# A Novel Joint Radio Resource Management Approach with Reinforcement Learning Mechanisms

L. Giupponi, R. Agusti, 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 novel JRRM strategy based on reinforcement learning mechanisms that control a Fuzzy-Neural algorithm to ensure certain QoS constraints. Three RATs (Radio Access Technologies), namely UMTS, GERAN and WLAN are considered as common available technologies to select. The Fuzzy logic allows for a very simple handling of the Joint Radio Resource Manager simply by activating a set of rules. The membership functions considered by these rules are adaptive so that a desired performance in terms of the probability of user satisfaction can be guaranteed by means of the reinforcement learning algorithm. Some illustrative simulation results to evaluate the behaviour of the proposed JRRM technique are presented.*

## 1. Introduction

In parallel with the development of 3G other wireless access technologies have experienced a significant growth and have arrived to the mass-market. This is the case of the Wireless Local Area Networks (WLAN), with IEEE 802.11 being one of their most representative members. WLAN technologies are able to provide much higher bandwidths than those currently available in the existing cellular systems, though in more reduced coverage areas. On the other hand, in the field of cellular systems, the extension of 2G systems to 2.5G including packet transmission capabilities in the radio interface has been a first milestone in the evolution path of 2G cellular systems towards 3G.

As a result, 3G is coexisting not only with previous 2G and 2.5G systems but also with WLAN systems. These new scenarios must indeed be regarded as a new challenge to offer an efficient and ubiquitous radio access by means of a coordinate use of the available Radio Access Technologies (RATs). In this way, not only the user can be served through the RAT that fits better to the terminal capabilities and service requirements, but also a more efficient use of the available radio resources can be achieved. This challenge calls for the introduction of new Radio Resource Management (RRM) algorithms operating from a common perspective that take into account the overall amount of resources in the available RATs, and therefore are referred as JRRM (Joint Radio Resource Management) algorithms. These new scenarios include reconfigurability capabilities at different levels of the network and terminals [1].

Not many approaches to the JRRM concepts leading to attain QoS with an optimal usage of the radio resources can be encountered in the literature so far. An IP end-to-end architecture involving different network domains is presented in [2], being the JRRM a key element. In turns, [3] presents an interesting framework for the provision of JRRM algorithms to deal with the high degree of complexity associated to heterogeneous networks scenarios. The benefit related to load balancing among the different RATs involved appears in [4]. On the other hand, the architecture impacts in terms of loose, tight and very tight coupling have been introduced in the 3GPP for GERAN and UMTS [5]. All the above contributions, among others, have been basically focused on partial aspects concerning JRRM and no specific algorithms have been provided to assess relative improvements among different JRRM strategies even in simple scenarios.

This paper presents a comprehensive scenario where developing JRRM strategies taking full advantage of the reconfigurable equipment capabilities and the diversity offered by available RATs in a multi-radio environment. In that respect, a Joint RRM framework for algorithm development based on a Fuzzy-neural methodology was already presented in [6]. In such uncertain scenarios, learning from interaction is a foundational idea underlying learning theories and intelligence. 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 over the Fuzzy-neural methodology in order to cope with the complexities and uncertainties risen by these new scenarios.

The rest of the paper is organised as follows. In Section 2, the proposed Fuzzy-neural approach as the basis for JRRM formulation is described. For a better understanding of the proposed framework, the different steps are illustrated. Section 3 describes the considered scenario as well as some considerations about the RATs and functionalities included in the simulation model. In turn, Section 4 presents some results to analyse the behaviour of the proposed JRRM strategy. Finally, Section 5 summarises the conclusions reached in this work.

## 2. Fuzzy neural based JRRM algorithms

The fuzzy subset methodology has been proved to be good at explaining how to reach the decisions from imprecise information by using the concepts of fuzzifier and defuzziffier rules and the inference engine concept [7]. The use of this methodology has been widely proposed in different fields in the literature [3][8]. In the framework of heterogeneous networks, one of the problems that JRRM algorithms must face is the existence of uncertainties when comparing different measurements belonging to different RATs that are necessarily of a different nature together with subjective criteria that have to do with techno-economic issues. As a result, the use of fuzzy logic as a robust decision making procedure becomes a possible solution for JRRM algorithm development. However, pattern aspects like the selected membership functions and their particular shapes are still rather subjective in this solution. On the other side, the use of neural networks that are good in recognizing patterns by means of learning procedures could also be considered. As a consequence, hybrid systems incorporating both fuzzy and neural methodologies have been proposed in different fields to overcome the aforementioned drawbacks of fuzzy and neural based systems respectively [9][11]. Taking these considerations into account, a Fuzzy-neural framework is proposed in this paper as a good candidate for the solution of JRRM related issues.

