A Fuzzy-Neural Based Approach for Joint Radio Resource Management in a Beyond 3G Framework

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Abstract

This paper presents a comprehensive framework to develop Joint RRM (Radio Resource Management) strategies taking full advantage of the reconfigurable equipment capabilities and the diversity offered by available RATs (Radio Access Technologies) in a multi-radio environment. The envisaged JRRM treatment calls for establishing links with all the entities involved, first at functional level, identifying realistic scenarios in terms of deployment, technologies and services and managing the emerging complexity with proper algorithms. Then, a Fuzzy-neural methodology framework able to cope with the complexities and uncertainties these new scenarios rise is presented. In particular both technical and economical aspects are considered when selecting a particular RAT. Finally some significant examples of the algorithm behaviour are shown.

1. Introduction

The introduction of reconfigurability capabilities at different levels of the network opens new perspectives in the way how radio resources are managed. Indeed, in a multi radio environment, the capabilities brought by reconfigurable equipments offer the possibility to increase spectrum efficiency by developing appropriate mechanisms allowing a better management of radio resources in order to get the QoS required. This calls for the introduction of new algorithms but also the introduction of an enabling architecture model to support such algorithms. Nevertheless, the full deployment success of such new solutions will directly depend on their economical viability [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. So, [2] presents an IP end to end architecture involving different network domains 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. Highlighting vertical or intersystem handover between RATs as a basic requirement in heterogeneous networks has also been provided in [4][5]. The benefit related to load balancing among the different RATs involved appears in [6]. 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 [7]. Furthermore, the provision of cellular and IEEE 802.X WLAN integration by means of tight coupling architecture has also been invoked to be able to extend JRRM beyond cellular technologies [8].

All the above contributions, among others, have been basically focused in partial aspects concerning JRRM and no specific algorithms have been provided to assess relative improvements among different JRRM strategies even in simple scenarios. A comprehensive JRRM treatment calls for establishing links with all the entities involved, first at functional level, identifying realistic scenarios in terms of deployment, technologies and services and managing the emerging complexity with proper algorithms.

This paper presents a comprehensive scenario where developing Advanced RRM (Radio Resource Management) strategies taking full advantage of the reconfigurable equipment capabilities and the diversity offered by available RATs (Radio Access Tecnologies) in a multi-radio environment. In that respect, it is also presented a Joint RRM framework proposal for algorithms development based in a Fuzzy-neural methodology able to cope with the complexities and uncertainties these new scenarios rise.

The rest of the paper is organised as follows. In Section 2, the multi-radio environment scenario is described by identifying the different entities involved and the envisaged functionalities arising in a true Beyond 3G context. The specific role of JRRM and its interaction with the rest of entities is further detailed, this including the main inputs and outputs for a general JRRM algorithm. The proposed Fuzzy neural approach as the basis for JRRM formulation is described in Section 3. For a better understanding of the proposed framework, the different steps are illustrated with some particular examples. Finally, Section 4 presents some results to analyse the behaviour of the proposed JRRM strategy.

2. Joint RRM in a Beyond 3G Framework

The perspective of Beyond 3G system 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. In addition to the need for a proper interworking among RATs (Radio Access Technologies), a new dimension into the radio resource management problem is introduced. 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 the allocation and de-allocation of radio resources (e.g. time slots, codes, frequency carriers, etc.) within a single or between different radio access systems for the fixed spectrum bands allocated to each of these systems. With JRRM a more efficient usage of the radio resources will follow.

In addition to the above, the traditional concept of static allocation of licensed spectrum resources to networks operators in wireless communications seems not to be the most suitable approach in Beyond 3G scenarios, characterised by changing traffic along time and space, changing availability of RATs, etc. In order to overcome these constraints and to achieve a better utilization of the scarce spectrum, Advanced Spectrum Management (ASM) techniques are envisaged: ASM enables to manage dynamically the allocation, de-allocation and sharing of spectrum blocks within a single or between different radio access systems so that spectrum bands allocated to each of the systems are not fixed. On one hand, the Spectrum Brokerage (SB) approach considers spectrum to be a tradable economic good similar to stocks or real estate, etc.

