A Novel Approach for Joint Radio Resource Management Based on Fuzzy Neural Methodology

Lorenza Giupponi, *Member, IEEE*, Ramon Agustí, *Member, IEEE*, Jordi Pérez-Romero, *Member, IEEE*, and Oriol Sallent Roig

***Abstract*—In this paper, an innovative mechanism to perform joint radio resource management (JRRM) in the context of heterogeneous radio access networks is introduced. In particular, a fuzzy neural algorithm that is able to ensure certain quality-of-service (QoS) constraints in a multicell scenario deployment with three different radio access technologies (RATs), namely, the wireless local area network (WLAN), the universal mobile telecommunication system (UMTS), and the global system for mobile communications (GSM)/Enhanced Data rates for GSM Evolution (EDGE) radio access network (GERAN), is discussed. The proposed fuzzy neural JRRM algorithm is able to jointly manage the common available radio resources operating in two steps. The first step selects a suitable combination of cells built around the three available RATs, while the second step chooses the most appropriate RAT to which a user should be attached. A proper granted bit rate is also selected for each user in the second step. Different implementations are presented and compared, showing that the envisaged fuzzy neural methodology framework, which is able to cope with the complexities and uncertainties of heterogeneous scenarios, could be a promising choice. Furthermore, simulation results show that the reinforcement learning mechanisms introduced in the proposed JRRM methodology allow guaranteeing the QoS requirement in terms of the so-called user dissatisfaction probability in the presence of different traffic loads and under different dynamic situations. Also, the proposed framework is able to take into consideration different operator policies as well as different subjective criteria by means of a multiple decision-making mechanism, such as balancing the traffic among the RATs or giving more priority to the selection of one RAT in front of another one.**

***Index Terms*—Beyond third-generation (3G) networks, fuzzy neural controllers, joint radio resource management (JRRM), radio access technology (RAT) selection.**

I. Introduction

WIRELESS mobile digital communication systems have been releasing services to the mass market for more than a decade, first focusing on voice service and, more recently, on a variety of data services. In this context, the problem faced by a network operator is to offer a system where the network usage is maximized for a given set of quality-of-service (QoS) requirements. In the traditional approach to solving this problem, two aspects can be clearly distinguished: network planning (i.e., the design of the fixed network infrastructure in terms of the number of cell sites, cell site location, number and architecture of concentration nodes, etc.) and radio resource management (RRM) (i.e., for a given network deployment, the way radio resources are dynamically managed in order to meet the instantaneous demand of the users moving around the network).

In the framework of second-generation (2G) time-division multiple access (TDMA)-based mobile systems, e.g., global system for mobile communications (GSM), network planning is key. For a given network configuration, there is an almost constant value for the maximum capacity, and radio resource allocation actions in the short-term scale have a limited impact. On the contrary, in the framework of third-generation (3G) mobile systems, the situation is significantly different as long as code division multiple access (CDMA) becomes the dominant technology. The reasons are twofold. First, in CDMA-based systems, there is no constant value for the maximum available capacity since it is tightly coupled with the amount of interference in the air interface. Second, the multiservice scenario drops for some services the constant delay requirement and, consequently, opens the ability to exploit RRM functions to guarantee a certain target QoS, to maintain the planned coverage area, and to offer a high capacity while using the radio resources in an efficient way [1].

In turn, the perspective of Beyond 3G systems is that of heterogeneous networks, where the multiplicity of access technologies as well as the diversity of terminals with reconfigurability capabilities will be key in order to allow users on the move to enjoy seamless wireless services, irrespective of geographical location, speed, and time of day [2]. In this scenario, joint resource radio management (JRRM) is the identified process to manage dynamically and coordinately the allocation and deallocation of radio resources (e.g., time slots, codes, frequency carriers, etc.) between different radio access technologies (RATs) for the spectrum bands allocated to each of these systems. With JRRM, a more efficient usage of the radio resources will follow.

Some approaches to the JRRM problem are available in the open literature, and most of them are focused on functional and architectural behaviors. For example, [3] presents an Internet protocol (IP)-based end-to-end architecture involving different network domains where JRRM becomes a key element. In turn, [4] presents an interesting framework for the provision of JRRM algorithms to deal with the high degree of complexity associated with heterogeneous network scenarios. Another interesting contribution to JRRM can be encountered in [5],

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The authors are with Universitat Politècnica de Catalunya (UPC), Barcelona, Spain (e-mail: lorenza.giupponi@tsc.upc.edu; ramon@tsc.upc.edu; jorperez@tsc.upc.edu; sallent@tsc.upc.edu).

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where the analytic hierarchy process (AHP) and grey relational processes are jointly used as a tool to introduce priorities among user preferences, service applications, and network conditions in heterogeneous networks involving universal mobile telecommunication systems (UMTS) and wireless local area networks (WLANs). In [6], the benefits of JRRM, in terms of intersystem handover and intersystem-network-controlled cell reselection, are analyzed in a heterogeneous UMTS terrestrial radio access network (UTRAN)-GSM/EDGE radio access network (GERAN) scenario. Furthermore, the provision of cellular and IEEE 802.X WLAN integration, by means of loose and tight coupling architectures, has also been invoked in order to extend JRRM capabilities, including noncellular technologies in [7]. The benefit related to load balancing among the different RATs involved appears in [8], and meaningful combinations for RATs are analyzed in [9]. In standardization, the impacts of JRRM over network architecture have been introduced by the Third Generation Partnership Project (3GPP) for GERAN and UMTS, with both centralized and decentralized approaches [8], [10]. In addition, a 3GPP-WLAN interworking architecture has been finalized [11].

Nevertheless, not many specific algorithms have been provided in the open literature that assess relative improvements among different JRRM strategies, even in simple scenarios. In this paper, a comprehensive JRRM treatment is presented in a mobile, multiuser, multicell, and multi-RAT scenario. In such uncertain scenarios, learning from interaction is a foundational idea underlying learning theories and intelligence, which is a basis for the so-called cognitive networks [12]. Interacting produces a wealth of information about cause and effect, about the consequences of actions, and about what to do in order to achieve explicit goals. Taking this into account, this paper introduces the use of reinforcement learning mechanisms based on neural networks over a fuzzy logic-based methodology in order to cope with the complexities raised in heterogeneous radio access network scenarios. As a result, the novelty of the JRRM approach proposed in this paper consists of taking advantage of the fuzzy set concept and of the learning capabilities of neural networks in order to make decisions about RAT selection and bit rate allocation in a scenario with several available RATs. In particular, the benefits of the fuzzy-based decision making are twofold. On the one hand, it allows dealing with the vagueness and uncertainty that are typical of heterogeneous scenarios, where dissimilar technical decision making inputs have to be taken into account in order to perform RAT selection and bit rate allocation. On the other hand, it allows encompassing in the decision making process the nonspecificity inherent in human formulation of preferences, which is useful since the particular user and operator preferences have to be considered before making the final RAT selection decision. Furthermore, the learning capabilities embedded in the neural network allow interactions with the surrounding environment aimed at performing JRRM operation from a user-centric perspective. This innovative fuzzy neural-based JRRM approach significantly extends the preliminary work carried out by the authors in [13] and [14], where this approach was explored and assessed in simplified scenarios and without self-adaptive components. Further, the promising results obtained in [13] and [14] have motivated to undertake the progress described in the rest of this paper, where more realistic multicellular scenarios have been considered, and further advances in terms of user-centric concepts and implementation approaches have been achieved.

The full set of results provides the sufficient insight into the problem to allow one to state that the present fuzzy neural framework can be a firm candidate for JRRM.

Specifically, the aim of this paper is to propose a JRRM scheme in a cellular scenario, including UMTS, GERAN, and WLAN 802.11b, as available RATs. This scheme should provide, at each mobile position and along the service connection time, the most suitable RAT and allocated bit rate. The proposed fuzzy neural approach will be presented, assessed, and compared to other JRRM reference options. Then, a scalable JRRM architecture that is based on a two-step functional procedure will show its ability to be managed by simple policy procedures. Finally, a framework that is able to incorporate additional decision criteria, such as user demand and operator preference, is also considered in order to study the impact that personalization in the service provision might have in the final JRRM behavior. This procedure is based on the combination of fuzzy logic with AHP [15], [16].

In the above context, the rest of the paper is organized as follows. In Section II, the framework for JRRM development in multi-RAT and in multicell systems is described. In Section III, the proposed fuzzy neural JRRM algorithm is detailed. Section IV presents the specific scenario where the proposed strategies are evaluated. Section V presents some representative results and reveals the potentials of the proposed approach. Finally, Section VI summarizes the main conclusions reached.

II. Framework for JRRM Strategy Development

The JRRM concept is intended to achieve an efficient usage of the joint pool of the radio resources available, belonging to a variety of RATs in a certain service area. In this respect, it is necessary to progress toward specifying the operational framework and the required functionalities to achieve these targets.

The proposed JRRM scheme will incorporate three main RRM functions: RAT and cell selection (i.e., the functionality set to decide the RAT and the cell the mobile has to be attached to at session start), bit rate allocation (i.e., the functionality set to decide the most suitable bit rate or bandwidth for each RAT and accepted user), and admission control (i.e., the functionality set to decide whether a request to set up a connection can be accepted).

The inputs available for JRRM decisions are mainly the following:

1) RATs deployed, bandwidth available for each RAT, and scenario configuration (e.g., base station maximum transmitted power level, code sequences available in case of CDMA-based RATs);
2) measurements coming from the different RANs (e.g., load levels) as well as measurements coming from the user equipments (UEs), such as the received power levels, the path loss, or the chip energy over noise and

interference spectral density (Ec/Io) in the case of CDMA-based RATs;
3) techno-economic and subjective aspects, including operator policies, that may prefer the use of certain RATs over others for different reasons (e.g., commercial strategies, radio network ownership, etc.) as well as subscriber profiles and user preferences (e.g., considering QoS versus cost).

In order to envisage proper JRRM algorithm development frameworks, it is important to consider that the variety of JRRM inputs belonging to different RATs will provide, in general, imprecise and very dissimilar information. This is reflected in, for example, the initial driving inputs for RAT selection and vertical handover, which have to be extracted from the received pilot signals, although such signal strengths may not be comparable for the different RATs. Similarly, cell loads from different RATs are not directly comparable. In addition, other aspects, like the mobile speed, favor more or less a particular RAT according to the network layout.