For a better understanding of the JRRM framework statement, the objective of the problem considered here is to select the most appropriate RAT taking into account different algorithm inputs that include system measurements. Furthermore, a certain amount of resources (i.e. bit rate or bandwidth) are also allocated in the selected RAT by the algorithm. In addition, the proposed algorithm could easily be extended to take into account techno-economical aspects like user/operator subjective preferences in terms of e.g. cost, by combining the decision of the fuzzy neural algorithm with the user/operator preferences by means of a multiple decision procedure [6]. According to Figure 1, three main blocks are identified, named fuzzy neural, reinforcement learning and multiple decision making. These blocks represent a general framework including both technical and economical aspects. Nevertheless, the focus of the paper will be on the fuzzy neural algorithm including reinforcement learning so the multiple decision making procedure will not be considered. The description of the fuzzy neural blocks and reinforcement learning algorithm is detailed in the following subsections.

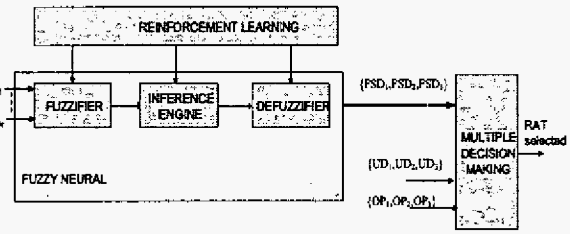



**Figure 1. Block diagram of the proposed JRRM algorithm**

### 2.1 Fuzzy Neural algorithm

The purpose of the fuzzy neural algorithm is to obtain for each RAT a numerical indication (denoted as Fuzzy Selected Decision: FSD) between 0 and 1 of the suitability to select the RAT. The decision is obtained from a set of input linguistic variables ($LV_i$), reflecting technical measurements. This decision is taken in three steps, as depicted in Figure 1.

**Step 1. Fuzzification.** The objective of this process is to assign, for each input linguistic variable, a value between 0 and 1 corresponding to the degree of membership of this input to a given Fuzzy Subset or Term. A Fuzzy Subset is a linguistic subjective representation of the input variable. A total of 7 linguistic variables are considered here to describe the proposed JRRM approach. They are:

$SS_{UMTS}$, $SS_{GERAN}$, $SS_{WLAN}$: Received Signal Strength for each of the considered RATs.

$RA_{UMTS}$, $RA_{GERAN}$, $RA_{WLAN}$: Resource Availability in each of the considered RATs.

MS: Mobile Speed.

Although other variables could have been chosen, it has been considered that the selected ones capture the main aspects influencing over the final performance.

The degree of membership value is obtained through the membership functions $\mu_X(LV_i)$ where $LV_i$ is the linguistic input variable and X the fuzzy subset. A number of Fuzzy Subsets are considered for each one of the linguistic variables:

Fuzzy subset for RA: $X \in$ {L (Low), M (Medium) and H (High)}

Fuzzy subset for MS: $X \in$ { L (Low) and H (High)}
Fuzzy subset for SS: $X \in$ {L (Low) and H (High)}

The shape of each membership function is a bell shaped function easy to derivate in the reinforcement learning procedure.

**Step 2. Inference Engine.** For each combination of fuzzy subsets from step 1, the inference engine makes use of some predefined fuzzy rules to indicate, for each RAT, the suitability of selecting it. So, at the output of this step there will be a combination of three output linguistic variables D ($D_{UMTS}$, $D_{GERAN}$, $D_{WLAN}$) each with four fuzzy subsets: Y(yes), N (not), PY (probably yes) and PN (probably not) with different degrees of membership for each linguistic variable. In turn, in order to take into account bandwidth allocation, other two output linguistic variables B ($B_{UMTS}$, $B_{GERAN}$) are considered, each one with three fuzzy subsets: H (high), M (Medium), L(Low). No provision for bandwidth has been considered for WLAN as long as 802.11b can not guarantee any rate. An example of an inference rule could be: If ($SS_{UMTS}$=H, $SS_{GERAN}$=L, $SS_{WLAN}$=L, $RA_{UMTS}$=H, $RA_{GERAN}$=H, $RA_{WLAN}$=M, MS=L) then ($D_{UMTS}$=Y, $D_{GERAN}$=N, $D_{WLAN}$=N, $B_{UMTS}$=H, $B_{GERAN}$=L).

