Joint Radio Resource Management algorithm for multi-RAT networks

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 presents a joint radio resource management algorithm to operate in a heterogeneous network scenario including cellular and wireless local area network radio access technologies. It makes use of a methodology based on Fuzzy-Neural systems in order to carry out a coordinated management of the radio resources among the different access networks. In order to reveal the potentials of the proposed algorithm, it is compared with other strategies in a multicellular and multi-RAT scenario.**

I. Introduction

The perspective of Beyond 3G mobile communications 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 the day [1]. In addition to the need for a proper interworking among Radio Access Technologies (RATs), a new dimension is introduced into the Radio Resource Management (RRM) problem. That is, instead of performing the management of the radio resources independently for each RAT, some form of overall and global management of the pool of radio resources can be envisaged. Joint Radio Resource Management (JRRM) is the envisaged process to manage dynamically and coordinately the allocation and de-allocation of radio resources (e.g. time slots, codes, frequency carriers, etc.) between different radio access systems for the spectrum bands allocated to each of these systems, so that a more efficient usage of the radio resources will follow [2].

Not many approaches to the JRRM problem are available in the open literature so far. For example, [3] presents an interesting framework for the provision of JRRM algorithms dealing with the high complexity associated to heterogeneous networks. The benefit related to load balancing among the different RATs involved appears in [4][5]. Furthermore, the provision of cellular and IEEE 802.X Wireless Local Area Networks (WLAN) integration by means of tight coupling architecture has also been invoked to extend JRRM capabilities including non-cellular technologies [6]. However, the interest has been mainly focused on architectural aspects concerning JRRM and not many specific algorithms have been provided to assess relative improvements among different strategies even in simple scenarios.

In this paper a comprehensive JRRM treatment is presented in a mobile, multiuser, muticell and multi-RAT scenario, including a user centric approach, in the sense that a guaranteed contracted QoS is offered to the users regardless of their location and the RAT they are attached to. The variety of JRRM inputs, belonging to different RATs, will provide dissimilar information. Consequently, Fuzzy logic, good at explaining how to make suitable decisions from imprecise and dissimilar information, is a good candidate to deal with the JRRM problem because it is able to simplify a large state space of solutions by means of reasonable rules. However, these rules cannot be acquired automatically and the functions in charge of converting a crisp value into a fuzzy value are rather subjective. In order to overcome fuzzy logic limits, and considering that learning from interactions is a foundational idea in such uncertain scenarios, reinforcement learning mechanisms based on neural networks may also be applied. Neural networks are good at recognizing patterns, but, they find difficulties at explaining how they reach the decisions. Taking this into account, this paper introduces the combined use of two intelligent techniques [7][8], fuzzy logic based methodology and neural networks, thus proposing an innovative Fuzzy Neural based JRRM approach that incorporates admission control and bit rate allocation functions. In the preliminary work carried out by the authors [9][10] this approach has already been explored and assessed in simplified scenarios. In turn, this paper extends the previous works by considering a multi-cell scenario and comparing the proposed strategy with other reference JRRM algorithms.

The rest of the paper is organised as follows. In Section II the proposed Fuzzy Neural JRRM algorithm is detailed, focusing on the neural network structure that allows the application of a reinforcement learning mechanism. Section III presents the multi-cell and multi-RAT scenario where the proposed strategy is evaluated. Section IV is devoted to present some representative results, comparing the performance of the fuzzy-neural JRRM algorithm with other strategies. Finally, Section V summarises the conclusions.

II. Fuzzy Neural JRRM Algorithm

The proposed JRRM algorithm operates in a heterogeneous scenario with three available RATs, namely

UMTS, GERAN and WLAN and the objective is to provide, for each user, the most appropriate RAT and bit rate allocation, taking into account the user 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-Based Decision 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 IV for each specific RAT), together with the mobile speed MS. Furthermore, the reinforcement learning algorithm operates according to the measured user non-satisfaction probability, $P_l(t)$, defined as the probability that the bit rate allocated to a user is below a threshold specified in its contract.
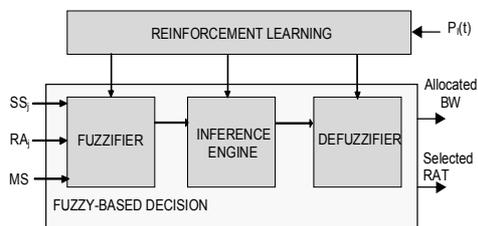

