HWNs. Despite the emergence of other solutions to deal with the same problem, such as LTE license-assisted access (LTE-LAA) which enables the operation of LTE in unlicensed spectrum [3, 11], the role of RAT selection will remain important.

In this work, we aim to investigate how applying net neutrality-compliant RAT selection policies would affect the generated revenue and the QoS per-

ceived by both high and low-priority traffic, where the high-priority traffic is represented by SS and the low-priority traffic is represented by IAS. To the best of our knowledge, no other work has been conducted in this direction where RAT selection policies are investigated, with net neutrality integration.

The rest of the paper is organized as follows. In Section D.2, the motivation and related work are presented. Section D.3 describes the system model. In Section D.4, we introduce the studied RAT selection strategies and their implementation. In Section D.5, we provide an analysis of the obtained results. Finally, we conclude in Section D.6.

## D.2 Motivation and Related Work

Net neutrality has been heavily discussed in the past decade as a potential way to prevent the ISPs from exercising any type of discrimination on the Internet traffic. Content providers, in general, support net neutrality especially in monopolistic regimes where an ISP might have pricing power over the Internet access market. The ISPs, on the other hand, argue that service differentiation is crucial, giving them incentive to further invest in expanding their infrastructure and provide better QoS [16]. Wu in [17] expanded the net neutrality debate by suggesting that policymakers ought to consider how to apply net neutrality regulations to wireless networks. This was opposed by a number of economists (e.g. [5]) who argued that, unlike the wired market, the competition will remain high in the wireless one.

Martínez et al. in [14] provided an initial analysis of the impact of net neutrality on quality of experience-based differentiation in mobile networks. In [6], the authors focused on the content provider discrimination and discussed the impact of some of the disruptive network applications on net neutrality. Some other works, e.g. [12, 16], proposed alternative regulations to net neutrality. Authors in [13] studied the paid prioritization where the content providers decided to pay for this priority in monopolistic access market. They showed that, with ISP's optimal pricing, the service differentiation became efficient and the social welfare among the different content providers was close to its maximum. Altman et al. in [1] presented a bargaining framework to decide how much the ISP should charge the content provider.

In our work, we focus on one ISP and study how the generated revenue as well as the social benefit and the blocking probability of the offered traffic would be affected when net neutrality regulation is integrated within the applied RAT selection policies in heterogeneous wireless networks.

## D.3 System Model

We consider a heterogeneous wireless network consisting of LTE and WiFi that coexist in the same geographical area. The traffic arrivals to the different base stations (BSs) are independently distributed. Hence, and without loss of generality, we can shift our focus to a single cell that corresponds to the coverage area of one cellular BS. The cellular RAT has global coverage, overlaying the WLAN i.e. within the coverage of the considered BS, one or more WLAN access point(s) might be found. This is similar to the model considered in [9].

Two types of traffic are carried, namely SS and IAS traffic, where IAS is charged a price $P_l$, while SS is charged the same price $P_l$ in the case where this latter is not granted any preferential treatment, and a price $P_h > P_l$ otherwise. Naturally, this pricing differentiation affects the traffic distribution among SS and IAS. In this paper, we adopt that, and the percentage of traffic that is being sent as SS traffic can be computed with the help of the following demand function that was proposed in [4] and has been adopted in the literature e.g., [7]:

$$D[P_h] = e^{-(\frac{P_h}{P_l}-1)^2}. \tag{D.1}$$

## D.4 RAT Selection Strategies

We consider five RAT selection strategies for the admission of SS and IAS traffic. The first strategy is revenue-maximizing and does not take into account net neutrality restrictions, while the four others are net neutrality-compliant. Our objective is to give insight into how the revenue and the QoS are affected when net neutrality regulations are applied. A comparison of the considered RAT selection policies is provided in Table D.1.

### D.4.1 Description of the RAT Selection Strategies

Table D.1: Comparison of the studied policies.

| Policy A | Policy B | Policy C | Policy D | Policy E |
|---|---|---|---|---|
| Priority for SS<br>Revenue-maximizing<br>SS charged $P_h$<br>Non-net-neutral<br>Handover of IAS traffic allowed | Equal treatment for SS & IAS<br>LTE-first admission<br>Equal pricing<br>Net-neutral<br>No handover | Reserved capacity for SS<br>LTE-first admission<br>SS charged $P_h$<br>Net-neutral<br>No handover | Equal treatment for SS & IAS<br>WLAN-first admission<br>Equal pricing<br>Net-neutral<br>No handover | Reserved capacity for SS<br>WLAN-first admission<br>SS charged $P_h$<br>Net-neutral<br>No handover |

- *Policy A - Revenue-maximizing policy:* With this policy, the decision of traffic admission is taken based on the generated revenue solely, i.e. neither net neutrality nor QoS requirements are taken into consideration. For its higher contribution in the generated revenue, SS is granted high priority in getting admitted to the network and in getting served in LTE. A handover of one or more IAS sessions might be performed between LTE and WiFi in case there was need to redistribute the traffic, allowing to accommodate more sessions in the system. In return, the price charged to SS traffic is $P_h$. Due to the preferential treatment granted to SS traffic over IAS traffic, Policy A is considered a non-net-neutral one [10].

- *Policy B - LTE-First policy and strictly net-neutral:* This policy is strictly net-neutral in the sense that no privileges are granted to any type of traffic; arriving SS and IAS sessions are admitted and served with equal priority. The admission is LTE-first based, where the arriving traffic is admitted first to LTE as long as LTE has enough free resources, and afterwards to WiFi when LTE becomes overloaded. SS and IAS are charged the same price $P_l$.

- *Policy C - LTE-First net-neutral policy with exemption to SS:* This policy follows the net neutrality regulations which allow to grant exemption to SS traffic. Similar to Policy B, the traffic admission is also LTE-first based. In addition, a part of the resources pool in LTE is reserved to SS traffic, while the remaining LTE resources and the whole WiFi resources can be accessed and used by both types of traffic. With policy C, SS traffic is charged $P_h$ for the reserved bandwidth it is granted in LTE, while IAS traffic is charged $P_l$. Fig. D.1 provides an abstraction of the system model where a portion of the LTE capacity is dedicated to SS traffic i.e. LTE resources are divided into two parts: reserved capacity (for SS traffic only) and common capacity (for both SS and IAS traffic).

- *Policy D - WLAN-First policy and strictly net-neutral:* This policy admits the arriving traffic on a WLAN-first basis i.e. traffic is admitted to WLAN until this latter becomes overloaded, and to LTE afterwards. Policy D treats both SS and IAS traffic equally, and both are charged the same price $P_l$.

- *Policy E - WLAN-First net-neutral policy with exemption to SS:* Similarly to policy D, the traffic is admitted on WLAN-first basis. However, part of LTE resources is reserved for SS traffic, while the remaining LTE resources and the entire WiFi resources can be occupied by

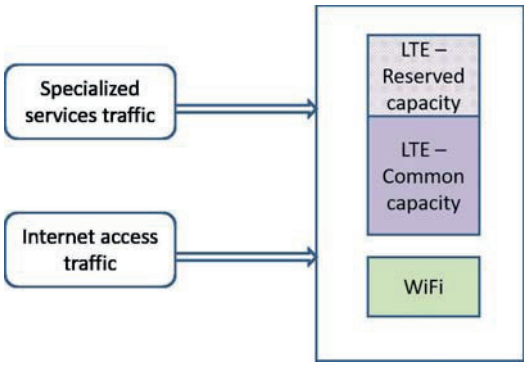



Figure D.1: System model - net-neutral policy with exemption to SS traffic.

both SS and IAS traffic. SS traffic is charged $P_h$ and IAS traffic is charged $P_l$.

### D.4.2 Implementation of the RAT Selection Strategies

Policy A aims to distribute the traffic among LTE and WiFi in a way that maximizes the generated revenue. This scenario can be modeled with the help of Markov Decision Process (MDP). In the following, the notation RAT $i$ will be used to identify the available RATs, where RAT 1 designates LTE and RAT 2 designates WiFi. Similarly, class $j$ traffic represents SS for $j = 1$ and IAS for $j = 2$.

The MDP model is identified by the following components:

- State space:

$$S = \left\{ \boldsymbol{s} = [s_1, s_2] = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}] \in \mathbb{Z}_+^4 \right\} \tag{D.2}$$

  where $n_{i,j}$ represents the number of ongoing sessions of class $j$ traffic in RAT $i$, $i \in \{1, 2\}$ and $j \in \{1, 2\}$.

