Fuzzy Neural Control for Economic-Driven Radio Resource Management in Beyond 3G Networks

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Abstract— **Joint Radio Resource Management (JRRM) is the envisaged process aimed at optimizing the radio resource usage of wireless systems to satisfy the requirements of both the network operators and the users in the context of future generation wireless networks. In particular, this paper proposes a two-layered JRRM framework to improve the efficiency of multi-radio and multi-operator cellular scenarios. On the one hand, the intra-operator JRRM relies on fuzzy-neural mechanisms with economic-driven reinforcement learning techniques to exploit radio resources within a single operator domain. Micro-economic concepts are included in the proposed approach, so that user profile differentiation can be considered when making a JRRM decision. On the other hand, inter-operator JRRM enables subscribers to obtain service through other operators, if the home operator network is blocked. Simulation results in a number of different scenarios show that inter-operator agreements established in a cooperative scenario benefit both the operators and users, which enables efficient load management and increased operator revenue.**

I. INTRODUCTION

In the last two decades, cellular communication systems have experienced significant evolution, leading to the deployment of a variety of Radio Access Technologies (RATs). Currently, second generation (2G) technologies (e.g. Global System for Mobile Communications – GSM) coexist with 2.5G and 3G standards (e.g. General Packet Radio Service – GPRS – and Universal Mobile Telecommunications System – UMTS). Besides that, several technologies are currently available. For example, EDGE (Enhanced Data rates for Global Evolution) is an evolution of GPRS with data rates up to 60 Kb/s per time slot together with improved spectrum efficiency; HSDPA (High Speed Downlink Packet Access) is an evolution of Wideband Code Division Multiple Access (WCDMA) to improve the bit rate to 10 Mb/s. At the same time, as 3G standards are introduced, other air interfaces have been developed and standardized. In particular, IEEE 802 produces an evolving family of standards, such as 802.11 local, 802.15 personal, 802.16 and 802.20 metropolitan and 802.22 regional area networks.

In an environment of multiple RATs, it raises the notion of being *always best connected*. This refers to being connected in the best possible way, combining for instance wide area coverage of cellular systems with WLAN (Wireless Local Area Network) high bandwidth hot spots. According to this concept, the different radio networks are components of a heterogeneous radio access network. In Beyond 3G vision, all systems will constitute possible access interfaces to a common IP based core network. In this scenario, an operator owns several components of the composite radio infrastructure, that is, it can own licenses for deploying and operating different RATs. This calls for new interworking mechanisms among radio access systems to exchange signalling and traffic load as they have already been considered e.g. between GSM/EDGE and WCDMA-based systems [2][3] and between WLAN and cellular networks [4]-[10]. Besides, IEEE 802.21 is developing a standard to enable handover and interoperability between heterogeneous access networks [11]. The IEEE P1900 standard project family [12] defines standards dealing with new technologies and techniques focusing on the autonomous and decentralised operation of next generation networks.

The introduction of the heterogeneous radio access network concept, together with the availability of multimode terminals capable of accessing different technologies, introduces a new dimension in the radio resource management problem. Instead of performing the management of radio resources independently for each RAT, some form of global management can be envisaged. In this heterogeneous scenario, Joint Radio Resource Management (JRRM) is the suitable process to manage dynamically and coordinate the allocation and deallocation of radio resources among different radio access systems. JRRM strategies may be activated within a single operator domain (i.e. intra-operator JRRM) to support a variety of objectives, such as avoiding disconnections due to the lack of coverage in the current RAT, blocking due to the overload in the current RAT, possible improvement of Quality of Service by changing the RAT, support of user's preferences in terms of RATs, support of the operator's preferences for RAT usage or load balancing among RATs. Besides, in a multi operator context, they could also be activated (i.e. inter-operator JRRM) to exploit complementary characteristics existing both spatially and temporally among traffic characteristics of different operators. In this sense, radio resource trading among operators coexisting in the same region may be considered a more efficient method for overall radio resource usage.

In standardization and literature, the intra-operator JRRM problem has been targeted from a technical perspective [2][3][13][14]. However, in a heterogeneous network context, making technical considerations about the dynamic behaviour of the network only provides a narrow approach to a problem that, due to the interrelationship among user preferences, operator business models, different investments in the different RATs, etc., should be naturally regarded from a broader perspective. In fact, it should be considered that both the users' and the network operators' satisfaction strongly depend not only on resource allocation and the quality the users perceive from a service, but also on pricing policies, such as the price the user pays for the service. As a result, in this paper, micro-economic concepts have been introduced together with radio-interface management decisions.

On the other hand, JRRM in a multi-operator context has been examined from various perspectives in the literature. In [15], resource brokerage functionalities in a Beyond 3G network, enabling cooperation among different network providers are introduced. In [16], the network operators are considered competitive actors in a scenario characterized by user-centric vision. Finally, in [17], entities that are introduced in a multi-RAT and multi-operator scenario are discussed.

To the best of the author's knowledge, no other work in the literature has proposed a solution for JRRM at both intra- and inter- operator levels. As a result, in this paper, we present a comprehensive treatment in a mobile, multiuser, multicell, multi-RAT and multi-operator scenario, where intra-operator and inter-operator JRRM are combined in a two-layered JRRM strategy to fully exploit the available radio resources and improve the network operators' revenue.

The first layer of the proposed approach is in charge of dealing with intra-operator JRRM. To address this objective, we make use of a solution based on a fuzzy neural network (FNN). Using intelligent techniques has been considered in the open literature as an effective method of dealing with problems associated with radio resource management, such as handoff decision (e.g. [18][19]), connection admission control (e.g. [20]), power control (e.g. [21]), channel allocation (e.g. [22][23]) and QoS provisioning (e.g. [24][25]). In the particular case of JRRM, the advantage of this choice is two-fold. On the one hand, we can exploit the capability of fuzzy logic controllers (FLC) to make effective decisions in situations where the available sources of information are qualitatively interpreted and heterogeneous in nature, as is the case for available inputs in mobile environments. Moreover, policies issued by the operators can fit properly into this FLC by means of the fuzzy rule base. On the other hand, by improving the fuzzy logic controller with learning capabilities of neural networks, we provide a framework capable of interacting with the surrounding environment and accordingly self-tuning and acting, which is the major pillar of the so called *cognitive networks* [26], which perfectly fits the variable conditions in mobile scenarios. This fuzzy neural network has already been presented in [27], where a technical study of multi-service provision in a multi-RAT and single-operator scenario has been introduced. In this paper, we further extend this approach by including micro-economic considerations in the JRRM decision making process. Thus, we present an economic-driven approach, and highlight advantages arising from this solution, specifically decision comprehensiveness and performance improvement. Furthermore, the single operator solution presented in [27] is extended to a multi operator solution: if an operator is unable to properly provide service to its users by means of the intra-operator JRRM, due to the current traffic conditions, the second layer of the proposed approach (inter-operator JRRM) is triggered to improve radio resource usage by trading resources with other operators. The inter-operator operation is managed by means of a third trusty party, referred to as *Metaoperator*, and is built upon by extending the intra-operator mechanisms using a multiple objective decision making process based on the combination of fuzzy set theory and the Analytic Hierarchy Process [30][31].

As a result, the innovative contributions of this paper can be summarized as follows:

1- Proposal of a framework to deal with JRRM in a multi-cell and multi-RAT scenario at both intra and inter-operator levels.
2- Proposal of a FNN including micro-economic concepts, as a solution for the intra-operator JRRM.
3- Proposal of trading/pricing strategies among operators, as a solution for the inter-operator JRRM.

The rest of the paper is organized as follows. In section 2, we present the two-layered architecture proposed in this paper for JRRM. Section 3 and section 4 describe the two layers with details. Section 5 is devoted to the presentation of simulation scenarios where the proposed approach has been evaluated. Section 6 describes representative simulation results. Finally, section 7 concludes summarising the main results of the work.

II. System Architecture

The JRRM scheme proposed in this paper will incorporate two main radio resource management functionalities:

- RAT and cell selection (i.e. the functionality that decides the RAT and cell the mobile has to be attached to).
- Bit rate allocation (i.e. the functionality that decides the most suitable bit rate or bandwidth for each accepted user in the selected RAT).

The JRRM algorithm is activated every time a new user asks for admission in the system and periodically during the user session. It assures the dynamic allocation and de-allocation of radio resources in the scenario and selection of the most suitable RAT.

Our proposal to make such a decision consists of a two-layered solution.

A. Layer 1: Intra-operator JRRM

The solution proposed for intra-operator JRRM is based on a fuzzy neural network (FNN), which considers as decision making inputs the information coming from the different RATs belonging to a certain operator.

The reason for this choice is that the variety of JRRM inputs belonging to the different RATs will provide, from a technical perspective, very dissimilar and heterogeneous information. Then, the initial driving inputs for RAT selection, such as the power level of the received signals and the cell loads, have to be properly considered in a comprehensive RAT selection decision making process but are not directly comparable because related to different RATs. Other technical aspects associated with the mobile user, such as mobile speed or battery life, may favour a particular RAT (for example WLAN would be an inappropriate choice for high speed users) in an imprecise manner. On the other hand, besides the technical aspects of the decision making process, economic and subjective inputs must be considered. Specifically, both the users' and the operator's preferences in terms of which is the appropriate RAT to serve a given traffic, beyond purely network performance issues, obey subjective imprecise mechanisms. Users' preferences may depend on a trade-off QoS versus cost. A user may prefer connecting to a less expensive RAT at the expense of the perceived QoS. In turn, the operator's preferences may be driven by the return on a certain investment in the infrastructure of a certain RAT.

In recent years, fuzzy logic methodology has been proven to make suitable decisions from imprecise and dissimilar information [33]. Furthermore, it allows for encompassing in the decision making process the no specificity inherent in human formulation of preferences, which is useful in this problem to balance the so many heterogeneous inputs before making the final RAT selection decision. Consequently, a JRRM scheme based on a FLC is considered in this study. The key concept in our approach is that fuzzy logic transforms heterogeneous inputs of a JRRM scheme into homogeneous membership values. These membership values are then processed by means of the so-called inference engine, where reasonably defined rules are capable of simplifying the large state space of solutions existing in such a complex JRRM problem. However, we have to keep in mind that in certain applications one of the main weakness of a decision making process based on a FLC is its high dependability on the particular membership functions and on their particular shapes, which can strongly affect the performance. Therefore, the use of neural networks can be considered [28] to properly tune the membership functions selected for the FLC, thus developing a hybrid solution incorporating both fuzzy logic and neural networks. In particular, we propose the use of a reinforcement learning algorithm to tune the FLC parameters defining the membership functions' shapes, with the aim of maintaining at a certain desired rate a Key Performance Indicator, which reflects the user satisfaction under both technical and economic perspectives. Then, the resulting framework is able to make decisions in an environment characterized by high heterogeneity in the decision making inputs, and at the same time introducing techno-economic based learning mechanisms. The JRRM decisions auto-adapt themselves to the changing traffic, mobility, propagation conditions and user profiles to satisfy user requirements. The appropriateness of this choice has already been demonstrated from a purely technical perspective in [27], where the proposed approach was compared in terms of performance to four alternative JRRM strategies, which have been described in both the literature and standardization [2][3][13]. Also, other authors have utilized the fuzzy neural methodology to solve problems related to radio resource management in heterogeneous networks [29].

With respect to system architecture, a high level allocation of the intra-operator JRRM functions in a heterogeneous cognitive network is shown in Figure 1. In particular, it is assumed in this paper that the operator service area is sub-divided into domains, each of them including a sub-set of cells belonging to different RATs. Each domain is managed by a FNN, which is in charge of executing the Fuzzy Neural JRRM algorithm for the set of cells under its domain. Note that the architectural model in Figure 1 could be implemented in many different ways, ranging from residing the Fuzzy Neural JRRM functionalities into existing network nodes, e.g. a Radio Network Controller, Base Station Controller, Access Point Controller, etc., to allocating them to new network nodes, e.g. in the form of external servers. As a result, the proposed system architecture could be mapped on the envisaged approach in 3GPP standardization body [2][3].