The adaptive, flexible and tunable framework resulting from the conjunction of ASM, JRRM and the local RRM techniques applied at individual RAT level may suggest revisiting the static network planning concept. Definitively, reconfigurable technology will significantly change the operational mechanisms. Dynamic Network Planning and flexible network Management (DNPM) refers to the radio network planning, self tuning network parameters and flexible management processes interworking with JRRM and ASM processes. It can be envisaged that an operator can expect that in his operational area some of the coverage will be offered using the classical method, (e.g., single air interface, fixed functionality and capability of base station), whereas in some special areas, DNPM will be applied.

The ultimate realization of DNPM, ASM, JRRM and RRM in a consistent and coherent way would allow the achievement of unprecedented spectrum efficiencies and a high efficiency in radio resources usages on top of the potential capabilities provided by the physical layer design of the involved RATs.

The high level relationships among the different elements described in the previous section are summarised in Figure 1. The main distinguishing factor in this context is the time scale or frequency at which the interactions between elements occur and/or actions from a given element are taken. In particular, it can be envisaged that:

• Network deployment (i.e. the number of cell sites and their locations) can be seen as static for the study of JRRM purposes, since it can change in the order of months/weeks depending on the network maturity status.
• DNPM acts in a rather long term scale (e.g. once or twice a day), in response to very significant demand profiles changes. An example of a situation triggering DNPM would be a temporal event (e.g. mass meeting).
• JRRM. For a given configuration in the scenario and for the period of time that all the RATs and amount of radio resources assigned to the cells in the scenario remain fixed, it will be the responsibility of JRRM to achieve a good efficiency in the overall usage of the radio resources. Given that JRRM has the perspective of several RATs below, it is expected that interactions occur in the order of minutes/seconds, thus responding to some higher level objectives such as load balancing among RATs.
• Local RRM. This element will cope with the most dynamic elements of the scenario, such a traffic variability (i.e. short term variations on the offered load), user mobility (i.e. the different amount of radio resources needed as the user moves closer or farther from the cell site and at a certain mobile speed) and propagation/interference conditions within a given RAT. Actions of the corresponding functionalities may occur in a very short time scale, in the order of seconds (e.g. handover between contiguous cells belonging to the same RAT) or milliseconds (e.g. packet scheduling).

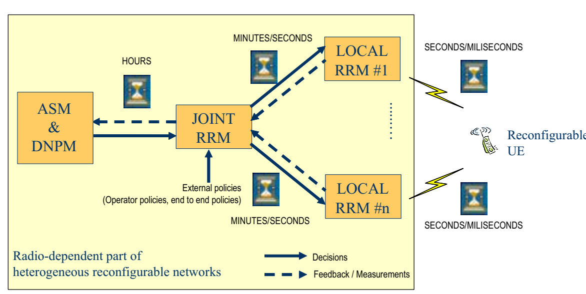

Figure 1 DNPM,SM, JRRM and RRM framework

The ASM&DNPM, JRRM and Local RRM model can be seen as a hierarchical structure, where the underlying level is characterised by a reduced set of parameters which are made visible to the overlying level. Thus, provided that the set of parameters are suitably chosen to capture the essential of a given entity, the overlying level does not need to be aware of the detailed behaviour of the underlying level in order to make suitable decisions affecting the underlying level. These parameters, provided in the form of feedbacks/measurements, can be configured either periodic or event-triggered.

For the variety of entities that may potentially be involved (i.e. several Local RRM such as UMTS, GSM, GPRS, JRRM and ASM&DNPM) it is important to assure the consistency among the decisions taken at the different hierarchical levels in order to achieve an overall coherent behaviour. The parameters that are feasible to be exchanged depend on the heterogeneous network architecture and the coupling scheme. For tight coupling schemes, JRRM and Local RRM may tend to collapse into one single element, then providing to JRRM overall and detailed radio resource management functionalities.

3. Fuzzy neural based JRRM algorithms

With respect to JRRM, the algorithm will consider the decisions coming from ASM&DNPM as a configuration input. Besides, feedbacks and measurements coming from the different Local RRM will also act as algorithm inputs, with much higher dynamism associated to them. The algorithm will also consider relevant operator-based information such as:

1. QoS parameters per traffic class (e.g. 1% BLER for conversational, 95% percentile delay target for interactive, etc.) and/or subscriber type
2. Subscriber differentiation elements (e.g. prioritisation for gold, silver, bronze, etc.)
3. Operator policies

Finally, user preferences may also be considered in order to take JRRM decisions. Figure 2 summarises the set of JRRM algorithm inputs.