- Action space: the action space of the MDP model is defined as the set of vectors $\boldsymbol{a}$ as follows:

$$A = \{\boldsymbol{a} = [a_1, a_2], a_1 \in \{-1, 0, 1\}, a_2 \in \{-1, 0, 1\}\} \tag{D.3}$$

  A vector $\boldsymbol{a} = [a_1, a_2]$ represents the action taken following each decision epoch, where $a_j$ denotes the action resulting from the arrival of a class $j$ session. A decision can be either to admit the arriving session

to LTE, admit it to WiFi or block it. We define $a_j$ as follows:

$$a_j = \begin{cases} -1, & \text{if the session is admitted to LTE.} \\ 1, & \text{if the session is admitted to WiFi.} \\ 0, & \text{if the session is blocked.} \end{cases}$$

- Policy: For each state $\boldsymbol{s} = [s_1, s_2] \in S$, an action $\boldsymbol{a} \in A_s$ is chosen according to a policy $\pi_s \in \Pi$, where $A_s \subset A$ represents the set of feasible actions for state $\boldsymbol{s}$ and $\Pi$ is a set of admissible policies defined as:

$$\Pi = \{\pi : S \rightarrow A | \pi_s \in A_s, \forall \boldsymbol{s} \in S\} \tag{D.4}$$

- Reward function: the reward function that we want to maximize reflects the revenue achieved by the admission of both classes of traffic. Hence, the reward function for choosing action $\boldsymbol{a} \in A_s$, when the system is in state $\boldsymbol{s} \in S$ can be defined as follows:

$$\begin{aligned} r(\boldsymbol{s}, \boldsymbol{a}) = w_{1,1} \cdot \delta(-a_1) - k_{c,w} \cdot n_{h,2} \cdot h \\ + w_{2,1} \cdot \delta(a_1) - k_{w,c} \cdot n_{h,2} \cdot h \\ + w_{1,2} \cdot \delta(-a_2) + w_{2,2} \cdot \delta(a_2) \end{aligned} \tag{D.5}$$

  where:
  $w_{i,j} \in \mathbb{R}_+$ is the weight associated with the admission of a class $j$ session into RAT $i$, $\mathbb{R}_+$ being the set of non-negative real numbers,
  $k_{c,w}$ is the cost associated for handing off an IAS session from LTE to WiFi and $k_{w,c}$ is the cost associated for handing off an IAS session from WLAN to LTE,
  $n_{h,2}$ represents the number of IAS sessions handed off from one RAT to another,
  $h$ is a variable that takes 1 as value if a vertical handover was performed, and 0 otherwise,
  and $\delta(x)$ is a function defined as:

$$\begin{cases} 0, & \text{if } x \leq 0 \\ 1, & \text{if } x > 0 \end{cases}$$

Since our objective is to maximize the revenue, the weights $w_{i,j}$ in the reward function are assigned the value $P_h$ for $j = 1$ and $P_l$ for $j = 2$. For more details about the MDP modeling, the reader is referred to [9].

To implement Policies B, C, D and E, a 4-dimensional Markov chain has been used where the transitions between states are defined according to the definition of the policies (either LTE-first or WLAN-first), and the resource reservation for SS traffic is also taken into account for Policies C and E.

Table D.2: System parameters

| Parameter | Symbol | Value |
|---|---|---|
| Average session holding time - SS traffic | $1/\mu_1$ | 200 s |
| Average session holding time - IAS traffic | $1/\mu_2$ | 150 s |
| Total traffic intensity | $\rho$ | 2-12 Erlang |
| Price charged for high-priority traffic | $P_h$ | 1.6 MU |
| Price charged for low-priority traffic | $P_l$ | 1 MU |

## D.5 Numerical Results

The values of the different system parameters used in this work are summarized in Table D.2. The total arrival requests follow a Poisson process with traffic intensity $\rho$. Each of these requests may randomly choose SS or IAS due to pricing and to the probability to choose SS which is given by (D.1). As a result, the traffic intensities of SS and IAS, denoted by $\rho_1$ and $\rho_2$, can be respectively found as:

$$\rho_1 = D[P_h] \cdot \rho$$

$$\rho_2 = (1 - D[P_h]) \cdot \rho$$

where $D[P_h]$ is found from (D.1). As for the call holding time, it is assumed to be inelastic, i.e. the average duration of the service is independent of the allocated number of channels. Particularly, it follows an exponential distribution with mean $1/\mu_1$ and $1/\mu_2$ for SS and IAS traffic respectively. For Policies C and E, the value of 15% is assigned to the ratio of reserved capacity in LTE for SS traffic.

### D.5.1 Revenue

The term revenue, as used in this paper, designates the charges paid by the users in exchange for the services they are receiving. It is hence the amount paid by them for transmitting their traffic over the network in monetary unit (MU).

The revenue achieved when applying the different RAT selection policies is depicted in Fig. D.2. With Policy A, which is the revenue maximizing policy, SS sessions are charged $P_h$ and are granted, in return, higher priority in getting admission to the system and in using LTE network over the IAS traffic. Moreover, a handover of IAS traffic is also allowed whenever there is the need to re-distribute the traffic among LTE and WiFi in order to admit more sessions. Policy A is hence the one that allows to achieve the highest

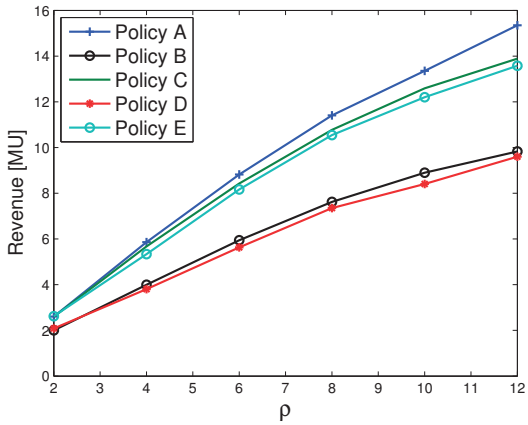



Figure D.2: Revenue achieved in monetary unit [MU].

revenue among the five studied policies. With Policies C and E, SS sessions are also charged $P_h$ in exchange for the reserved resources they are getting in LTE. The results show that Policy C is able to achieve higher revenue than Policy E. This is because Policy C fully exploits LTE resources before admitting traffic to WiFi, while Policy E admits the traffic to WiFi first which has local coverage and this can result in loss of some of the traffic sent to WiFi and, consequently, a decrease in the revenue. Policies B and D offer equal treatment to both SS and IAS traffic which are also charged equally. Both achieve lower revenue than the other policies with some advantage to Policy B which admits the traffic on LTE-first basis, unlike Policy D.

In comparison with what is achieved by the revenue-maximizing non-net-neutral policy, i.e. Policy A, the difference in revenue highly depends on the adopted net-neutral policy, which varies from less than 10% up to 30% as shown in Fig. D.2.

Regardless of the adopted RAT selection policy, the achieved revenue is affected by the ratio $P_h/P_l$. To illustrate this, we plotted in Fig. D.3 the revenue obtained by Policy C for different ratios $P_h/P_l$. It is shown that the achieved revenue first increases with the increase of $P_h/P_l$, then starts to decrease. This is because when the price $P_h$ of SS traffic becomes too high compared to $P_l$, the users will tend to send the majority of traffic as low-priority traffic as can be deduced from (D.1), which will result in a decrease of the revenue.

Another important parameter that affects the revenue achieved by applying Policies C and E is the share of bandwidth that is reserved to SS traffic. This parameter will be further investigated in Section D.5.4.

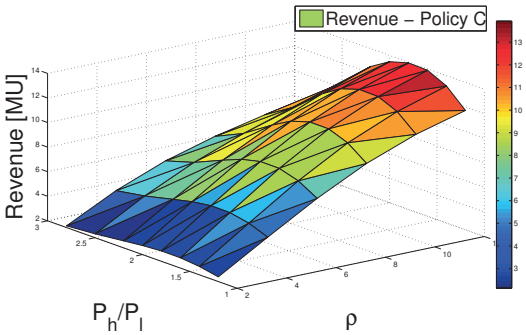



Figure D.3: Revenue of policy C for different pricing ratios $\frac{P_h}{P_l}$.

### D.5.2 Social Benefit

We define the social benefit as the total number of admitted sessions into the network regardless of the traffic type. This metric offers insight into the user experience. Fig. D.4 depicts the number of admitted sessions realized by all five RAT selection policies. Policy A is able to admit the highest number of sessions. Policy B comes in the second place despite its low achieved revenue observed in Fig. D.2. This indicates that Policy B performs well in terms of session admission and the low revenue is mainly due to the difference in pricing between the two types of traffic. A similar observation can be noticed with Policy E in the sense that the relatively high revenue achieved by this policy is also due to the difference in pricing, which indicates that Policy E admits mostly SS sessions, resulting in high revenue but low number of total admitted sessions.

The results show also that the policies that offer equal traffic treatment perform better in terms of social benefit than their respective policies that reserve capacity to SS traffic (i.e. Policy B outperforms C, and D outperforms E). Nevertheless, the difference in terms of social benefit achieved by the studied policies is generally small, e.g. less than 5% shown in Fig. D.4.