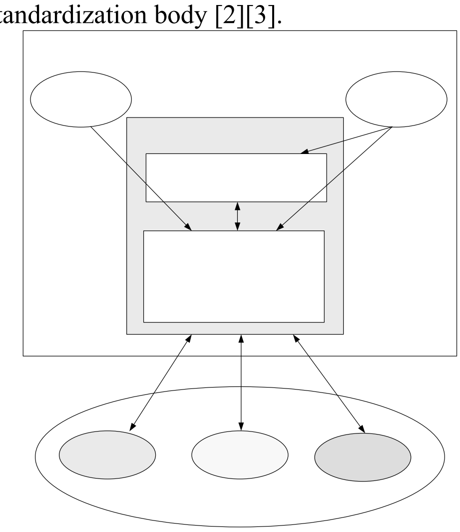

Figure 1: Proposed system architecture for the intra-operator JRRM execution based on fuzzy neural methodologies.

B. Layer 2: Inter-operator JRRM

To further improve radio resource usage achieved by means of the intra-operator JRRM, we propose to exploit the potential complementary characteristics of traffic distribution experienced by *N* operators, through radio resource trading among them. In particular, the envisaged technical solution assumes the previous establishment of inter-operator agreements maintained and guaranteed by a Metaoperator [32] (see Figure 2), to which each network operator can transfer its rights in case the intra-operator JRRM cannot satisfy user satisfaction constraints. In this way, the potentially dissatisfied user is awarded access to the service through another network operator, selected as a result of a decision making process performed by the Metaoperator, who acts as a third trusty party.

It is worth mentioning that this proposal is based on the idea that both operators participating in the trading process benefit from the establishment of inter-operator agreements. In particular, the operator "renting" radio resources takes advantage of this exchange in the short term, in terms of revenue from the service provision for the user. On the other hand, the operator "borrowing" radio resources benefits over the long term since the user, instead of being blocked, is provided with service in a transparent manner. Consequently, the user is not motivated to churn.

In this paper, we will refer to the operator who was contracted by the user, as the *H-operator* (i.e. Home operator), and to the operator who actually provides service to the user, as the *S-operator* (i.e. Serving operator). From Figure 2 it can be noticed that the *i*-th network operator is characterized by its own intra-operator JRRM entity, which makes decisions regarding the RAT and the bandwidth, within its own network domain by means of the fuzzy neural framework.

When the *i*-th intra-operator JRRM makes a decision leading to blocking (i.e. a user is blocked if at session start a sufficient amount of bandwidth cannot be allocated for it, so that the session is not initiated) or dropping (i.e. a user is dropped if during the user session, the user handing over to another cell and/or RAT cannot be provided with a sufficient amount of bandwidth in order to continue the session already initiated), the *i*-th network operator sends the Metaoperator a request of admission for the potentially blocked/dropped user in another operator's network, informing about the contracted QoS. The trading agent asks the rest of *N*-1 operators, who are willing to accept the user, to trigger their JRRM entity and return the information corresponding to the potential allocation of the user. According to the information collected from the *N*-1 potential serving operators, a decision process is triggered at the Metaoperator and the most suitable S-operator is selected. As shown in Figure 2, the Metaoperator consists of two building blocks, namely pricing block and trading agent, which will be described in section 4. With respect to implementation feasibility, it is worth noting that inter-operator operation follows similar mechanisms as those already available in case of International Mobile Roaming. Additionally, another option for radio resource trading would be that the H-operator selects a S-operator among N-1 available, without the Metaoperator acting as a third trusty party.

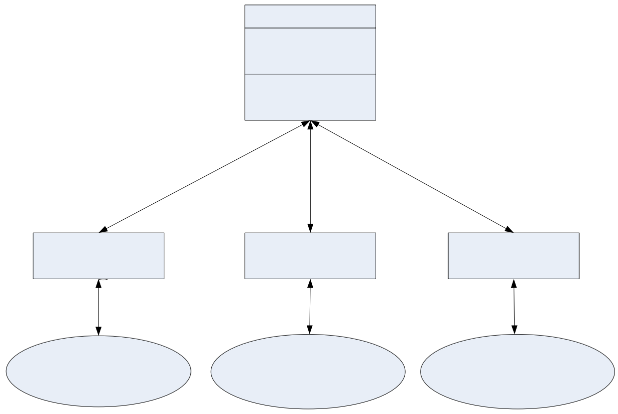

Figure 2: Proposed system architecture for inter-operator JRRM execution in a multi-operator scenario.

III. Intra-Operator JRRM

The intra-operator approach presented in this paper takes the FNN presented in [28] and adapts it to issues specific to JRRM. The FNN here introduced consists of reinforcement learning and a FLC implementing the fuzzifier, the inference engine and the defuzzifier.

The FNN works in two modes. The first one is the "down-up" process, through which the FLC, based on the selected input linguistic variables, generates the corresponding output linguistic variables, according to which JRRM decision is made. The second working manner is the "up-down" process, during which the reinforcement signal is propagated from the top to the bottom of the FNN structure to adjust the FNN parameters, as will be described in the second part of this section.

In the following, we first describe the FLC and the reinforcement learning algorithm used to tune the FLC parameters. Afterwards, we introduce the micro-economic concepts that will be used to select an adequate reinforcement signal to define the user satisfaction from both technical and economic perspectives. Finally, we pay attention to the practical feasibility of the proposed FNN. Without loss of generality, we will describe a FNN in a scenario characterized by three different RATs.

A. Fuzzy Logic Controller

Inputs of the FNN are a set of linguistic variables, which correspond to different measurements. Selection of these linguistic variables has to take into account the most relevant parameters that influence RAT selection and bandwidth allocation.

As a result, we classify them among three groups of inputs:

- Coverage indicators, in order to make RAT/cell selection and bit rate allocation coherently with the cell coverage in the scenario.
- Cell load indicators, in order to avoid situations in which the cell load reaches high values, thus degrading the performance.

- Context aware indicators relative to the mobile. Some examples may be the mobile speed or the battery life.

On the other hand, the outputs of the FNN are subdivided into two groups, and they are the driving indicators that perform cell/RAT selection and bit rate allocation:

- To perform cell/RAT selection, each RAT is characterized by an indicator referred to as Fuzzy Selected Decision (FSD) value, which takes values in the range [0,1] and reflects the appropriateness of selecting a RAT before others.
- To perform bit rate allocation, an output value, indicated as BW, is associated with each RAT giving an indication for the amount of bandwidth which should be assigned to the user.

The FNN can be graphically represented by the 5-layered structure described in Figure 3. Nodes in layer 1 are input linguistic nodes and nodes in layer 5 are output linguistic nodes. The output linguistic nodes are in charge of pumping decision signals out of the network during the "down-up" process and feeding the reinforcement signal r(t) into the network during the "up-down" process. The remaining layers are referred to as hidden layers and they implement the FLC. The nodes in layer 2 and layer 4 are term nodes, which act as membership functions of the input and output linguistic variables, respectively. The implementation of the fuzzification/defuzzification functions is depicted in Figure 3. The nodes in layer 3 are rule nodes and they implement the inference engine; each layer 3 node represents a fuzzy rule and all the nodes form the fuzzy rule base of the FLC. The input and output linguistic nodes and their corresponding term nodes are fully connected between layer 1 and layer 2 and between layer 4 and layer 5, respectively. In turn, the links between layer 2 and layer 3 and between layer 3 and layer 4 operate as inference engine: the links between layer 2 and layer 3 define preconditions of the rule nodes, whereas the links between layer 3 and layer 4 define the consequences.

Each layer k consists of N_k nodes (k=1,….,5). The i-th node at layer k is characterized by p inputs, $u_1^k,...,u_p^k$, coming from layer k-1 nodes, which are processed by the activation function f_i^k. The output of the i-th node of the k-th layer will be indicated as o_i^k and will be given by

$$o_i^k = f_i^k\left(u_1^k,...,u_p^k\right) \tag{1}$$

where $i = 1,..., N_k$.

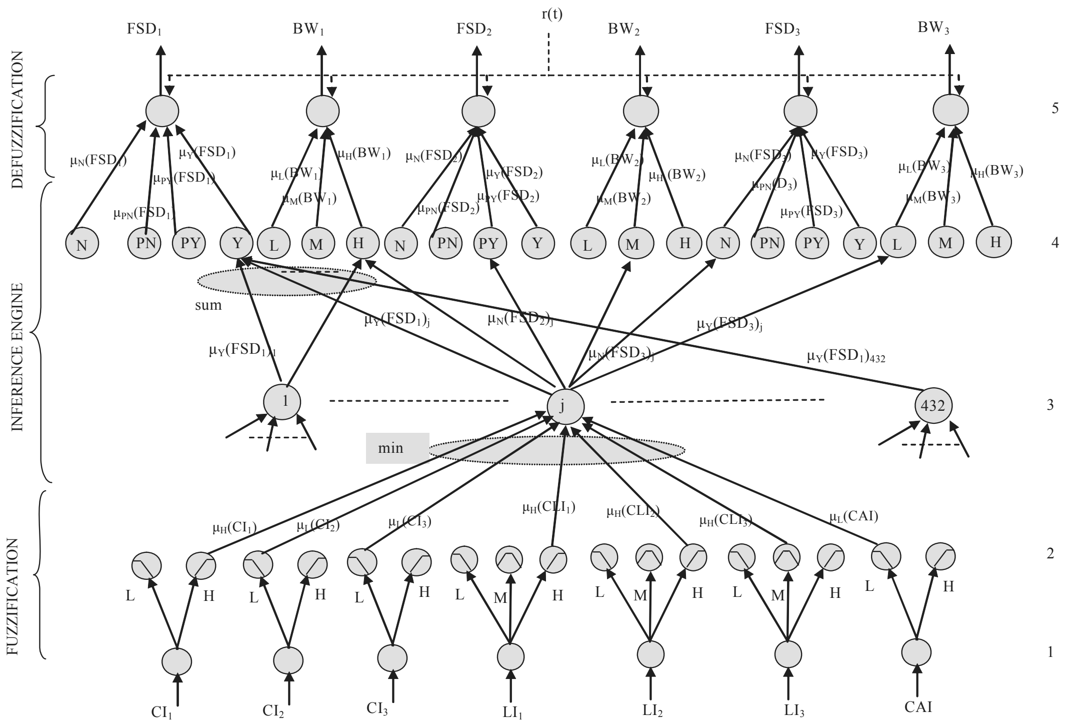

Figure 3: Layered Fuzzy Neural scheme

Layer 1

The first layer nodes are input nodes, so that they just feed the input data without change into the network. We consider 7 input linguistic variables (i.e. N_1=7):
- Coverage Indicator (CI) for each of the considered RATs: CI_j, j = 1, 2, 3.
- Cell Load Indicator for each of the considered RATs: LI_j, j = 1, 2, 3.
- Context Aware Indicator (CAI) with respect to the user.

Layer 2

The second layer nodes execute the fuzzification operation. They calculate the degree of membership for the input received by the input node to the particular fuzzy set associated with the second layer node, which is defined by a membership function. In case of Gaussian membership functions, for the i-th layer 2 node:

$$f_i^2\left(u_i^2\right)=\exp\left(-\left(u_i^2-m_i^2\right)^2 \Big/ \left(\sigma_i^2\right)^2\right) \qquad (2)$$

where m_i^2 and σ_i^2 are the mean and variance of the i-th Gaussian membership function at layer 2, u_i^2 is one of the seven input linguistic variables and $i=1,\ldots,N_2$.
The term sets defined for each input linguistic variable are:
- $T(CI_j)$ = T{Low, High}
- $T(LI_j)$ = T{Low, Medium, High}
- T(CAI) = T{Low, High}

Where j = 1, 2, 3, so that, layer 2 consists of N_2=17 nodes.
Notice that, in terms of the coverage indicator, the selected fuzzy sets take two values, either Low or High. In turn, the load indicator is represented by three fuzzy sets (Low, Medium or High), which suggests that a higher level of granularity is required for this parameter since it has a stronger impact over resource allocation. Finally, the context aware indicator is also considered with two fuzzy sets, either Low or High, since it is used in the RAT selection only as an indication that some RATs may not be appropriate for certain users (e.g. WLAN would be an inappropriate choice for high speed users).