As a result, since the fuzzy logic-based methodology has been proven to be good at explaining how to reach suitable decisions from imprecise and dissimilar information, the framework for JRRM strategy development proposed here will consider this approach. In fact, fuzzy logic strategies have been widely proposed in the literature in many different fields of knowledge [4], [17]–[21] because, by means of defining reasonable rules, it is possible to simplify the large state space of solution possibilities existing in a complex problem, which saves relevant effort. Therefore, this strategy could also be retained as a solution for JRRM, while keeping in mind that pattern aspects, like the selected membership functions and their particular shapes, included in the fuzzy methodology are still rather subjective. On the other hand, the use of neural networks, which are good at recognizing patterns by means of learning procedures, can also be considered by tuning these membership functions properly, thus developing hybrid solutions incorporating both fuzzy and neural methodologies. Using intelligent techniques has been considered in the open literature as an effective method for dealing with the problems related to RRM, such as handoff decision (e.g., [18] and [19]), connection admission control (e.g., [20]), power control (e.g., [21]), and channel allocation (e.g., [22] and [23]). Each of these intelligent techniques has a particular computational property (ability to learn, explanation of decisions, etc.) that makes it suitable for a particular application and not for others. For example, while neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. On the other hand, fuzzy logic systems are good at explaining their decisions from imprecise information, but they cannot automatically acquire the rules they use to make the decisions or to tune the functions that convert a crisp value (i.e., a numeric value) into a fuzzy quantity. Due to the limitations of these two techniques, intelligent hybrid systems that combine them, overcoming the limits of each one, have been created. Such solutions have been proposed in the literature in different fields [23], [24]. In this context, a fuzzy neural framework is proposed as a suitable candidate for the solution of JRRM related issues.

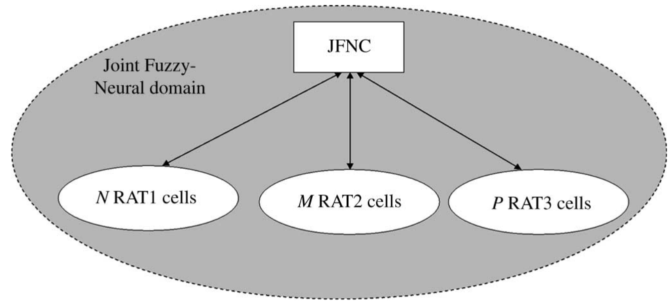

Fig. 1. Proposed network architecture for the execution of the fuzzy neural JRRM algorithm.

In terms of network architecture, a high-level allocation of JRRM functions in a heterogeneous RAT scenario is shown in Fig. 1. In particular, it is assumed in this paper that the service area is subdivided into joint fuzzy neural domains, each of them including a subset of cells belonging to different RATs. Each domain is managed by a joint fuzzy neural controller (JFNC), which is in charge of executing the JRRM algorithm for the set of cells under its domain. Note that the architectural model in Fig. 1 could be implemented in many different ways, ranging from residing the JFNC functionalities into existing networks nodes (e.g., a radio network controller, RNC; base station controller, BSC; access point controller, APC) up to allocating them in new network nodes (e.g., in the form of external servers). This way, the proposed architecture could be mapped on the envisaged approach in 3GPP [8], [10]. The paper assumes a scenario with a single operator owning all the RATs. However, a scenario encompassing the hypothesis of the existence of agreements among different operators can also be considered by making use of entities like a trusted third party [25].

III. Fuzzy Neural JRRM Algorithm

The proposed framework for JRRM algorithm implementation based on fuzzy neural mechanisms consists of three main blocks, as shown in Fig. 2, identified as fuzzy-based decision, reinforcement learning, and multiple objective decision making, respectively.

The fuzzy-based decision, reinforcement learning, and multiple objective decision making algorithms are executed every time a new user asks for admission in the system and during the user session. It assures the dynamic allocation and deallocation of radio resources in the scenario and the selection of the most suitable RAT, while keeping the desired QoS requirements of all admitted users.

The inputs of the fuzzy-based decision block are a set of linguistic variables LV_i corresponding to different measurements. The selection of these linguistic variables has been made taking into account the following most relevant parameters that influence the RAT selection and bandwidth allocation:

1) signal strength with respect to the considered RATs, in order to make RAT/cell selection and bit rate allocation coherently with the cell coverage in the scenario;
2) cell load, in order to avoid, as much as possible, congestion situations (i.e., situations in which the load reaches high values, thus degrading performance);

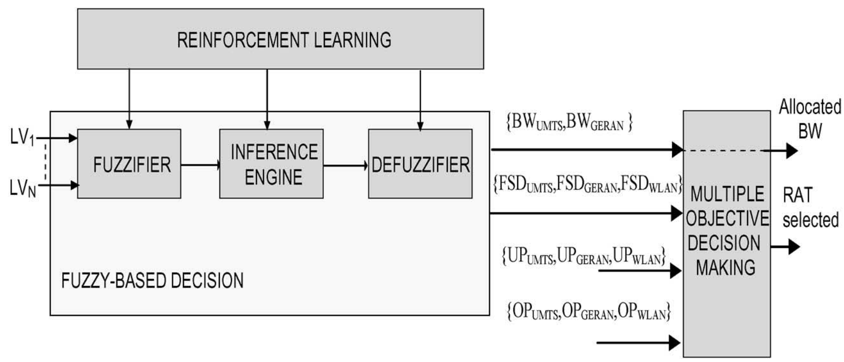

Fig. 2. Block diagram of the proposed JRRM algorithm.

3) mobile speed, in order to indicate the inappropriateness of selecting certain RATs (e.g., WLAN would be an inappropriate choice in case of high-speed users).

In addition, subjective and techno-economic criteria in the form of user preferences (UP) and operator preferences (OP) are inputs of the multiple objective decision making block, since it is considered that they are key elements that should play a role in the JRRM decision, as emphasized in Section II.

On the other hand, the outputs of the fuzzy neural algorithm are subdivided into two groups, which are the driving indicators to perform cell/RAT selection and bit rate allocation.

1) To perform cell/RAT selection, each RAT is characterized by an indicator, which takes values in the range [0, 1], referred to as fuzzy selected decision (FSD) value, which evaluates the appropriateness of selecting a RAT in front of the others.
2) To perform bit rate allocation, an output value (B) is associated to each RAT, which gives an indication of the amount of bandwidth that should be assigned to the user.

In the following subsections, the purpose of each block represented in Fig. 2 is detailed.

A. Fuzzy-Based Decision

This process is executed in three steps by the fuzzifier, inference engine, and defuzzifier blocks.

Step 1. Fuzzifier: The fuzzifier carries out the fuzzification process, the objective of which is to assign, for each input linguistic variable, a value (between 0 and 1) that corresponds to the degree of membership of this input to a given fuzzy set. A fuzzy set is a linguistic subjective representation of the input variable. A total of seven linguistic variables is considered here to describe the proposed JRRM approach. They include the following:

1) SS_{UMTS}, SS_{GERAN}, SS_{WLAN} (received signal strength for each of the considered RATs);
2) RA_{UMTS}, RA_{GERAN}, RA_{WLAN} (resource availability in each of the considered RATs);
3) MS (mobile speed).

A linguistic variable is characterized by a term set. Specifically, the term sets considered here for each linguistic variable are

$$\begin{aligned} X(SS_{UMTS}) &= X(SS_{GERAN}) = X(SS_{WLAN}) \\ &= X\{L, H\} \end{aligned} \quad (1)$$

$$\begin{aligned} X(RA_{UMTS}) &= X(RA_{GERAN}) = X(RA_{WLAN}) \\ &= X\{L, M, H\} \end{aligned} \quad (2)$$

$$X(MS) = X\{L, H\} \quad (3)$$

where H stands for "high," M for "medium," and L for "low."

Each element of the term set is a fuzzy set $X_j(LV_i)$ with membership function $\mu_{X_j}(LV_i)$. Thus, the function of the fuzzifier is to map the numeric value of the linguistic variable $LV_i(t)$ to the fuzzy set $X_j(LV_i(t))$ with a degree of membership $\mu_{X_j}(LV_i)$.

The shape of a membership function can be a triangle, a trapezoid, or a bell-shaped function. Due to the fact that a bell-shaped function is easy to derivate, which is useful when the reinforcement learning is activated, this is the membership function shape chosen for the proposed algorithm [17].

Notice that, in terms of the signal strength, the selected fuzzy sets may take two values: low or high. In turn, the resource availability is represented by three fuzzy sets—low, medium, or high—reflecting that a higher level of granularity is required for this parameter since it has a stronger impact over the resource allocation. Finally, the mobile speed is also considered with two fuzzy sets: low or high. Considering that the speed is used in the RAT selection only as an indication that some RATs may not be appropriate for high-speed users, not much granularity is required when using this parameter so that its term set consists of only two fuzzy sets. Notice that the number of values in each term set has been chosen in order to have a limited number of combinations among them.

The information corresponding to the input linguistic variables is periodically reported to the JFNC. This information includes the signal strength at the user receiver measured in different ways according to the RAT considered. In the case of UTRAN, the signal strength is measured by the received signal code power (RSCP) of the pilot channel [26]. For GERAN, the measure corresponds to the power received in the broadcast channel [27]. Finally, for WLAN, the beacon signal transmitted by the access point is measured [28]. In addition to this, the mobile speed should also be available to the JFNC. Several possibilities could be envisaged to estimate the mobile speed, for example, based on doppler frequency, positioning, cell reselection, handover rates, etc. However, it is worth noting that the envisaged algorithm does not require very accurate mobile speed estimations, since just an indication of the

TABLE I
EXAMPLE OF INFERENCE RULES

IF							THEN				
SS_{UMTS}	SS_{GERAN}	SS_{WLAN}	RA_{UMTS}	RA_{GERAN}	RA_{WLAN}	MS	D_{UMTS}	D_{GERAN}	D_{WLAN}	B_{UMTS}	B_{GERAN}
H	L	L	H	H	M	L	Y	N	N	H	L
H	L	L	M	H	M	L	PY	N	N	M	L
H	L	L	L	H	M	L	PN	PN	N	L	L

inappropriateness of selecting some RATs (e.g., WLAN) in the case of high-speed users is required. Concerning the resource availability, it is defined as $1-\rho$, where ρ is the resource occupation (i.e., the ratio between the average resource occupation in a cell over a defined period of time and the maximum available resources). The resource occupation is RAT dependent. In the case of UTRAN, it corresponds to the cell load factor. For GERAN, it is measured as the ratio between the number of occupied slots and the total number of slots. Finally, for WLAN, it is the ratio between the current and the maximum available throughput.

Step 2. Inference Engine: In a fuzzy controller, the dynamic behavior of the system is characterized by a set of linguistic rules expressing the decision policies and defined as follows:

IF (a set of conditions are satisfied) THEN (a set of consequences can be inferred).

These rules are predefined and stored in the so-called fuzzy rule base. Each rule is characterized by a precondition depending on a particular combination of the fuzzy sets described in step 1 and by a consequence indicating, in linguistic terms and for each RAT, the suitability of selecting each RAT and the corresponding allocated bit rate. As a result, the output of the inference engine is still a fuzzy value defined with respect to two groups of output linguistic variables. On the one hand, the decision $D(D_{UMTS}, D_{GERAN}, D_{WLAN})$ output linguistic variables have been defined with the following term sets:

$$\begin{aligned} X(D_{UMTS}) &= X(D_{GERAN}) = X(D_{WLAN}) \\ &= X\{Y, PY, PN, N\} \end{aligned} \tag{4}$$

where Y stands for "yes," PY for "probably yes," PN for "probably not," and N for "not."