### D.5.3 Blocking Probability

#### SS traffic

The blocking probability of SS traffic obtained with the studied RAT selection schemes is depicted in Fig. D.5. Policy D, which admits the traffic on WLAN-First basis without bandwidth reservation for SS traffic, performs the worst. This is due to the possibility of loss of traffic when admitted to WLAN. Policies B and E have comparable performance when the traffic

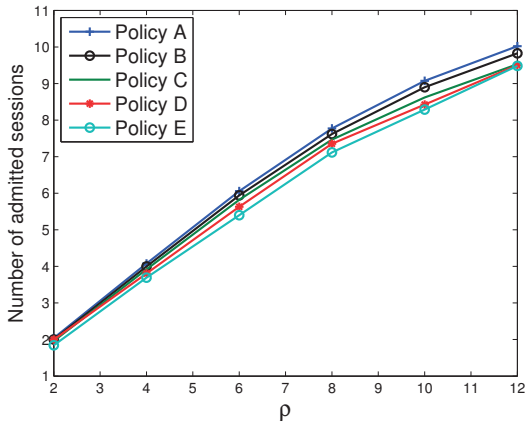



Figure D.4: Social benefit.

load is low. However, when the traffic load increases, Policy E outperforms Policy B. This is mainly due to the capacity reservation in LTE for SS traffic that Policy E allows. As for Policy A, despite granting priority to SS traffic, it does not outperform Policy C. This is due to the way the reward function (D.5) is built, where only revenue maximization has been considered without taking QoS into account. Policy C allows to realize the lowest blocking probability for SS traffic among all studied policies and this is because it combines both bandwidth reservation for SS traffic and LTE-First admission.

#### IAS traffic

Fig. D.6 depicts the blocking probability of IAS traffic obtained with the considered RAT selection policies. With Policy B, where the two classes of traffic receive equal treatment, the blocking probability of IAS traffic is the lowest. The result of Policy A is in the middle, while the policies that reserve capacity for SS traffic (Policies E and C) perform the worst, which shows that reserving bandwidth for SS traffic has clear effect on the blocking probability of IAS traffic. The results show also that the blocking probability obtained by the WLAN-First based policies D and E is higher than that by their respective LTE-First based Policies B and C.

### D.5.4 Proportion of Reserved Capacity for SS Traffic

When studying the performance of Policies C and E, we have to take into account that the obtained results are dependent on the share of the reserved

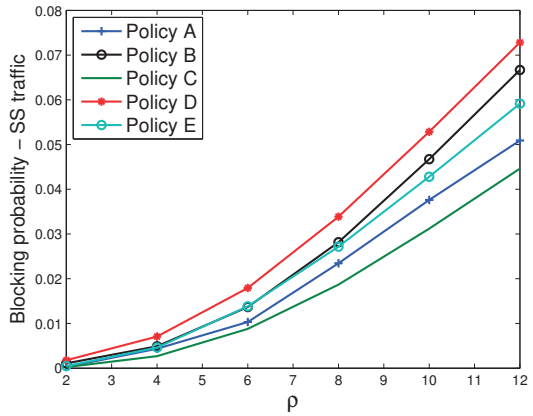



Figure D.5: Blocking probability - specialized services traffic.

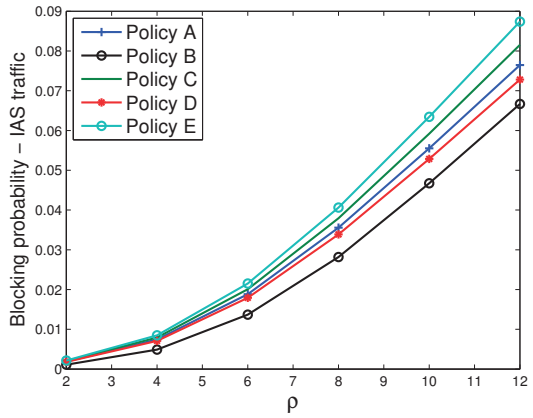



Figure D.6: Blocking probability - Internet access traffic.

capacity in LTE for SS traffic. It is hence interesting to investigate how varying the proportion of the reserved capacity for SS would affect the revenue and the blocking probability of both SS and IAS traffic. Since Policy C achieves higher revenue than Policy E, we shift our focus to Policy C to study its performance with three values of the proportion of reserved capacity : 10%, 15% and 20%.

### Revenue

The revenue obtained by Policy C for the different proportions of reserved LTE bandwidth is depicted in Fig. D.7. It is shown that when we increase the share of reserved capacity in LTE, the revenue starts to increase in

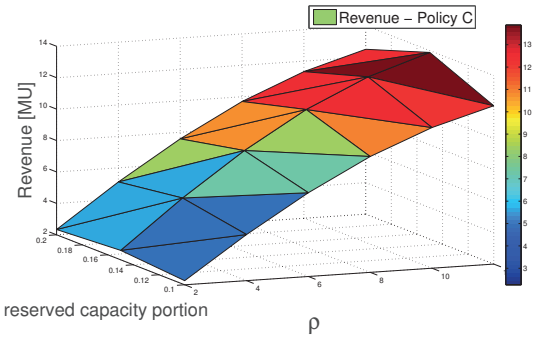



Figure D.7: Revenue in monetary unit [MU] - different ratios of reserved capacity.

the beginning. Then when this share becomes relatively high, the revenue starts again to decrease. The reason is that, when large portion of bandwidth is reserved, this will result in "wasted" resources, and consequently, a significant portion of IAS traffic will be rejected. This results in loss of the revenue that could have been realized if the resources were better managed to allow the accommodation of a higher number of IAS sessions.

**Blocking probability**

- SS traffic: It is evident that the increase of the share of reserved bandwidth in LTE will lead to a decrease of the blocking probability of SS traffic as depicted in Fig. D.8.
- IAS traffic: when the share of reserved bandwidth in LTE for SS traffic is small, the blocking probability of IAS traffic is low (Fig. D.9). However, when this share increases, higher blocking probability of IAS traffic is observed.

## D.6 Conclusion

In this work, we discuss net neutrality and highlight its impact on the revenue and the QoS of both SS and IAS traffic in a heterogeneous LTE / WiFi network. We study the performance of five different RAT selection policies: a revenue-maximizing policy that is not compliant to net neutrality, and four other net-neutral policies. The results show that, even though, as expected, applying net neutrality regulations can lead to a decrease in

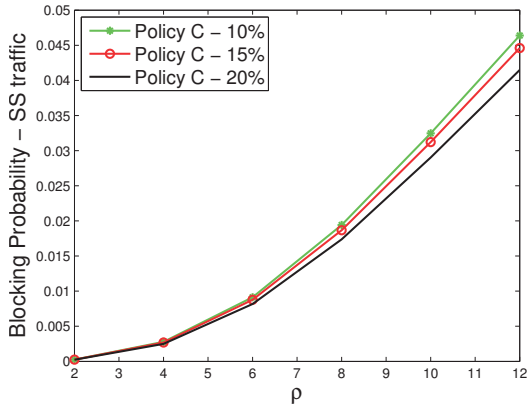



Figure D.8: Blocking probability of SS - different ratios of reserved capacity.

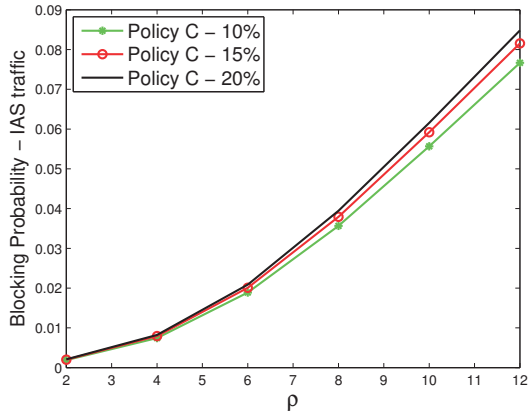



Figure D.9: Blocking probability of IAS - different ratios of reserved capacity.

revenue, this decrease can be reduced by choosing proper net-neutral RAT selection policies. In terms of social benefit, even though a similar decrease can be observed, the decrease is so small that the difference may be neglected in deciding which policy to use. Concerning QoS, applying net neutrality regulations with bandwidth reservation for SS traffic can lead to a decrease in the blocking probability of this latter. However, for IAS traffic, the lowest blocking probability is achieved with the policies that are strictly net-neutral. Finally, the choice of the share of reserved LTE resources for SS traffic is investigated.

We conclude that in order to support net neutrality and at the same time maximize revenue and meet the QoS requirements, the RAT selection

policy has to be designed / chosen carefully. We believe that, though far from exhaustive, the results in this paper on the considered policies shed light on further study along this direction.

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# References


[1] Altman E, Hanuwa MK, Sundaresan R. Nonneutral network and the role of bargaining power in side payments. *NET-COOP 2010-4th Workshop on Network Control and Optimization*. 2010 Nov 29.

[2] BEREC. Berec guidelines on the implementation by national regulators of European net neutrality rules. *http://berec.europa.eu/eng/document_register/subject_matter/berec/regulatory_best_practices/guidelines/6160-berec-guidelines-on-the-implementation-by-national-regulators-of-european-net-neutrality-rules*. 2016 Aug.

[3] Chen B, Chen J, Gao Y, Zhang J. Coexistence of LTE-LAA and Wi-Fi on 5 GHz with corresponding deployment scenarios: A survey. *IEEE Communications Surveys & Tutorials*. 2017 Jan 1;19(1):7-32.

[4] Fishburn PC, Odlyzko AM. Dynamic behavior of differential pricing and quality of service options for the Internet. *Decision Support Systems*. 2000 Mar 31;28(1):123-36.

[5] Hahn RW, Litan RE, Singer HJ. The Economics of ´Wireless Net Neutrality´. *Journal of competition law and economics*. 2007 Aug 4;3(3):399-451.

[6] Hosein P, Choi W, Seok W. Disruptive network applications and their impact on network neutrality. *Advanced Communication Technology (ICACT), 2015 17th International Conference on*. 2015 Jul 1 (pp. 663-668). IEEE.