Layer 3

The third layer nodes calculate the degree of membership of the precondition of the fuzzy logic rule corresponding to the specific node by means of the AND operator, so that the i-th rule node takes the minimum among the p received inputs from layer 2:

$$f_i^3\left(u_1^3,u_2^3,\ldots,u_p^3\right)=\min\left(u_1^3,u_2^3,\ldots,u_p^3\right) \qquad (3)$$

where $i=1,\ldots,N_3$. Considering the dimension of the term sets defined in layer 2, N_3=432.

Layer 4

The fourth layer nodes sum the degree of membership of the layer 3 nodes, with the same i-th layer four node as a consequence, to identify the degree of membership for the consequent part of the rule. So,

$$f_i^4\left(u_1^4,u_2^4,\ldots,u_q^4\right)=\min\left(\sum_{j=1}^{q}u_j^4,1\right) \qquad (4)$$

where q is the number of layer 3 nodes with the i-th layer 4 node as a consequence, and $i=1,\ldots,N_4$.
At layer 5, there are two groups of nodes. The first one corresponds to the RAT selection procedure (i.e. FSD_j, j = 1, 2, 3), whereas the second corresponds to the bit rate allocation (i.e. BW_j, j = 1, 2, 3).
The term sets defined for each output linguistic variable are:
- $T(FSD_j)$ = T{Yes, Probably Yes, Probably Not, Not}
- $T(BW_j)$ = T{Low, Medium, High}

where j = 1, 2, 3, so that, layer 4 consists of N_4=21 nodes.

Layer 5

The fifth layer nodes finally perform the defuzzification function computing the output according to the center of area method:

$$f_i^5\left(u_1^5,u_2^5\ldots,u_r^5\right)=\frac{\sum_{j=1}^{r}m_j^5\sigma_j^5u_j^5}{\sum_{j=1}^{r}\sigma_j^5u_j^5} \qquad (5)$$

where m_j^5 and σ_j^5 are the mean and the variance of the j-th Gaussian function of the r layer 4 nodes that are connected to the i-th layer 5 node. That is, r is the number of inputs of the i-th layer 5 node, coming from layer 4 nodes. Besides, $i=1,\ldots,N_5$, where N_5=6.
Finally, the outputs of the network are the result of the defuzzification function:

$$FSD_i=\frac{\sum_{j\in T_i}m_j^5\sigma_j^5u_j^5}{\sum_{j\in T_i}\sigma_j^5u_j^5} \qquad i=1,2,3 \qquad (6)$$

where T_i, is the set of layer 4 nodes connected with the layer 5 nodes providing FSD_i, with i = 1, 2, 3. Similarly, in terms of the allocated bandwidth, it will be given at the output of layer 5 as follows:

$$BW_i=BW_{i,MAX}\frac{\sum_{j\in W_i}m_j^5\sigma_j^5u_j^5}{\sum_{j\in W_i}\sigma_j^5u_j^5} \qquad (7)$$

$BW_{i,,MAX}$ is the maximum bit rate that can be allocated in RAT_i. In turn, W_i is the set of layer 4 nodes connected with the layer 5 nodes that provide BW_i, with i=1, 2, 3.
Once the FNN has been defined by means of the five layers, the input/output linguistic variables and the corresponding term sets, it is necessary to set up the FNN structure by defining the fuzzy inference rules contained in the fuzzy rule base and the initial shape and position of the membership functions. This set up phase is performed off-line, and after, the reinforcement learning is in charge of adjusting the on-line parameters defining FNN structure. The off-line set up of FNNs is a rapidly developing research field and several methods exist in the open literature. They

can be intuitive and based on logical operations derived from the expert knowledge of the variables to define (e.g. intuition, inference methods [33]) or they can make use of more complex algorithms based on e.g. neural networks, genetic algorithms, pattern recognition, inductive reasoning, etc. [33]. The first group of procedures has been intensively adopted in literature [34]. For example, in the case of inference rules, many experts have found that they provide a convenient way to express their knowledge, since in our daily life, most of the information on which our decisions are based on is linguistic, rather than numeric in nature. On the other hand, the second group of mechanisms performs well, if training data are available off-line [28]. Nevertheless, for the JRRM application, it would be very difficult and expensive to obtain an off-line comprehensive training data file to establish the neural network because the JRRM decisions depend on many time-variant factors (e.g. traffic loads, signal strengths, etc.), which can hardly be captured in a training data file. In addition, methods using databases to formulate rules and membership functions may be computationally very expensive if the database is large. As a result, the choice of which method to use depends on the problem size and problem type.

Consequently, in case of JRRM, the authors consider that a suitable method of setting up off-line the network is to define both the membership functions and the fuzzy inference rules by means of intuition and the knowledge the network operator has of the problems associated with determining the FNN structure. For example, a coverage membership function is first reasonably defined considering measurements such as the sensitivity levels and the power received at the cell edge.

The offline definition of the membership functions will be introduced in section 5, together with the simulation scenario. With respect to the membership function shapes, a bell shaped function is selected since it is easy to derive, which is useful when reinforcement learning is activated. The fuzzy inference rules contained in the fuzzy rule base are described in ANNEX A together with the rationale based on which they have been defined.

B. Reinforcement Learning

The reinforcement learning procedure is executed in concert with each FLC execution to activate an error back-propagation learning algorithm that minimizes a quadratic error function, by means of the propagation of an error term from the top to the bottom of the 5-layered structure. The error propagation updates the means and standard deviations of the fuzzification and defuzzification bell-shaped membership functions. The quadratic error function for minimization is defined as:

$$E(t)=\frac{1}{2}\left(y^{*}-y(t)\right)^{2} \tag{8}$$

where y* denotes the target value of a certain Key Performance Indicator and the reinforcement signal is defined as r(t)=y*- y(t). Consequently, as a result of the reinforcement learning procedure, the algorithm adapts its parameters to minimise (8), which is equivalent to maintain the overall Key Performance Indicator value at the desired target rate.

During each fuzzy neural JRRM execution, the FLC computes the output linguistic variables FSD_i and BW_i for RATs i = 1, 2, 3, hence selecting a RAT and a bit rate to be allocated in this RAT. Consequently, the Key Performance Indicator at time *t* can be measured, thus generating the error term that is propagated through the multilayered system. The general learning rule for a parameter *w(t)* to update (e.g. a mean or standard deviation of the different membership functions) is:

$$w(t+1)=w(t)+\gamma\cdot\left(-\frac{\partial E(t)}{\partial w(t)}\right) \tag{9}$$

where γ is the learning rate.

In the fifth layer, taking into account (5) and (9), corrections of the mean m_i^5 and the standard deviation σ_i^5 of the membership function are given, respectively, by:

$$m_i^5(t+1)=m_i^5(t)+\gamma\left[y^{*}-y(t)\right]\frac{\sigma_i^5 u_i^5}{\sum_{j=1}^{p}\sigma_j^5 u_j^5} \tag{10}$$

$$\sigma_i^5(t+1)=\sigma_i^5(t)+\gamma\left[y^{*}-y(t)\right]\frac{m_i^5 u_i^5\left(\sum_{j=1}^{p}\sigma_j^5 u_j^5\right)-\left(\sum_{j=1}^{p}m_j^5\sigma_j^5 u_j^5\right)u_i^5}{\left(\sum_{j=1}^{p}\sigma_j^5 u_j^5\right)^2} \tag{11}$$

where *p* is the number of nodes at layer 4 connected to the *i*-th layer 5 node and $i=1,\ldots,N_5$.

In the third and fourth layers, there are no parameters to tune. On the other hand, to obtain corrections for the mean m_i^2 and standard deviation σ_i^2 in the second layer, the error term has to be propagated from the top to the bottom of the 5-layered structure, so that, by applying the delta learning rule, we obtain:

$$\delta_i^2=\frac{\partial E(t)}{\partial f_i^2}=\sum_n\frac{\partial E(t)}{\partial u_n^4}\sum_k\frac{\partial u_n^4}{\partial u_k^3}\frac{\partial u_k^3}{\partial f_i^2} \tag{12}$$

where $n=1,\ldots,N_4$, $k=1,\ldots,N_3$ and $i=1,\ldots,N_2$.

Then,

$$\frac{\partial E(t)}{\partial t}=\left(y^{*}-y(t)\right)\frac{m_n^5\sigma_n^5\left(\sum_{j=1}^{p}\sigma_j^5 u_j^5\right)-\left(\sum_{j=1}^{p}m_j^5\sigma_j^5 u_j^5\right)\sigma_n^5}{\left(\sum_{j=1}^{p}\sigma_j^5 u_j^5\right)^2} \tag{13}$$

$$\frac{\partial u_n^4}{\partial u_k^3}=\begin{cases}1\, if\ k-th\, layer\, 3\, node\, is\, connected\, to\, n-th\, layer\, 4\, node\\ 0\, otherwise\end{cases} \tag{14}$$

$$\frac{\partial u_k^3}{\partial f_i^2}=\begin{cases}1\ \ if\ the\, i-th\, node\, is\, the\, \min\, among\, the\, k\, layer\, 3\, inputs\\ 0\, otherwise\end{cases} \tag{15}$$

$$m_i^2(t+1)=m_i^2(t)+\gamma\delta_i^2\cdot e^{f_i^2}\,\frac{2\left(u_i^2-m_i^2\right)^2}{\left(\sigma_i^2\right)^2} \tag{16}$$

$$\sigma_i^2(t+1)=\sigma_i^2(t)+\gamma\delta_i^2\cdot e^{f_i^2}\,\frac{2\left(u_i^2-m_i^2\right)}{\left(\sigma_i^2\right)^3} \tag{17}$$

C. Economic-driven JRRM

The cellular wireless business must establish an appropriate balance between economics and radio resource usage, since pricing, resource deployment and allocation strategies determine user satisfaction and operator exploitation results. Users without adequate QoS are likely dissatisfied. However, user feelings also depend on the price paid for the service, since users offered very high QoS at a very high price may be dissatisfied, as well. Moreover, the satisfaction concept is different if it is measured from a user-centric or a network-centric perspective, although both strongly depend on the bandwidth allocation and pricing policies. As a result, in this paper, two metrics have been identified to quantify user and operator satisfaction.

- User-centric metric: User Acceptance

From the user perspective, the notion of user acceptance of a given service is thought to be an appropriate indicator of user satisfaction, since it includes a trade-off between the price paid and the perceived quality. Specifically, user acceptance can be defined as the probability that users are satisfied with the service obtained from the network, in accordance with their payment obligations. Therefore, user acceptance should be, on the one hand, an increasing function of the utility *u* that the user perceives from a given service, which is related mainly to QoS parameters like e.g. bandwidth, delay, etc., and on the other hand a decreasing function of the price *p* that the user pays for that service. Then, a suitable definition of the user acceptance is given by [35]:

$$A(u,p)=1-\exp\left(-Cu^{\mu}p^{-\varepsilon}\right) \tag{18}$$

where C, μ and ε are constants representing the different user sensitivity to utility and price.

