Supervised Learning for a Fuzzy Neural Network Implementing Joint Radio Resource Management in a Multi-Radio Access Technology Scenario

L. Giupponi, R. Agustí, J. Pérez-Romero, O. Sallent
Universitat Politècnica de Catalunya (UPC)
c/ Jordi Girona, 1-3, Campus Nord, 08034, Barcelona, Spain
email: [lorenza.giupponi, ramon, jorperez, sallent]@tsc.upc.edu

Abstract

This paper focuses on the analysis of the training mechanisms of a Fuzzy Neural Network (FNN) designed to perform Joint Radio Resource Management (JRRM) in a multi-Radio Access Technology (multi-RAT) scenario. Two supervised learning algorithms based on reinforcement learning mechanisms are presented. The first one modifies the membership function shapes (i.e. the mean and standard deviation parameters) in order to minimize a particular error function. The second one, according to the same guiding principle, is as well capable of modifying the structure of the FNN, either adding granularity to the fuzzy description of the output linguistic variables (i.e. adding new nodes), or modifying the consequences inferred by the fuzzy control rules. Simulation results will show that the Fuzzy Neural JRRM performances can be improved by means of the proposed on-line structure/parameter learning algorithm.

Keywords: Joint Radio Resource Management, RAT Selection, QoS, Supervised learning.

1 Introduction

In the forthcoming heterogeneous wireless scenarios, the multiple available access systems will be combined on a common platform in an optimum way according to the Always Best Connected (ABC) concept [1]: the perspective of Beyond 3G networks is to allow users to access any kind of wireless service in any geographical location at any given time by making use of the multiplicity of access technologies together with terminals with reconfigurability capabilities [2]. The internetworking among different Radio Access Technologies (RATs) proposed in the Beyond 3G networks introduces a new dimension in the radio resource management. New algorithms taking into account the overall amount of resources in the RATs have to be introduced. In this scenario, Joint Radio Resource Management (JRRM) is the identified process to manage dynamically and co-ordinately the allocation and de-allocation of radio resources (e.g. time slots, codes, frequency carriers, etc.) between different RATs for the spectrum bands allocated to each of these systems so that a more efficient usage of the radio resources will follow.

The development of JRRM solutions should deal with imprecise and dissimilar information in order to make appropriate decisions on e.g. RAT and bandwidth allocation. In fact, the key driving inputs of the decision making process, such as the received pilot signal and the cell loads may not be comparable for the different RATs. In addition to this, the QoS versus cost qualitative information as perceived by the user, as well as the operator policies can impact the RAT decision. As a result of that, fuzzy logic, which has been proved to be able to provide an effective mean of capturing the approximate and inexact nature of complex problems, has been considered as an appropriate candidate to solve the JRRM problem. However, the performances of a Fuzzy Controller depend on the way it is designed, particularly on the size of the term sets, on the membership function shapes and on the Fuzzy Inference rules, which keep a certain subjectivity in the way how they are set. Therefore, and to avoid this subjectivity, our proposal also takes into account reinforcement learning mechanisms based on Neural networks, which tune the membership function shapes and consequently the input/output variables of the fuzzy control rules. This innovative Fuzzy Neural JRRM algorithm has already been presented by the authors in [3][4], where the Fuzzy Neural Network (FNN) modifies the values of the parameters (i.e. membership function shapes) by means of the reinforcement learning algorithm to maintain a desired QoS constraint, thus constituting a parameter learning approach. However, the modification of the structure of the network in the learning procedure is not considered in the previous studies. Then, as a difference from the previous publications in which the FNN structure is an input of the JRRM algorithm, this paper analyses the benefits that can be obtained by introducing a combined structure and parameter learning approach in a FNN-based JRRM algorithm.