Notice that, since we are considering 7 linguistic variables, there would be $3^3 2^3 2=432$ input combinations. It is considered that each of the 432 input combinations has a metric value given by the minimum of the membership values of the corresponding 7 linguistic variables involved. Then, assuming that the above example corresponds to the j-th combination, the output value would be: $\mu_Y(D_{UMTS})_j=\mu_N(D_{GERAN})_j=\mu_N(D_{WLAN})_j=\mu_H(B_{UMTS})_j=\mu_L(B_{GERAN})_j=\min[\mu_H(SS_{UMTS}), \mu_L(SS_{GERAN}), \mu_L(SS_{WLAN}), \mu_H(RA_{UMTS}), \mu_H(RA_{GERAN}), \mu_M(RA_{WLAN}), \mu_L(MS)]$. This value incorporates the commitment of all the involved variables on the reliability of this combination So as a result of these rules, and for every input combination, an output combination with a numerical membership value is obtained for each RAT.

The outputs from all the different combinations leading to the same fuzzy subset of a given output linguistic variable (e.g. all the combinations leading to $D_{UMTS}$=PN) should be considered together in order to obtain the membership value for this subset. Particularly, it is assumed that the total membership value will be the sum of the numerical outputs from each combination. As an example, and for the fuzzy subset $D_{UMTS}$=PN, the membership value would be:

$$\mu_{PN}(D_{UMTS}) = \min\left(1, \sum_j \mu_{PN}(D_{UMTS})_j\right) \qquad (1)$$

where j accounts for all the combinations leading to $D_{UMTS}$=PN. Summarising, as a result of the inference engine there will be three linguistic variables $D_{UMTS}$, $D_{GERAN}$, $D_{WLAN}$ each one with four fuzzy subsets (Y,PY,PN,N) and two linguistic variables $B_{UMTS}$, $B_{GERAN}$ each one with three fuzzy subsets (H,M,L) and a membership value for each linguistic variable in each fuzzy subset.

**Step 3. Defuzzification.** Finally, the defuzzification procedure converts the outputs of the inference engine into a crisp value, that is, a number ranging between 0 and 1, named Fuzzy Selected Decisions: $FSD_{UMTS}$, $FSD_{GERAN}$ and $FSD_{WLAN}$ for each RAT. Possible values of FSD based in the centre of area deffuzification method would be [9]:

$$FSD_{UMTS} = \frac{m_{N1}\sigma_{N1}\mu_N(D_{UMTS}) + m_{PN1}\sigma_{PN1}\mu_{PN}(D_{UMTS}) + m_{PY1}\sigma_{PY1}\mu_{PY}(D_{UMTS}) + m_{Y1}\sigma_{Y1}\mu_Y(D_{UMTS})}{\sigma_{N1}\mu_N(D_{UMTS}) + \sigma_{PN1}\mu_{PN}(D_{UMTS}) + \sigma_{PY1}\mu_{PY}(D_{UMTS}) + \sigma_{Y1}\mu_Y(D_{UMTS})} \qquad (2)$$

$$FSD_{GERAN} = \frac{m_{N2}\sigma_{N2}\mu_N(D_{GERAN}) + m_{PN2}\sigma_{PN2}\mu_{PN}(D_{GERAN}) + m_{PY2}\sigma_{PY2}\mu_{PY}(D_{GERAN}) + m_{Y2}\sigma_{Y2}\mu_Y(D_{GERAN})}{\sigma_{N2}\mu_N(D_{GERAN}) + \sigma_{PN2}\mu_{PN}(D_{GERAN}) + \sigma_{PY2}\mu_{PY}(D_{GERAN}) + \sigma_{Y2}\mu_Y(D_{GERAN})} \qquad (3)$$