Similarly, there will be two output linguistic variables corresponding with the allocated bit rate $B(B_{UMTS}, B_{GERAN})$, each with the following term sets:

$$X(B_{UMTS}) = X(B_{GERAN}) = X\{H, M, L\} \tag{5}$$

where H stands for "high," M for "medium," and L for "low."

It is worth mentioning that the bandwidth allocation for WLAN is not considered here as a fuzzy neural algorithm output. The reason is that current WLAN systems (i.e., 802.11b) are not able to guarantee a bandwidth rate. Nevertheless, the proposed strategy could be easily extended to also consider WLAN bandwidth assignments in case.

An example of three inference rules is shown in Table I.

Assuming that the jth rule corresponds to the first row in Table I, the membership value of the output jth rule is defined as

$$\begin{aligned} \mu_Y(D_{UMTS})_j &= \mu_N(D_{GERAN})_j = \mu_N(D_{WLAN})_j \\ &= \mu_H(B_{UMTS})_j = \mu_L(B_{GERAN})_j \\ &= \min\left[\mu_H(SS_{UMTS}), \mu_L(SS_{GERAN})\right. \\ &\qquad \mu_L(SS_{WLAN}), \mu_H(RA_{UMTS}) \\ &\qquad \mu_H(RA_{GERAN}), \mu_M(RA_{WLAN}) \\ &\qquad \left.\mu_L(MS)\right]. \end{aligned} \tag{6}$$

Then, finally, the consequences of the rules in the fuzzy rule base leading to the same fuzzy set of a given output linguistic variable have to be combined in order to obtain the membership value of this fuzzy set. In particular, it is computed as the sum of the membership values of all the rules having that fuzzy set as a consequence.

Step 3. Defuzzifier: Finally, the defuzzifier executes the defuzzification, which consists of converting the outputs of the inference engine into a crisp value, denoted as fuzzy selected decision (FSD), indicating the suitability of selecting each RAT. The three outputs—FSD_{UMTS}, FSD_{GERAN}, and FSD_{WLAN}—are then obtained. The defuzzification method considered is the center of area method [17]. Similarly, the defuzzification process also provides the allocated bit rate by means of the outputs BW_{UMTS} and BW_{GERAN}.

B. Layered Fuzzy Neural Controller

The above steps of the fuzzy-based decision procedure can be graphically represented by means of a five-layered structure used in neural networks, which enables the use of reinforcement learning to adjust the different membership functions. This fuzzy neural structure is shown in Fig. 3 and is composed of a set of nodes belonging to the different layers.

Each node in the kth layer $(k = 1, \ldots, 5)$ is numbered by a cardinal i ranging from 1 to the number of nodes in the kth layer.

The basic structure of each node is shown in Fig. 4, where u_i^k represents the ith input signal for the kth layer, and p represents the number of inputs connected to the node. Each node is characterized by an integration function $f(u_1^k, u_2^k, \ldots, u_p^k)$, which combines the different inputs, and by an activation function $a(f)$, which provides the output.

In the following subsections, the characterization of the different layers corresponding to the down/up operation according to the proposed fuzzy neural JRRM approach is provided.

Layer 1: In this layer, there are as many nodes as the number of input linguistic variables (i.e., seven). The nodes in this layer just transmit input values to the next layer

$$f_i^1 = u_i^1 \qquad i = 1, \ldots, 7 \tag{7}$$

$$a_i^1 = f_i^1 \qquad i = 1, \ldots, 7. \tag{8}$$

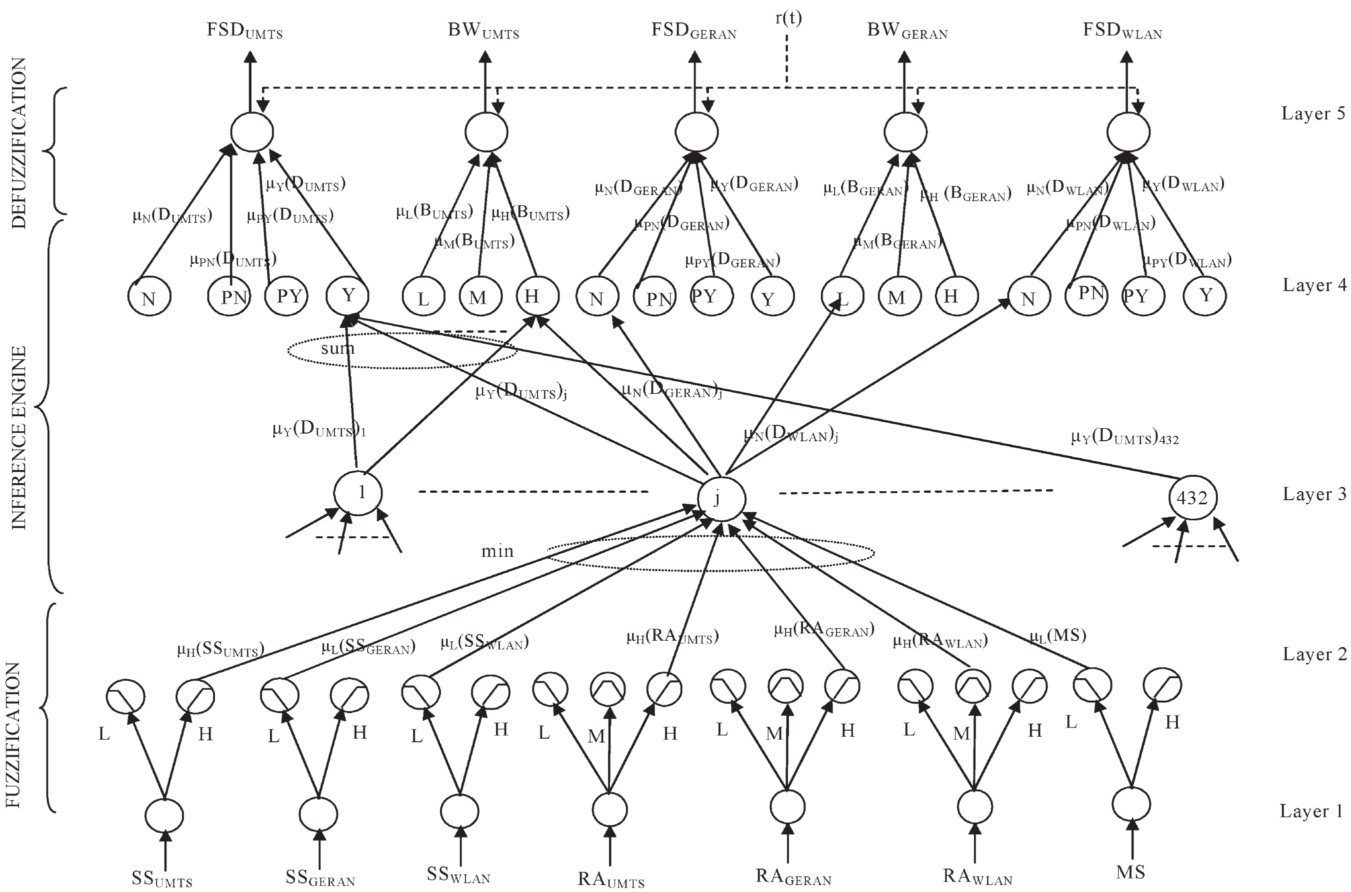

Fig. 3. Layered fuzzy neural scheme.

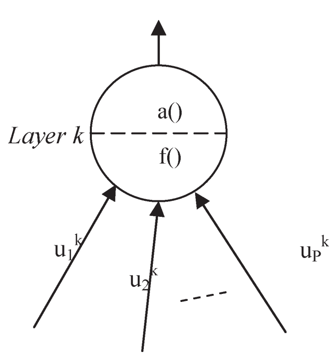

Fig. 4. Basic structure of a node in the fuzzy neural scheme.

Layer 2: The nodes in this layer correspond to the fuzzification procedure. According to the dimension of the term sets previously described, in this layer, there are 17 nodes. Each node performs a bell-shaped function, which is defined by

$$f_i^2 = -\frac{\left(u_i^2 - m_i^2\right)^2}{\left(\sigma_i^2\right)^2}, \qquad i = 1, \ldots, 17 \tag{9}$$

$$a_i^2 = e^{f_i^2}, \qquad i = 1, \ldots, 17 \tag{10}$$

where m_i^2 and σ_i^2 are, respectively, the mean and variance of the bell-shaped membership function associated to the ith node in layer 2.

Layer 3: The nodes in this layer correspond to the different combinations existing in the inference engine. Then, denoting as $|X(LV_i)|$ the number of elements in the term set X corresponding to linguistic variable LV_i, the number of nodes of this layer is

$$\begin{aligned} &|X(MS)| \times |X(SS_{UMTS})| \times |X(SS_{GERAN})| \\ &\times |X(SS_{WLAN})| \times |X(RA_{UMTS})| \times |X(RA_{GERAN})| \\ &\times |X(RA_{WLAN})| = 2 \cdot 2^3 \cdot 3^3 = 432. \end{aligned} \tag{11}$$

Each layer 3 node is linked to seven layer 2 nodes, corresponding to the seven input linguistic variables. The links are used to perform precondition matching of fuzzy control rules. Therefore, each node should perform the AND operation

$$f_i^3 = \min\left(a_j^2\right) \; \forall \text{ layer 2 node } j \text{ linked to a layer 3 node } i \qquad 1 \le i \le 432. \tag{12}$$

Similarly, the output function of each layer 3 node simply transfers the same value obtained in the input function

$$a_i^3 = f_i^3, \qquad 1 \le i \le 432. \tag{13}$$

Layer 4: In this layer, there are two groups of outputs. The first one corresponds to the RAT decision D_{UMTS}, D_{GERAN}, and D_{WLAN}, while the other one is for the allocated bit rate B_{UMTS} and B_{GERAN} with the term sets defined in (4) and (5). Since there is one node for each of the fuzzy sets in the considered term set, there are a total of 18 nodes in layer 4. Each node performs a fuzzy OR operation integrating the input coming from the layer 3 nodes that have the same consequence (i.e., leading to the same RAT decision or bit rate allocation). It is given by

$$f_i^4 = \sum_{j \in C_i} a_j^3, \qquad i = 1, \ldots, 18 \tag{14}$$

where C_i is the set of layer 3 nodes that are connected to the considered ith layer 4 node

$$a_i^4 = \min\left(1, f_i^4\right), \qquad i = 1, \ldots, 18. \tag{15}$$

Layer 5: Each node of this layer carries out the defuzzification procedure. Hence, there are two kinds of nodes: the FSD values and the BW values. The number of nodes is then five. The function used to carry out the centre of area defuzzification method is

$$f_i^5 = \sum_{j \in T_i} m_j^5 \sigma_j^5 u_j^5, \qquad i = 1, \ldots, 5 \tag{16}$$

$$a_i^5 = \frac{f_i^5}{\sum_{j \in T_i} \sigma_j^5 u_j^5}, \qquad i = 1, \ldots, 5 \tag{17}$$

where m_j^5 and σ_j^5 are the centers and the widths of membership functions. Furthermore, T_i is the set of layer 4 nodes connected to the considered layer 5 node. For instance, in the case $i = 1$ corresponding to the FSD_{UMTS} output (Fig. 3), the considered layer 4 nodes are $j = 1$ (corresponding to $D_{UMTS} = N$), $j = 2$ (corresponding to $D_{UMTS} = PN$), $j = 3$ (corresponding to $D_{UMTS} = PY$), and $j = 4$ (corresponding to $D_{UMTS} = Y$). The values of the inputs u_i^5 are the corresponding outputs of the layer 4 nodes.