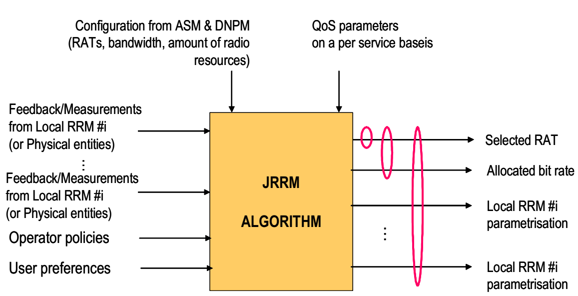

Figure 2 Preliminary framework for a general JRRM algorithm.

Changes in the RATs which users are attached to at a given point of the time are driven by JRRM decisions. These decisions are the result of decision making algorithms, which must secure that the operator is extracting the most from the network provided that users are always serviced according to the contract agreed from which the user profile is extracted.

The decision making process should consider all the relevant elements taking part in the decision but not too many in order to make the process manageable. As in any algorithm inputs are needed and an output including the decision criteria is expected. Despite of the commonly agreed advantages which could be obtained by using JRRM techniques, so far no JRRM algorithms and the correspondent performance assessments based on realistic criteria have been published. That is due to the difficulties that have to be faced to make a proper decision in the presence of multiple variables of both subjective and technical nature.

In order to envisage proper JRRM algorithm 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 feature of some key JRRM driving inputs in the decision making process is reflected for example in:

• The initial driving for Vertical Handover has to be extracted from the received pilot signals, but such signal strengths may not be comparable for the different RATs to aid in the decisions.

• Cell loads from different RATs are not directly comparable and the RAT selection decision is not based in the strict comparison of the same parameters.

• Mobile speed favors more or less a particular RAT according the network layout

• QoS versus cost qualitative information as perceived by users as well as the operator policies impact the RAT decision somehow in addition to other technical drivers

• RANs are becoming very complex and uncertainties appear in the decision making process due to the necessary simplifications taken to make decisions

The fuzzy subset methodology has been proved to be good at explaining how to reach the decisions from imprecise information, and then it could also be retained as a solution for JRRM. However pattern aspects like the selected membership functions and their particular shapes are still rather subjective. 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. In this context, a Fuzzy-neural framework is proposed in this paper as a good candidate for the solution of JRRM related issues.

A robust decision making procedure, based in the Fuzzy set theory can be adopted using the concepts of fuzzifier and defuzziffier rules and the inference engine concept [9][10]. This strategy has been widely proposed in the literature [3][11][12]. The use of neural networks that are good in recognizing patterns by means of learning procedures has been proposed to be used in hybrid systems to overcome the aforementioned drawbacks of Fuzzy based Systems [13][14].

The proposed Fuzzy-neural JRRM algorithm assumes the existence of three different RATs: UMTS, GERAN and WLAN. 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 both measurements and user/operator subjective preferences (e.g. cost) Nevertheless, the framework can be readily extended to the allocation of resources (e.g. bandwidth) in the selected RAT. According to Figure 3, three main blocks are identified, named fuzzy neural, reinforcement learning and decision making. The purpose of each of these blocks is detailed in the following subsections.

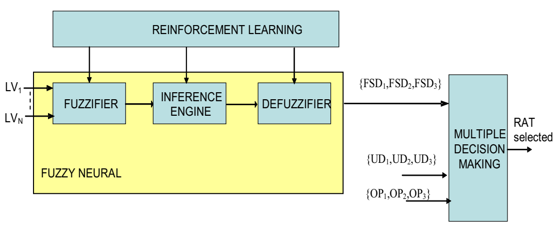

Figure 3 Block diagram of the proposed JRRM algorithm

3.1. Fuzzy neural algorithm

For each RAT a numerical indication (Fuzzy Selected Decision: FSD) between 0 and 1 of the suitability to select the RAT is issued taking into account the input linguistic variables. This decision is taken in three steps, as depicted in Figure 3.

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. The linguistic variables are denoted by LV_i. 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.

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:

1. Fuzzy subset for RA: X $\in$ {L (Low), M (Medium) and H (High)}
2. Fuzzy subset for MS: X $\in$ { L (Low) and H (High)}
3. Fuzzy subset for SS: X $\in$ {L (Low) and H (High)}

An example of membership function for the example of the linguistic variable SS_{GERAN} is shown in Figure 4.