$$FSD_{WLAN} = \frac{m_{N3}\sigma_{N3}\mu_N(D_{WLAN}) + m_{PN3}\sigma_{PN3}\mu_{PN}(D_{WLAN}) + m_{PY3}\sigma_{PY3}\mu_{PY}(D_{WLAN}) + m_{Y3}\sigma_{Y3}\mu_Y(D_{WLAN})}{\sigma_{N3}\mu_N(D_{WLAN}) + \sigma_{PN3}\mu_{PN}(D_{WLAN}) + \sigma_{PY3}\mu_{PY}(D_{WLAN}) + \sigma_{Y3}\mu_Y(D_{WLAN})} \qquad (4)$$

Where $m_{Ni}$, $m_{PNi}$, $m_{PYi}$, $m_{Yi}$ and $\sigma_{Ni}$, $\sigma_{PNi}$, $\sigma_{PYi}$, $\sigma_{Yi}$ (i=1,2,3) are parameters of the algorithm. Once at this point, the selected RAT is the one getting the highest crisp value of FSD.

Similar functions are considered to decide the corresponding bandwidth allocation:

$$BW_{UMTS} = BW_{UMTS,max}\frac{m_{L1}\sigma_{L1}\mu_L(B_{UMTS}) + m_{M1}\sigma_{M1}\mu_M(B_{UMTS}) + m_{H1}\sigma_{H1}\mu_H(B_{UMTS})}{\sigma_{L1}\mu_L(B_{UMTS}) + \sigma_{M1}\mu_M(B_{UMTS}) + \sigma_{H1}\mu_H(B_{UMTS})} \qquad (5)$$

$$BW_{GERAN} = BW_{GERAN,max}\frac{m_{L2}\sigma_{L2}\mu_L(B_{GERAN}) + m_{M2}\sigma_{M2}\mu_M(B_{GERAN}) + m_{H2}\sigma_{H2}\mu_H(B_{GERAN})}{\sigma_{L2}\mu_L(B_{GERAN}) + \sigma_{M2}\mu_M(B_{GERAN}) + \sigma_{H2}\mu_H(B_{GERAN})} \qquad (6)$$

Again, $m_{Li}$, $m_{Mi}$, $m_{Hi}$ and $\sigma_{Li}$, $\sigma_{Mi}$, $\sigma_{Hi}$ (i=1,2) are parameters of the algorithm. $BW_{UMTS,max}$ and $BW_{GERAN,max}$ are the maximum bandwidths available at UMTS and GERAN, respectively.

## 2.2 Reinforcement Learning

This procedure is used to suitably tune the parameters (means, deviations, shapes, etc.) of the different functions involved in the fuzzy logic controller. After a first selection of the parameters, they are adjusted by means of the reinforcement learning procedure [9] in order to ensure a certain target value of a given QoS parameter. Particularly, the proposed JRRM algorithm considers the ratio of non-satisfied users (i.e. the users that receive a bandwidth below a certain desired value $BW_D$). Then the input signal for the reinforcement learning procedure would be:

$$r(t) = P_t^* - P_t(t) \qquad (7)$$

where $P_I$* would be the target value of the ratio of non-satisfied users (e.g. 2% of unsatisfied users) and $P_I(t)$ the real value measured at time t. In order to ensure the corresponding target value the reinforcement learning algorithm adjusts the different parameters to minimise the error E(t) defined as:

$$E(t)=\frac{1}{2}(P_I^*-P_I(t))^2 \quad (8)$$

Then, the criterion to update a parameter w(t) in any membership function (e.g. w(t) can be any of the parameters in the fuzzification and defuzzification functions like $m_{Ni}$, $\sigma_{Ni}$, $m_{Hi}$, $\sigma_{Hi}$, ...) would be:

$$w(t+1)=w(t)+\eta\left(\frac{\partial E(t)}{\partial w(t)}\right)=w(t)+\eta(P_I^*-P_I(t))\frac{\partial P_I(t)}{\partial w(t)} \quad (9)$$

where $\eta$ is the learning rate and the membership parameters w are moved to reduce the error E(t). The derivatives of $\partial P_I(t)/\partial w(t)$ for parameters w(t) of the defuzzification process are computed from the derivative of expressions (2) to (6). In turn, for the parameters w(t) belonging to the membership functions of the fuzzification process, the error signal is back propagated from the defuzzification to the fuzzification process [9].