Notice that a_i^5 provides the FSD values as follows:

$$FSD_{UMTS} = \frac{\sum_{j \in T_{UMTS}} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in T_{UMTS}} \sigma_j^5 u_j^5} \tag{18}$$

$$FSD_{GERAN} = \frac{\sum_{j \in T_{GERAN}} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in T_{GERAN}} \sigma_j^5 u_j^5} \tag{19}$$

$$FSD_{WLAN} = \frac{\sum_{j \in T_{WLAN}} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in T_{WLAN}} \sigma_j^5 u_j^5}. \tag{20}$$

T_{UMTS}, T_{GERAN}, and T_{WLAN} are, respectively, the set of layer 4 nodes connected to the layer 5 nodes providing FSD_{UMTS}, FSD_{GERAN}, and FSD_{WLAN}. Similarly, in terms of allocated bandwidth, it will be given at the output of layer 5 as follows:

$$BW_{UMTS} = BW_{UMTS,MAX} \frac{\sum_{j \in W_{UMTS}} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in W_{UMTS}} \sigma_j^5 u_j^5} \tag{21}$$

$$BW_{GERAN} = BW_{GERAN,MAX} \frac{\sum_{j \in W_{GERAN}} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in W_{GERAN}} \sigma_j^5 u_j^5} \tag{22}$$

where $BW_{UMTS,max}$ and $BW_{GERAN,max}$ are the maximum bit rate that can be allocated in UMTS and GERAN, respectively. In turn, W_{UMTS} and W_{GERAN} are now the set of layer 4 nodes connected to the layer 5 nodes that provide BW_{UMTS} and BW_{GERAN}, respectively. For instance, in the case of the node providing BW_{UMTS} (Fig. 3), the considered layer 4 nodes in W_{UMTS} are $j = 5$ (corresponding to $B_{UMTS} = L$), $j = 6$ (corresponding to $B_{UMTS} = M$), and $j = 7$ (corresponding to $B_{UMTS} = H$).

Once the fuzzy neural network 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 structure of the fuzzy neural network by defining the fuzzy inference rules contained in the fuzzy rule base and the initial shape and position of the membership functions. It is worth noting that this set-up phase is performed off-line and that afterward, the reinforcement learning is in charge of adjusting online the parameters defining the fuzzy neural network structure. The off-line set up of fuzzy neural networks is a rapidly developing research field, and there exist several methods 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, rank ordering, angular fuzzy sets methods [17]), or they can make use of more complex algorithms based on, for example, neural networks, genetic algorithms, pattern recognition, inductive reasoning, etc. [17]. The first group of procedures has been intensively adopted in the literature [29]. For example, in case of inference rules, many experts have found that they provide a convenient way to express their knowledge since, in our daily lives, most of the information on which our decisions are based 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 [24]. Nevertheless, for the JRRM application, it would be very difficult and expensive to obtain off-line a comprehensive training data file to set up the neural network, because the JRRM decisions depend on many time-variant factors (e.g., traffic loads, signal strengths, etc.) that 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 on the problem type.

Consequently, in case of JRRM, the authors consider that a suitable method to set up the network off-line is to define both the membership functions and the fuzzy inference rules by means of the intuition and the knowledge the network provider has of the problem to face and of all the elements determining the fuzzy neural network structure. For example, a signal strength membership function is first reasonably defined considering measurements such as the sensitivity levels at the cell edge.

C. Reinforcement Learning Procedure

This procedure is developed in order to determine appropriate membership functions for the layer 2 and 5 nodes, specifically the m_i^2, σ_i^2, m_i^5, and σ_i^5 values corresponding to the fuzzification and defuzzification steps. The mean m_i and the standard deviation σ_i of the membership functions in the second and forth layers are first set off-line.

Successively, these parameters are dynamically adjusted by means of the reinforcement learning procedure that acts according to a reinforcement signal $r(t)$, depending on a desired output quality measurement. In the layered fuzzy neural structure shown in Fig. 3, this reinforcement signal is introduced at layer 5 and is propagated from top to bottom in order to adjust the specific parameters in lower layer nodes. Notice that the proposed JRRM algorithm does not require a very accurate initial selection of the membership function parameters, since a most appropriate tuning will be successively provided online by the reinforcement learning algorithm.

In this paper, the reinforcement signal will be set in order to achieve a desired value of the "dissatisfaction probability," defined as the probability that a user does not receive its desired bandwidth according to its specific contract. Notice that this type of measurement introduces a user-centric approach in the proposed algorithm while, at the same time, allows a quantification of the degree of quality that is being perceived by services that differ from the classical constant bit rate ones like, for example, speech.

The reinforcement signal is then defined as

$$r(t) = (P_I^* - P_I(t)) \tag{23}$$

where $P_I(t)$ is the current measured dissatisfaction probability at time t and where P_I^* is the desired target value of this probability. Then, the goal of the reinforcement learning is to minimize the error function given by

$$E(t) = \frac{1}{2} r(t)^2 = \frac{1}{2} \left(P_I^* - P_I(t)\right)^2. \tag{24}$$

Let us assume that w is a general adjustable parameter (e.g., any of the means and deviations of the membership functions at layers 5 and 2). The general learning rule for this parameter is given by

$$w(t+1) = w(t) + \gamma \left(-\frac{\partial E(t)}{\partial w(t)} \right) \tag{25}$$

where γ is the learning rate. The learning rule can be expressed as a function of the dissatisfaction probability as

$$w(t+1) = w(t) + \gamma r(t) \frac{\partial P_I(t)}{\partial w(t)}. \tag{26}$$

In the following, the computations of $\partial P_I(t)/\partial w(t)$ layer by layer, starting at the output nodes (i.e., corresponding to the up/down operation), are presented.

The updating rule for a layer 5 parameter is given by

$$\frac{\partial P_I(t)}{\partial w(t)} = \frac{\partial P_I(t)}{\partial a_i^5} \frac{\partial a_i^5}{\partial w(t)} = \frac{\partial P_I(t)}{\partial a_i^5} \frac{\partial a_i^5}{\partial f_i^5} \frac{\partial f_i^5}{\partial w(t)} \tag{27}$$

where the subindex i stands for the ith node, and a_i^5 and f_i^5 are defined in (17) and (18). Then, the updating rule for the mean values m_i^5 is given by

$$m_i^5(t+1) = m_i^5(t) + \gamma \cdot r(t) \cdot \frac{\sigma_i^5 u_i^5}{\sum\limits_{j \in T_i} \sigma_j^5 u_j^5}. \tag{28}$$

In the same way, the updating rule for σ_i^5 is

$$\sigma_i^5(t+1) = \sigma_i^5(t) + \gamma \cdot r(t) \cdot \frac{m_i^5 u_i^5 \left(\sum\limits_{j \in T_i} \sigma_j^5 u_j^5 \right) - \left(\sum\limits_{j \in T_i} m_j^5 \sigma_j^5 u_j^5 \right) u_i^5}{\left(\sum\limits_{j \in T_i} \sigma_j^5 u_j^5 \right)^2}. \tag{29}$$

In relation to the membership functions in the layer 2 mean and dispersion parameters, the reinforcement signal propagated from layer 5 to layer 2 is defined as follows:

$$\delta_i^2 = \frac{\partial E(t)}{\partial f_i^2} = \sum_n \frac{\partial E(t)}{\partial u_n^4} \sum_k \frac{\partial u_n^4}{\partial u_k^3} \frac{\partial u_k^3}{\partial f_i^2} \tag{30}$$

where $n = 1, \ldots, 18$ corresponds to the layer 4 nodes, $k = 1, \ldots, 432$ corresponds to the layer 3 nodes, and finally, $i = 1, \ldots, 7$ corresponds to the layer 2 nodes.

Furthermore, the intermediate derivatives are given by

$$\frac{\partial E(t)}{\partial u_n^4} = r(t) \cdot \frac{m_n^5 \sigma_n^5 \left(\sum\limits_{j \in T_n} \sigma_j^5 u_j^5 \right) - \left(\sum\limits_{j \in T_n} m_j^5 \sigma_j^5 u_j^5 \right) \sigma_n^5}{\left(\sum\limits_{j \in T_n} \sigma_j^5 u_j^5 \right)^2} \tag{31}$$

$$\frac{\partial u_n^4}{\partial u_k^3} = \begin{cases} 1, & \text{if } k\text{th layer 3 node is connected} \\ & \quad \text{to } n\text{th layer 4 node} \\ 0, & \text{otherwise} \end{cases} \tag{32}$$

$$\frac{\partial u_k^3}{\partial f_i^2} = \begin{cases} 1, & \text{if } i\text{th layer 2 node provides the min} \\ & \quad \text{among rule node } k \text{ inputs} \\ 0, & \text{otherwise.} \end{cases} \tag{33}$$

Then, the adaptive rules for a generic mean and dispersion of the ith node of layer 2 are given by

$$m_i^2(t+1) = m_i^2(t) + \gamma \delta_i^2 \cdot e^{f_i} \frac{2\left(u_i^2 - m_i^2\right)^2}{\left(\sigma_i^2\right)^2} \tag{34}$$

$$\sigma_i^2(t+1) = \sigma_i^2(t) + \gamma \delta_i^2 \cdot e^{f_i} \frac{2\left(u_i^2 - m_i^2\right)^2}{\left(\sigma_i^2\right)^3}. \tag{35}$$

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) In order to achieve the fuzzy-based decision with respect to the RAT and bandwidth allocation, the type of operations to be performed 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 in layer 5. Note that the implementation of the membership functions in layer 2 can be done by means of look-up tables, thus only requiring a memory access. As a result of that, the number of operations to achieve a decision per user is on the order of 5000, which turns into a requirement of about 100 μs 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., on 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 layers 2 and 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.

D. Multiple Objective Decision Making

In a heterogeneous framework, the RAT selection decision may not depend only on radio interface related issues such as resource availability or signal strength but on qualitative or techno-economic inputs as well. In particular, as shown in Fig. 2 the proposed multiple objective decision making block takes as input the output of the fuzzy neural block (FSD), as well as the UP (i.e., the preference of the user with respect to the allocation of one or another RAT, which can take into account quality versus cost aspects) and the OP (i.e., the preference of the operator with respect to the allocation of one or another RAT, which may be based on, for example, business models).