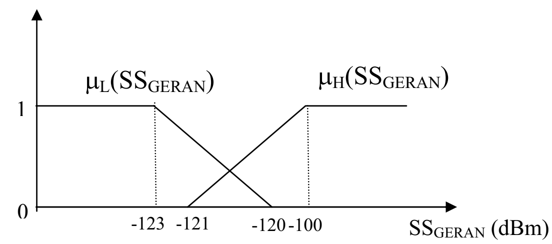

Figure 4 Example of membership functions for the fuzzy subsets of linguistic variable SS_{GERAN}

The shape of each membership function can be a triangle, a trapezoid or a bell shaped function easy to derivate in case of feedback training in order to adjust the function parameters as well as the overlapping degree between functions.

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. 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).
Notice that, since we are considering 7 linguistic variables, there would be $3^3 2^3 2=432$ input combinations. 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. For the example combination above, the output value would be: $\mu_Y(D_{UMTS})_j=\mu_N(D_{GERAN})_j=\mu_N(D_{WLAN})_j=\min[\mu_H(SS_{UMTS}), \mu_L(SS_{GERAN}), \mu_L(SS_{WLAN}), \mu_H(RA_{UMTS}), \mu_H(RA_{GERAN}), \mu_M(RA_{WLAN}), \mu_L(MS)]$. 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

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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 a membership value for each linguistic variable in each fuzzy subset.

It is worth mentioning that the proposed strategy can be extended with new linguistic variables. In particular, bandwidth B1 and B2 corresponding to UMTS and GERAN could also be selected according to the same methodology. No provision for bandwidth has been realized for WLAN as much as 802.11b can not guarantee any rate. Then, the JRRM algorithm would take over actions belonging to the own RRM entities of UMTS and GERAN. This actions could be extended beyond the rate selection and in the extreme situation to take over totally of the RRM functions of each involved RAT.

Step 3.- Defuzzification. Finally, the defuzzification, 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 [13]:

$$FSD_{UMTS} = \frac{m_N\sigma_N\mu_N(D_{UMTS}) + m_{PN}\sigma_{PN}\mu_{PN}(D_{UMTS}) + m_{PY}\sigma_{PY}\mu_{PY}(D_{UMTS}) + m_Y\sigma_Y\mu_Y(D_{UMTS})}{\sigma_N\mu_N(D_{UMTS}) + \sigma_{PN}\mu_{PN}(D_{UMTS}) + \sigma_{PY}\mu_{PY}(D_{UMTS}) + \sigma_Y\mu_Y(D_{UMTS})} \qquad (2)$$

$$FSD_{GERAN} = \frac{m_N\sigma_N\mu_N(D_{GERAN}) + m_{PN}\sigma_{PN}\mu_{PN}(D_{GERAN}) + m_{PY}\sigma_{PY}\mu_{PY}(D_{GERAN}) + m_Y\sigma_Y\mu_Y(D_{GERAN})}{\sigma_N\mu_N(D_{GERAN}) + \sigma_{PN}\mu_{PN}(D_{GERAN}) + \sigma_{PY}\mu_{PY}(D_{GERAN}) + \sigma_Y\mu_Y(D_{GERAN})} \qquad (3)$$

$$FSD_{WLAN} = \frac{m_N\sigma_N\mu_N(D_{WLAN}) + m_{PN}\sigma_{PN}\mu_{PN}(D_{WLAN}) + m_{PY}\sigma_{PY}\mu_{PY}(D_{WLAN}) + m_Y\sigma_Y\mu_Y(D_{WLAN})}{\sigma_N\mu_N(D_{WLAN}) + \sigma_{PN}\mu_{PN}(D_{WLAN}) + \sigma_{PY}\mu_{PY}(D_{WLAN}) + \sigma_Y\mu_Y(D_{WLAN})} \qquad (4)$$

where m_N, m_{PN}, m_{PY}, m_Y and σ_N, σ_{PN}, σ_{PY}, σ_Y are parameters of the algorithm. Once at this point, the decision on the selected RAT could be made as that getting the highest crisp value. However, in the next sections, it will be explained that this decision can be combined with other input criteria in a multiple decision problem like the one given in [10].