[7] Hou J, Yang J, Papavassiliou S. Integration of pricing with call admission control to meet QoS requirements in cellular networks. *IEEE Transactions on parallel and distributed systems*. 2002 Sep;13(9):898-910.

[8] Jordan S. Traffic management and net neutrality in wireless networks. *IEEE Transactions on Network and Service Management*. 2011 Dec;8(4):297-309.

[9] Khloussy E, Gelabert X, Jiang Y. Investigation on MDP-based radio access technology selection in heterogeneous wireless networks. *Computer Networks*. 2015 Nov 14;91:57-67.

[10] Krämer J, Wiewiorra L, Weinhardt C. Net neutrality: A progress report. *Telecommunications Policy*. 2013 Oct 31;37(9):794-813.

[11] Kwon HJ et al. Licensed-assisted access to unlicensed spectrum in LTE release 13. IEEE Communications Magazine. 2017 Feb;55(2):201-7.

[12] Ma RT, Misra V. The public option: A nonregulatory alternative to network neutrality. *IEEE/ACM Transactions on Networking (TON)*. 2013 Dec 1;21(6):1866-79.

[13] Ma RT, Wang J, Chiu DM. Paid prioritization and its impact on net neutrality. *IEEE Journal on Selected Areas in Communications*. 2017 Feb;35(2):367-79.

[14] Martínez L, Álvarez San-Jaime O, Markendahl J. Net neutrality principles and its impact on quality of experience based service differentiation in mobile networks. *Regional Conference of the International Telecommunications Society (ITS)*. 2015 Oct 25;28.

[15] Sørensen F. On the origin of specialised services. *https://eng.nkom.no/topical-issues/news/on-the-origin-of-specialised-services*. 2014 Jun 6.

[16] Tang J, Ma RT. Regulating monopolistic ISPs without neutrality. *Network Protocols (ICNP), 2014 IEEE 22nd International Conference on*. 2014 Oct 21 (pp. 374-384).

[17] Wu T. Wireless carterfone. *International Journal of Communication*. 2007;1:389-426.

# Appendix E

# Publication E

Elissar Khloussy and Yuming Jiang; Revenue-Maximizing Radio Access Technology Selection with Net Neutrality Compliance in Heterogeneous Wireless Networks; Wireless Communications and Mobile Computing journal, 2018.

**Abstract**

The net neutrality principle, also known as Open Internet, states that users should have equal access to all Internet content and that Internet Service Providers (ISPs) should not practice differentiated treatment on any of the Internet traffic. While net neutrality aims to restrain any kind of discrimination, it also grants exemption to a certain category of Internet traffic known as specialized services (SS), by allowing the ISP to dedicate part of the resources for the latter. In this work, we consider a heterogeneous LTE / WiFi wireless network and we investigate revenue-maximizing Radio Access Technology (RAT) selection strategies that are net neutrality-compliant, with exemption granted to SS traffic. Our objective is to find out how the bandwidth reservation for SS traffic would be made in a way that allows to maximize the revenue while in compliance with net neutrality, and how the choice of the ratio of reserved bandwidth would affect the revenue. The results show that reserving bandwidth for SS traffic in one RAT (LTE) can achieve higher revenue, but this gain in revenue is minimal. On the other hand, when the capacity is reserved across both LTE and WiFi, higher social benefit in terms of number of admitted users can be realized, as well as lower blocking probability for the Internet access traffic.

**Keywords**

*radio access technology (RAT) selection, Markov decision processes (MDPs), net neutrality, heterogeneous wireless networks, Poisson Point Process.*

## E.1 Introduction

Heterogeneous Wireless Networks (HWNs), where two or more Radio Access Technologies (RATs) coexist in the same geographical area, offer several opportunities to the Internet Service Provider (ISP) such as multiple connectivity options and a low-cost coverage expansion [24]. The ISPs, facing the fast increase in traffic demands, have interest in making the best utilization of all available resources in the HWN in order to increase the capacity of the network and meet, as much as possible, their customers' expectations and demands.

Managing resources in HWNs involves setting up policies that regulate how the arriving traffic is distributed and served among the available RATs. A well known key mechanism for resource management in HWNs scenarios is RAT selection. It consists of taking a decision, at each arrival of a new call request, on whether to accept this call or not, and the RAT to which it can be admitted.

The decision taken by the RAT selection policy is based on the objective set by the ISP such as the maximization of the generated revenue. However, it is important to set rules that regulate how the traffic is served in order to avoid that the ISP exercises any kind of traffic discrimination. Hence, the principle of net neutrality has gained lots of attention recently.

The main idea behind net neutrality is that ISPs should treat all Internet traffic equally regardless of the content, application, device, sender or receiver. While net neutrality principle states that all Internet traffic has to receive equal treatment, an exemption is granted to some non-Internet access services that require high transmission quality, known as specialized services (SS) [3]. Some examples of SS include VoLTE, linear broadcasting IPTV, and real-time health services [19]. In order to secure higher Quality of Service (QoS) to SS, the ISP is allowed to dedicate a certain amount of bandwidth to those services, without causing a degradation of the QoS experienced by the Internet access services (IAS) traffic.

However, in order to follow the net neutrality regulations, the ISPs might lose some of the generated revenue. Having revenue maximization as our main focus, we address the following problem: *how the bandwidth reservation for SS traffic would be made in a way that allows to maximize the revenue while in compliance with net neutrality, and how the choice of the ratio of reserved bandwidth would affect the revenue?*

In the present work, we derive RAT selection policies that allow to maximize the revenue while being net neutrality-compliant at the same time. We consider an integrated Long Term Evolution (LTE) / Wireless Fidelity (WiFi) heterogeneous network. The optimal RAT selection policies are derived with the help of Markov Decision Process (MDP). Two types

of traffic are considered, namely SS and IAS traffic. To reserve bandwidth for SS traffic, two cases are proposed: bandwidth reserved in LTE only, and bandwidth reserved in the whole HWN. Our aim is to figure out which way of bandwidth reservation is better to adopt, and to investigate how the revenue would be affected by the choice of the ratio of reserved bandwidth to SS traffic.

The main contributions of this paper can be summarized as follows:

1. Investigation of the MDP-based approach for RAT selection, with focus on revenue maximization as objective.
2. Integration of net neutrality in the RAT selection policy, with two variants of bandwidth reservation for SS traffic.
3. The impact of the ratio of reserved bandwidth for SS traffic is studied with both variants.
4. The coverage probability of WLAN is analytically modeled with the help of Poisson Point Process (PPP).
5. The spatial distributions of the cellular base stations (BS), WiFi access points (AP) as well as the users are also captured with PPP.

The remaining of the paper consists of the following parts: Section E.2 presents the motivation and related work in the literature. Section E.3 describes the system model. In Section E.4, the components of the MDP problem are presented. Section E.5 presents and analyzes the obtained results. Finally, we conclude this study in Section E.6.

## E.2 Motivation and Related Work

Net neutrality has been heavily discussed in the past decade as a potential way to prevent the ISPs from exercising any type of discrimination on the Internet traffic. Content providers, in general, support net neutrality especially in monopolistic regimes where an ISP might have pricing power over the Internet access market. The ISPs, on the other hand, argue that service differentiation is crucial for QoS enhancement [21].

The use of capacity increase as an alternative to deal with QoS concerns resulting from applying net neutrality has been addressed in the literature. While this seems plausible, early study, e.g. [18], already showed that the relationship between the net neutrality regulation and investment incentives is subtle, and that it is difficult to draw general unambiguous conclusions regarding this issue. In addition, recent study, e.g. [16], further shows that

when strict net neutrality is applied, the ISPs will no longer have incentive to invest in expending their infrastructure and enhance the QoS.

Wu in [23] expanded the net neutrality debate by suggesting that policy-makers ought to consider how to apply net neutrality regulations to wireless networks. This was opposed by a number of economists (e.g. [8]) who argued that, unlike the wired market, the competition will remain high in the wireless one.

Martínez et al. in [17] provided an initial analysis of the impact of net neutrality on quality of experience-based differentiation in mobile networks. In [9], the authors shed light on the content provider discrimination and discussed the impact of some of the disruptive network applications on net neutrality. In some other work, e.g. [15, 21], alternative regulations to net neutrality have been proposed. Authors in [16] studied the paid prioritization where the content providers decide to pay for this priority in monopolistic access market. They showed that, with ISP's optimal pricing, the service differentiation becomes efficient and the social welfare among the different content providers is close to its maximum. Altman et al. in [1] presented a bargaining framework to decide how much the ISP should charge the content provider.

In a previous work [12], we investigated MDP as a tool for modeling revenue-maximizing RAT selection policies. However, net neutrality was not taken into account in the derived model. The way the traffic was handled provided privileges to the high-priority traffic in getting admission to LTE which offers better QoS guarantees, at the expense of blocking or handing over part of the low-priority traffic from one RAT to another. This allows to achieve higher revenue but violates the net neutrality regulations.

Net neutrality and its integration in RAT selection policies have been addressed in [13], where the performance of various RAT selection strategies that are net neutrality-compliant was compared. The objective was to give insight into the effect of applying net neutrality regulations on the revenue and the QoS.