The framework for the multiple objective decision making is introduced in [15] and [16] as a general basis and considered here as a particular case for JRRM application. The criteria considered for each RAT are $C_1 = FSD$, $C_2 = UP$, $C_3 = OP$. If they were equally important, the decision for each RAT would be given by $D_i = C_{i1} \cap C_{i2} \cap C_{i3}$ or equivalently by $D_i = \min(FSD_i, UP_i, OP_i)$ for the ith RAT ($i = UMTS$, $GERAN$, or $WLAN$). Then, the selected RAT would be that having the maximum value of D_i.

Due to the fact that the different criteria may have a different subjective importance, a number $\alpha \geq 0$ indicative of the importance of the criterion is introduced so that the more important the criterion, the higher the value of α. Then, the decision is made according to

$$D = C_{i1}^{\alpha_1} \cap C_{i2}^{\alpha_2} \cap C_{i3}^{\alpha_3} \tag{36}$$

where

$$\frac{1}{N} \sum_{n=1}^{N} \alpha_n = 1 \tag{37}$$

N being the number of criteria (i.e., $N = 3$ in this case). This way, the criteria of weak importance have less influence over the selected decision.

A suitable method for computing α_i is given in [15], based on the relative importance between criteria. Specifically, the different criteria are compared in such a way that a_{ij} represents the relative importance of criterion i with respect to criterion j. Then, the $N \times N$ matrix B is defined with components b_{ij}

$$\begin{cases} b_{ii} = 1 \\ b_{ij} = a_{ij}, i \neq j \\ b_{ji} = 1/b_{ij}. \end{cases} \tag{38}$$

Then, the α_n are given by the components of the vector obtained from the product of the number of criteria N and the unit eigenvector corresponding to the highest eigenvalue of matrix B.

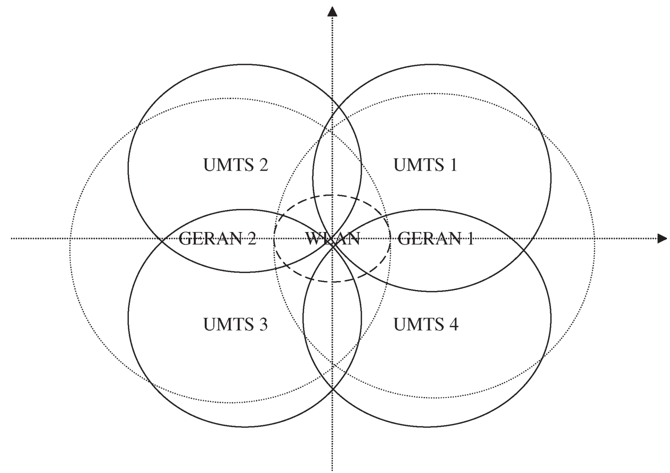

Fig. 5. Considered multi-cell scenario.

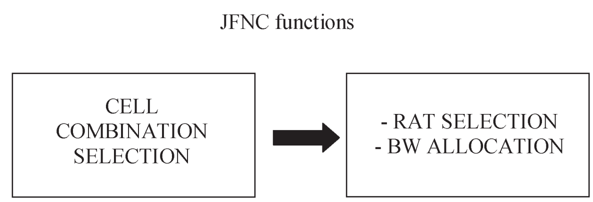

Fig. 6. Functions of the joint fuzzy neural controller.

IV. Scenario Model for JRRM Evaluation

In order to evaluate the JRRM fuzzy neural algorithm, a multicell scenario, with a seven cell deployment, including four UMTS base stations, two GERAN base stations, and one WLAN access point, has been envisaged, as illustrated in Fig. 5. Each cell is characterized by a given coverage area and by its corresponding RAT. The considered scenario consists of circular cells defining WLAN, UMTS, and GERAN dominant areas.

In this scenario, both the RAT and the cell need to be selected for each user during the execution of the JRRM algorithms. To this end, a two-step procedure has been considered in the JFNC introduced in Fig. 1 in order to decouple the cell selection from the RAT selection and bandwidth allocation processes, as outlined in Fig. 6.

It is assumed that the JRRM procedure explained in Section III is executed for each user after having selected a combination of cells from the available RATs (i.e., a UMTS cell, a GERAN cell, and a WLAN access point). The rationale behind this split of functionalities is to have a limited number of inputs in the fuzzy-based decision procedure, thus obtaining a more scalable JRRM procedure.

In the following subsections, different approaches for the cell combination selection functions are explored.

A. Cell Combination Selection

The cell combination selection function is in charge of selecting for a given subscriber one cell for each of the considered RATs (i.e., UMTS, GERAN, and WLAN). The considered scenario consists of eight combinations of cells: C_1 (WLAN, $UMTS_1$, $GERAN_1$), C_2 (WLAN, $UMTS_2$, $GERAN_1$), C_3 (WLAN, $UMTS_3$, $GERAN_1$), C_4 (WLAN, $UMTS_4$, $GERAN_1$), C_5 (WLAN, $UMTS_1$, $GERAN_2$), C_6 (WLAN, $UMTS_2$, $GERAN_2$), C_7 (WLAN, $UMTS_3$, $GERAN_2$), and C_8 (WLAN, $UMTS_4$, $GERAN_2$).

Two possible criteria have been envisaged to perform the combination selection.

1) Signal strength criterion. The combination is built selecting, for each RAT, the cell providing the best signal strength at the user receiver.
2) Fuzzy criterion. The fuzzy system is first applied to all the combinations. Successively, the maximum FSD value among the ones corresponding to the UMTS, GERAN, and WLAN cells belonging to each combination is taken as the indicator of the appropriateness of selecting one of them. Consequently, the selected combination will be that providing the highest FSD. Notice that, compared to the signal strength criterion, the fuzzy criterion also allows consideration of the effects of load and mobile speed.

It is worth noting that, in a given deployment scenario, some combinations could be disregarded in advance if the corresponding cells do not overlap, thus reducing the number of computations so that the scalability can prevail.

B. RAT Selection and Bit Rate Allocation

The RAT selection and bit rate allocation are implemented by means of the fuzzy-based decision, reinforcement learning, and multiple decision-making algorithms explained in Section III and constitute the final JRRM step once a particular combination selection has been retained. This process is carried out at the admission control phase and along the active users' sessions, thus checking whether a horizontal or vertical handover is required.

In order to apply the fuzzy neural JRRM algorithm in the JFNC, two different approaches are considered. The first approach is a fuzzy neural system per combination. In this case, there is a separate fuzzy neural system for each combination. The system inputs are the input linguistic variables computed according to the base stations that form part of the combination. Each fuzzy neural system evolves independently from the others, which means that a different reinforcement learning mechanism is applied to each combination (i.e., layers 2 and 4 parameters in Fig. 3 are adapted as a result of the evolution of the dissatisfaction probability for those users associated with that particular combination). The second approach is a fuzzy neural system per scenario. In this case, there is a single fuzzy neural system for the whole scenario. The system inputs are the input linguistic variables computed according to the base stations that belong to the combination previously selected for the mobile that has activated the algorithm execution. The reinforcement signal is the dissatisfaction probability of all the users in the scenario.

In order to study the suitability of the different alternatives identified here, the approaches to select the most suitable combination and the most suitable RAT will be combined and assessed. Then, four possible implementations are considered.

1) Implementation no. 1 considers the signal strength criterion to perform combination selection and a fuzzy neural system per scenario to perform RAT selection.
2) Implementation no. 2 considers the signal strength criterion to perform combination selection and a fuzzy neural system per combination to perform RAT selection.
3) Implementation no. 3 considers the fuzzy criterion to perform combination selection and a fuzzy neural system per scenario to perform RAT selection.
4) Implementation no. 4 considers the fuzzy criterion to perform combination selection and a fuzzy neural system per combination to perform RAT selection.

C. Performance Measurements

With respect to performance measurements, the concept of service dissatisfaction is considered. A user is "dissatisfied" if at least one of the following situations occurs.

1) The fuzzy neural system assigns to it an amount of bandwidth lower than the desired one according to its contract.
2) The user is in "outage," which means that the received power does not satisfy the sensitivity criterion, which is defined differently for each of the RATs, as detailed below.

For UMTS, the required transmission power $P_{T,i}$ by a given ith user in the uplink is given by [1]

$$P_{T,i} = \frac{L_{p,i} P_N}{1 - \eta_{UL}} \frac{1}{\frac{W}{\left(\frac{E_b}{N_0}\right)_i R_{b,i}} + 1} \tag{39}$$

where $L_{p,i}$ is the Path Loss, $R_{b,i}$ is the bit rate for the ith user, $E_b/N_0 = 3$ dB is the QoS target, $\eta_{UL} = 0.75$ 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. According to this expression, if the required power is higher than the maximum available power at the terminal (e.g., $P_{T,i} > 21$ dBm), the user is in outage.

In turn, for WLAN and GERAN, the condition to be in outage is that the received power is below a sensitivity threshold: set to -93 dBm for WLAN and -87 dBm for GERAN as representative values.

In order to properly capture the performance of the system, the following measurements are also considered to complement the "dissatisfaction" probability:

1) Blocking probability. A user is blocked if, at the session start, the JRRM algorithm assigns to the user a bandwidth of 0 kb/s.
2) Dropping probability. A user is dropped if, after changing the current cell combination that is being considered in the bandwidth allocation for a given user, the JRRM algorithm assigns to the user a bandwidth of 0 kb/s, which means that a horizontal or a vertical handover failure has occurred. 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 in this paper.

Notice that a user in outage, before being dropped out, is considered dissatisfied. The reason of this choice is that this kind of situation allows the reinforcement learning algorithm to "learn" the most appropriate way to make a decision. In fact, it is assumed that users are moving in an area where there is always at least one available RAT, so an outage can only be originated from a wrong JRRM decision in terms of either RAT selection or bandwidth allocation (e.g., a high bandwidth to a user at the cell edge). Consequently, this situation can be corrected by exploiting the learning capabilities of the proposed framework, without having to drop the call.

V. Results and Discussion

A. Parameter Definition

The proposed fuzzy neural strategy has been first evaluated through simulations in the reference multicell scenario shown in Fig. 5 in order to analyze its behavior and to tune and validate the parameters that have more impact on the final decision.

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) $\epsilon[0, 50\ \text{km/h}]$ and a randomly chosen direction. The propagation model considered for UMTS and GERAN is given by $\mathrm{L} = 128,\ 1 + 37,\ 6\ \log\ \mathrm{d}\ (\mathrm{km})$, which assumes that the frequency band is similar for both systems (i.e., GERAN: 1710–1785 MHz; UMTS: 1900–2025 MHz) [30]). For WLAN, since the conditions are different (e.g., different frequency bands, access point located indoor, lowest height, etc.) the propagation losses inside the hot spot are modeled by $\mathrm{L} = 20\ \ \log \mathrm{d(m)} + 40$ [31]. The beginning and the end of the user's activity periods are defined according to a Poisson scheme with an average of six calls per hour and an average call duration of 180 sec. The maximum bit rate available to the users in a UMTS and GERAN cell is 384 and 96 Kb/s, respectively. In addition, it is assumed that the user contractual bit rate is 192 Kb/s for UMTS and 40 Kb/s for GERAN.