Figure 1 Procedures in the proposed JRRM algorithm

A. Fuzzy Based Decision procedure

The fuzzy-based decision procedure operates in three steps, namely fuzzification, inference engine and defuzzification [9], which can be graphically represented by means of a layered neural network structure as shown in Figure 2. The i-th node in the k-th layer ($k=1,...,5$) is characterised by a function $f_i^k(.)$ with input parameters u_1^k, $u_2^k,..., u_M^k$. These parameters are the outputs of the M nodes of the preceding layer that are connected with the considered node. In the following, 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. 7 in the considered approach. The nodes in this layer just transmit input values to the next layer, so that:

$$f_i^1 = u_i^1 \qquad i=1,\ldots,7 \qquad (1)$$

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 neural network, as depicted in Figure 2. The procedure to specify the initial membership functions employs the statistical clustering technique of Kohonen's feature-maps algorithm [11]. Each layer 2 node performs a bell-shaped membership function defined by:

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

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 executes some predefined *if-then* fuzzy rules, referred to as inference rules. The inference rules can be seen as implementations of network operator policies to balance the traffic distribution. Each rule is associated with a node in layer 3 and consequently with a combination that includes one term for each of the seven input linguistic variables. According to the Term sets dimension, layer 3 consists of 432 nodes, each of them having seven input connections coming from layer 2. The function of a layer 3 node is:

$$f_i^3 = \min\left(a_n^2\right) \ \forall \ \text{layer 2 node } n \text{ linked to layer 3 node } i \qquad (3)$$

where $i=1,\ldots,432$. The output connections of layer 3 nodes are defined by the inference rules, which provide, for each combination of terms, 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. The Fuzzy sets for D_j are Y(yes), PY (probably yes), PN (probably not) and N (not), in turn, for B_j they are L(low), M(medium) and H(high). An example of fuzzy rule is given in Table I. Notice that the fuzzy rule associated with a given combination, i.e. with a given layer 3 node, determines the connections of this node with the layer 4 nodes.

TABLE I EXAMPLE OF INFERENCE RULES

INPUT							OUTPUT				
SS_1	SS_2	SS_3	RA_1	RA_2	RA_3	MS	D_1	D_2	D_3	B_1	B_2
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

Layer 4. The nodes in layer 4 correspond to the different terms associated with the outputs of the inference engine, i.e. with the decisions D_j ($j=1,2,3$) and B_j ($j=1,2$), thus having a total of 18 nodes. The function of a layer 4 node is given by:

$$f_i^4 = \min(1, \sum_{n \in Ci} a_n^3) \qquad i=1,\ldots,18 \qquad (4)$$

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

Layer 5. Each node of this layer 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 or bandwidth. There are 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:

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

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 centres and the widths of membership functions. Similarly, for the two nodes providing the allocated bit rate the function is:

$$BW_i = BW_{i,MAX} \cdot \frac{\sum_{j \in W_i} m_j^5 \sigma_j^5 u_j^5}{\sum_{j \in W_i} m_j^5 u_j^5} \qquad i=1,2 \qquad (6)$$

$BW_{i,MAX}$ 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.

B. Reinforcement Learning procedure

This procedure is developed in order to determine appropriate values for m_j^2, σ_j^2, m_j^5 and σ_j^5 determining the membership functions in the different layer 2 and 5 nodes. After an initial selection, these parameters are dynamically adjusted according to a reinforcement signal $r(t)$ that depends on a desired output quality measurement, in our case the user non-satisfaction probability $P_I(t)$. In the layered Fuzzy Neural structure shown in Figure 2, this reinforcement signal is introduced at layer 5 and is propagated from top to bottom

in order to adjust the specific parameters in the lower layer nodes. In this paper, the reinforcement signal $r(t)$ is defined as the difference between $P_I(t)$, the current measured non-satisfaction probability at time t and P_I^*, the desired target value of this probability. Then, the goal of the reinforcement learning is to minimize the error function given by:

$$E(t) = \frac{1}{2} r(t)^2 = \frac{1}{2} \left(P_I^* - P_I(t) \right)^2 \qquad (7)$$

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:

$$w(t+1) = w(t) + \gamma \left(-\frac{\partial E(t)}{\partial w(t)} \right) \qquad (8)$$

where γ is the learning rate. The updating rule for the mean value m_j^5 is given by:

$$m_i^5(t+1) = m_i^5(t) + \gamma \cdot r(t) \cdot \frac{\sigma_i^5 u_i^5}{\sum_{j \in T_i} \sigma_j^5 u_j^5} \qquad (9)$$