## 3. Simulation scenario and considerations

The proposed Fuzzy-neural algorithm has been evaluated through simulations in a simplified scenario in order to analyse its behaviour and to tune and validate the parameters that have more impact over the final decision. The considered scenario consists in three concentric cells, with radii R1, R2 and R3, defining WLAN, UMTS and GERAN dominant areas respectively. A mobility model with users moving according to a random walk inside the coverage area is adopted. 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=128.1+37.6 log d(km) [10]. For WLAN the propagation losses are modelled by L= 20 logd(m)+40. Call arrivals follow a Poisson scheme with an average number of 6 calls per user and hour and exponential call duration with average 180 s.

A single UTRAN FDD carrier is considered for UMTS, with a maximum uplink load factor of 0.75. In turn, for GERAN, coding scheme CS-4 is considered, thus having a maximum bit rate per carrier of 160 kb/s.

Results are presented for the uplink direction, and the considered possible bit rates for each RAT 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 it is considered that the 11 Mb/s total bandwidth available is equally distributed among the WLAN 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. A single access point is considered. It is worth mentioning that CFP (Contention free period) mechanisms allow that different users share a WLAN channel simply scheduling the transmissions on top of the MAC so that the same bit rate per user is allocated [13].

The allocated bit rate decided by the fuzzy neural algorithm will be given by rounding (5) or (6) to the closest bit rate for UMTS or for GERAN, respectively.

The RA (Resource availability) is defined here as RA=1-$\rho$ depending on each RAT, as follows:

For UMTS, $\rho$ is the uplink cell load factor

For GERAN $\rho$=Number of occupied slots /Total number of slots

For WLAN: $\rho$=Current Throughput/Maximum Throughput

With respect to performance measurements, the concepts of service non-satisfaction and outage are considered. Then, on one hand a user is "not satisfied" when the allocated bandwidth is below a certain value, for instance 40 kb/s if the assigned RAT is GERAN and 192 kb/s if the assigned RAT is UMTS or WLAN. On the other hand, a user can also be "not satisfied" if it is "in outage" for the considered RAT, which means that the fuzzy system assigns a RAT to the user but the received power is below the minimum requirement.

The required transmitted power by a given user in UMTS is [14].

$$P_{T,i}=\frac{L_{p,i}}{1-\eta_{UL}}\frac{1}{\frac{W}{\left(\frac{E_b}{N_0}\right)R_{b,i}}+1} \quad (10)$$

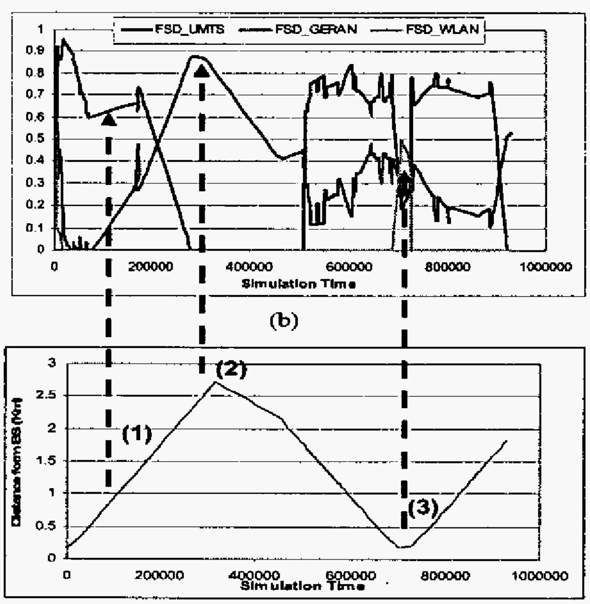
with $P_{T,i}$, $L_{p,i}$ and $R_{b,i}$ being the transmitted power, the path loss and the bit rate for the i-th user, respectively. $(Eb/No)_i$=3dB is the target requirement, $P_N$=-106 dBm the receiver thermal noise power, W=3.84Mc/s the bandwidth and $\eta_{UL}$ the uplink load factor, which depends on the number of allocated users and their bit rates [12]. The maximum power available at the terminal is 21 dBm, so that if ($P_{T,i}$>21 dBm), the user will be in outage

In case of GERAN it is assumed that there is no outage since GERAN covers the entire area. In case of WLAN the user is in outage if the received power is below a sensitivity value of -139 dBm.