3.2.- Reinforcement learning

This procedure is used to suitably select the parameters (means, deviations, shapes, etc.) of the different functions involved in the fuzzy logic controller. An initial training process with fed data is carried out in order to do a first selection of the parameters. Afterwards, these parameters are adjusted by considering the reinforcement learning procedure. The objective is to minimise some function that can be related to a performance measurement. Clear references should be used as input feedback for training approach. References [13][14] are used as a guide. For example in [14] the probability of handover failure is used as performance measurement.

3.3.- Multiple decision making

Often occurs that qualitative or techno-economic inputs are to be considered in order to make selections on the most suitable RAT or also the allocated bandwidth in the above scenario. As shown in Figure 3, the Multiple Decision Making block decides on technical related inputs coming from the defuzzifier and also from techno-economic related inputs such as User Demand and Operator Preferences. Thus, this block is able to jointly consider radio interface related issues (such as RA, SS, MS) with economic-based components in order to devise a proper decision.

-*User Demand:* The operator tries to maximize the user demand of their services, then an objective at this point will be to get a maximum in the demand curves. For example, the well known Cobb-Douglas in economics could be retained here as the User Demand: $A(u, p) = 1-\exp(-Cu^{\mu} p^{-\varepsilon})$, u is the utility perceived by the user, p is the price of the service and C is a proportionality parameter.

- *Operator Preferences:* The operator could have RAT preferences based on spectrum available and interoperator agreements in case not all the RATs are owned by the same operator. At this time, it will be assumed that User Demand and Operator Preferences are decoupled at the short term.

In terms of procedure, the Multiple Decision Making then could decide based on the decision strategy mentioned in [10], according to the three considered criteria (i.e. technical criterion C_1, user demand C_2 and operator preferences C_3). For each RAT a membership value is used to define how good each criterion is fulfilled: for the technical criterion the FSD values obtained by the fuzzy-neural algorithm are considered, for the user demand the utility-price expressions are considered and, finally, the operator preferences are set in a more subjective way according to operator agreements and policies. The Multiple Decision Making will issue for each RAT a membership value by weighting the importance of each of the three criteria and finally the RAT with the higher membership value at the end will be selected. For RAT_j let $C_{i,j}^{a_i}$ be the input membership value corresponding to criterion C_i and let a_i a weighting factor that takes into account the relative importance of criterion C_i with respect to the other criteria. The output membership value corresponding to RAT_j will be given by:

$$O_{RATj} = C_{1,j}^{a_1} \cap C_{2,j}^{a_2} \cap C_{3,j}^{a_3} = \min(c_{1,j}^{a_1}, c_{2,j}^{a_2}, c_{3,j}^{a_3}) \quad (5)$$

Finally, the RAT with the highest O_{RATj} will be selected. In order to obtain the weighting factors, the procedure described in [10] is used depending on the relative importance of each criterion. As an example, assume that the user preference (C_2) is three times more important than the technical criterion C_1, and assume that C_3 is two times more important than C_1. This would lead to the following matrix:

$$B = \begin{bmatrix} 1 & 1/3 & 1/2 \\ 3 & 1 & 3 \\ 2 & 1/3 & 1 \end{bmatrix} \quad (6)$$

where the element $b_{i,j}$ is the relative importance of criterion C_i compared to criterion C_j. It is shown in [10] that the appropriate weights a_i are given by the components of the vector obtained from the product of the number of criteria (3 in this example) and the unit eigenvector corresponding to the highest eigenvalue of matrix A, which leads to:

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = 3 \begin{bmatrix} 0.16 \\ 0.59 \\ 0.25 \end{bmatrix} = \begin{bmatrix} 0.48 \\ 1.77 \\ 0.75 \end{bmatrix} \quad (7)$$

4. Results

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, as shown in Figure 5. Table 1 presents the specific values for the cell radii, the transmitted power of the pilot channels and the propagation models being used. A mobility model with users moving according to random rectilinear trajectories inside the coverage area is adopted.

The set of considered membership functions for the seven input linguistic variables are depicted in Figure 6. It should be mentioned that the resource availability for UMTS is measured in terms of the cell load factor, while for GERAN it is measured as the remaining bit rate in the cell (a single carrier is assumed) and for WLAN it is measured as the number of users that can still be served according to the remaining cell capacity. The total available bandwidth in WLAN is assumed to be 11 Mb/s. The reference signal strength membership functions have been devised after link budget calculations.