In the present work, we model two variants of RAT selection policy, that differ by the way the bandwidth reservation for SS traffic is exercised. Both are net neutrality-compliant and aim to maximize the generated revenue. By comparing their performance, we try to find the most appropriate way of bandwidth reservation for SS traffic, and investigate the impact of the ratio of this reserved bandwidth on the generated revenue.

## E.3 System Model

### E.3.1 Network Architecture

We consider the case of an LTE / WiFi overlay network [20]. The traffic arrivals to the different BSs are independently distributed. Hence, and without loss of generality, we can shift our focus to a single cell $C_{targ}$ that corresponds to the coverage area of one cellular BS. LTE has global coverage, overlaying the WLAN i.e. within the coverage of the considered BS there exists one or more WiFi AP(s).

Two types of traffic are served, namely SS and IAS traffic, where IAS is charged a price $P_l$, while SS is charged a price $P_h > P_l$. Naturally, this pricing differentiation affects the traffic distribution among SS and IAS. In this paper, we adopt that, and the ratio of traffic that is being sent as SS traffic out of the total traffic can be computed with the help of the following demand function that was proposed in [6] and has been adopted in the literature e.g. [10]:

$$D[P_h] = e^{-(\frac{P_h}{P_l}-1)^2}, \tag{E.1}$$

which implies that, out of the total traffic, the ratio of IAS traffic is $(1 - e^{-(\frac{P_h}{P_l}-1)^2})$.

### E.3.2 Spatial Distribution

Because of the overlay nature of our studied HWN scenario, a connection request might occur either in an area that is covered by the cellular RAT only, or in a dual coverage area. In the latter case, an arriving session request can be admitted to LTE or to WiFi depending on the decision provided by the RAT selection policy. Here arises the need for getting knowledge regarding the spatial distribution of the BSs and the APs. The considered network architecture can be seen as a 2-tier heterogeneous network, where tier-1 is LTE and tier-2 is WiFi. A spatial point process, such as PPP provides a concise and tractable model for HWNs, by offering a statistical modeling for the spatial distribution of the BSs and APs. In fact, PPP model has been used extensively for modeling unplanned networks [11] which is typically the case of WLAN APs' deployment. In our considered scenario, the different aspects of the PPP model can be described as follows:

- The positions of BSs / APs belonging to tier-k are modeled according to a homogeneous PPP $\phi^{(k)}$ with intensity $\lambda^{(k)}$, where $\lambda^{(k)}$ is defined

as the number of BSs /APs per area unit, and $k \in \{1, 2\}$ with $k = 1$ refers to LTE and $k = 2$ refers to WiFi.

- Users are also scattered in the plane according to a homogeneous PPP $\phi^{(u)}$ with intensity $\lambda^{(u)}$ users per area unit, independently of $\phi^{(k)}$.

Through PPP modeling, different metrics can be captured. In the following, we derive the probability for a user to be under tier-k's coverage, and the traffic arrival rates.

### Coverage probability

The cellular system has global coverage i.e. all users in the considered HWN fall under the coverage of the cellular RAT. Hence, the coverage probability of LTE is $P_{c,1} = 1$.

As for the coverage probability of WiFi, it can be derived with the help of PPP as follows. First, we assume that each AP covers a circular area of known radius $R$, i.e. the transmission of each AP can be received clearly by users residing at a distance not exceeding $R$. Second, the interference from neighboring APs is considered negligible. Hence, a typical user is said to be under the coverage of WLAN if the distance $r$ separating this user from the nearest AP is less than $R$. Therefore, the probability that a user is under WLAN coverage is equivalent to the cumulative distribution function of $r$, namely $\mathbb{P}[r < R]$. Without loss of generality, we consider that the typical user is located at the origin of the plane under consideration [11]. Then, knowing that the null probability of a 2D Poisson process in an area $Z$ is $exp(-\lambda Z)$ [2], we can derive the coverage probability of WiFi $P_{c,2}$ as follows:

$$\mathbb{P}[r > R] = \mathbb{P}[\phi^{(2)} \cap b(0, R) = 0] = e^{-\pi\lambda^{(2)}R^2} \tag{E.2}$$

where $b(0, R)$ is the Euclidean ball of radius $R$ centered at origin. Hence, the coverage probability of tier-2 is given by:

$$P_{c,2} = \mathbb{P}[r < R] = 1 - \mathbb{P}[r > R] = 1 - e^{-\pi\lambda^{(2)}R^2} \tag{E.3}$$

### Traffic arrivals and holding times

With the assumption that each user of class $i$, $i \in \{1, 2\}$ ($i = 1$ represents SS and $i = 2$ represents IAS) generates traffic following a Poisson distribution with average $\sigma_i$ calls/second, the traffic arrival rates $\lambda_1$ and $\lambda_2$ of classes 1 and 2 respectively can be easily derived as follows:

$$\lambda_1 = \sigma_1 \cdot D[P_h] \cdot \lambda^{(u)} \cdot |C_{targ}| \text{ arrivals/second} \tag{E.4}$$

$$\lambda_2 = \sigma_2 \cdot (1 - D[P_h]) \cdot \lambda^{(u)} \cdot |C_{targ}| \text{ arrivals/second} \tag{E.5}$$

where $|C_{targ}|$ is the area covered by the targeted cell $C_{targ}$ (in area unit), and $D[P_h]$ is found from (E.1).

Note that in (E.4) and (E.5), $\lambda^{(u)} \cdot |C_{targ}|$ appears in both $\lambda_1$ and $\lambda_2$, together with $\sigma_1$ and $\sigma_2$ respectively. To simplify the representation, in later analysis and results, we will simply use $\lambda_1 = \sigma_1 D[P_h]$ and $\lambda_2 = \sigma_2(1-D[P_h])$ with $\sigma_1$ and $\sigma_2$ normalized against $\lambda^{(u)} \cdot |C_{targ}|$.

As for the call holding time for class $i$, the traffic of each class is assumed to be inelastic, i.e. the average duration of the service is independent of the allocated number of channels, and following exponential distribution with mean $1/\mu_i, i \in \{1, 2\}$.

## E.4 Markov Decision Process Formulation

An MDP model is provided to derive the optimal RAT selection policy which maximizes our objective function. This model can be uniquely identified by five components: the state space, decision epochs, action space, state dynamics and the reward function. We define each of these components in the following subsections.

### E.4.1 State Space

The state space represents the number of ongoing sessions in the HWN i.e. the number of SS sessions being served in LTE and WiFi, and similarly, the number of IAS sessions being served in both LTE and WiFi. For ease of representation in MDP, we model the problem with one particular AP in WLAN that we call the targeted AP. Hence, a 4D-MDP serves to build our model. On the other hand, we assume a fixed total capacity for both RATs, each being partitioned into a fixed number of basic bandwidth units (bbu) as in, e.g. [7, 20, 22]. This implies that a limited number of sessions can be served simultaneously by each RAT. The total capacities of LTE and WiFi can be defined as integers that we denote by $C_1$ and $C_2$ respectively. Any newly arriving session that cannot be granted its required amount of bbu is blocked. Thus, by restricting the number of ongoing connections in the system, the delivered QoS to the different connections can be maintained at an acceptable level. To simplify the notation, we refer to each type of served traffic as class $i$, with $i = 1$ denotes SS traffic and $i = 2$ denotes IAS traffic.

We define the following row vectors:

- State vector of LTE:
  $\boldsymbol{s_1} = [n_{1,1}, n_{1,2}] \in \mathbb{Z}_+^2$
- State vector of WiFi:
  $\boldsymbol{s_2} = [n_{2,1}, n_{2,2}] \in \mathbb{Z}_+^2$
- State vector of the system:
  $\boldsymbol{s} = [s_1, s_2] = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}]$

where:
$n_{j,i}$ denotes the number of sessions of class $i$ in RAT $j$, $j \in \{1, 2\}$, with $j = 1$ refers to LTE and $j = 2$ refers to WiFi,
$\mathbb{Z}_+$ represents the set of non-negative integer numbers.

The state space $S$ of the system, which is the set of all feasible states, differs according to the RAT selection policy. The following two cases are to be distinguished: reserved bandwidth for SS traffic in LTE only, and reserved bandwidth for SS in both LTE and WiFi.

- State space - reserved bandwidth in LTE only
  In this case, the state space can be defined as follows:

$$S = \big\{\boldsymbol{s} = [s_1, s_2] = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}] \in \mathbb{Z}_+^4, \\ n_{1,1} + n_{1,2} \leq C_1, \quad n_{2,1} + n_{2,2} \leq C_2, \quad n_{1,2} \leq (C_1 - C_{1,res})\big\} \tag{E.6}$$

  where $C_{1,res}$ represents the number of reserved bbu in LTE for the usage of SS traffic.

- State space - reserved bandwidth in LTE and WiFi
  In this case, the reserved bandwidth for SS traffic is spread across the available RATs, namely LTE and WiFi. The state space in this case becomes:

$$S = \big\{\boldsymbol{s} = [s_1, s_2] = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}] \in \mathbb{Z}_+^4, \\ n_{1,1} + n_{1,2} \leq C_1, \quad n_{2,1} + n_{2,2} \leq C_2, \quad n_{1,2} + n_{2,2} \leq (C_1 + C_2 - C_{res})\big\} \tag{E.7}$$

  where $C_{res}$ denotes the number of bbu reserved for SS traffic in both LTE and WiFi.