The Neuro-Fuzzy algorithm is activated every 100 ms so that the allocated resources can be changed dynamically to the active users.

## 4. Results

An initial result is shown in Figure 2 to present the behaviour of the FSD values under a controlled situation. There are 12 users scattered in the scenario, with a generation rate of 6 calls per user and hour on the average, and an average call duration of 180 s. A reference mobile is assumed to move in a straight direction from the centre to the cell edge and then in the back direction. The cell radius is 0.2 km for WLAN, 2km for UMTS and 3km for GERAN. Furthermore, 4 carriers are available in this case in the GERAN cell. In Figure 2(a), the distance of this reference mobile to the cell site as the user moves around is shown as a function of the simulation time measured in frames of 10ms. In turn, in Figure 2(b) the time evolution of the FSD for the three RATs of the reference mobile is plotted. The allocated RAT is the one with the highest FSD. It can be noticed that the allocated RAT changes as the mobile moves around. In particular, the arrows stress three representative snapshots: 1) At about 1 km distance UMTS is the preferred network. In this case WLAN is not available, while GERAN is not the best option 2) At about 2.5 km, the FSD value for GERAN indicates that GERAN would be the choice (clearly, at this distance there is neither UMTS nor WLAN availability) and 3) Close to the cell site, the choice is for WLAN.




(a)

**Figure 2. RAT allocated versus distance**

In turn, the capacity to control the system performance with the tools provided by the reinforcement learning mechanisms is shown in Figure 3, where the convergence of the percentage of non-satisfied users is plotted for two different target values, $P_1$*=3% and 1%. In this case the cell radius is 0.2 km for WLAN and 2 km for UMTS and GERAN. For GERAN a single carrier has been considered. It can be observed that, after an initial starting up process, the steady situation is attained and the probability of users not being satisfied with the service is not significantly impacted in the rest of the system evolution. That is, once overcome the initial transient, the membership functions adjust their values in the normal operative phase and the $P_1$* target is practically attained regardless the actual number of active users, user's position, speed and mobility features, and propagation losses variation.

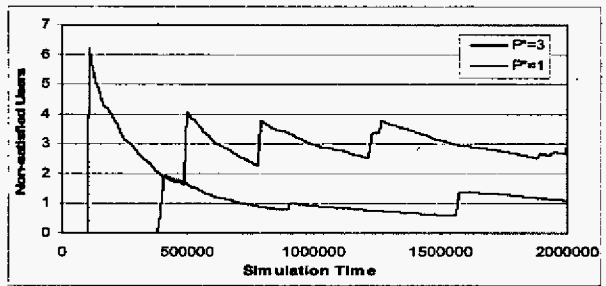



**Figure 3. Percentage of non satisfied users towards convergence at starting up phase**

Figure 4 shows the evolution of the probability of non-satisfied users and the blocking probability as a function of the number of users in the scenario. The presented values correspond to the average quantities measured after simulation convergence. It can be observed that the proposed JRRM algorithm is able to keep the non-satisfied users ratio at the target value of 3% for the admitted users, at the expense of an increase in the blocking probability. In that sense, the JRRM algorithm executes an inherent admission control by blocking a user when, at the session start, the allocated bandwidth to him is 0. Notice that the blocking probability starts to increase when the number of admitted users reaches the capacity limit for the considered scenario.