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

$$\sigma_i^5(t+1) = \sigma_i^5(t) + \gamma \cdot r(t) \cdot \frac{m_i^5 u_i^5 \left(\sum_j \sigma_j^5 u_j^5 \right) - \left(\sum_j m_j^5 \sigma_j^5 u_j^5 \right) u_i^5}{\left(\sum_j \sigma_j^5 u_j^5 \right)^2} \qquad (10)$$

In relation to the parameters conforming the membership functions in layer 2, the adaptive rules for a generic mean and dispersion of the i-th node of layer 2 are given by:
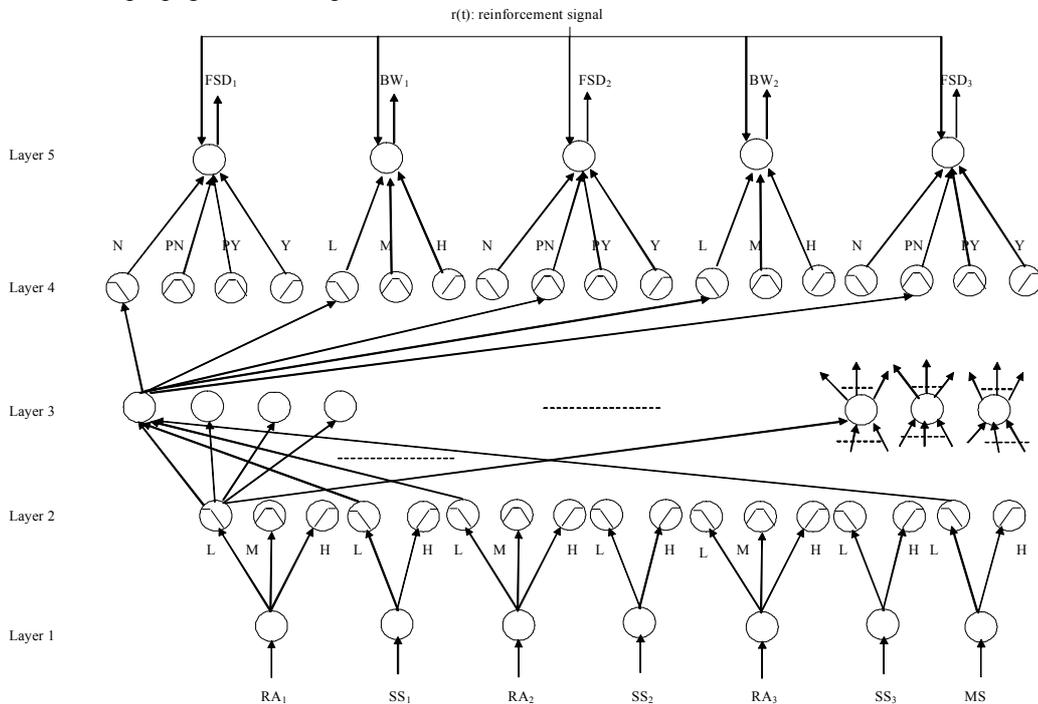

Figure 2 Layered Fuzzy Neural Structure

$$m_i^2(t+1) = m_i^2(t) + \gamma \delta_i^2 \cdot e^{f_i^2} \frac{2(u_i^2 - m_i^2)}{(\sigma_i^2)^2} \qquad (11)$$

$$\sigma_i^2(t+1) = \sigma_i^2(t) + \gamma \delta_i^2 \cdot e^{f_i^2} \frac{2(u_i^2 - m_i^2)^2}{(\sigma_i^2)^3} \qquad (12)$$

where it is defined the reinforcement signal propagated from layer 5 to layer 2 as follows:

$$\delta_i^2 = \frac{\partial E(t)}{\partial f_i^2} = \sum_n \frac{\partial E(t)}{\partial u_n^4} \sum_k \frac{\partial u_n^4}{\partial u_k^3} \frac{\partial u_k^3}{\partial f_i^2} \qquad (13)$$

where n=1,...,18 correspond to the layer 4 nodes, k=1,...,432 correspond to the layer 3 nodes and finally i=1,...,7 correspond to the layer 2 nodes. Furthermore, $\partial u_n^4 / \partial u_k^3$ is 1 if the k-th layer 3 node is connected with the n-th layer 4 node and 0 otherwise. Similarly, $\partial u_k^3 / \partial f_i^2$ is 1 if the i-th layer 2 node is connected with the k-th layer 3 node and 0 otherwise. Similarly, $\partial E(t)/\partial u_n^4$ is computed as:

$$\frac{\partial E(t)}{\partial u_n^4} = r(t) \cdot \frac{m_n^5 \sigma_n^5 \left(\sum_{j \in T_n} \sigma_j^5 u_j^5 \right) - \left(\sum_{j \in T_n} m_j^5 \sigma_j^5 u_j^5 \right) \sigma_n^5}{\left(\sum_{j \in T_n} \sigma_j^5 u_j^5 \right)^2} \qquad (14)$$

III. SCENARIO FOR JRRM EVALUATION

In order to evaluate the proposed JRRM Fuzzy Neural algorithm a multi-cell scenario has been identified and modelled. It includes 4 UMTS base stations, 2 GERAN base stations and one WLAN hot spot as illustrated in Figure 3 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 150 m.