The utility *u* is a function that in turn depends on the specific service characteristics and the elasticity of the applications. Inelastic applications (e.g. real time voice) are characterized by a step utility function depending on e.g. whether the allocated bandwidth B is above or below a given threshold. On the other hand, elastic applications (e.g. data applications) exhibit more flexible behaviours in the sense that the utility is a smoother function of the allocated bandwidth. Particularly, a suitable definition of the utility is given by:

$$u(B)=\frac{(B/K)^{\xi}}{1+(B/K)^{\xi}} \tag{19}$$

where $0.2\le K\le 4.2$ and $2\le\xi\le 20$ are tuneable parameters [35]. We will consider $K=2$, $\xi=2.2$ and $C=0.05$. Notice that, a value of user acceptance A means that during A% of the time, the user considers the QoS received as satisfying with respect to the price paid.

In order to consider that different users may exhibit a different sensitivity relative to the specific service, two user profiles are considered in this paper. The corresponding acceptance functions are plotted in Figure 4 (i.e. μ=2 and ε=1.5 for consumer users and μ=40 and ε=2.5 for business users) as a function of the allocated bandwidth. The consumer profile represents the population segment for which the price is more relevant than the allocated bandwidth. Therefore, its acceptance is high even for relatively low bandwidths and decreases rapidly for high bandwidths because they are unwilling to pay for them. On the contrary, the business profile represents the population segment for which the most important thing is the allocated bandwidth rather than the price. Consequently, their acceptance is low for low bandwidths and decreases slowly for high bandwidths.

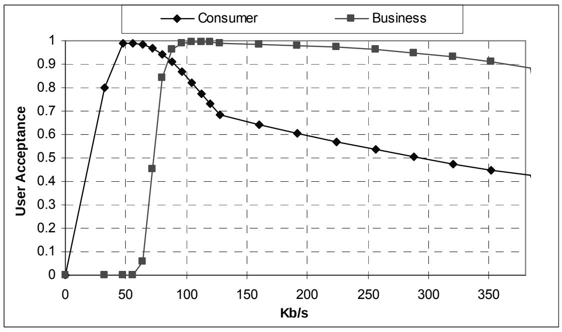

Figure 4: User acceptance of consumer and business user profiles.

- Network-centric metric: network revenue

From the network operator perspective, the revenue is considered as the network metric to define operator satisfaction. The operator revenue can be formulated as a function of the price that the users are paying and the user acceptance, in the sense that only users accepting the service will be in practice generating revenue. This leads to the following definition of revenue [35]:

$$R=\sum_{i=1}^{N_u}p_iA\left(u_i(B_i),p_i\right) \tag{20}$$

where N_u is the number of users, p_i is the price paid by the *i*-th user for the bandwidth B_i and $A(u_i,p_i)$ is the corresponding user acceptance.

Using the FNN presented in the first part of this section as a foundation, we can now select the Key Performance Indicator parameter to define the reinforcement signal by including micro-economic concepts introduced in this section. To this aim, the reinforcement signal selected for the FNN is defined based on the user acceptance function.

More specifically, the error signal to be minimized by the reinforcement learning procedure is defined based on (8), with $y(t)=A(t)$ and $y^*=A^*$, where *A(t)* is the current overall user acceptance averaged over the number of users in the scenario and A^* is its target value. In this manner, it is possible to obtain a JRRM framework that makes RAT selection and bandwidth allocation decisions, which are driven by the ultimate objective of maintaining the overall user acceptance value, at a certain desired rate.

C. Practical feasibility of the FNN

With respect to the numerical complexity of the proposed algorithm, it should be mentioned that the number of operations in the procedure is low enough to ensure operation in real time by means of software approaches. In that sense, the required operations should be considered at the following two levels:

1.- To achieve the fuzzy-based decision with respect to the RAT and bandwidth allocation, the type of performed operations are essentially comparisons according to the inference rules at layer 3 and sums of the different layer 3 outputs. Also, a small number of multiplications and divisions are required for layer 5. The implementation of membership functions for layer 2 can be performed by means of look-up tables, thus only requiring memory access. As a result, in our approach, the number of operations to achieve a decision per user is on the order of 5000, which turns into a requirement of about 100μs per user on a single state-of-the-art general-purpose processor (e.g. 2 GHz). Then, real time operation is feasible even with a high number of users, since the time constraints are typically fixed at the radio frame-time scale (e.g. in the order of tenths of milliseconds).

2.- With respect to the reinforcement learning algorithm, the effect is the modification of the parameters of the membership functions at layer 2 and layer 5 used by the fuzzy-based decision procedure according to the system evolution. Since this modification occurs at the long-term, it does not pose constraints for real-time operation.

IV INTER-OPERATOR JRRM

The inter-operator JRRM operation is centered on the notion that the establishment of inter-operator agreements is aimed at improving radio resource usage of all the operators involved in the trading process, as well as their revenue, all while maintaining the target value for overall user satisfaction. The establishment of these agreements can be based on different solutions [15]-[17]. In this paper, we envisage a Metaoperator in charge of dealing with the inter-operator operations. As depicted in Figure 2, the Metaoperator consists of two building blocks, namely the trading agent and the pricing block. The trading agent is in charge of performing the S-operator decision making process. On the other hand, the pricing block defines the different business model options to exchange users among operators. The two blocks are described with further details in the following.

A. Trading Agent

The trading agent implemented in the Metaoperator is the actor that provides the bridge among different operators by making transactions for offering and demanding radio resources. Different forms of market basis can be envisaged (e.g. auction mechanisms, game theory, etc.). In particular, in this paper, the trading agent is implemented by means of a multiple criteria decision maker based on the combination of fuzzy set theory and Analytic Hierarchy Process [30][31], which is a powerful technique that considers more than one criteria, each one weighted with respect to its relative importance to the problem, when making decisions. In fact, in a multi-RAT and multi-operator scenario, the most suitable RAT and bandwidth to allocate depends on many heterogeneous inputs (i.e. technical, subjective, economic, etc), so that a framework capable of taking into account multiple criteria to make a decision is considered an appropriate choice.

In a scenario where *N* operators (OPs) coexist, the multiple objective decision maker aims to select the most appropriate S-operator among the *N*-1 alternatives, taking into account a certain number of decision criteria. In particular, the following criteria are considered:

C_1 - FSD

C_2 - User acceptance, A

The FSD value is considered as an appropriate decision criterion since its computation captures the main technical indicators reflecting the specific network context. In turn, user acceptance of the service has been selected as the second considered criterion because it encompasses both utility and pricing considerations and serves as a reliable indicator of both user satisfaction and operator revenue. In particular, whenever a certain user is transferred to another operator, the two decision criteria with respect to the *i*-th alternative operator OP_i, are $C_{i1}=FSD_i$ and $C_{i2}=A_i$, respectively, which are the FSD associated with the RAT selected for the user by OP_i if it was chosen as S-operator and the corresponding user acceptance. According to the theory of decision based on fuzzy sets, the decisions are made in two steps:

- For each alternative OP_i, select its smallest value for any of the criteria. So, for OP_i, the decision value is $D_i = \min(FSD_i, A_i)$.
- Select the operator with the highest value D_i for the optimal decision.

So far, this procedure assumes that the two decision criteria are equally important. However, if the decision criteria had different degrees of importance, it would be possible to combine the decision process described above with the Analytic Hierarchy Process.

B. Pricing Block

The transaction between H-operator, Metaoperator and S-operator has to be transparent to the user involved in the trading process. Consequently, the price actually charged to the user should be independent of the operator which is actually providing the service, and equal to the price *p* charged by the H-operator under normal operation. Then, it is assumed that the total revenue generated by the user is shared between the two involved operators, so that the H-operator offering the potentially dropped/blocked user to the trading agent will maintain keep a revenue (1-α)p from this user, while the S-operator will receive αp, where 0≤α≤1.

Depending on the value selected for α, different business models can be envisaged. For example, if α=1, then the business model is based on the agreement that the S-operator will get all the revenue from the transaction. In this case, the S-operator exploits its available radio resources more efficiently, thus improving its revenue. On the other hand, the H-operator also benefits because it guarantees customer satisfaction in a setting where it would not be possible to support the required QoS. In turn, if α<1, the business model considers that the H-operator has to be guaranteed with a percentage of the revenue derived by its contracted users. From the S-operator perspective, a possible approach for fixing α consists of relating it to the actual normalized load (η≤1) in its network, e.g. α=η. If the S-operator's network is highly loaded, a higher percentage of revenue should be guaranteed to incentivize the transaction.

In particular, we will consider three different business models:

- *No Inter-Operator Agreements (NIOA)*

This business model considers the classical approach, in which the operators in the scenario do not cooperate in order to take advantage of the complementary characteristics of their temporal/spatial traffic distribution.

- *S-Operator Gets All Revenue (SOGAR)*

Inter-operator agreements have been established, with α=1, so that the S-operator receives 100% of the income derived from supporting the service requested by the user.

- *Shared Revenue Based on Load (SRBL)*

Inter-operator agreements have been established and $\alpha=\eta$, where $\eta \leq 1$ is the normalized load. Then, the H-operator receives a percentage of the income derived from its subscribers, which depends on the average load of the S-operator, so that the more loaded the S-operator, the higher the income that it has to guarantee.

Finally, in order to analyze and compare profitability between operators, a new indicator referred to hereafter as *profit* (P) is defined. In this paper, the operator profit is calculated by subtracting the expenses (E) faced by the operator from its revenue. In particular, the expenses that will be considered only include the cost of infrastructure deployment.

$$P = R - E \tag{21}$$

V Definition of Simulation Scenarios

This section presents the multi-RAT, multicell and multi-operator simulation scenarios where the proposed fuzzy neural JRRM algorithm has been evaluated.

Each operator manages a deployment area where different RATs coexist. Without loss of generality, a scenario including the essentials of three RATs, namely, UMTS, GERAN and WLAN is retained to illustrate the behaviour of the proposed JRRM algorithm. A tight coupling interworking is considered as it can be easily managed when jointly UMTS and GERAN (GPRS/EDGE Radio Access Network) are considered [2][3]. Also a WLAN could be tightly coupled following e.g. the Generic Access Network model [7].

Two different deployment scenarios are considered and they will be associated with different operators depending on the specific case study. Deployment #1 (see Figure 5 (a)) consists of 4 UMTS base stations, 2 GERAN base stations and one WLAN access point. Cell radii are 150m for WLAN, 650m for UMTS and 1km for GERAN. Deployment #2 consists of 2 UMTS base stations, 2 GERAN base stations and one WLAN access point (see Figure 5 (b)). Table 1 summarizes the deployment characteristics including the number of frequency carriers for each cell and the cost per frequency carrier computed over unit time [40].

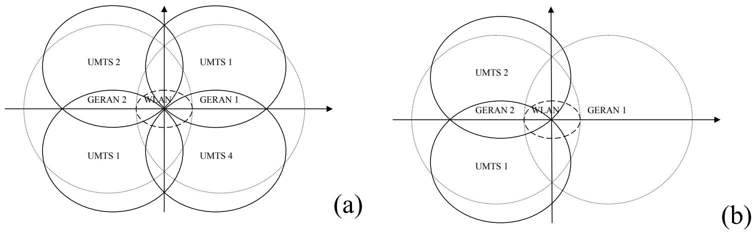

Figure 5: Simulation scenario: a) deployment #1 b) deployment #2.

Table 1: Infrastructure deployment

	Infrastructure deployment # 1		Infrastructure deployment # 2	
Base Station	# Freq carrier	Cost Freq carrier	# Freq carrier	Cost Freq carrier
WLAN	1	0.0112	1	0.0112
UMTS1	1	0.0865	0	0
UMTS2	1	0.0865	1	0.0865
UMTS3	1	0.0865	1	0.0865
UMTS4	1	0.0865	0	0
GERAN1	4	0.018*4	1	0.018
GERAN2	4	0.018*4	1	0.018
Economic units		=0.5		=0.22

To evaluate the proposed framework, we consider simulation scenarios where two operators, referred to as OP1 and OP2, coexist. Different simulation scenarios can be analyzed. The two operators are differentiated by: (1) Infrastructure deployment and (2) Market share.