Hybrid learning algorithms for neural networks have been used in different applications in the literature. Specifically, in [5] a hybrid learning algorithm combining an unsupervised learning algorithm to first train the network and a supervised learning procedure to tune the membership function shapes has been presented. The hybrid learning algorithm performs well if the training data are available off-line. Nevertheless, for the JRRM application, it is not possible to obtain a precise training data file to set up the neural network because 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. These training data would be difficult and expensive to obtain off-line. Furthermore, this approach does not have the ability to change the network structure dynamically, which may be foundational for the JRRM application in a heterogeneous reconfigurable network. Therefore, a different approach based on an on-line supervised structure/parameter learning algorithm and already proposed in [6] is here retained as a solution for the JRRM FNN training. This approach combines the error back propagation algorithm for the parameter learning (i.e. modification of means and standard deviations of the membership functions used in the fuzzification and defuzzification processes) with the fuzzy similarity concept to determine the degree of equality of two fuzzy sets in order to perform the structure learning (i.e. the inclusion of new additional membership functions to define the output linguist variables and the modification of the consequences of the fuzzy inference rules). So the proposed supervised structure/parameter learning algorithm can learn the proper size of the output linguistic variable term sets, the correct fuzzy inference rules and membership functions.

The rest of the paper is organized as follows. Section 2 introduces the proposed Fuzzy Neural JRRM algorithm, whose main functionalities, respectively the Fuzzy Logic Controller (FLC) and the On-line supervised structure/parameter learning algorithm, are presented in Section 3 and Section 4. Section 5 describes the multi-RAT scenario where the proposed strategy is evaluated. Section 6 is devoted to present some representative results. Finally, Section 7 summarizes the conclusions.

2 Fuzzy Neural JRRM algorithm

The proposed JRRM algorithm operates in a heterogeneous scenario with three available RATs, namely UMTS (Universal Mobile Telecommunications System), GERAN (GSM EDGE Radio Access Network) and WLAN (Wireless Local Area Network) and the objective is to provide, for each user, the most appropriate RAT and bit rate allocation, taking into account the user Quality of Service (QoS) constraints as well as different measurements. The Fuzzy Neural feature allows the introduction of learning procedures that provide the system with adaptive capabilities to achieve specific QoS requirements. Specifically, the proposed algorithm consists of the blocks shown in Figure 1 and identified as Fuzzy Logic Controller (FLC) and Reinforcement Learning.

It is assumed that the three RATs are numbered as follows: j=1 for UMTS, j=2 for GERAN and j=3 for WLAN, and the input linguistic variables of the algorithm are the signal strength SS_j (j=1,2,3) and the amount of resources available RA_j in each RAT (the concept of “resource availability” is RAT-dependant and will be detailed in Section 5 for each specific RAT), together with the mobile speed MS. Furthermore, the reinforcement learning algorithm operates according to the measured user dissatisfaction probability, $P_I(t)$, here defined as the probability that the bit rate allocated to a user is below a threshold specified in its Variable Bit Rate service contract.

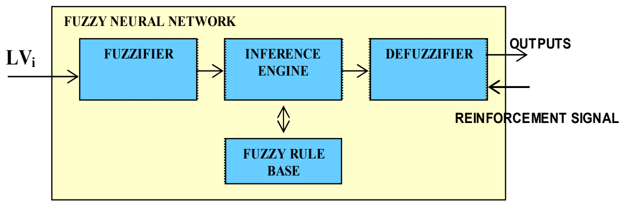

Figure 1 Procedures in the proposed JRRM algorithm

In the following sections, the FLC and the supervised learning algorithm based on reinforcement learning mechanisms will be detailed.

3 Fuzzy Logic Controller

The fuzzy-based decision procedure operates in three steps, namely fuzzification, inference engine and defuzzification, which can be graphically represented by means of a 5-layered network structure shown in Figure 2. The i-th of the FLC k-th layer is characterized by p input signals u_i^k, by an integration function $f_i^k\left(u_1^k, u_2^k, \ldots, u_p^k\right)$, which combines the different inputs and by an activation function $a_i^k(f)$, which provides the output. Notice that p is the number of the *(k-1)*-th layer nodes connected to the i-th node in the k-th layer. In the following, the characterization of the different layers defining the FLC implementing the proposed JRRM algorithm is presented.