Results obtained with the previous membership functions will be denoted as “reference simulations” and will be compared against other membership functions. Particularly, in order to see the effects of the linguistic variable RA_{UMTS}, another membership function has been considered for comparison purposes, as depicted in Figure 7. Notice that the difference with the reference function is that the low and medium membership functions are shifted to the right, so that the system tends to consider in more situations that the available resources are low or medium.

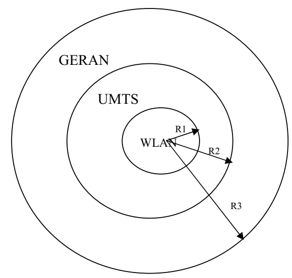

Figure 5 Simulated scenario

Table 1 Main scenario parameters

	WLAN	UMTS	GERAN
Radius	200 m	2 km	8 km
Tx Power	-10 dBm	30 dBm	41 dBm
Propagat. model	L= 20 logd(m)+40	L=128,1+37,6 log d (km)	L=128,1+37,6 log d (km)

The impact of the two membership functions are depicted in Figures 8 and 9, in terms of the probability of selecting the UMTS and the GERAN RATs depending on the measured Signal Strength. The simulation considers 30 pedestrian users with mobile speed 3 km/h. These simulations assume that the selection criterion is only based on FSD, and Operator and User preferences are not taken into account yet. As it can be observed, the range of signal strengths where the UMTS is selected is approximately between -70 and -110 dBm. Notice that for higher signal strengths the UMTS cell overlaps with the WLAN cell and the system tends to allocate WLAN. On the contrary, for lower signal strengths there is no UMTS coverage and the system always allocates GERAN.

Notice also that, in the region where UMTS and GERAN overlap, the system with the reference membership functions allocates UMTS with probability 70% and GERAN with 30%. On the contrary, when the modified membership function for RA_{UMTS} is considered, the system allocates UMTS only in 60% of the cases, since under this membership function, the UMTS resources are more likely declared as “low”. It is worth mentioning that, although the results are not shown for the sake of brevity, the WLAN selection is not affected by the variation of the RA_{UMTS} membership function. The reason is that, when there is WLAN coverage, the system tends to allocate WLAN no matter which are the resources available in UMTS.