Concerning infrastructure deployment, the investments of the two operators can be either the same (i.e. symmetric infrastructure deployment) or different (i.e. asymmetric infrastructure deployment). In the symmetric deployment, both OP1 and OP2 are characterized by infrastructure deployment #1 (notice that this corresponds to an investment of 0.5 economic units). In the asymmetric deployment, OP1 is characterized by the infrastructure deployment #1 (i.e. 0.5 economic units investment) whereas OP2 is characterised by the infrastructure deployment #2 (i.e. investment is reduced to 0.22 economic units). In terms of market share, the operators can be characterized by either the same (i.e. balanced market share) or a different (i.e. unbalanced market share) number of subscribers. Combining the different options, we can study four scenarios as summarized in Table 2.

Table 2: Simulation scenarios.

Scenario	Infrastructure Deployment	Market share
A)	Symmetric	Balanced
B)	Symmetric	Unbalanced
C)	Asymmetric	Balanced
D)	Asymmetric	Unbalanced

A mobility model with users moving according to a random walk model inside the coverage area is adopted with a randomly assigned mobile speed (MS) $\in[0,50\,Km/h]$ and a randomly chosen direction. The propagation model considered for UMTS and GERAN is given by L=128.1+37.6 log d (km), which assumes that the frequency band is similar for both systems (i.e. GERAN: 1710-1785 MHz; UMTS: 1900-2025 MHz) [36]. For WLAN, since the conditions are different (e.g. different frequency bands, access point located indoor, lowest height, etc.) the propagation losses inside the hotspot are modelled by L= 20 log d(m)+40 [37].

With respect to the traffic model, the beginning and the end of the user's activity periods are defined according to a Poisson scheme with an average of 6 calls per hour and user average call duration of 180 seconds. The maximum bit rate available to the users in a UMTS and GERAN cell is 384 Kb/s and 96 Kb/s, respectively. Results are presented for the uplink direction, and the considered possible bit rates for the different RATs are:

- For UMTS: 32 kb/s, 48 kb/s, 64 kb/s, 80 kb/s, 96 kb/s, 112 kb/s, 128 kb/s, 192 kb/s, 256 kb/s, 320 kb/s, 384 kb/s. A single carrier is considered. The maximum allowed uplink load factor is 0.75.
- For GERAN: 32 kb/s, 48 kb/s, 64 kb/s, 80 kb/s, 96 kb/s. It is assumed that four carriers are available in the GERAN cell for GPRS users, with coding scheme CS-4 [38], thus having a maximum bit rate in the cell of 640 kb/s.
- For WLAN, it is considered that the total available bandwidth (i.e. 11 Mb/s for IEEE 802.11b) is equally distributed among the WLAN users (i.e. the higher the number of users the lower the bandwidth per user will be). It is also assumed that more WLAN users are not accepted when the bandwidth per user is less or equal than 384 kb/s. A single access point is considered. It is worth mentioning that CFP (Contention free period) mechanisms enable different users to share a WLAN channel, simply by scheduling the transmissions on top of the Medium Access Control layer [39]. Consequently, no bandwidth allocation will be assumed at the output of FNN for WLAN. On the other hand, for UMTS and for GERAN, the allocated bit rate decided by the fuzzy neural algorithm will be given by rounding BW_{UMTS} or BW_{GERAN} to the closest bit rate.

The fuzzy neural algorithm is activated every 100 ms for the simulation purposes to re-allocate bandwidths and/or RATs to the currently admitted users as well as to include new users, so that the allocated resources can be changed dynamically.

With respect to the FNN described in section 3, we have considered:

- As coverage indicator, the signal strength (SS) with respect to three cells belonging to three different RATs: RAT_i , i=1, 2, 3. The signal strength is defined as the received power signal at the user terminal receiver.
- As cell load indicator, the resource availability (RA) with respect to three cells belonging to three different RATs: RAT_i, i= 1, 2, 3. The resource availability is a RAT-dependent concept and with respect to the different RATs is defined as follows:
- For UMTS, RA=1-η_{UL}, where η_{UL} is the uplink cell load factor.
- For GERAN, RA=640kb/s - ρ, where ρ is the current amount of kb/s already allocated in the corresponding cell.
- For WLAN, RA=Maximum number of users – number of users allocated in WLAN cell, where the maximum number of users is the number of users that could be allocated in WLAN considering a rate of 384 kb/s per user (i.e. 11 users).
- As a context aware indicator relative to the mobile, mobile speed (MS) is used to indicate the inappropriateness of selecting certain RATs according to the network layout.

The initial membership functions defined offline (before reinforcement learning operation) are depicted in Figure 6, whereas the fuzzy inference rules contained in the fuzzy rule base are defined in ANNEX A. The learning rates γ that have been considered are:

- γ to tune the membership functions at layer 5: 0.00001;
- γ to tune the RA membership function for UMTS at layer 2: 0.00001;
- γ to tune the RA membership function for GERAN at layer 2: 0.0001;
- γ to tune the RA membership function for WLAN at layer 2: 0.0001;
- γ to tune the SS membership functions for all RATs at layer 2: 0.001;
- γ to tune the MS membership functions at layer 2: 0.0001;

Simulation results have been obtained considering that the target user acceptance probability is retained to A*=0.8, which is considered a reasonable choice since it means that 80% of the time, the user is satisfied with the service perception according to the price paid for it.

It is worth noting that when a user is in outage, the bandwidth assigned to the user is computed as zero, so that the utility and consequently the corresponding user acceptance are zero as well. A user is considered in outage if:

(1) A user is in outage in UMTS whenever the required transmission power $P_{T,i}$ by the i-th user in the uplink is higher than the maximum available power at the terminal (e.g. $P_{T,i}$ >21 dBm), where $P_{T,i}$ is given by (22):

$$P_{T,i} = \frac{L_{p,i} P_N}{1-\eta_{UL}} \frac{1}{\frac{W}{\left(\frac{E_b}{N_0}\right)_i R_{b,i}} + 1} \qquad (22)$$

$L_{P,i}$ is the Path Loss and $R_{b,i}$ is the bit rate for the *i*-th user; E_b/N_0=3 dB is the target requirement, η_{UL} =0.75 is the uplink cell load factor, P_N=-106 dBm is the noise power and W=3.84 Mc/s is the WCDMA chip rate.

(2) A user is in outage in GERAN and WLAN when the received power does not satisfy the sensitivity criterion (e.g. for GERAN it is below -87 dBm and for WLAN it is below -94 dBm in case of multicell scenario).

The retained performance measurements are:

- *Blocking*: A user is blocked, if at session start, the JRRM algorithm assigns a bit rate of 0 Kb/s.

- *Dropping*: A user is dropped, if after a change in the serving cell, the JRRM assigns a bit rate of 0 Kb/s. Furthermore, a user is also dropped, if it is continuously in outage during more than a given timeout. A reference value of 3 s has been considered for simulation purposes.

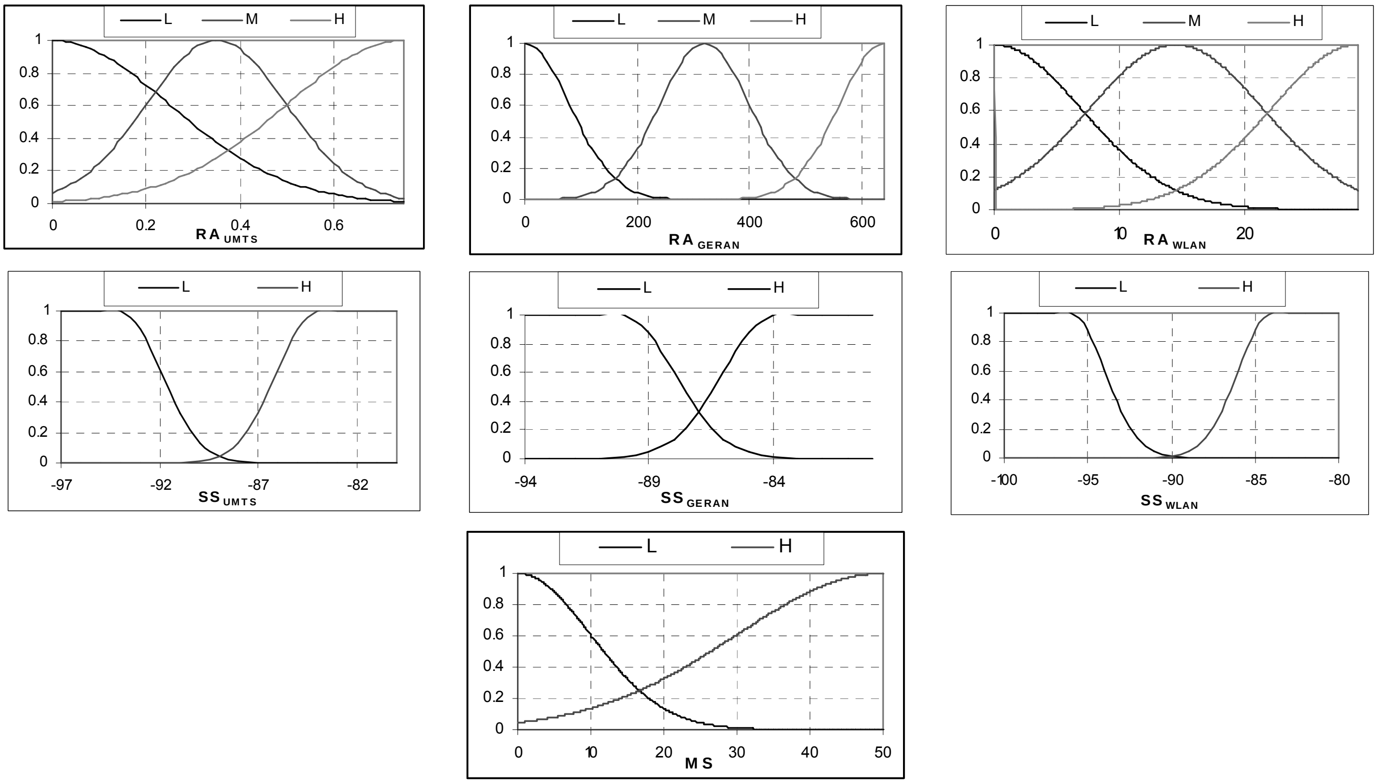

Figure 6: Initial membership functions

VI SIMULATION RESULTS AND DISCUSSION

In this section, we first present results examining FNN behaviour. In particular, we show that the proposed approach guarantees a user-centric vision and user profile differentiation by making JRRM decisions leading to the maintenance of an overall value of user acceptance at a desired target rate, regardless of user class (i.e. consumer or business). Additionally, we demonstrate that the proposed JRRM scheme is able to consider the user preference, in terms of utility and price, when selecting the RAT and the bandwidth. We will consider two different simulations, where a certain number of consumer and business users, respectively, are located in a scenario A where two operators coexist.

Then, we present simulation results to evaluate the inter-operator operation. To this end, the users located in the scenario are uniformly distributed between the two classes of traffic and they are subscribers of two operators OP1 and OP2. In this case, the market share between the two operators will depend on the particular scenario (see Table 2).

The inter-operator operation will be evaluated in terms of improved profit and radio resource usage. In particular, we will study, the impact of different business models, the impact of different market shares and the impact of different infrastructure investments.

Finally, to generalize the proposed approach, we will consider a more complex simulation scenario, where five operators characterized by different infrastructure deployments and market shares coexist.
The number of users in all presented figures represents the sum of users belonging to OP1 and OP2. Furthermore, a statistical analysis of performances in terms of minimum, maximum, average and standard deviation values of the simulations has been realized, but for the sake of simplicity has been shown only for one figure as it will be detailed in section 6.D.