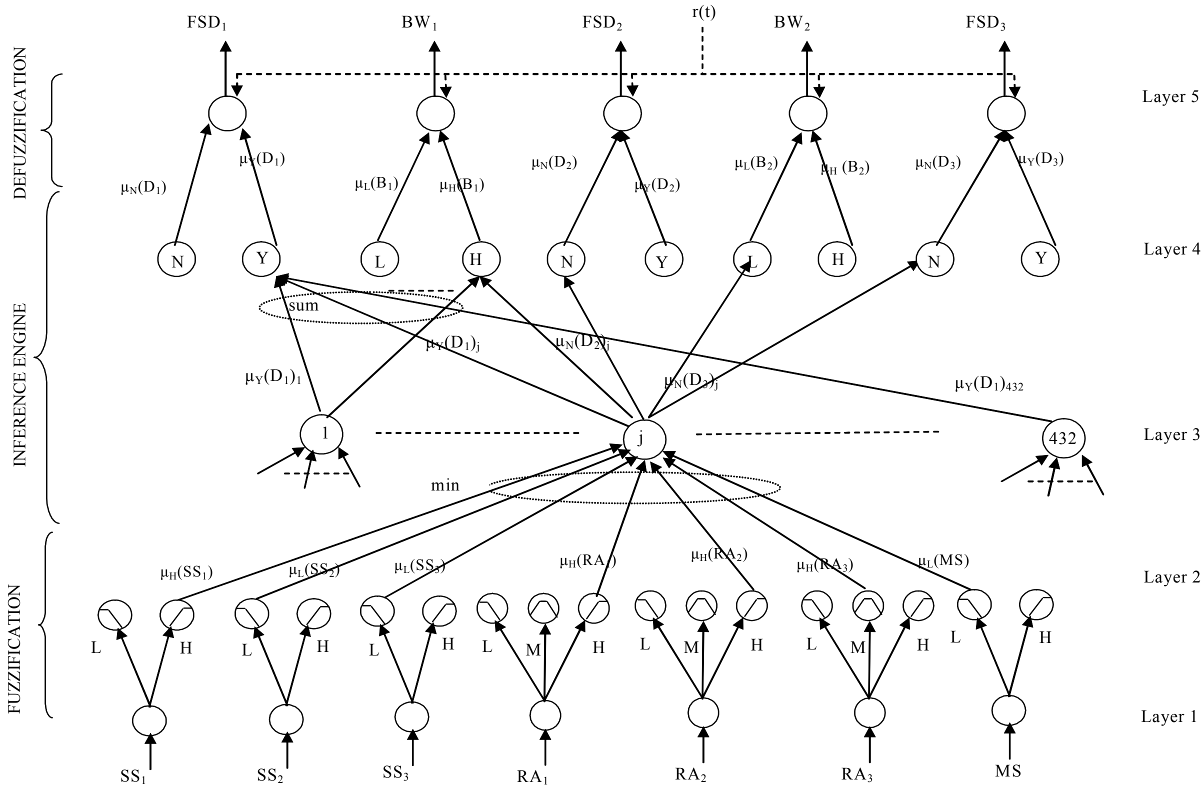

Figure 2 Layered Fuzzy Neural Structure ($\mu_X(y)$ represents the degree of membership of LV_i y to the fuzzy set x

Layer 1. In this layer there are as many nodes as the number of input linguistic variables (LV_i), i.e. 7 in the considered approach. The nodes in this layer just transmit input values to the next layer, so that:

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

$$a_i^1 = f_i^1 \qquad i=1,\ldots,7 \tag{2}$$

Layer 2. The nodes in this layer execute the fuzzification procedure, which assigns to each input linguistic variable a value between 0 and 1 corresponding to the degree of membership in a given fuzzy set. For the signal strength SS_j (j=1,2,3) input linguistic variables, the term set contains the fuzzy sets L(low) and H(high). For the resource availability RA_j (j=1,2,3) variables the fuzzy sets are L(low), M(medium) and H(high) reflecting that a higher level of granularity is required for this input since it has a stronger impact over the resource allocation. Finally, for the mobile speed MS, the fuzzy sets are L(low) and H(high). The speed is used only as an indication for the RAT selection in the sense that some RATs (e.g. WLAN) may not be appropriate for high speed users. However, not much granularity is required when using this parameter. The selected term sets lead to a total of 17 layer 2 nodes in the FNN. Each layer 2 node performs a bell-shaped membership function defined by:

$$f_i^2 = \frac{\left(u_i^2 - m_i^2\right)^2}{\left(\sigma_i^2\right)^2} \qquad i=1,\ldots,17 \tag{3}$$

$$a_i^2 = e^{-f_i^2} \qquad i=1,\ldots,17 \tag{4}$$

where m_i^2 and σ_i^2 are respectively the mean and variance of the bell-shaped function associated to the *i*-th node in layer 2.