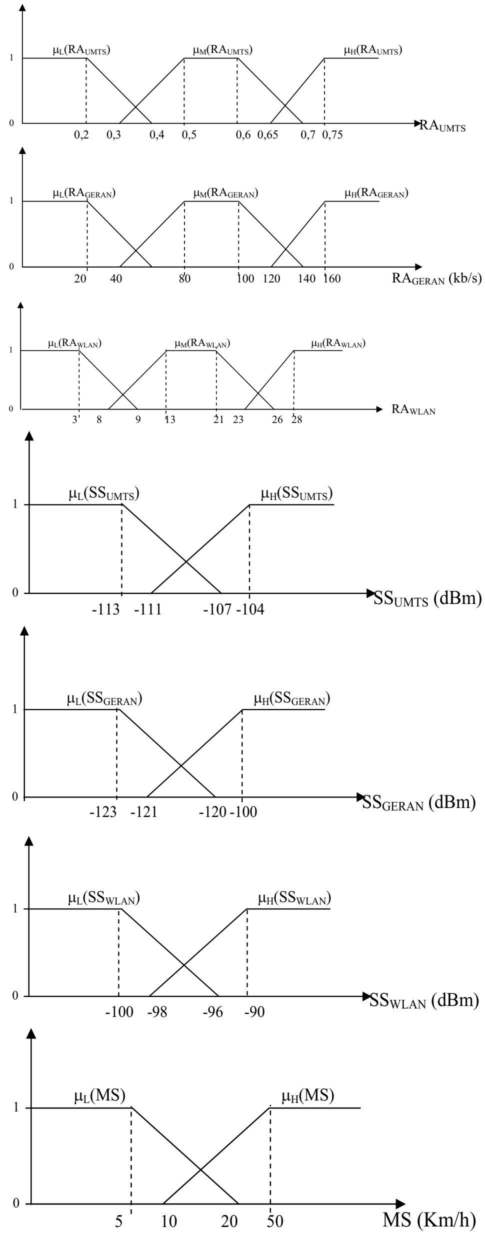

Figure 6 Reference Membership Functions

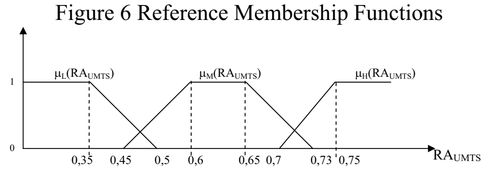

Figure 7 Modified membership functions for RA_{UMTS}

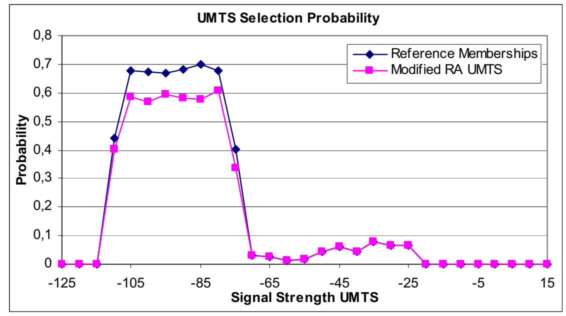

Figure 8 Impact of the RA_{UMTS} membership functions over the probability of selecting UMTS

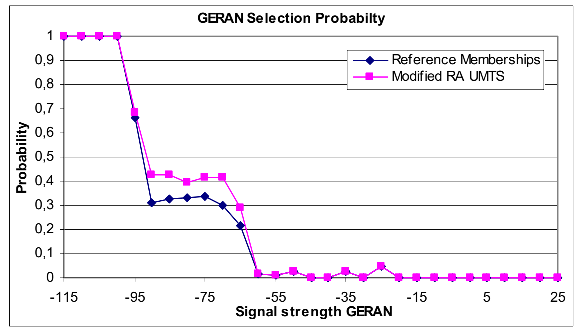

Figure 9 Impact of the RA_{UMTS} membership functions over the probability of selecting GERAN

The next results are intended to see the impact of the membership functions corresponding to the UMTS signal strength. Particularly, the membership functions for SS_{UMTS} shown in Figure 10 have been considered. These new membership functions are shifted to the right with respect to the reference functions. Consequently, the system will more likely declare the UMTS coverage as "low".

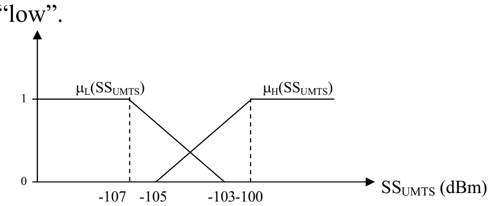

Figure 10 Modified membership functions for SS_{UMTS}

Results are shown in Figure 11. It is observed that the major differences arise between the selection of GERAN and UMTS approximately when SS_{UMTS} is below -100 dBm. Note that in this region, with the modified SS_{UMTS} membership functions the system tends to allocate GERAN instead of UMTS. The results in terms of bandwidth are shown in Table 2. Notice that, since GERAN is selected with a higher probability, the allocated bandwidth is lower in the modified SS_{UMTS} case, and the reduction is much more significant than when the RA_{UMTS} membership functions were varied.

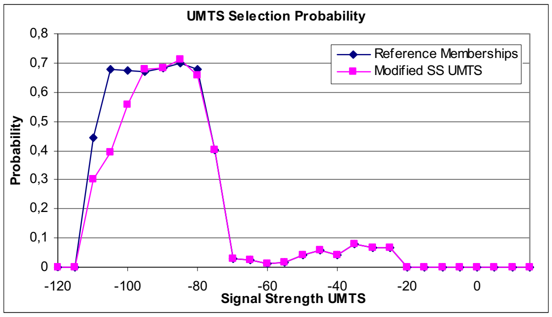

Figure 11 Impact of the SS_{UMTS} membership functions over the probability of selecting UMTS

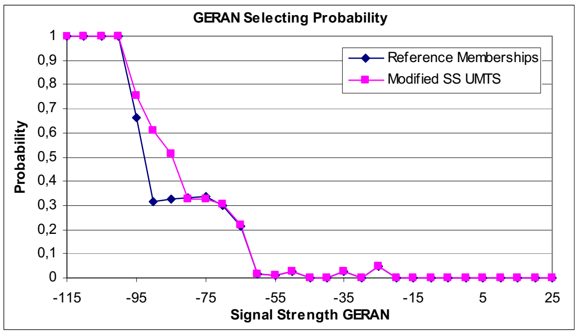

Figure 12 Impact of the SS_{UMTS} membership functions over the probability of selecting GERAN

Table 2 Impact of the SS_{UMTS} membership functions over the allocated bandwidth