A. Study of the behaviour of the FNN

As described in section 3, the reinforcement learning mechanism allows setting the average value of an objective and measurable Key Performance Indicator (i.e. the user acceptance) to a target value. The objective of the simulation described in this section is to demonstrate that the average user acceptance can be set to the target rate A*=0.8, for both consumer and business users, and the system is able to maintain this value during the whole simulation time, as depicted in Figure 7. Furthermore, during the simulation time, FNN has to cope with two sharp traffic variations. At simulation start, the whole system switches from a situation in which no mobile is located in the scenario, to another one with 200 users uniformly distributed between the two operators (i.e. each operator has 100 subscribers). Also, at simulation frame 300000, 100 additional users join the scenario, 50 of them are OP1 subscribers and the remaining 50 are OP2 subscribers. Finally, at simulation frame 700000, 100 users, uniformly distributed among the two operators, leave the scenario. Notice that, at simulation start, a transient period during which the fuzzy neural machine converges to the desired condition is necessary. Corresponding to the second and third traffic changes, the average value of user acceptance does not vary significantly. The reason is that the reinforcement learning's interactions with the surrounding environment are effective enough to activate the necessary modifications on the neural network parameters, so that the average value of user acceptance is maintained at the desired rate, despite changes in the environment.
It is worth noting that the same behaviour has been observed for both consumer and business users, which demonstrates that the reinforcement learning identifies the appropriate parameters to satisfy requirements for both classes of traffic, characterized by different user profiles.
Furthermore, Table 3 presents some illustrative performance figures of the proposed intra-operator implementations of the algorithm. A total of 200 consumer and business users, uniformly shared between two operators characterized by the same infrastructure deployment, has been considered. Simulation results show that the greater willingness of business users to pay for high bandwidths turns into an overall increase in the allocated bandwidth with respect to consumer users. In particular, the average bandwidth assigned to consumer users and business users is 74Kb/s and 168 Kb/s, respectively. Similarly, and due to the higher bit rates available in UMTS, the allocation of business users in UMTS is up to 6% higher than the allocation in GERAN, while the opposite occurs for consumer users. The higher amount of bandwidth allocated for business users translates into a higher operator revenue from this class of users, since they are willing to pay a higher price for the good perception of the service.

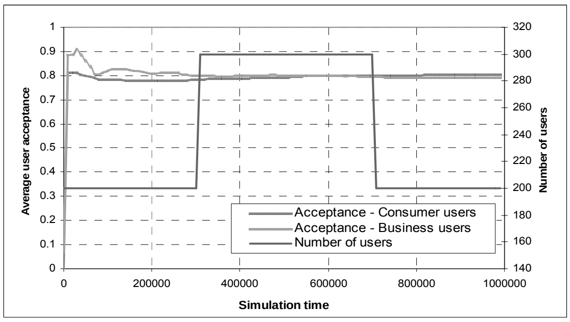

Figure 7: Time evolution of user acceptance.

Table 3: Consumer and Business Performance Values.

	Consumer users	*Business users*
% UMTS Selection	46.5	52.9
% GERAN Selection	53	47
%WLAN Selection	0.5	0.1
Revenue	1.57	4.74
Average assigned bandwidth	74 Kb/s	168 Kb/s

B. Improved revenue and radio resource usage through inter-operator agreements.

First, let us consider a scenario characterized by symmetric conditions for the two operators, in terms of both infrastructure deployment and market share (i.e. scenario A). In this sense, the operators are likely to be highly loaded in the same time and space conditions, thus reducing their complementary characteristics to a minimum. Then, in such a situation, cooperation among operators occurs mainly to face blockings or droppings associated with sporadic overload situations.
Figure 8 and Figure 9 compare performance in terms of blocking and dropping probabilities obtained in the considered simulation scenario for two cases: inter-operator agreements have been established among the two operators (i.e. in both SOGAR and SRBL cases) and inter-operator agreements have not been established. Simulation results show an important reduction in both blocking and dropping probabilities when inter-operator agreements have been established.
The benefits obtained in the case of inter-operator agreements can also be read in terms of increment of radio interface usage. In fact, if the maximum tolerable blocking

probability is set to e.g. P_B= 2%, the maximum number of admitted users increases to 36% (i.e. capacity gain ΔC from 250 to 340 users), as shown in Figure 8, with respect to the case that inter-operator agreements have not been established. This capacity gain can be translated into a profit gain ΔP of up to 34%, as shown in Figure 10.

Notice as well that, since the infrastructure deployment is symmetric and the market is equally shared between the two operators, the profit is almost equally distributed between the two operators. For the sake of simplicity, Figure 10 represents the aggregated profit for the two operators. In addition, the choice of the business model (i.e. SOGAR and SRBL) does not impact the profit distribution between the operators or their performance figures, since the percentage of exchanges between OP1 and OP2 is similar in both directions. As a result, only the results regarding the SOGAR model are shown in Figure 10.

As an additional illustrative result, we analyze the gain when three operators coexist in the same scenario. In this case the radio resource usage can be even improved. The increment of capacity, with respect to the case that inter-operator agreements have not been established, increases to 54% (i.e. capacity gain from 350 to 540 users), as shown in Figure 11 (where for the sake of simplicity only results related to the SOGAR business model have been shown), which can be translated into a revenue gain up to 60%, which occurs because more operators are taking part in the trading process, thus improving the trunking gain and the complementary characteristics of the traffic in the scenario.

On the other hand, if instead of considering a scenario characterized by a balanced market share, we consider a simulation scenario where the two operators are characterized by the same infrastructure deployment, but where the market is not equally shared between the two operators (i.e. scenario B), we can obtain further benefits in terms of radio resource usage and operator revenue. In particular, we consider that OP1 controls 2/3 of the market share, whereas the remaining part is managed by OP2 (i.e. with 300 users, 200 users are OP1 subscribers, so that OP1 is their H-operator, whereas the remaining 100 are OP2 subscribers, so that OP2 is their H-operator). In this case, the capacity gain for P_B=2% is increased to 54% (i.e. capacity gain from 220 to 340 users), which can be translated into a profit gain up to 43%, with respect to the case that inter-operator agreements have not been established when considering the aggregated profit of the two operators. Reasons for the additional percentage improvement in operator profit is that in a scenario where the two operators are, on average, equally loaded (i.e. balanced market share), the complementary characteristics to be exploited by the trading mechanisms among operators are reduced to a minimum. On the contrary, the unbalanced market share increases the complementary characteristics of traffic distribution to be exploited by the proposed algorithm.

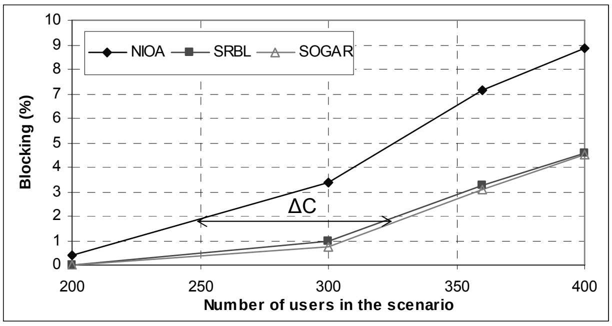

Figure 8: Blocking performance comparison – scenario A with two operators.

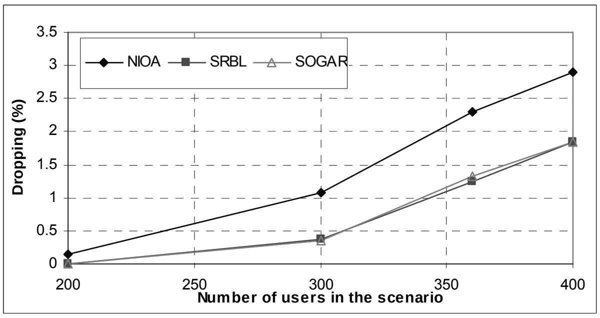

Figure 9: Dropping performance comparison – scenario A with two operators.

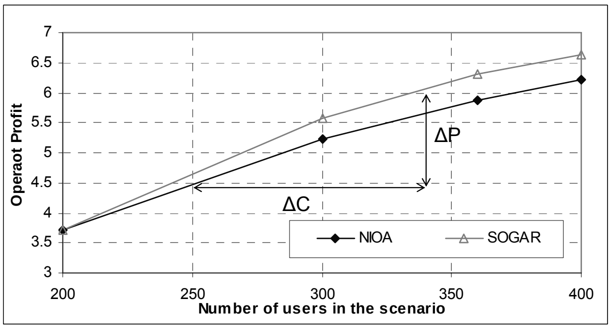

Figure 10: Profit comparison – scenario A with two operators.

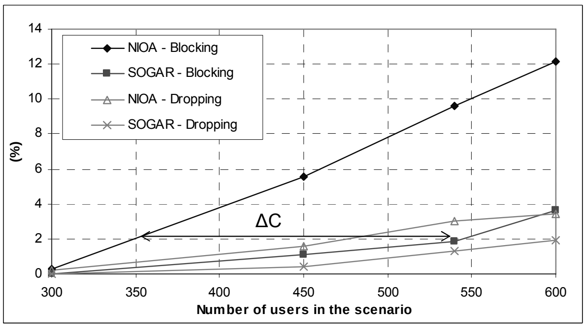

Figure 11: Blocking and Dropping performance comparison – scenario A with three operators.

C. Impact of different business models.

Let us consider a scenario where the two operators have the same infrastructure deployment, but unbalanced market share (i.e. scenario B). OP1 controls 2/3 of the market share, whereas the remaining part is managed by OP2. In this case, the probability of OP2 acting as S-operator for OP1's subscribers is much higher than the reverse, since OP1 has more subscribers than OP2 and the infrastructure deployments of the two operators are the same. In particular, with a low load of 200 users, simulation results, not shown here for the sake of brevity, reveal that 100% of the inter-operator exchanges are in the OP1→OP2 direction. However, when the number of users increases, some blockings or droppings occur with OP2. Therefore, some users need to be transferred in the OP2→OP1 direction. As an example, with 400 users in the scenario, 85% of exchanges are OP1→OP2 and the remaining 15% are OP2→OP1.

Other considerations can be made observing Figure 12, which shows the OP1 and OP2 profits, respectively, for different business models. First, it is worth mentioning that in this scenario, OP2 is the operator that benefits more economically by the establishment of agreements with OP1 (up to 36% and 25% of profit increment in case of SOGAR and SRBL business models, respectively, with respect to the case that inter-operator agreements have not been established, NIOA). In fact, the direction of exchanges is mostly in the OP2 direction. However, OP1 also takes advantage of the agreements, since some users that would have been blocked have instead been satisfactorily served by OP2. The exchange operation is transparent to the users, so that in the long term, they are not motivated to churn from OP1 to another operator. Additionally, the operator with a higher number of subscribers (i.e. OP1) profits from the business model SRBL (up to 11% of revenue increment with respect to the case that inter-operator agreements have not been established), which guarantees a percentage of revenue derived by its subscribed users to the H-operator. On the other hand, the operator characterized by the lowest portion of market share (i.e. OP2) takes more advantage in terms of profit by the business model SOGAR (up to 36% of improvement in revenue with respect to the case that inter-operator agreements have not been established), which guarantees 100% of the revenue derived by inter-operator exchanges to the S-operator.

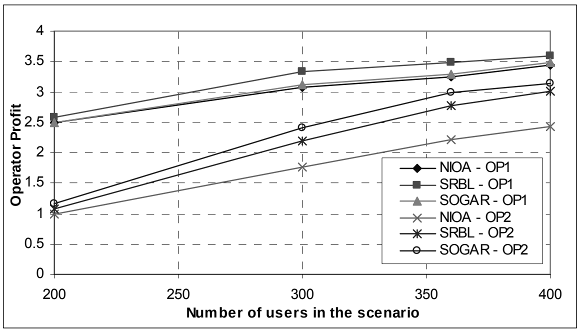

Figure 12: OP1 and OP2 profit for different business models – scenario B.