Layer 3. This layer corresponds to the inference engine, which is the control mechanism that applies the *if-then* fuzzy inference rules in the fuzzy rule base. Each rule is associated with a node in layer 3 and the 7 inputs to this node are the precondition of the fuzzy inference rule. According to the input linguistic variable term set dimension, layer 3 consists of $2 \cdot 2^3 \cdot 3^3 = 432$ nodes. The function of a layer 3 node is:

$$f_i^3 = \min\left(a_n^2\right) \ \forall \text{layer2 node } n \text{ linkedto layer3 node } i \tag{5}$$

$$a_i^3 = f_i^3 \tag{6}$$

where i=1,…,432. The output connections of layer 3 nodes are the consequences inferred by the fuzzy rules, which provide a linguistic indication D_j (*j*=1,2,3) of the suitability of selecting each RAT and an indication B_j (*j*=1,2) of the bit rate to allocate. Notice that with respect to the bandwidth no specific allocation is given in case of WLAN (j=3) as much as IEEE 802.11b can not guarantee any rate. Nevertheless, the extension to include also bandwidth allocation in WLAN would be straightforward. The dimension of the term sets for D_j and B_j can be increased by the structure learning procedure. The initial simple structure designed consists of the following fuzzy sets for D_j: Y(yes), and N (not). In turn, for B_j they are L(low) and H(high).

Layer 4. In the forth layer the degree of membership of the consequent parts of the fuzzy rules is calculated by a fuzzy OR operation integrating the inputs coming from the layer 3 nodes that have the same consequence. The initial simple FNN structure considered consists of 10 nodes at layer 4.

$$f_i^4 = \min(1, \sum_{n \in Ci} a_n^3) \qquad i=1,\ldots,10 \tag{7}$$

$$a_i^4 = f_i^4 \qquad i=1,\ldots,10 \tag{8}$$

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

Layer 5. The output of the inference engine is so far a fuzzy set, so that a defuzzification procedure is necessary to transform the fuzzy quantities into crisp values. Each node of layer 5 carries out the defuzzification procedure, which provides, for each RAT, an indicator of the suitability to select it, denoted as Fuzzy Selected Decision (FSD), and the allocated bit rate. There is a total of 5 nodes in this layer. For the three nodes providing the FSD, (i.e. FSD_1 for UMTS, FSD_2 for GERAN and FSD_3 for WLAN) the function is:

$$FSD_i = \frac{\sum_{j \in T_i} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in T_i} m_j^5 u_j^5} \qquad i=1,2,3 \tag{9}$$

where T_i is the set of layer 4 nodes connected with the considered layer 5 node. m_j^5 and σ_j^5 are the centers and the widths of membership functions. Similarly, for the two nodes providing the allocated bit rate the function is:

$$BW_i = BW_{i,MAX} \cdot \frac{\sum_{j \in W_i} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in W_i} m_j^5 u_j^5} \qquad i=1,2 \tag{10}$$

$BW_{i,MAX}$ is the maximum bit rate that can be allocated in the corresponding RAT. W_i is the set of layer 4 nodes connected with the considered layer 5 node.

4 On-Line Supervised Structure/Parameter Learning Algorithm

The proposed algorithm uses the fuzzy similarity measure to perform the structure learning and the backpropagation algorithm to perform parameter learning. At every JRRM decision making, the supervised learning algorithm is activated and first it is established whether or not to perform the structure learning. A new node (i.e. a new membership function) may be added in this case, otherwise just some fuzzy inference rule consequences may be properly modified. After the structure learning process, the current membership functions are adjusted by means of the parameter learning procedure already presented in [4]. Before the network is trained, the initial simple structure with 10 layer 4 nodes, introduced in section 3, is considered.

The goal of the supervised learning procedure is to minimize the error function given by:

$$E(t) = \frac{1}{2} r(t)^2 = \frac{1}{2}\left(P_I^* - P_I(t)\right)^2 \tag{11}$$

where $P_I(t)$ is the current measured dissatisfaction probability (i.e. the average ratio between the number of dissatisfied users and the total number of users) and P_I^* is its desired target value. Then, let 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:

$$w(t+1) = w(t) + \gamma\left(-\frac{\partial E(t)}{\partial w(t)}\right) \tag{12}$$

where γ is the learning rate.