### E.4.2 Decision Epochs and Actions

At each arrival of a class $i$ session request, $i \in \{1, 2\}$, the RAT selection policy makes a decision concerning the admission of this new session. A

decision epoch occurs at each new session request. It is defined as the time following immediately an arrival event. As for the events of call completion, they do not require any decision to be taken by the system.

The action taken following each decision epoch can be defined as a vector $\boldsymbol{a} = [a_1, a_2]$ where $a_i$ denotes the action resulting from the arrival of a class $i$ session. A decision can be either to admit the arriving session to LTE, admit it to WiFi or block it. $a_i$ can be defined as follows:

$$a_i = \begin{cases} -1, & \text{if the session is admitted to LTE.} \\ 1, & \text{if the session is admitted to WiFi.} \\ 0, & \text{if the session is blocked.} \end{cases}$$

The action space of the MDP is defined as the set of vectors $\boldsymbol{a}$ as follows:

$$A = \{\boldsymbol{a} = [a_1, a_2], a_1 \in \{-1, 0, 1\}, a_2 \in \{-1, 0, 1\}\} \tag{E.8}$$

However, for a given state $\boldsymbol{s} \in S$, the decision should always lead to a state $\boldsymbol{s'}$ that is also in $S$. Moreover, when the system is in state (0,0,0,0), the action (0,0) should be avoided in order for the system to keep evolving. Hence, for a given state $\boldsymbol{s} = [n_{1,1}, n_{1,2}, n_{2,1}, n_{2,2}] \in S$, the state action space $A_s \subset A$ is given by:

$$\begin{aligned} A_s = \{&\boldsymbol{a} \in A : a_i \neq -1 \text{ if } [s_1 + e_i^u, s_2] \notin S, \\ &a_i \neq 1 \text{ if } [s_1, s_2 + e_i^u] \notin S, \\ &a_i = 0 \text{ if } [s_1 + e_i^u, s_2] \notin S \text{ and } [s_1, s_2 + e_i^u] \notin S, \\ &a \neq (0,0) \text{ if } s = (0,0,0,0)\} \end{aligned} \tag{E.9}$$

Where $e_i^u \in \{0, 1\}^2$, is a vector of zeros except for the $i^{th}$ element which is equal to 1.

### E.4.3 State Dynamics

The state dynamics of the MDP are defined by two parameters, namely the expected sojourn time and the transition probabilities.

#### Expected sojourn time

The sojourn time $\tau(s, a)$ is defined as the expected time for the system to stay in state $\boldsymbol{s} \in S$ given that action $\boldsymbol{a} \in A_s$ is chosen, until a new state is entered. The sojourn time is used to compute the transition probabilities for a continuous-time MDP, and its value can be expressed as [5, 14]:

$$\tau(s, a) = [\lambda_1 |a_1| + (n_{1,1} + n_{2,1})\mu_1 + \lambda_2 |a_2| + (n_{1,2} + n_{2,2})\mu_2]^{-1} \tag{E.10}$$

Where $\lambda_i$ is the arrival rate for class $i$ traffic, $i \in \{1, 2\}$ found from (E.4) and (E.5), and $1/\mu_i$ is the mean value of the call holding time of class $i$.

### Transition probabilities

Let $P_{ss'}(a)$ denote the transition probability from state $\boldsymbol{s} = [s_1, s_2] \in S$ to state $\boldsymbol{s'} \in S$, $\boldsymbol{s} \neq \boldsymbol{s'}$, provided that action $\boldsymbol{a} \in A_s$ is chosen. The state transition probabilities can thus be written as:

$$P_{ss'}(\boldsymbol{a}) = \begin{cases} \lambda_1 \delta(-a_1)\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} + e_1^u, \boldsymbol{s_2}]. \\ \lambda_2 \delta(-a_2)\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} + e_2^u, \boldsymbol{s_2}]. \\ \lambda_1 P_{c,2}^* \delta(a_1)\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} + e_1^u]. \\ \lambda_2 P_{c,2}^* \delta(a_2)\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} + e_2^u]. \\ \mu_1 n_{1,1}\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} - e_1^u, \boldsymbol{s_2}] \ . \\ \mu_2 n_{1,2}\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1} - e_2^u, \boldsymbol{s_2}]. \\ \mu_1 n_{2,1}\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} - e_1^u]. \\ \mu_2 n_{2,2}\tau(\boldsymbol{s}, \boldsymbol{a}), & \text{if } \boldsymbol{s'} = [\boldsymbol{s_1}, \boldsymbol{s_2} - e_2^u]. \\ 0, & \text{otherwise.} \end{cases} \tag{E.11}$$

Where:
$P_{c,2}^*$ is the coverage probability of the targeted AP: $P_{c,2}^* = \frac{P_{c,2}}{|C_{targ}|\lambda^{(2)}}$, and $\delta(x)$ is a function defined as:

$$\begin{cases} 0, & \text{if } x \leq 0 \\ 1, & \text{if } x > 0 \end{cases}$$

## E.4.4 Policy and Reward Function

For each state $\boldsymbol{s} = [s_1, s_2] \in S$, an action $\boldsymbol{a} \in A_s$ is chosen according to a policy $\pi_s \in \Pi$, where $\Pi$ is a set of admissible policies defined as:

$$\Pi = \{\pi : S \to A | \pi_s \in A_s, \forall \boldsymbol{s} \in S\} \tag{E.12}$$

The reward function for choosing action $\boldsymbol{a} \in A_s$, when the system is in state $\boldsymbol{s} \in S$ can be defined as follows:

$$r(\boldsymbol{s}, \boldsymbol{a}) = w_{1,1} \cdot \delta(-a_1) + w_{1,2} \cdot \delta(-a_2) + w_{2,1} \cdot \delta(a_1) + w_{2,2} \cdot \delta(a_2) \tag{E.13}$$

where $w_{j,i} \in \mathbb{R}_+$ is the weight associated with the admission of a class $i$ session into RAT $j$, $\mathbb{R}_+$ being the set of non-negative real numbers. Since

our objective is to maximize the revenue, the weights $w_{j,i}$ in the reward function are assigned the value $P_h$ for $i = 1$ and $P_l$ for $i = 2$.

By solving the MDP, an optimal policy $\pi^*$ that maximizes the reward function can be found. The RAT selection module will then, based on the optimal policy provided by the MDP, decide on the admission or rejection for each arriving session. A summary of the notations used in the paper is presented in Table E.1.

## E.5 Numerical Results

In this section we present and analyze the results obtained from the implementation of the two variants of the net neutral revenue-maximizing RAT selection policy, namely bandwidth reservation for SS in LTE only and bandwidth reservation for SS in the HWN as a whole. In addition, the results obtained from a *non-net neutral* revenue-maximizing RAT selection policy (introduced in [12, 13]) are presented as reference. The non-net neutral policy prioritizes the admission of SS services traffic, and allows the handover of IAS traffic between LTE and WiFi when there is need to free resources for SS traffic.

To solve the MDP problem and find the optimal policy, we used the relative value iteration algorithm, defined in the MDP toolbox (developed by [4]). If not otherwise stated, the values of the system parameters used in our analysis are as shown in Table E.2.

### E.5.1 Revenue

The term revenue, as used in this paper, designates the charges paid by the customers in exchange for the services they are receiving. In our case, it is the amount paid by them for transmitting their traffic over the ISP's network in monetary unit (MU).

The revenue achieved when applying the two variants of the net neutral RAT selection policy along with that achieved by the non-net neutral one is depicted in Fig. E.1, for the values of average session holding times ($1/\mu_1$ and $1/\mu_2$) stated in Table E.2, and by varying the average call arrival rates $\sigma_1$ and $\sigma_2$ (i.e. varying $\lambda_1$ and $\lambda_2$ (c.f. (E.4))). The x-axis represents the total traffic intensity $\rho = \lambda_1/\mu_1 + \lambda_2/\mu_2$. As expected, the non-net neutral policy is the one that achieved the highest revenue. In addition, the results show that both net neutral variants have comparable performance in terms of revenue with an advantage to reserving capacity in LTE. Because LTE has global coverage and better QoS guarantees than WiFi, reserving

Table E.1: Table of notations.