D. Impact of infrastructure investment

We now consider a scenario where the operators are characterized by different infrastructure deployments and the same market share (i.e. scenario C). In particular, OP1 invests in the infrastructure deployment depicted in Figure 5 (a), whereas the deployment of OP2 is depicted in Figure 5 (b).

Observing the profit simulation results depicted in Figure 13, two tendencies can be highlighted when low (i.e. 60 or 80 users) or a high (i.e. more than 80 users) traffic demand is considered. For business model NIOA (see Figure 13), when the traffic demand is low, the OP1 and OP2 profits are almost similar, despite the different infrastructure deployments. On the one hand, the revenue of OP1 is not high enough to compensate for the high infrastructure investment. On the other hand, due to the infrastructure deployment of OP2, which provides only GERAN coverage in an area of the scenario (see Figure 5 (b)), blockings/droppings are likely to occur also in cases of low traffic demand, thus reducing the OP2's revenue and consequently OP2's profit.

Additionally, when the revenue distribution is regulated by the business model SRBL, which guarantees a percentage of revenue to the H-operator (notice that the direction of exchanges in scenario C is in most of the cases OP2→OP1), the lower cost of infrastructure invested by OP2 and the percentage of revenue (1-α)p from subscribers served by OP1 results in OP2 achieving a higher profit than OP1 (e.g. with 60 users, the profit of OP2 is 59% higher than the profit of OP1).

In turn, in the case of the SOGAR business model, since the direction of exchanges is mostly OP2→OP1, the additional revenue αp from OP1 subscribers enables OP1 to achieve better profit performance than OP2.

On the other hand, with more than 80 users, independent of the business model considered, OP1 outperforms OP2 in terms of profit, since it is capable of providing service to more users than OP2, which in turn has to use the OP1 infrastructure to provide service to them. When the traffic demand is high, the higher operator revenue achieved by serving a higher number of users and by resource trading enables OP1 to compensate for the high infrastructure investment costs and generates higher profit than the case in which the operator invested less on infrastructure.

It is worth noting that the SOGAR model guarantees that the operator investing more on infrastructure benefits, to a larger extent, in terms of profit by the cooperative establishment of inter-operator agreements. In particular, with 120 users, the profit of OP1 is 1.3 and 2.6 times higher than the profit of OP2, with SRBL and SOGAR models, respectively. It is worth mentioning that the OP1 infrastructure costs are 2.3 times higher than OP2 costs (i.e. the cost of infrastructure of OP1 and OP2 is 0.5 and 0.22, respectively), which are on the same order of magnitude for the profit ratio in the case of SOGAR (i.e. 2.6).

In this sense, we conclude that SOGAR business model guarantees a fairer distribution of income among the cooperative operators than the SRBL business model, by guaranteeing a higher revenue to the operator that actually provides service to the users. In this model, the H-operator benefits in a more indirect manner, as long as its subscribers do not face service limitations and, consequently, do not feel motivated to churn.

To further study the impact of infrastructure investments, a sensitivity-type simulation has been considered, where two operators are characterized by the same market share, but by different infrastructure deployments. The deployments are represented by means of a y factor indicating the relation between the cost of one operator's infrastructure and the total cost of the scenario's infrastructure. Figure 14 represents the operator profit as a function of its infrastructure share (i.e. y) when 150 users, uniformly distributed between the two operators, are considered.

In the case of NIOA business model, the operator profit increases with the percentage of infrastructure share, but when the operator controls more than 50% of the infrastructure in the scenario, the operator profit does not increase anymore, since this infrastructure is sufficient to provide service to the operator subscribers. Consequently, profit in this case remains constant. On the other hand, in the case of SRBL business model, the operator profit is always higher than the NIOA case. The reason is that when the operator is characterized by less than 50% of the infrastructure in this scenario, it cannot provide service to its subscribers, and consequently, a portion is served by other operators that are characterized by a higher infrastructure share in the scenario. A percentage 1-α of the revenue from these users is maintained by the H-operator, so that in case of low infrastructure share, the SRBL model still results in operator profit increases. In turn, in the case of SOGAR model (α=1), the profit of the operator characterized by low infrastructure share y is similar to the NIOA case, since the operator primarily behaves as the H-operator.

When y=50%, the two operators are characterized by the same infrastructure deployments, so that, taking into account that the two operators are also characterized by the same market share, the business model does not affect the profit distribution in the scenario.

A different tendency in profit distribution can be observed when the operator controls a more significant percentage of infrastructure in the scenario, so that, for y>50% the operator is economically benefited by both SRBL and SOGAR business models, since it can provide service to the subscribers with a lower y. Notice that the SOGAR model provides a higher profit than SRBL in this case, since the direction of exchanges is mostly from the operator characterized by a lower y to that characterized by a higher y.

For the operator profit results shown in Figure 14, a representative statistical analysis of performances has been realized, as observed from the picture, representing the minimum and maximum values for each simulation result, which were obtained over 100 runs. Also, an evaluation in terms of average values and standard deviation has been realized. For example, for the results corresponding to y=50% i.e. operator profit equal to 1.2, the average value over 100 runs is 1.18, with a standard deviation of 0.06.

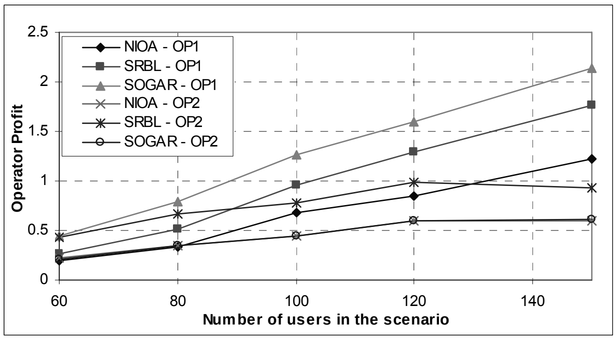

Figure 13: OP1 and OP2 Profits for different business models – scenario C.

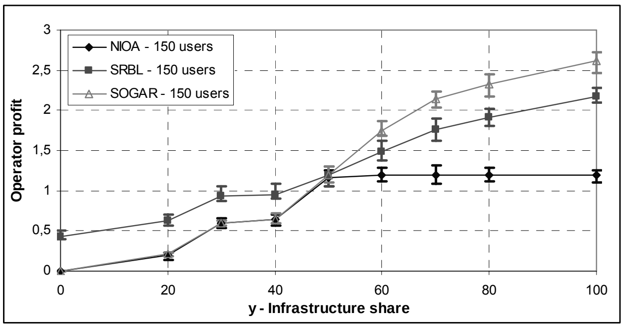

Figure 14: Operator profit versus infrastructure share y

E. Impact of different market shares

To study the impact of different market shares we consider two operators characterized by the same infrastructure deployment, which is represented in Figure 5 (a). In this scenario an increasing number of users is considered to be demanding service. Different market shares are taken into account by modifying the value of a variable x, which represents the relation between the number of users of one operator and the total number of users in the scenario.

For a situation of medium traffic demand (i.e. 300 users), Figure 15 shows the operator profit when considering different values of market share *x* for a given operator in the scenario.

From Figure 15, we first observe that the establishment of inter-operator agreements (i.e. SRBL or SOGAR) allows for improvements in the network operator's profit, with respect to the case that inter-operator agreements have not been established. In particular, two tendencies can be observed. When the operator is characterized by low market share, the operator acts in most of the cases as the S-operator. Consequently, it is economically benefited by SOGAR business model, since according to this model, it can maintain 100% of the revenue from users. In turn, under similar conditions, the SRBL business model provides a lower profit to the operator since the S-operator keeps a percentage $\alpha<1$ of the revenue coming from the users it serves.

On the other hand, when the operator is characterized by a high market share, the operator acts in most of the cases as the H-operator so that it is benefited by the SRBL business model. In turn, in case of the SOGAR business model, there is no economic benefit for the operator with respect to NIOA model, since in this case $\alpha=1$. However, the benefit of the operator is long-term, since its subscribers are not motivated to churn because they were transparently provided with service by another operator.

To sum up, Figure 16 summarizes the conclusion obtained in sections 6.D and 6.E. As the percentage of infrastructure deployment in the scenario increases with respect to the market share, the operator prefers the SOGAR business model since it can maintain 100% of revenue from the users because of the infrastructure deployed. In turn, as the percentage of market share increases with respect to the infrastructure deployment, the operator prefers the SRBL business model, since it can maintain a percentage $\alpha<1$ of the revenue from its subscribed users that it cannot provide with service, due to the reduced infrastructure deployment with respect to market share.

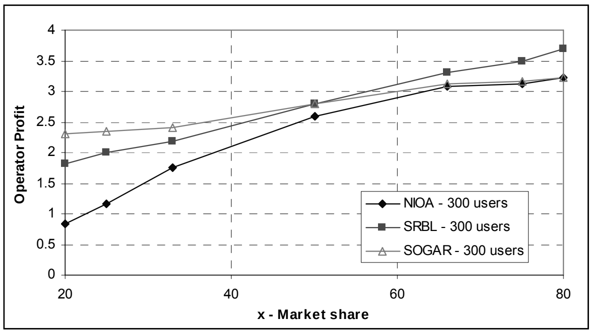

Figure 15: Operator profit versus market share between two operators

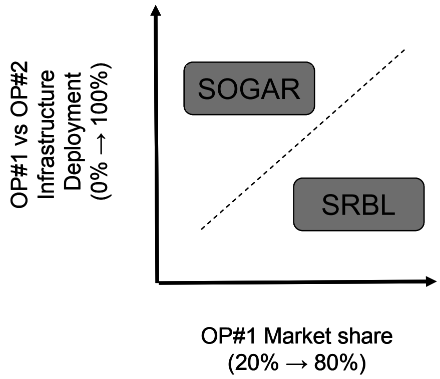

Figure 16: Conclusion on the impact of infrastructure deployment and of market share

F. Multi-operator scenario characterized by more than two operators

The objective of this section is to generalise the previous conclusions to a scenario with more operators. For that purpose, we assume a scenario characterized by five operators, whose infrastructure deployments and traffic conditions are summarised in Table 4. The chosen infrastructure deployments are deployments 1 and 2. We consider two traffic situations, the first one characterized by low traffic conditions and the second by high traffic conditions.

Table 4: Scenario characteristics

OPERATOR	INFRASTRUCTURE DEPLOYMENT	HIGH TRAFFIC CONDITIONS	LOW TRAFFIC CONDITIONS
1	1	150 USERS	50 USERS
2	1	30 USERS	10 USERS
3	2	150 USERS	50 USERS
4	2	150 USERS	50 USERS
5	2	30 USERS	10 USERS

Table 5 presents the blocking rate for the two traffic conditions with the considered business models. Thanks to the establishment of inter-operator agreements, the blocking rate in the scenario is reduced from 8.8% and 19.55%, in case of low and high traffic conditions, respectively, to 0% and 6.99%. This result shows that improved radio resource usage can be achieved by means of establishing inter-operator agreements, as depicted in subsection *B*, where the improved revenue and radio resource usage obtained through inter-operator agreements were studied in the context of scenarios characterized by two and three operators.

Table 6 and Table 7 summarize the results obtained in terms of operator profit in the case of five operators. In case of NIOA, under both low and high traffic conditions, the operator with the highest profit is OP1, since it is characterized by the highest investment in infrastructure and the highest market share. On the other hand, OP2, despite having invested the same in infrastructure as OP1, has a reduced number of subscribers, and consequently a lower profit. Notice that in case of low traffic conditions, it cannot recover from the inversion in infrastructure, which is reflected with a negative profit value. OP3 and OP4, which are characterized by the same infrastructure deployment and the same market share (scenario A), have the same profit. Notice that this profit is lower than OP1 profit, since OP1 has invested more in infrastructure and consequently can provide service to more users. Finally, OP5, as OP2, is characterized by a reduced market share, however in contrast to OP2, OP5 has invested in the reduced infrastructure deployment, consequently, his profit is higher than OP2's.