At layer 5, the updated values for the mean and standard deviation for the i-th node are indicated as $m^5_{i\text{-}new}$ and $\sigma^5_{i\text{-}new}$

$$m_{i-new}^5(t) = m_i^5(t) + \gamma r(t) \cdot \frac{\sigma_i^5 u_i^5}{\sum_{j \in T_i} \sigma_j^5 u_j^5} \tag{13}$$

$$\sigma_{i-new}^5(t) = \sigma_i^5(t) + \gamma \cdot r(t) \cdot \frac{m_i^5 u_i^5 \left(\sum_j \sigma_j^5 u_j^5\right) - \left(\sum_j m_j^5 \sigma_j^5 u_j^5\right) u_i^5}{\left(\sum_j \sigma_j^5 u_j^5\right)^2} \tag{14}$$

In this step, the fuzzy similarity concept, introduced in section 4.1, is used in order to establish whether or not the FNN structure should be changed. In the following sub-sections, the fuzzy similarity concept and the way it is used to learn the FNN structure are introduced.

4.1 Fuzzy Similarity Measure

The fuzzy similarity measure *E(A,B)* of two fuzzy sets A and B with membership functions μ_A and μ_B indicates the degree of equality between A and B. *E(A,B)* takes values in the range [0,1] and the higher *E(A,B)* is, the more similar A and B are. Thus, *E(A,B)*=1, if A=B. The geometric derivation of the fuzzy similarity measure *E(A,B)* used in this paper is provided in [7].

4.2 Steps of the Supervised Structure/ Parameter Learning Algorithm

Based on the Fuzzy Similarity Measure concept introduced above, the proposed learning algorithm operates in the following steps at every decision making instant and for every pair $\left(m^5_{i-new}, \sigma^5_{i-new}\right)$.

Step 1- Find the closest node at layer 4

Among the current membership functions of the output linguistic variables, the procedure aims at finding the most similar one (i.e. that of the closest node) to the expected membership function, by measuring their fuzzy similarity. Let $M(m_i,\sigma_i)$ represent a bell-shaped membership function with mean m_i and standard deviation σ_i. Then, the selected node, denoted as *i-closest*, is the one having the maximum of this similarity, given by:

$$SIM = E\left[M\left(m^5_{i-new}, \sigma^5_{i-new}\right), M\left(m^5_{i-closest}, \sigma^5_{i-closest}\right)\right] = \max_{j\in T_i} E\left[M\left(m^5_{i-new}, \sigma^5_{i-new}\right), M\left(m^5_j, \sigma^5_j\right)\right] \quad (15)$$

Notice that T_i (i.e. the layer 4 nodes connected to the layer 5 node) contains 2 nodes when considering the initial simple structure introduced in Section 3.

Step 2- Analysis of the Fuzzy Similarity Measure

After the most similar membership function $M\left(m^5_{i-closest}, \sigma^5_{i-closest}\right)$ to the expected membership function $M\left(m^5_{i-new}, \sigma^5_{i-new}\right)$ has been found, the following adjustments are made:

- If the degree of similarity SIM is below a value α properly selected, then a new node (i.e. a new membership function) $M\left(m^5_{i-new}, \sigma^5_{i-new}\right)$ has to be created at layer 4, and this will be now the *i-closest* node. Besides, the structure learning process to properly modify the inference rules taking into account the new node and detailed in the following subsection 4.3, has to be executed.
- Otherwise, if the degree of similarity SIM is higher than a value α, and the *i-closest* node is not the *i*-th node the learning procedure is dealing with, no additional nodes are added, but the structure learning defined in the following sub-section 4.3 has to be executed in order to modify some consequences inferred by some inference rules.
- If none of the previous conditions is satisfied (i.e. the degree of similarity SIM is higher than α and the *i-closest* node is the *i*-th node), then the following parameter adjustments are made effective:

$$m^5_i(t+1) = m^5_{i-new}(t) \text{ and } \sigma^5_i(t+1) = \sigma^5_{i-new}(t) \quad (16)$$

Step 3- Layer 2 Parameter Learning

From layer 3 only the parameter learning is performed. In layer 4 and 3 there are no parameters to tune. In relation to the membership functions of layer 2, the error term given by (11) that is propagated from the top to the bottom of the multilayered structure, the partial derivatives and the adaptive rules for a generic mean and dispersion of the *i*-th node of layer 2 are given in [4].