A mobility model with users moving according to a random walk model inside the coverage area is adopted with a randomly assigned mobile speed between 0 and 50 km/h and a randomly chosen direction. The propagation model considered for UMTS and GERAN is given as a function to the distance d by L(dB)=128.1+37.6log(d(km)). The shadowing model considers a standard deviation of 7 dB and a decorrelation length of 20 m. For WLAN the propagation losses inside the hotspot are modelled by L(dB)= 20 log(d(m))+40. The beginning and the end of the user's activity periods are defined according to a Poisson scheme with an average of 6 calls per hour and user and an average call duration of 180 seconds.

Results are presented for the uplink direction. For UMTS the considered possible bit rates are 32 kb/s, 48 kb/s, 64 kb/s, 80 kb/s, 96 kb/s, 112 kb/s, 128 kb/s, 192 kb/s, 256 kb/s, 320 kb/s and 384 kb/s. A single carrier is reused in all the UMTS cells. Perfect power control is assumed with an Eb/No target of 3 dB and a maximum load factor of 0.75. In turn, for GERAN, the possible bit rates are 32 kb/s, 48 kb/s, 64 kb/s, 80 kb/s and 96 kb/s. Each GERAN cell contains four carriers, using coding scheme CS-4, thus having a maximum aggregated bit rate in each cell of 640 kb/s. For WLAN, a single access point is considered and the total bandwidth available (11 Mb/s) is equally shared by the users. It is also assumed that no more WLAN users are accepted when the bandwidth per user is less or equal than 384 kb/s.
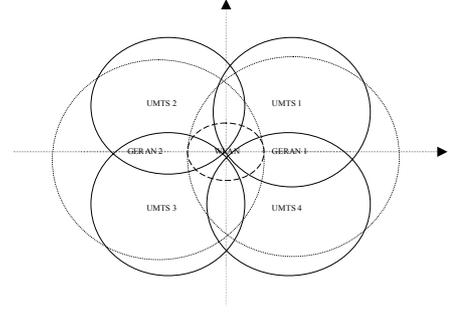

Figure 3 Considered Multicell scenario

The Fuzzy Neural algorithm is activated every 100 ms to re-allocate bandwidths and/or RATs to the currently admitted users as well as to include new users, so that the allocated resources can be changed dynamically. It is assumed that the JRRM procedure is executed for each user after selecting a combination of one UMTS cell, one GERAN cell and one WLAN access point. In particular, for each RAT, the cell with the highest signal strength at the user receiver is chosen.

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

The retained performance measurements are:

- Service non-satisfaction: 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 whenever, after a change in the serving cell, the JRRM assigns a bit rate of 0 kb/s.

IV. RESULTS AND DISCUSSION

The performance of the proposed Fuzzy Neural JRRM algorithm in the previously described scenario has been compared with three alternative algorithms. The first alternative algorithm does not take into account the JRRM concept, and it is denoted as Non-JRRM, (NJRRM). The users will be attached to a RAT randomly chosen among the

ones in which the mobile measures a signal strength (SS) higher than the sensitivity. The second approach is denoted as Load-based JRRM (LJRRM) and takes into consideration the JRRM concept by selecting the least loaded RAT from those fulfilling the minimum sensitivity criterion. Finally, the third approach selects the RAT in which the mobile measures the lowest path loss, and it is denoted as Path-Loss JRRM (PLJRRM). In all the three cases, once the RAT has been selected, the bandwidth assigned to each user is the maximum bandwidth considered for this RAT (i.e. 384 kb/s in UMTS, and 96 kb/s for GERAN).