Mobiles	Ref. Simulation	Modified SS_{UMTS}	% Reduction
10	270.3 kb/s	250.2 kb/s	- 7.4%
30	170.9 kb/s	153.9 kb/s	-9.9%
50	146.6 kb/s	129.1 kb/s	-11.9%
70	137.9 kb/s	119.2 kb/s	-13.5%

Finally, the last set of simulations tries to analyse the impact of the operator and user preferences over the final RAT selection. The reference simulations have been compared with a new simulation set in which the techno-economic criteria OP and UD are different. In particular, some simulations have been carried out modifying both the Operator Preferences and the User Demand according to the following weights, shown in Table 3.

Table 3 Techno-economic selection criteria when modifying both Operator Preferences and User Demand

	WLAN	UMTS	GERAN
OP	0.1	0.9	0.1
UD	0.9	0.1	0.1

Notice that in this case the operator prefers the allocation in UMTS while the user prefers the allocation in WLAN. Furthermore, the matrix showing the relative importance of each criterion is given by:

$$B = \begin{bmatrix} 1 & 0.25 & 0.333333 \\ 4 & 1 & 5 \\ 3 & 0.2 & 1 \end{bmatrix} \quad (8)$$

Notice that the UD is assumed 5 times more important than OP. This is reflected finally in the results, and the impact is that WLAN is always allocated in its coverage area, as shown in Figure 13. The probability of selecting UMTS also shows significant changes, as WLAN, within its targeted coverage area (SS from -72 to -109 dBm approximately) as shown in Figure 14. In turn, the low values of OP and UD make hat GERAN does not reveal a lot of changes with respect to the reference case as shown in Figure 15.

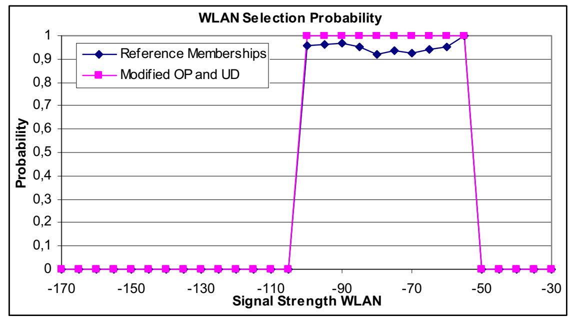

Figure 13 Impact of the OP and UD criteria over the probability of selecting WLAN

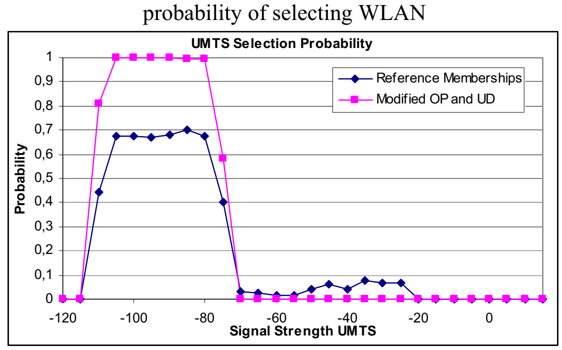

Figure 14 Impact of the OP and UD criteria over the probability of selecting UMTS

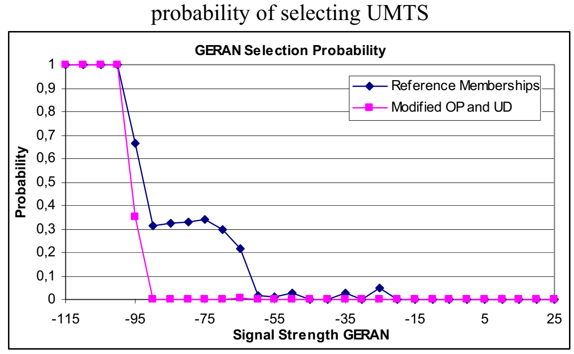

Figure 15 Impact of the OP and UD criteria over the probability of selecting GERAN

5. Conclusions

A comprehensive scenario where to develop Joint RRM (Radio Resource Management) strategies has been presented in a multi-radio environment. A Fuzzy-neural methodology framework for JRRM treatment able to cope with the complexities and uncertainties these new scenarios rise has been proposed. In particular both technical and economical aspects were introduced when selecting a particular RAT. Finally, the way for further developments is set up and some significant promising results are given.

Acknowledgments

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