| Symbol | Description |
|---|---|
| $\lvert C_{targ} \rvert$ | Coverage area of the targeted LTE base station |
| $\phi^{(k)}$ | Poisson Point Process distribution of RAT $k$ |
| $R$ | Radius of the circular area covered by an AP |
| $r$ | Distance separating a typical user from the nearest AP |
| $\lambda^{(k)}$ | Number of BS / AP per unit area of RAT $k$ |
| $\lambda^{(u)}$ | Number of camping users per unit area |
| $\lambda_i$ | The arrival rate of class $i$ |
| $p_{c,k}$ | Coverage probability of RAT $k$ |
| $\sigma_i$ | The average number of sessions per second generated by a class $i$ user |
| $1/\mu_i$ | The average session holding time of class $i$ |
| $C_k$ | Capacity (number of channels) of RAT $k$ |
| $n_{j,i}$ | Number of sessions of class $i$ in RAT $j$ |
| $\boldsymbol{s_k}$ | The state vector of RAT $k$ |
| $\boldsymbol{s}$ | The state vector of the system |
| $S$ | The state space of the system |
| $a_i$ | The action resulting from the arrival of a class $i$ session |
| $\boldsymbol{a}$ | Vector representing the action taken following a decision epoch |
| $A$ | The action space of the MDP |
| $A_s$ | The action space of state $\boldsymbol{s}$ |
| $C_{1,res}$ | Number of reserved bbu for SS traffic in LTE |
| $C_{res}$ | Number of reserved bbu for SS traffic in the HWN |
| $\tau(s,a)$ | Expected sojourn time in state $\boldsymbol{s}$ when action $\boldsymbol{a}$ is chosen |
| $P_{ss'}(\boldsymbol{a})$ | Transition probability from state $\boldsymbol{s}$ to state $\boldsymbol{s'}$ when action $\boldsymbol{a}$ is chosen |
| $P^*_{c,2}$ | Coverage probability of the targeted AP |
| $\pi_s$ | Policy chosen at state $\boldsymbol{s}$ |
| $\Pi$ | Set of admissible policies |
| $r(\boldsymbol{s},\boldsymbol{a})$ | Reward function for state $\boldsymbol{s}$ when action $\boldsymbol{a}$ is chosen |
| $w_{j,i}$ | Weight associated for admitting a class $i$ session in RAT $j$ |
| $\pi^*$ | Optimal RAT selection policy |
| $P_h$ | Price charged for SS traffic |
| $P_l$ | Price charged for IAS traffic |
| $\rho$ | Total traffic load = sum of traffic load of SS and IAS traffic |

capacity in LTE to SS traffic allows larger number of SS sessions to be admitted to the system, resulting in higher revenue as compared to the case where the bandwidth reservation is done across LTE and WiFi.

To show the impact of varying the session durations on the revenue, we experimented with fixed arrival rates with values $\sigma_1 = 0.028$ and $\sigma_2 =$

Table E.2: System parameters.

| Parameter | Symbol | Value |
|---|---|---|
| Capacity of LTE | $C_1$ | 30 bbu |
| Capacity of WiFi | $C_2$ | 5 bbu |
| Price charged for SS traffic | $P_h$ | 1.6 monetary unit (MU) |
| Price charged for IAS traffic | $P_l$ | 1.0 MU |
| Reserved bandwidth for SS traffic in LTE | $C_{1,res}$ | 5 bbu |
| Reserved bandwidth for SS traffic in the HWN | $C_{res}$ | 5 bbu |
| Total traffic intensity | $\rho$ | 2 to 12 Erlang (E) |
| Ratio of SS traffic | $D[P_h]$ | 0.69 |
| Average Session holding time - SS traffic | $1/\mu_1$ | 200 s |
| Average Session holding time - IAS traffic | $1/\mu_2$ | 150 s |

0.03, and varied the average session holding times (Fig. E.2). In this case, similar trends are observed as in Fig. E.1. We notice, however, that the achieved revenue has become lower as compared to the case where the session durations are fixed. This is because, for the same traffic intensity level, Fig. E.1 is resulted from higher traffic rates (or indeed higher call arrival rates) with shorter session duration times, while Fig. E.2 is from lower traffic rates (or indeed lower call arrival rates) with longer session duration times. As a result, the wireless resources become reserved for shorter time and more calls could be admitted for the case of Fig. E.1, providing higher revenue. While for the case of Fig. E.2, with increased session duration times, implying lower call arrival rates with the same traffic intensity level, the wireless resources become reserved for longer time, fewer arrivals will be admitted giving hence lower revenue.

### E.5.2 Social Benefit

The social benefit is a metric that offers insight into the user experience, and is defined as the total number of admitted sessions into the network regardless of the traffic type. Fig. E.3 depicts the number of admitted sessions obtained by the three considered RAT selection policies. We observe that the non-net neutral policy is the one that achieves the highest social benefit as it allows to re-arrange the traffic between LTE and WiFi in order to admit the highest possible number of sessions. It is also shown that, when reserving capacity for SS spans the whole HWN, it becomes possible to admit more sessions (particularly IAS sessions) than in the case where the reserved bandwidth is in LTE only, and therefore a better social benefit is realized.

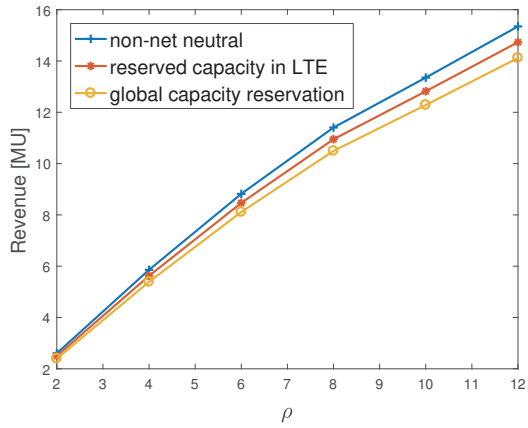


Figure E.1: Revenue achieved in monetary unit [MU] - fixed session durations.

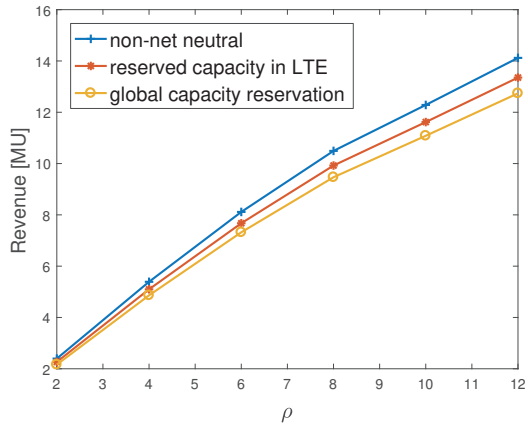


Figure E.2: Revenue achieved in monetary unit [MU] - fixed arrival rates.

### E.5.3 Blocking Probability

The blocking probability obtained by the considered RAT selection policies is depicted in Fig. E.4 and Fig. E.5 for SS and IAS traffic respectively. We observe that the blocking probability for SS traffic is lower when the reserved bandwidth is in LTE only, while for IAS traffic it is the opposite, which also confirms the results for revenue and social benefit depicted in Fig. E.1, Fig. E.2, and Fig. E.3. On the other hand, while the non-net neutral policy provides the lowest blocking probability for SS traffic due to the priority granted to the latter, it provides the highest blocking probability for IAS traffic.

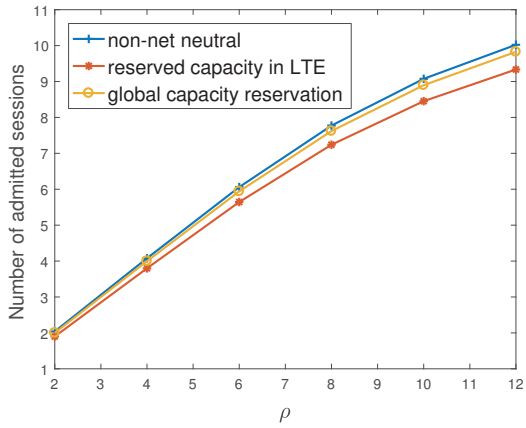


Figure E.3: Social benefit.

Having compared the three performance metrics (revenue, social benefit, and blocking probability), we conclude that reserving capacity for SS traffic in the whole HWN offers more advantages despite an insignificant loss in revenue, by providing a better social benefit and lower blocking probability for IAS traffic.

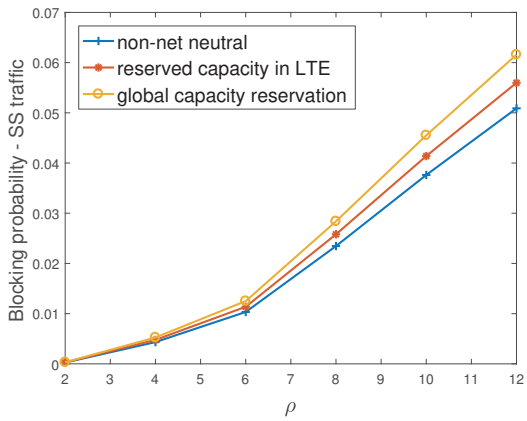


Figure E.4: Blocking probability - specialized services traffic.

### E.5.4 Reserved Capacity for SS - Impact on Revenue

In this part, we investigate the impact of the ratio of reserved capacity for SS traffic on the generated revenue for both studied scenarios, namely when the dedicated capacity for SS traffic is reserved in LTE only, and

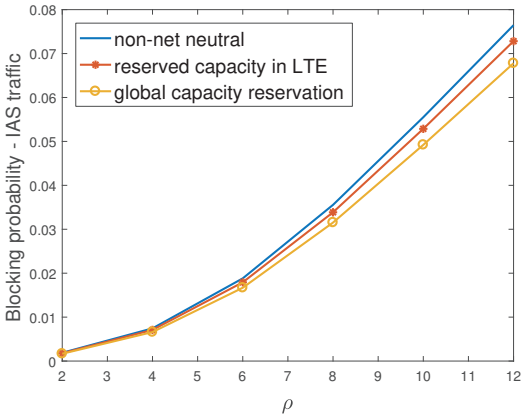


Figure E.5: Blocking probability - Internet access traffic.

when it is reserved across the HWN. Unlike the investigation above where the reserved capacity for SS is fixed as shown in Table E.2, the values of reserved capacity ratio vary from 0% to 20% in the investigation of this subsection.