4.3 Structure Learning

When entering this process, it means that the *i*-th term node in layer 4 is not properly assigned as consequence of some fuzzy inference rules and, on the contrary, its more proper consequence should be the *i*-closest node. It should be mentioned that in this procedure only those rules having one or more consequences with a degree of membership higher than a threshold β are considered for modification. The reason of this is that only these rules have consequences with a degree of membership high enough to contribute to the wrong result of judgment.

So, let consider the *i*-th node at layer 4 which has inputs from the *j*-th node at layer 3. Let a^3_j be the degree of membership of the *j*-th rule (node) at layer 3. If $a^3_j(t) \geq \beta$, then the consequences of the *j*th rule node should be changed from the *i*-th to the *i-closest* node.

5 Scenario For JRRM Evaluation

In order to evaluate the effects of the on-line supervised structure/parameter learning algorithm over the Fuzzy Neural JRRM, a scenario consisting of three RATs, namely, UMTS, GERAN and WLAN, has been identified and modeled. Each cell is characterized by a circular coverage area. The cell radius for UMTS is 650 m, for GERAN is 1 Km and for WLAN is 150m. A mobility model with users moving according to a random walk model is adopted, with randomly assigned speed between 0 and 50 Km/h.

The 1800 MHz band is assumed for GERAN. Consequently, due to the proximity between UMTS and GERAN bands, the same propagation model can be considered for both systems. It is given by L(dB)=128.1+37.6log(d(Km)) [8]. The shadowing model considers a standard deviation of 7 dB and a decorrelation length of 20m. For WLAN, the propagation losses inside the hotspot are modelled by

L(dB)=20log(d(m))+40 [9]. The beginning and the end of the user activity periods are defined according to a Poisson scheme with an average arrival rate of 6 calls per hours and user, and average call duration of 180 s. The simulation time is measured in frames of 10ms. Results are presented for the uplink direction. A single UTRAN FDD carrier is considered for UMTS, with a maximum uplink factor of 0.75. For GERAN, four carriers are considered, using coding scheme CS-4, thus having a maximum aggregated bit rate in each cell of 640 Kb/s. The considered potential bit rates are:

UMTS: {32, 48, 64, 80, 96, 112, 128, 192, 256, 320, 384} Kb/s

GERAN: {32, 48, 64, 80, 96} Kb/s

For WLAN, a single access point is considered and the total bandwidth available (i.e.11 Mb/s) is equally shared by the users assigned to this RAT.

The resource availability used as input of the Fuzzy Neural algorithm is defined for UMTS as $RA_1=1-\eta_{UL}$, where η_{UL} is the uplink cell load factor [10]. For GERAN, $RA_2=640-\rho$, where ρ is the current amount of Kb/s already allocated in the corresponding cell. Finally, for WLAN, $RA_3=28-\rho$, where ρ is the number of users currently allocated in WLAN.

The retained performance measurements are:

- Service dissatisfaction: A user is not satisfied either when the allocated bit rate is below the contractual bit rate (i.e. 192 kb/s for UMTS and 40 kb/s for GERAN) or when the allocated bit rate is higher than the contractual bit rate but the user is in outage. A user is in outage in UMTS whenever the required transmission power is higher than 21 dBm the maximum power available at the terminal. In turn, in GERAN and WLAN, the user is in outage when the received power is below the sensitivity, defined as -87 dBm for GERAN and -93 dBm for WLAN.

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

- Dropping: A user is dropped if after a change in the camping cell, the JRRM algorithm assigns a bit rate of 0Kb/s.

6 Discussion and Results

In order to show the benefits that can be obtained by means of the on-line supervised structure/parameter learning algorithm, simulation results expressed in terms of blocking and dropping performances are compared to the ones obtained by the FNN with only parameter learning (i.e. tuning the membership function shapes). In both cases, the FNN is first set up off-line in the following way: the term set dimension of the input/output linguistic variable is the one described in Section 3; the fuzzy inference rules are determined by the expert knowledge of the decision policies and the membership function initial shape is defined by the statistical clustering technique of Kohonen's feature-maps algorithm [11].