When considering the establishment of inter-operator agreements, the operator with highest benefit is OP2, which, due to the reduced market share, is characterized by the highest amount of capacity to "rent". That is, as explained in subsection *B*, the unbalanced market share characteristics of OP2 with respect to the other operators, increase the complementary characteristics of traffic distribution to be exploited by the proposed algorithm. Also, OP5 is characterized by a reduced market share. Consequently, it benefits from the establishment of inter-operator agreements, but at a lower percentage than OP2, due to the reduced infrastructure deployed with respect to OP2. Because OP2 mostly acts as the S-operator, it benefits from both SOGAR and SRBL, but at a higher percentage by SOGAR. In fact, as demonstrated in subsections *C, D* and *E*, where the impact of different business models, different infrastructure deployments and different market shares were studied, the operator characterized by a low market share and a high infrastructure deployment benefits from the SOGAR business model.

Also, OP1 is benefited by the establishment of inter-operator agreements, in both SOGAR and SRBL cases (23.8% and 20.4% of profit increment with respect to NIOA in case of high traffic conditions). The reason is that OP1, as OP2 and OP5, serves OP3 and OP4 users, which cannot be provided with service in their home networks due to their reduced infrastructure deployments. It is worth noting that, as already shown in subsection *D* where the impact of different infrastructure deployments was studied, the operator investing more in infrastructure (i.e. OP1) benefits more from the SOGAR business model relative to SRBL.

On the contrary, the operators investing less in infrastructure (i.e. OP3 and OP4) benefit from the SRBL business model, since they can keep a percentage of the revenue coming from their subscribers, despite having deployed a more reduced infrastructure than OP1 and OP2. It is worth noting that OP3 and OP4 do not benefit in the short term by SOGAR business model. However, they take advantage from the establishment of inter-operator agreements based on the SOGAR model in the long term, since the users are provided with service in a transparent manner, and therefore will not be motivated to churn. Notice that, OP3 and OP4, characterized by the same conditions in terms of market share and infrastructure, present very similar results in terms of profit (i.e. scenario A).

Finally, as explained in subsection *D* with respect to the impact of different infrastructure deployments, further considerations can be made comparing results obtained in case of low and high traffic conditions. In case of SRBL and in low traffic conditions, OP3 and OP4, despite their reduced infrastructure deployment, outperform OP1 in terms of profit. The reason is that OP1 revenue is not high enough to compensate for high investment in infrastructure deployment. In turn, in case of SOGAR, OP1 can keep the revenue coming from the OP3 and OP4 users because of the establishment of inter-operator agreements. As a result, having invested in infrastructure more than OP3 and OP4, it is economically benefited with respect to them, which results in SOGAR being a fairer business model than SRBL. On the other hand, when the traffic condition is high, OP1 is the operator that correctly estimates the necessary infrastructure to be deployed. Consequently, it outperforms OP3 and OP4 in terms of profit in both SRBL and SOGAR cases. Similar considerations can also be made for OP2 and OP5, which are characterized by the same market share, but by different infrastructure deployments. Under low traffic conditions, OP2 does not compensate for the investments on infrastructure, in both NIOA and SRBL cases, and consequently looses more than OP5, who made an investment that was more comparable to its market share. In turn, the SOGAR model allows OP2 to take advantage of its infrastructure, so that OP2 outperforms OP5 in terms of profit. Finally, under high traffic conditions, OP2 can compensate for the high infrastructure costs because of the revenue generated from other operators' users, which results in a profit higher than OP5.

Table 5: Improved Radio Resource Usage

BLOCKING RATE (%)	NIOA	SOGAR/SRBL
LOW TRAFFIC CONDITIONS	8.88	0
HIGH TRAFFIC CONDITIONS	19.55	6.99

Table 6: Improved operator profit – High traffic conditions

HIGH TRAFFIC CONDITIONS	OP1	OP2	OP3	OP4	OP5
NIOA	2.35	0.06	1	1	0.08
SOGAR	2.91	2.42	1	1	0.3
SRBL	2.83	1.7	1.45	1.45	0.2

Table 7: Improved operator profit – Low traffic conditions

LOW TRAFFIC CONDITIONS	OP1	OP2	OP3	OP4	OP5
NIOA	0.38	-0.3	0.4	0.4	-0.1
SOGAR	1.1	0.27	0.4	0.4	-0.08
SRBL	0.71	-0.21	0.85	0.85	-0.09

VII Conclusion and Future Works

This paper has presented a comprehensive framework to deal with JRRM at both the intra-operator and inter-operator levels. A two-layered approach to improve radio resource usage and operator revenue has been proposed.

First, an intra-operator JRRM based on fuzzy neural methodology has been presented. This approach allows dealing with the vagueness and dissimilarity typical of a heterogeneous Beyond 3G network and allows for the introduction of cognitive-based mechanisms to interact with the surrounding environment to maintain a certain degree of user satisfaction. Furthermore, the introduction of micro-economic concepts allows for the making of a more intelligent JRRM decision and also takes into account the particular user profile in the decision making process. Simulation results show that the user acceptance of both consumer and business users can be maintained at a desired value and the RAT selection and bit rate allocation for each user are made according to their particular profile. In particular, in terms of RAT assignment, simulation results show that the economic-driven JRRM assigns a consumer user to the GERAN RAT and a business user to a UMTS RAT with higher probability, whereas in terms of bit rate allocation, the average bandwidth assigned to business users is higher than that assigned to consumer users.

Second, the inter-operator JRRM has been described and evaluated in different scenarios where multiple operators coexist and each is characterized by certain infrastructure deployment and a certain market share. The profit has been introduced as a reliable indicator for the financial situation of the operator since it includes the revenue from the service provision to the users and the operator's investment in infrastructure. Three different business models have been evaluated based on the sharing of revenue generated by the users transferred from one operator to another.

Simulation results have shown that the establishment of inter-operator agreements is beneficial because of both network performance (i.e. blocking/dropping probability reduction and capacity gain) and operator revenue improvement. These benefits can be improved if the two operators are characterized by complementary traffic distribution, e.g. unbalanced market share, or if more than two operators take part in the trading process.

Furthermore, the business model denoted here as SOGAR, which guarantees 100% of revenue derived by a user to the operator that actually provides service for it (i.e. the S-operator), benefits the operator that correctly estimates the infrastructure deployment necessary to satisfy the service demand and properly invests. In this case, the H-operator takes advantage of the fact that its users are not motivated to churn because they have been provided with service in a transparent manner.

Finally, with respect to future works, a Fuzzy Neural decentralized JRRM can be studied. This is in line with Working Group IEEE P1900.4 standard project, which proposes a policy-based radio resource usage scheme, where decision making is shared between the network and the mobile terminals.

Appendix A

This Appendix contains the list of 432 inference rules (see Table 8) considered in the FNN of OPi when the three RATs developed by OPi are WLAN, UMTS and GERAN and the seven input linguistic variables are: the signal strength and the resource availability as coverage and load indicators, respectively, and the mobile speed.

The rationale behind these rules is if the signal strength (i.e. SS) received from one RAT is Low (i.e. L), then this RAT will not (i.e. N) be assigned. Otherwise, the amount of bandwidth to assign to the user depends on the available resources (i.e. RA) in that RAT. If RA is High (i.e. H), then the bandwidth to assign is High (i.e. H). If RA is Medium (i.e. M), then the bandwidth to assign is Medium (i.e. M). If RA is Low (i.e. L), then the bandwidth to assign is Low (i.e. L).

On the other hand, if the user receives a signal strength High from both a UMTS and a GERAN cell, (i.e. SS_{UMTS} is H and SS_{GERAN} is H) and if UMTS is characterized by a High resource availability (i.e. RA_{UMTS} is H), the user will be assigned with higher priority to UMTS. If the user is in the coverage area corresponding to the WLAN Hotspot (i.e. SS_{WLAN} is H), WLAN will always be preferred to both GERAN and UMTS due to the higher bandwidth attained at reduced costs.

Table 8: Fuzzy Rule base

IF							THEN					
SS_{UMTS}	SS_{GERAN}	SS_{WLAN}	RA_{UMTS}	RA_{GERAN}	RA_{WLAN}	MS	FSD_{UMTS}	FSD_{GERAN}	FSD_{WLAN}	BW_{UMTS}	BW_{GERAN}
L	L	L	L,M,H	L,M,H	L,M,H	L	N	N	N	L	N
L	L	H	L,M,H	L,M,H	H	L	N	N	Y	L	L
L	L	H	L,M,H	L,M,H	M	L	N	N	PY	L	L
L	L	H	L,M,H	L,M,H	L	L	N	N	PN	L	L
L	H	L	LM,H	H	L,M,H	L	N	Y	N	L	H
L	H	L	L,M,H	M	L,M,H	L	N	PY	N	L	M
L	H	L	L,M,H	L	L,M,H	L	N	PN	N	L	L
L	H	H	L,M,H	L,M,H	H	L	N	N	Y	L	L
L	H	H	L,M,H	H	M	L	N	Y	PY	L	H
L	H	H	L,M,H	M	M	L	N	PY	PY	L	M

L	H	H	L,M,H	L	M	L	N	PN	PY	L	L
L	H	H	L,M,H	H	L	L	N	Y	PN	L	H
L	H	H	L,M,H	M	L	L	N	PY	PN	L	M
L	H	H	L,M,H	L	L	L	N	PN	PN	L	L
H	L	H	L,M,H	L,M,H	H	L	N	N	Y	L	L
H	L	H	H	L,M,H	M	L	Y	N	PY	H	L
H	L	H	M	L,M,H	M	L	PY	N	PY	M	L
H	L	H	L	L,M,H	M	L	PN	N	PY	L	L
H	L	H	H	L,M,H	L	L	Y	N	PN	H	L
H	L	H	M	L,M,H	L	L	PY	N	PN	M	L
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H	L	L	H	L,M,H	L,M,H	L	Y	N	N	H	L
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H	H	L	H	L,M,H	L,M,H	L	Y	N	N	H	L
H	H	L	M	H	L,M,H	L	PY	Y	N	M	H
H	H	L	M	M	L,M,H	L	PY	PY	N	M	M
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H	H	L	L	H	L,M,H	L	PN	Y	N	L	H
H	H	L	L	M	L,M,H	L	PN	PY	N	L	M
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H	H	H	H	L,M,H	M	L	Y	N	PY	H	L
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H	H	H	L	H	L	L	PN	Y	PN	L	H
H	H	H	L	M	L	L	PN	PY	PN	L	M
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L	L	L,H	L,M,H	L,M,H	L,M,H	H	N	N	N	L	L
L	H	L,H	L,M,H	H	L,M,H	H	N	Y	N	L	H
L	H	L,H	L,M,H	M	L,M,H	H	N	PY	N	L	M
L	H	L,H	L,M,H	L	L,M,H	H	N	PN	N	L	L
H	L	L,H	H	L,M,H	L,M,H	H	Y	N	N	H	L
H	L	L,H	M	L,M,H	L,M,H	H	PY	N	N	M	L
H	L	L,H	L	L,M,H	L,M,H	H	PN	N	N	L	L
H	H	L,H	H	L,M,H	L,M,H	H	Y	N	N	H	L
H	H	L,H	M	H	L,M,H	H	PY	Y	N	M	H
H	H	L,H	M	M	L,M,H	H	PY	PY	N	M	M
H	H	L,H	L	H	L,M,H	H	PN	Y	N	L	H
H	H	L,H	L	M	L,M,H	H	PN	PY	N	L	M
H	H	L.H	M	L	L,M,H	H	PY	PN	N	M	L
H	H	L,H	L	L	L,M,H	H	PN	PN	N	L	L

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