In the first case, i.e. capacity reserved in LTE only, the revenue tends to increase with the increase of the reserved bandwidth up to a certain point, after which the revenue starts to decrease (Fig. E.6). This is due to the fact that when the ratio of reserved capacity is high, some resources will be reserved unnecessarily, while they could have been exploited to admit IAS traffic. We lose therefore some revenue that could have been achieved if more IAS traffic was admitted.

In the second case, where the bandwidth reservation for SS traffic is done across all RATs in the HWN, the behavior is similar (Fig. E.7). However, we notice that the graph is smoother than in the first case. This allows us to conclude that varying the ratio of reserved capacity for SS traffic in this case has less impact on the revenue than when we reserve capacity in LTE only. This is due to the possibility of admitting larger number of IAS sessions when the bandwidth reservation for SS traffic is done across the HWN.

## E.6 Conclusion

In this work, we present a model for RAT selection in HWNs where net neutrality is taken into consideration and with the objective of maximizing the revenue. We study particularly the exemption granted to SS traffic that the net neutrality regulation allows. Two variants of the RAT selec-

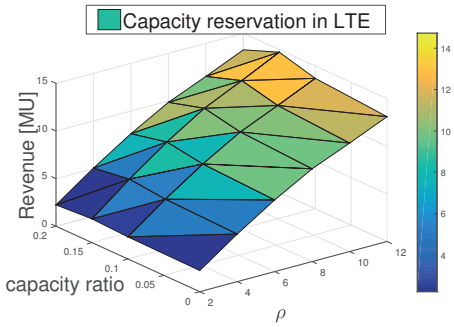


Figure E.6: Revenue - different ratio of reserved capacity (LTE only).

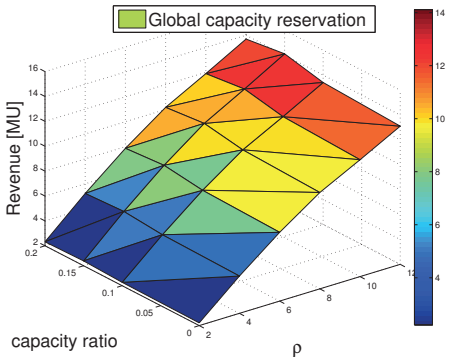


Figure E.7: Revenue - different ratio of reserved capacity (global reservation).

tion strategy are proposed, namely bandwidth reservation in LTE only, and bandwidth reservation in the whole HWN. The MDP formulation for the two variants is presented, and a model for the spatial distribution of the BSs, APs, and the users is provided. Our objective has been to give insight into how the bandwidth reservation for SS traffic should be made in order to ensure a maximum revenue while remaining compliant to net neutrality, and how the ratio of reserved bandwidth should be chosen. In terms of performance, we conclude that reserving resources in the whole HWN may be more beneficial as it guarantees better social benefit than the other variant, as well as lower blocking probability for IAS traffic, at the expense of

a marginal loss in the generated revenue. Moreover, the impact of the ratio of reserved capacity for SS traffic on the achieved revenue was investigated with both variants of the RAT selection policy.

As a final remark, using MDP in this work, we have managed to formulate the RAT selection problem. However, we were not able to obtain closed-form expression for the solution, i.e. expressing the revenue as an explicit function of the adopted net neutrality approach and the involved parameters. To address this limitation, we have resorted to using mathematical tool to numerically solve the MDP problem and get the results. The numerical results presented in the paper were obtained through implementing the mathematical model in MATLAB. By varying the inputs along different angels, mainly traffic density (either due to traffic rate changes or session service time changes) and the ratio of reserved capacity, we have tried to give an overall picture. For the use of the results in this paper, an ISP, given its traffic condition, could do similar numerical investigation (e.g. as for Fig. E.6) to find out how much capacity it could reserve for SS traffic to maximize the revenue.

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# References


[1] Altman E, Hanuwa MK, Sundaresan R. Nonneutral network and the role of bargaining power in side payments. *NET-COOP 2010-4th Workshop on Network Control and Optimization*, 2010 Nov 29.

[2] Andrews JG, Baccelli F, Ganti RK. A new tractable model for cellular coverage. *Communication, Control, and Computing (Allerton), 2010 48th Annual Allerton Conference on*. 2010 Sep 29 (pp. 1204-1211).

[3] BEREC. Berec guidelines on the implementation by national regulators of European net neutrality rules. *http://berec.europa.eu/eng/document_register/subject_matter/berec/regulatory_best_practices/guidelines/6160-berec-guidelines-on-the-implementation-by-national-regulators-of-european-net-neutrality-rules*. 2016 Aug.

[4] Chades I, Chapron G, Cros MJ, Garcia F, Sabbadin R. MDPtoolbox: a multi-platform toolbox to solve stochastic dynamic programming problems. Ecography 37:916-920.

[5] Chen H, Cheng CC, Yeh HH. Guard-channel-based incremental and dynamic optimization on call admission control for next-generation QoS-aware heterogeneous systems. *IEEE Transactions on Vehicular Technology*. 2008 Sep;57(5):3064-82.

[6] Fishburn PC, Odlyzko AM. Dynamic behavior of differential pricing and quality of service options for the Internet. *Decision Support Systems*. 2000 Mar 31;28(1):123-36.

[7] Falowo OE, Chan HA. Multiple-RAT selection for reducing call blocking/dropping probability in cooperative heterogeneous wireless networks. *EURASIP Journal on Wireless Communications and Networking*. 2012 Dec 1;2012(1):221.

[8] Hahn RW, Litan RE, Singer HJ. The economics of wireless net neutrality. *Journal of competition law and economics*. 2007 Aug 4;3(3):399-451.

[9] Hosein P, Choi W, Seok W. Disruptive network applications and their impact on network neutrality. *Advanced Communication Technology (ICACT), 2015 17th International Conference on*. 2015 Jul 1 (pp. 663-668). IEEE.

[10] Hou J, Yang J, Papavassiliou S. Integration of pricing with call admission control to meet QoS requirements in cellular networks. *IEEE Transactions on parallel and distributed systems*. 2002 Sep;13(9):898-910.

[11] Jo HS, Sang YJ, Xia P, Andrews JG. Heterogeneous cellular networks with flexible cell association: A comprehensive downlink SINR analysis. *IEEE Transactions on Wireless Communications*. 2012 Oct;11(10):3484-95.

[12] Khloussy E, Gelabert X, Jiang Y. Investigation on MDP-based radio access technology selection in heterogeneous wireless networks. *Computer Networks*. 2015 Nov 14;91:57-67.

[13] Khloussy E, Jiang Y. The impact of net neutrality on revenue and quality of service in wireless networks. *IEEE Consumer Communications & Networking Conference (CCNC)*. 2018 Jan 12-15.

[14] Kumar D, Altman E, Kelif JM. Globally optimal user-network association in an 802.11 WLAN & 3G UMTS hybrid cell. *Managing Traffic Performance in Converged Networks*. 2007 (pp. 1173-1187). Springer, Berlin, Heidelberg.

[15] Ma RT, Misra V. The public option: A nonregulatory alternative to network neutrality. *IEEE/ACM Transactions on Networking (TON)*. 2013 Dec 1;21(6):1866-79.

[16] Ma RT, Wang J, Chiu DM. Paid prioritization and its impact on net neutrality. *IEEE Journal on Selected Areas in Communications*. 2017 Feb;35(2):367-79.

[17] Martínez L, Álvarez San-Jaime O, Markendahl J. Net neutrality principles and its impact on quality of experience based service differentiation in mobile networks. *Regional Conference of the International Telecommunications Society (ITS)*. 2015 Oct 25;28.

[18] Pil Choi J, Kim BC. Net neutrality and investment incentives. *The RAND Journal of Economics*. 2010 Sep 1;41(3):446-71.

[19] Sørensen F. On the origin of specialised services. *https://eng.nkom.no/topical-issues/news/on-the-origin-of-specialised-services*. 2014 Jun 6.

[20] Stevens-Navarro E, Lin Y, Wong VW. An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks. *IEEE Transactions on Vehicular Technology*. 2008 Mar;57(2):1243-54.

[21] Tang J, Ma RT. Regulating monopolistic ISPs without neutrality. *Network Protocols (ICNP), 2014 IEEE 22nd International Conference on*. 2014 Oct 21 (pp. 374-384). IEEE.

[22] Wang Y, Pedersen KI, Mogensen PE, Sørensen TB. Carrier load balancing methods with bursty traffic for LTE-Advanced systems. *Personal, Indoor and Mobile Radio Communications, 2009 IEEE 20th International Symposium on*. 2009 Sep 13 (pp. 22-26). IEEE.

[23] Wu T. Wireless carterfone. *International Journal of Communication*. 2007;1:389-426.

[24] Yeh SP, Talwar S, Wu G, Himayat N, Johnsson K. Capacity and coverage enhancement in heterogeneous networks. *IEEE Wireless Communications*. 2011 Jun;18(3).