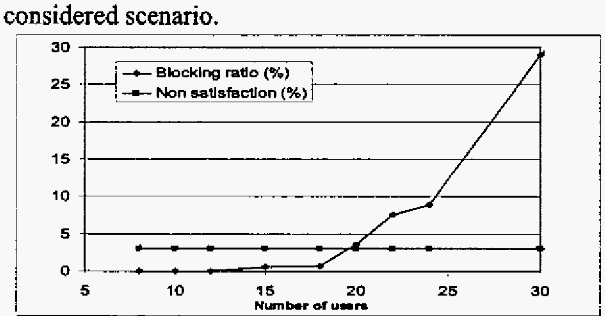



**Figure 4. Blocking ratio and non satisfaction probability measured after algorithm convergence**

Furthermore, the robustness of the convergence mechanisms under changes in the system state is shown through an additional experiment, in which the number of active users has been progressively increased. Figure 5 plots the number of active users and the evolution of the non-satisfaction probability. There are initially four users moving around the scenario and, at frame 1500000, four more users join progressively and demand services. It is assumed in this example that once a user has joined the system, it transmits continuously and moves around the scenario with a constant speed of 3 km/h. As long as the traffic increase can still be accommodated with the conjunction of the available RATs in the service area, the ratio of non-satisfied users keeps the target value $P_1$*=1%. Nevertheless, the fuzzy subset parameters are modified accordingly, and it could be observed (not shown for the sake of brevity) that the membership functions behave properly, for example, as the number of users increases the mean value of $RA_{UMTS}$ H decreases, while the mean value of $RA_{UMTS}$ L increases.

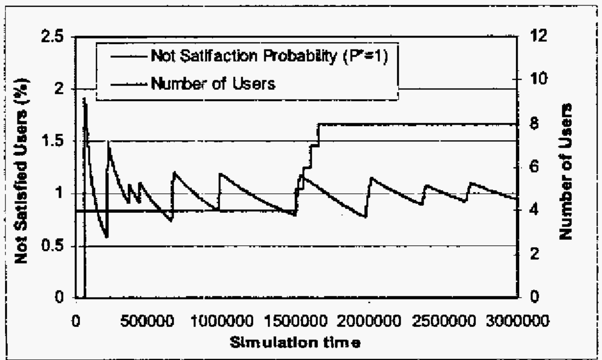



**Figure 5. Evolution of the non satisfaction probability measured when the offered load varies**

## 5. Conclusions

A novel JRRM proposal based on a Fuzzy-Neural algorithm with reinforcement learning has been introduced and analyzed in a scenario including UMTS, GERAN and WLAN radio access technologies. A simple cell deployment has been considered in order to easily evaluate the algorithm behaviour. The best RAT and the allocated bit rate are provided to each user in both the admission phase and along the session duration. The resulting Fuzzy neural scheme allows for a very simple handling of the Joint Radio Resource Manager by simply activating a set of rules. It has been shown that the reinforcement learning algorithm allows achieving the target value of the probability of non-satisfied users after a starting-up phase and this target value is maintained in the presence of varying traffic conditions during the operative phase.


## Acknowledgments

This work has been performed within the framework of the EU funded project E2R. The authors would like to acknowledge the contributions of their colleagues from E2R consortium. The work is also partially funded by the Spanish Research Council under COSMOS grant


## References


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

[2] V. Marques, R.L. Aguiar, C. Garcia, J.I. Moreno, C. Beaujean, E. Melin, M. Liebsch, "An IP-based QoS architecture for 4G operator scenarios" , IEEE Wireless Communications, Vol. 10, June 2003, pp. 54-62.

[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] 3GPP TR 25.891 v 0.3.0 "Improvement of RRM across RNS and RNS/BSS (Post Rel-5)"

[6]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.

[7]J.M. Mendel, "Fuzzy Logic Systems for Engineering: A Tutorial", Proceedings of the IEEE, Vol. 83, No.3, March, 1995, pp. 345-377.

[8]P.M.L. Chan, Y.F.Hu, R.E. Sheriff, "Implementation of Fuzzi Multiple Objective Decision Making Algorithm in a Heterogeneous Mobile Environment", Wireless Communications and Networking Conference, WCNC2002, pp. 332-336.

[9]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.

[10] 3GPP TR 25.942 "Radio Frequency (RF) system scenarios"

[11] 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.

[12]H. Holma, A. Toskala (editors), *W-CDMA for UMTS*, John Wiley and Sons, 2000

[13] J. L. Valenzuela, A. Monleón, I. San Esteban, M. Portolés, O. Sallent, "A Hierarchical Token Bucket Algorithm to Enhance QoS in IEEE 802.11b: Proposal, Implementation and Evaluation", Vehicular Technology Conference, VTC'04 Fall, Los Angeles, USA, 2004.

[14] O. Sallent, J. Pérez-Romero, R. Agustí, "Optimizing Statistical Uplink Admission Control for W-CDMA", Vehicular Technology Conference Conference VTC'03 Fall, Orlando, USA, 2003.