Results are presented for the uplink direction, and the considered possible bit rates for the different RATs are as follows.

1) For UMTS, the results are 32, 48, 64, 80, 96, 112, 128, 192, 256, 320, and 384 kb/s. A single UTRAN FDD carrier is considered. The maximum allowed uplink load factor is 0.75.
2) For GERAN, the results are 32, 48, 64, 80, and 96 kb/s. It is assumed that four carriers are available in the GERAN cell for GPRS users, with coding scheme CS-4 [32], thus having a maximum bit rate in the cell of 640 kb/s.
3) For WLAN, it is considered that the total bandwidth available (11 Mb/s) 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 no more WLAN users are 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 contention-free period (CFP) mechanisms allow different users to share a WLAN channel simply scheduling the transmissions on top of the MAC, which justifies the assumption that the same bit rate per user is considered [33].

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 for UMTS or for GERAN, respectively.

Cell radii of 150 m for WLAN, 650 m for UMTS, and 1 km for GERAN are retained.

The fuzzy neural algorithm is activated every 100 ms for the simulation purposes in order to reallocate 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.

The resource availability (RA) is a RAT-dependent concept and, for the different RATs used in the fuzzy neural JRRM algorithm, is defined as follows.

1) For UMTS, RA $= 1 - \eta_{\mathrm{UL}}$, where η_{UL} is the uplink cell load factor.
2) For GERAN, RA $= 640$ kb/s $- \rho$, where ρ is the current amount of kb/s already allocated in the corresponding cell.
3) 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.

In the following subsections, the different aspects of the proposed JRRM algorithm that have an influence over the final performance will be analyzed on a step-by-step basis in order to better clarify the relevant role played by each one.

B. Role of Membership Functions

The considered initial membership functions, which have been set up off-line (as explained in Section III), are depicted in Fig. 7. In order to analyze the impact of the membership function selection without initially including the reinforcement learning procedure, Fig. 8 plots alternative membership functions for the RA_{UMTS} and the RA_{GERAN} linguistic variables. The modified membership functions shown in Fig. 8 have been selected based on the reference membership functions from Fig. 7, maintaining their standard deviation values but modifying their mean values. In particular, the mean values of the RA_{UMTS} membership functions have been increased, while the mean values of RA_{GERAN} membership functions

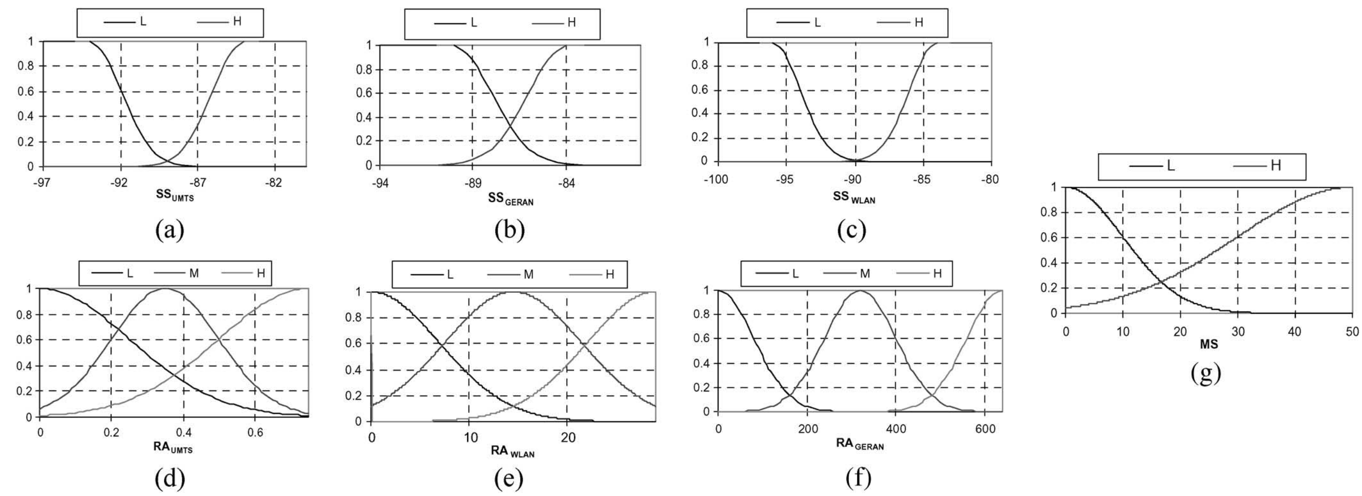

Fig. 7. Considered reference membership functions.

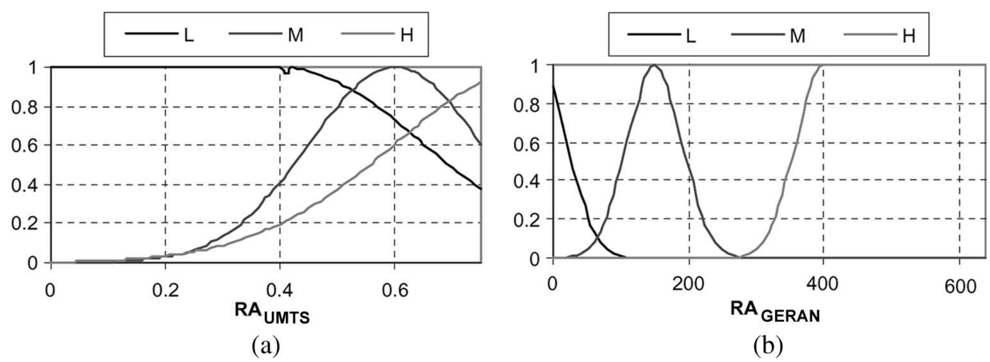

Fig. 8. Modified membership functions.

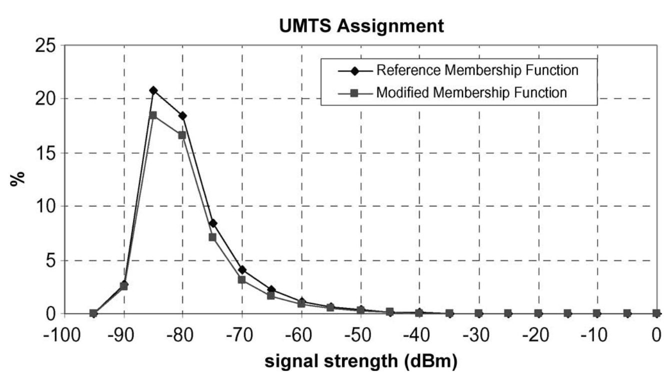

Fig. 9. Percentage of UMTS assignments as a function of the signal strength.

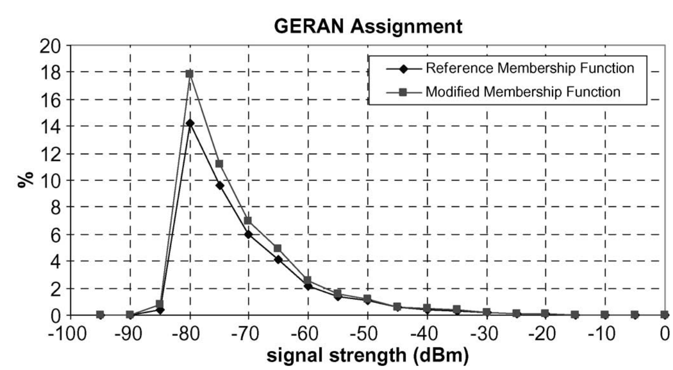

Fig. 10. Percentage of GERAN assignments as a function of the signal strength.

have been decreased so that the corresponding membership functions have been shifted to the right and to the left, respectively. The objective of these modifications is to show the impact that the membership function shapes and positions have on the final JRRM decision. Specifically, this impact is quantified in Figs. 9 and 10, where the UMTS and GERAN allocation probabilities are shown as a function of the signal strength (i.e., the percentage of times that, for a given value of the signal strength, UMTS or GERAN are allocated). Notice that, by moving the UMTS and GERAN membership functions toward higher and lower values, respectively, the meaning of the fuzzy sets low, medium, and high are modified. For example, by shifting the RA_{UMTS} membership functions to the right, the linguistic variable RA_{UMTS} is characterized as "low" with higher membership values with respect to the reference membership function case. Consequently, the GERAN percentage assignment is expected to increase and the UMTS one to decrease. This is reflected in Figs. 9 and 10, where the GERAN assignment becomes more likely and the UMTS one more unlikely, with respect to the reference simulation.

As a result of the previous considerations, the setting of means and standard deviations of membership functions represent a key element in the RAT selection decision. In order to eliminate the subjectivity that may characterize the membership

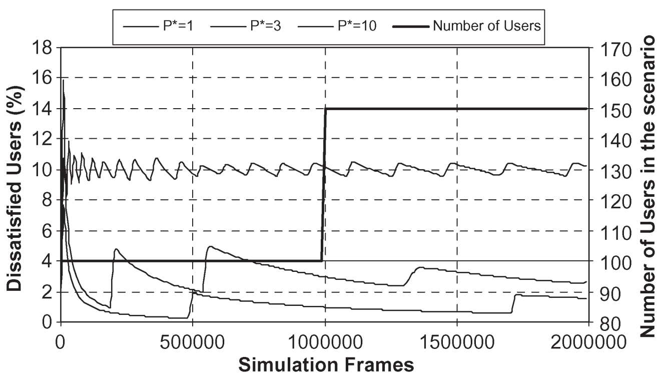

Fig. 11. Evolution of the dissatisfaction probability.

function shapes and positions setting, the reinforcement learning algorithm is applied.

C. Role of Reinforcement Learning

As described in Section III, the reinforcement learning mechanism allows one to set the average value of an objective and measurable parameter $\mathrm{P_I(t)}$ (i.e., dissatisfaction probability) to a target value $\mathrm{P_I^*}$. The objective of the experiment described in this section is to show that the target rate $\mathrm{P_I^*}$ can be set to any desired value (i.e., $\mathrm{P_I^*} = 1\%$, 3%, 10%), and the system is able to maintain this value during the whole simulation time, as shown in Fig. 11.

Furthermore, during the simulation time, in Fig. 11, the fuzzy neural system 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 a situation in which 100 users are moving around the scenario and demanding service. In addition to this, at simulation frame 1 000 000, 50 more users join the scenario. Notice that, at the beginning of the simulation, a transient period after which the fuzzy neural machine converges to the desired QoS condition occurs, whereas, in correspondence with the second traffic change, the user dissatisfaction does not significantly vary. The reason is that the reinforcement learning 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 dissatisfaction is maintained at the desired rate, in spite of the changes in the environment situation.