Figure 4 and Figure 5 show the comparison of performances obtained through the execution of the four algorithms in terms of blocking and dropping probability as a function of the number of users in the scenario. A target non-satisfaction probability of P_I^*=1% is considered in the fuzzy-neural JRRM algorithm. As a result of that, the reinforcement learning algorithm is able to keep the non-satisfaction probability at this target value while keeping low dropping and blocking probabilities. On the contrary, in the rest of algorithms the admitted users are always satisfied, because the allocated bit rate is always the maximum available one. Nevertheless, this is at the expense of a very high increase in both the dropping and blocking probabilities.
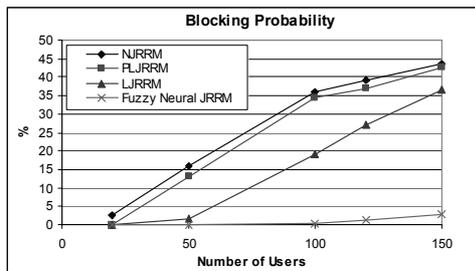

Figure 4 Blocking probability for the considered algorithms

In turn, Figure 6 presents the time evolution of the non-satisfaction probability with the fuzzy-neural JRRM algorithm for different target values P_I^*. It can be observed that the reinforcement learning is able to keep the non-satisfaction equal to the desired target in all the cases.

V. CONCLUSION

In this paper a Fuzzy Neural JRRM algorithm has been presented and analysed in a multi-cell scenario including UMTS, GERAN and WLAN access technologies. It has been shown that, in contrast to other JRRM algorithms, the proposed approach is able to keep a desired value of the user non-satisfaction probability while at the same time having low values of the dropping and blocking probabilities.
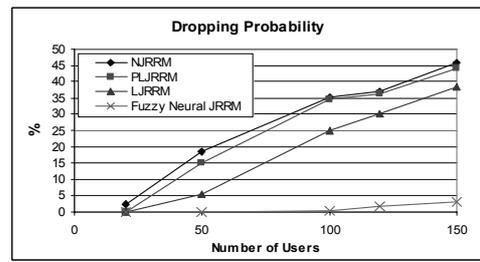
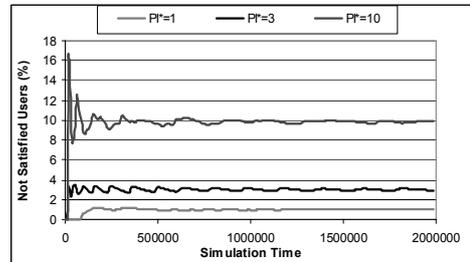## ACKNOWLEDGMENT

Figure 5 Dropping probability for the considered algorithms

Figure 6 Evolution of the non-satisfaction probability with the fuzzy-neural JRRM algorithm

REFERENCES

[1] E2R Project. http://e2r.motlabs.com

[2] J. Pérez-Romero, O. Sallent, R. Agustí, M. A. Díaz-Guerra, *Radio Resource Management Strategies in UMTS*, Ed. John Wiley & Sons, 2005

[3] P.M.L. Chan, R.E. Sheriff, Y.F. Hu, P. Conforto, C. Tocci, "Mobility Management Incorporating Fuzzy Logic for a Heterogeneous IP Environment", IEEE Communications Magazine, December 2001, pp. 42-51.

[4] 3GPP TR 25.881 v5.0.0 "Improvement of RRM across RNS and RNS/BSS (Release 5)"

[5] A. Tölli, P. Hakalin, H. Holma, "Performance Evaluation of Common Radio Resource Management (CRRM)", IEEE International Conference on Communications (ICC 2002), pp 112-124

[6] Q. Zhang, C. Guo, Z. Guo, W. Zhu, "Efficient Mobility Management for vertical Handoff between WWAN and WLAN", IEEE Communications Magazine, November 2003, pp. 102-108.

[7] K R Lo, C. B. Shung, "A Neural Fuzzy Resource Manager for Hierarchical Cellular Systems Supporting Multimedia Services", IEEE Transactions on Vehicular Technology, Vol. 52, No. 5, September 2003, pp. 1196-1206.

[8] C.T. Lin, C.S. George Lee "Neural-Network-Based Fuzzy Logic Control and Decision System", IEEE Transactions on Computers, Vol. 40, No.12, December 1991, pp. 1320-1336.

[9] R. Agusti, O. Sallent, J. Pérez-Romero, L. Giupponi "A Fuzzy-Neural Based Approach for Joint Radio Resource Management in a Beyond 3G Framework", First International Conference on Quality of Service in Heterogeneous Wired/Wireless Networks, Qshine'04, Dallas, USA, October, 2004.

[10] L. Giupponi, R. Agusti, J. Pérez-Romero, O. Sallent "A Novel Joint Radio Resource Management Approach with Reinforcement Learning Mechanisms", First IEEE International Workshop on Radio Resource Management for Wireless Cellular Networks, RRM-WCN'04, Phoenix, USA, April, 2005.

[11] T. Kohonen, *Self-Organization and Associative Memory*, Berlin, Germany: Springer-Verlag, 1988, p. 132