Figure 3 and Figure 4 plot the blocking and dropping probabilities as a function of the number of users in the scenario for the two considered approaches. It can be observed that the capability of learning from experience the most appropriate FNN structure allows providing a JRRM able to reduce blocking and dropping probabilities very significantly, as it is shown in Figure 3 and Figure 4.

These simulations have been carried out considering $\beta=0.45$ and $P^*=10\%$. In turn, the setting of the parameter α in the supervised learning strongly depends on the learning rate γ selected for layer 5 parameters. Particularly, the higher is γ, the faster the parameters of the different nodes will vary, which will impact on the threshold α to decide the addition of a new node. Consequently, it has been observed from previous experiments that an adequate setting of this threshold is $\alpha=1-0.5\gamma$, for $\gamma=10^{-4}$. On the other hand, and simply as a reference of the way how the FNN structure has been modified by the learning algorithm, when 45 users are moving in the scenario, it has been observed that the structure learning procedure has increased the number of layer 4 nodes from 10 to 30, thus obtaining a higher granularity in the description of the output linguistic variables. In addition to this, Figure 5 shows the evolution of the dissatisfaction probability for different target values P_I^*, revealing that the predefined QoS parameter P_I^* is kept constant thanks to the structure/parameter learning.

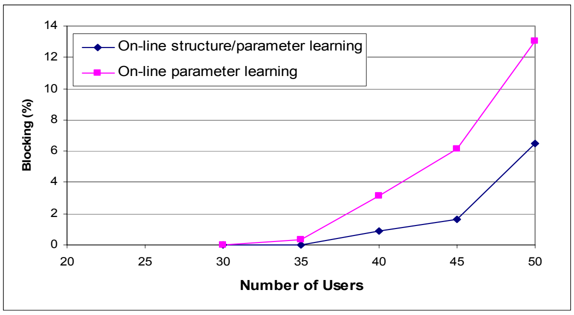

Figure 3 Blocking Performance Comparison

7 Conclusion

A supervised learning algorithm capable of modifying the structure and the parameters of a FNN implementing JRRM in a multi-RAT scenario has been presented. Reinforcement learning mechanisms allow maintaining to any desired rate a defined QoS parameter referred to as the dissatisfaction probability. Simulation results have shown that this procedure is able to improve performances, expressed in terms of blocking and dropping probability, with respect to a procedure applying just parameter learning. In addition to this, an on-line supervised learning algorithm is more suitable in a real-time environment, since it allows dynamic and automatic modifications of the structure of the FNN performing JRRM decisions, depending on the scenario conditions.

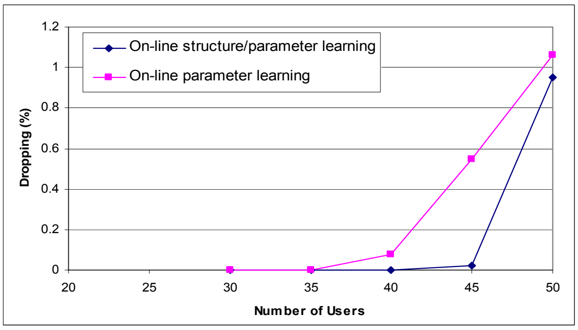

Figure 4 Dropping Performance Comparison

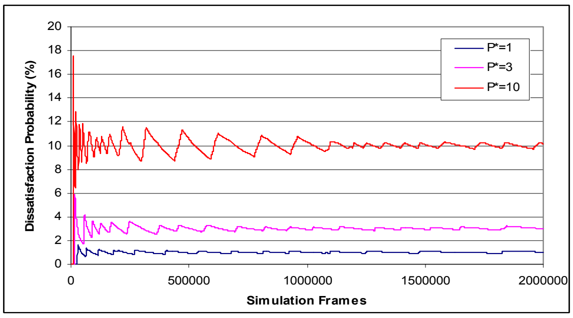

Figure 5 Behaviour of the evolution of dissatisfaction probability for different targets

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