D. Role of Inference Rules

As pointed out in Section III, the JRRM decision policies are expressed by means of the fuzzy control rules associated with the fuzzy inference engine. The results shown up to now have been obtained considering a set of inference rules referring to a situation where the UMTS RAT is preferred rather than the GERAN RAT. An illustrative subset of the 432 rules is shown in Table II.

If these rules are changed, a different distribution of the traffic is obtained. This means that the operator could select different inference rules according to specific operator policies or business models to match the particular operational needs.

In order to prove that the decision policies stated by the inference rules (IR) can modify the traffic distribution in the scenario, a new scenario characterized by nine carriers in GERAN, in order to offer a similar capacity to the one offered by UMTS, is considered. In this scenario, three sets of inference rules will be considered. The first one (UMTS Priority IR), shown in Table II, gives a higher priority to the UMTS selection; the second one (GERAN Priority IR) gives a higher priority to the GERAN selection; and the third one (Balanced IR) aims at balancing the traffic among UMTS and GERAN RANs. In Tables III and IV, illustrative subsets of balanced IR and GERAN priority IRs are shown, respectively.

The design strategy in the proposed fuzzy rule bases (i.e., Tables II–IV) is that if the signal strength (SS) is low for a RAT, the user would not (N) be assigned to that RAT; otherwise, the resource availability defines the appropriateness of the assignment according to the selected decision policy. For example, if the MS is H, there would be no chance for WLAN to be selected, even though SS_{WLAN} and RA_{WLAN} are H. Additionally, if SS_{UMTS} and SS_{GERAN} are H as well as RA_{UMTS} and RA_{UMTS}, the user would be assigned accordingly to the selected decision policy. Based on the GERAN priority IR, the most appropriate choice would be GERAN $(D_{GERAN} = Y, D_{UMTS} = N)$, whereas, based on the UMTS priority IR, it would be UMTS $(D_{UMTS} = Y, D_{GERAN} = N)$. Notice that, if SS_{WLAN} is H and RA_{WLAN} is H, the WLAN would always be preferred with respect to the other RATs in the case of low-speed users due to the capacity increase attained at low cost.

Fig. 12 shows the aggregate bandwidth allocated in each UTRAN and GERAN base stations for the different inference rules.

It can be noticed that the traffic load per RAT and cell varies according to the different policies because the inference rules determine the RAT selection and the bit rate allocation. In particular, according to the GERAN and the UMTS priority IRs, the traffic is mainly distributed within GERAN and UMTS RATs, respectively, whereas, according to the balanced IR, the traffic distribution is almost uniform among the different RATs. As a result of that, an operator could balance the traffic in the network or give more impact to a particular RAT, preserving the same performances in terms of dissatisfied users and keeping the blocking and dropping probabilities to nearly comparable rates, as is shown in Table V.

E. Role of Multiple Objective Decision Making

The purpose of the experiment included in this section is to show how the multiple objective decision block is able to distribute the traffic among the available RATs according to multiple decision criteria. In particular, considering that besides radio interface related aspects, the JRRM decision should also depend on techno-economic and subjective criteria, such as the operator preference and the user demand. There are three criteria taken into account by the decision maker in this section: the FSD (the only one considered up to now), the OP, and the UD, as described in Section III.

TABLE II
UMTS PRIORITY INFERENCE RULES

IF							THEN				
SS_{UMTS}	SS_{GERAN}	SS_{WLAN}	RA_{UMTS}	RA_{GERAN}	RA_{WLAN}	MS	D_{UMTS}	D_{GERAN}	D_{WLAN}	B_{UMTS}	B_{GERAN}
H	H	L	H	L,M,H	L,M,H	L	Y	N	N	H	L
H	H	H	H	L,M,H	M	L	Y	N	PY	H	L
H	H	H	H	L,M,H	L	L	Y	N	PN	H	L
H	H	L,H	H	L,M,H	L,M,H	H	Y	N	N	H	L
H	H	H	H,M,L	L,M,H	H	L	N	N	Y	L	L

TABLE III
BALANCED INFERENCE RULES

IF							THEN				
SS_{UMTS}	SS_{GERAN}	SS_{WLAN}	RA_{UMTS}	RA_{GERAN}	RA_{WLAN}	MS	D_{UMTS}	D_{GERAN}	D_{WLAN}	B_{UMTS}	B_{GERAN}
H	H	L	H	H	L,M,H	L	Y	Y	N	H	H
H	H	L	H	M	L,M,H	L	Y	PY	N	H	M
H	H	L	H	L	L,M,H	L	Y	PN	N	H	L
H	H	H	H	H	M	L	Y	Y	PY	H	H
H	H	H	H	M	M	L	Y	PY	PY	H	M
H	H	H	H	L	M	L	Y	PN	PY	H	L
H	H	H	H	H	L	L	Y	Y	PN	H	H
H	H	H	H	M	L	L	Y	PY	PN	H	M
H	H	H	H	L	L	L	Y	PN	PN	H	L
H	H	L,H	H	H	L,M,H	H	Y	Y	N	H	H
H	H	L,H	H	M	L,M,H	H	Y	PY	N	H	M
H	H	L,H	H	L	L,M,H	H	Y	PN	N	H	L
H	H	L	M	H	L,M,H	L	PY	Y	N	M	H
H	H	L	L	H	L,M,H	L	PN	Y	N	L	H
H	H	H	M	H	M	L	PY	Y	PY	M	H
H	H	H	L	H	M	L	PN	Y	PY	L	H
H	H	H	M	H	L	L	PY	Y	PN	M	H
H	H	H	L	H	L	L	PN	Y	PN	L	H
H	H	L,H	M	H	L,M,H	H	PY	Y	N	M	H
H	H	L,H	L	H	L,M,H	H	PN	Y	N	L	H
H	H	H	H,M,L	H,M,L	H	L	N	N	Y	L	L

TABLE IV
GERAN PRIORITY INFERENCE RULES

IF							THEN				
SS_{UMTS}	SS_{GERAN}	SS_{WLAN}	RA_{UMTS}	RA_{GERAN}	RA_{WLAN}	MS	D_{UMTS}	D_{GERAN}	D_{WLAN}	B_{UMTS}	B_{GERAN}
H	H	L	L,M,H	H	L,M,H	L	N	Y	N	L	H
H	H	H	L,M,H	H	M	L	N	Y	PY	L	H
H	H	H	L,M,H	H	L	L	N	Y	PN	L	H
H	H	L,H	L,M,H	H	L,M,H	H	N	Y	N	L	H
H	H	H	L,M,H	L,M,H	H	L	N	N	Y	L	L

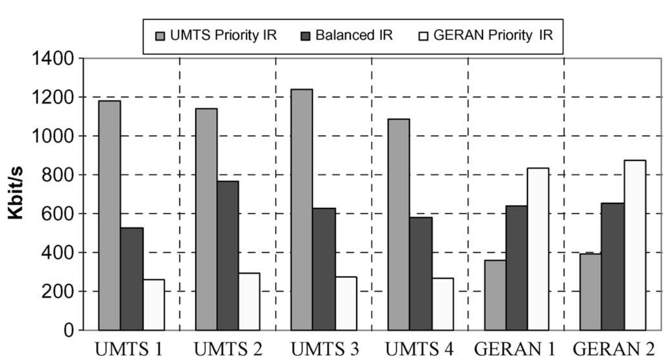

Fig. 12. Result of different inference rules' policies.

The simulations considered here assume 50 users in the scenario with four GERAN carriers in each cell. Implementation 3 and UMTS priority IRs are considered. It is supposed that both the users and the operator prefer the GERAN choice, according to the following membership values: $OP_{WLAN} = 0.1$, $OP_{UMTS} = 0.1$, $OP_{GERAN} = 0.9$, and $UD_{WLAN} = 0.1$, $UD_{UMTS} = 0.1$, $UD_{GERAN} = 0.9$.

TABLE V
BLOCKING AND DROPPING PROBABILITY FOR DIFFERENT INFERENCE RULES

	UMTS Priority IR	Balanced IR	GERAN Priority IR
Blocking (%)	1.06	0.91	1.61
Dropping (%)	1.42	1.03	1.81

In addition, a number is assigned to each criterion that is indicative of its importance in the decision. The matrix describing the relative importance of each criterion is shown in (40). The

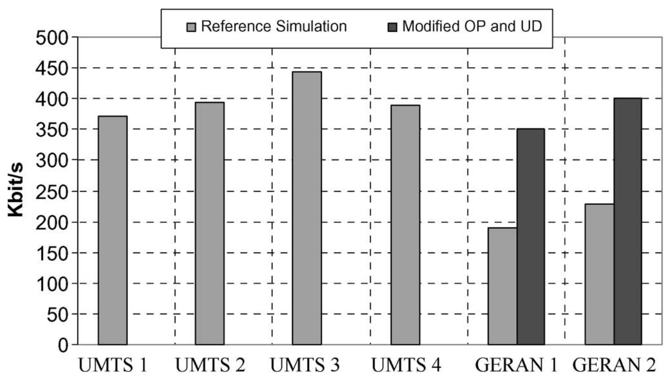

Fig. 13. Impact of OP and UD criteria in the traffic distribution.

first row in the matrix refers to the FSD criterion, the second row to the UD criterion, and the third row to the OP criterion.

$$B = \begin{bmatrix} 1 & 1/3 & 1/3 \\ 3 & 1 & 1 \\ 3 & 1 & 1 \end{bmatrix}. \tag{40}$$

According to (40), the UP and OP criteria are three times more important than the FSD criterion, and both criteria strongly prefer the GERAN decision rather than any other option. As a result, GERAN RAT is expected to be selected with higher probability than UMTS and WLAN. In practice, (40) can be changed dynamically in a rather slow way, and the membership values would depend on the user profile and the operator business models.

Fig. 13 shows that, with this new configuration, GERAN bandwidth assignment has grown, whereas UMTS RAT has never been selected, which is a consequence of the fact that the most important criteria for RAT selection are now UD and OP, which strongly prefer the GERAN assignment. In this case, both blocking and dropping probabilities are retained to 0.11%. In addition to this, it is worth mentioning that the dissatisfaction probability in both cases achieves the convergence to the target value of 10%.

F. Role of Different Implementation Types

In the following results, the four possible implementations mentioned in Section IV are analyzed and compared in terms of performances. In all cases, the dissatisfaction probability is retained to 10%. To this end, the blocking and dropping probabilities versus number of users resulting from applying the four schemes are depicted in Figs. 14 and 15.

With respect to the cell combination selection, it can be clearly observed that the fuzzy criterion (i.e., implementations 3 and 4) is more efficient than the signal strength criterion (i.e., implementations 1 and 2), which offers the lowest blocking and dropping probabilities. The reason is that the fuzzy criterion is able to take into consideration, by means of a comprehensive trade-off, more information in the decision, such as the load existing in each cell and the mobile speed. On the other hand, as long as a fuzzy neural system is considered for each combination (i.e., implementations 1 and 3), the percentage of users admitted in the scenario increases when compared to their counterpart of having a single fuzzy neural system per scenario.

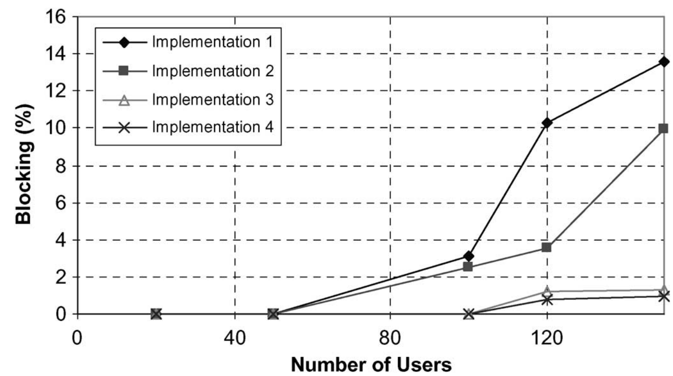

Fig. 14. Performance comparison of the different implementations in terms of blocking.

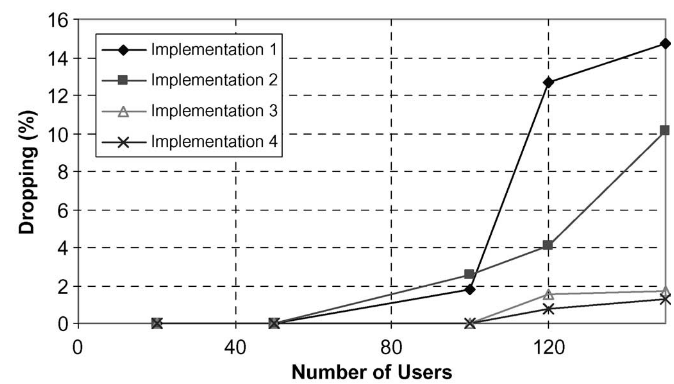

Fig. 15. Performance comparison of the different implementations in terms of dropping.

The reason is that, by means of different combinations, the specific characteristics of the traffic distribution in each instant of time are better captured.

G. Performance Comparison of the Proposed Fuzzy Neural Algorithm With Other Approaches

In order to compare the performances of the proposed fuzzy neural algorithm, four alternative algorithms are considered.

The first alternative algorithm, which does not take into account the JRRM concept, is denoted as non-JRRM (NJRRM). The either new or handoff call will be attached to a RAT randomly chosen among the ones in which the mobile measures a signal strength higher than the sensitivity. The second approach selects the RAT in which the mobile measures the lowest path loss, and it is denoted as path-loss-based JRRM algorithm (PLJRRM). Finally, the third approach takes into consideration the JRRM concept by aiming at balancing the cell load or resource occupation, as defined in Section III. Among the cells to which the either new or handoff user could be attached to according to a SS criterion, the least loaded RAT will be chosen. Then, the criterion is denoted as load-based JRRM (LJRRM). A conventional handoff initiation mechanism based on an signal strength threshold is considered for the three proposed algorithms.

The last JRRM approach, which is an optimization of the LJRRM algorithm, is based on [6] and [8]. It is referred to as LJRRM_Th. Besides considering a signal strength reason handover, LJRRM_Th takes into account a load reason handover.

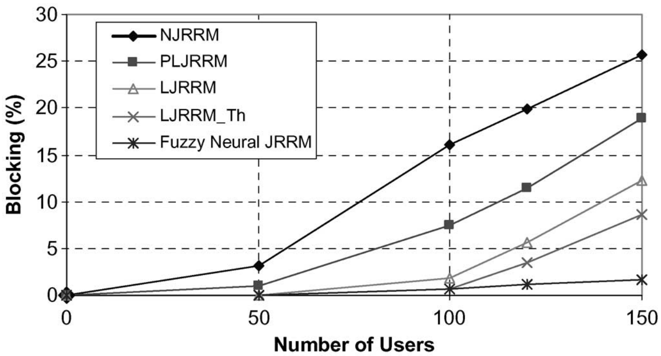

Fig. 16. Comparison between blocking probabilities.

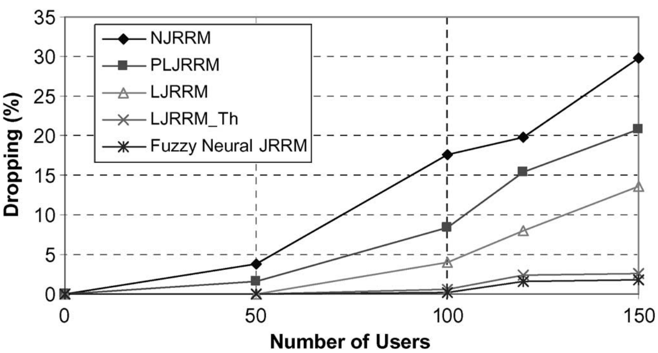

Fig. 17. Comparison between dropping probabilities.

To this end, a minimum load reason handover threshold is set to 80% load for each cell. If the current cell exceeds this threshold, the user could be handed over to another cell, thus aiming at a more effective load balancing procedure.

It is worth observing that, to the best of the authors' knowledge, even though it is possible to find in the open literature some JRRM frameworks able to perform RAT selection (i.e., [5] and [6]), no mechanism has been envisaged to assign variable bit rates during the user session, which is one of the innovative features of the proposed framework. Consequently, and in order to make a fair comparison, the alternative algorithms presented assign to the mobile users a constant bit rate equal to the average rate assigned by the fuzzy neural JRRM in case of maximum number of users considered (i.e., 150 users), which is 220 Kb/s and 56 Kb/s in the UMTS and GERAN cells, respectively.

In Figs. 16 and 17, the comparisons of performances are shown as a function of the number of users moving around the scenario. A dissatisfaction probability of 1% is considered in order to compare the blocking and dropping performances. The results clearly show the benefits offered by the proposed fuzzy neural JRRM in front of the other alternatives. In fact, with respect to the PLJRRM and LJRRM algorithms, the fuzzy-based approach allows one to take into account all the heterogeneous technical inputs that could affect the JRRM decision (i.e., cell load and signal strength). In addition, with respect to the LJRRM_Th, which takes into account load-based handovers besides the signal-strength-based ones, the fuzzy neural JRRM is characterized by more flexibility in the JRRM decisions, thanks to the capability of learning from experience and interacting with the environment embedded in the neural network.

It is also worth mentioning that, even though, according to the alternative JRRM strategies presented, the admitted users are always satisfied, because the allocated bit rate is constant and higher than the desired one, this is at the expense of a very high increase in both the dropping and blocking probabilities. On the other hand, the fuzzy neural JRRM algorithm allows keeping the dissatisfaction probability to the desired value (i.e., 1%) while achieving, at the same time, much lower dropping and blocking probabilities.

VI. Conclusion

In this paper, a fuzzy neural JRRM strategy for a multicell and multi-RAT scenario, including the UMTS, GERAN, and WLAN radio access technologies, has been proposed. The algorithm operates in two steps in order to select the most suitable RAT and cell to which each mobile should be attached. The first step selects a combination of three cells built around the three considered radio access technologies. To this end, a fuzzy-based approach has been proven to be more effective than a signal strength criterion. During the second step, the proposed JRRM selects the most appropriate RAT among the three considered and allocates a granted bit rate to each user. The role of each element of the discussed fuzzy neural system has been described in detail. Furthermore, the proposed algorithm allows implementing different operator policies as well as technical and subjective criteria, such as the operator and user preferences when performing the RAT selection by means of appropriate inference rules and a multiple decision mechanism. Moreover, a reinforcement learning mechanism is used in order to tune the considered membership functions, allowing the system to keep a defined QoS parameter to a contracted value. In particular, the proposed JRRM algorithm is able to keep the dissatisfaction probability to a target value under different varying conditions in terms of traffic, mobility, propagation, etc. Finally, the proposed algorithm has been compared to four alternative JRRM algorithms, showing that the discussed framework is able to keep a desired value of user dissatisfaction probability while, at the same time, having low values of dropping and blocking probabilities.

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Lorenza Giupponi (M'05) received the Engineer of Telecommunications degree from the University of Rome, "La Sapienza," Rome, Italy, in July 2002 and the Ph.D. degree from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in May 2007.

In 2003, she joined the Radio Communications Group of UPC, with a grant from the Spanish Educational Ministry, where she is currently an Assistant Professor with the Department of Signal Theory and Communications. Her research interests are in the field of mobile communication systems with an emphasis on radio resource and quality-of-service (QoS) management in heterogeneous networks.

Ramon Agustí (M'78) received the Engineer of Telecommunications degree from the Universidad Politécnica de Madrid, Madrid, Spain, in 1973 and the Ph.D. degree from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 1978.

In 1973, he joined UPC as Assistant Professor, and he became Full Professor in 1987. After graduation, he worked in the field of digital communications, with particular emphasis on transmission and development aspects in fixed digital radio, both in radio relay and mobile communications. For the last 15 years, he has been involved with mobile communication systems and has published about 200 papers in this area. He participated in the European programs COST 231 and COST 259 as the Spanish representative. He has also participated in the RACE, ACTS, and IST European research programs as a representative of his university as well as in many privately and publicly funded projects at the national level. He received the Catalonia Engineer of the year prize in 1998 and the Narcis Monturiol Medal in 2002 for his research contributions to the mobile communications field. He is part of the editorial board of several scientific international journals and has co-authored two books on mobile communications. In 2006, he headed the Inter-Ministerial Council for Research and Technological Innovation (CIRIT) of Catalonia.

Jordi Pérez-Romero (M'04) received the Engineer of Telecommunications and the Ph.D. degrees from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in December 1997 and April 2001, respectively.

In 1998, he joined the Radio Communications Group, with a grant from the Spanish Educational Ministry, and is currently an Associate Professor with the Department of Signal Theory and Communications at UPC. His research interests are in the field of mobile communication systems, especially packet radio techniques, spread-spectrum systems, radio resource and quality-of-service (QoS) management, and heterogeneous wireless networks. He has been involved in different European projects (WINEGLASS, ARROWS, EVEREST, E2R, NEWCOM, and AROMA) as well as in projects for private companies like Telefónica and Alcatel. He is the author of several published articles as well as the book *Radio Resource Management Strategies in UMTS*.

Dr. Pérez-Romero is currently the Associate Editor of *IEEE Vehicular Technology Magazine*.

Oriol Sallent Roig received the telecommunications engineer and Ph.D. degrees in 1994 and 1997, respectively, both from Universitat Politècnica de Catalunya, Barcelona, Spain.

He is an Associate Professor with the Universitat Politècnica de Catalunya. His research interests are in the field of mobile communication systems, especially radio resource and spectrum management for heterogeneous networks. He has published more than 100 papers in international journals and conferences. He has participated in several research projects of the 5th, 6th, and 7th Framework Programme of the European Commission and has served as a consultant for a number of private companies.