Hopfield Neural Network Algorithm for Dynamic Resource Allocation in WCDMA Systems

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***Abstract*-This paper proposes a Dynamic Resource Allocation (DRA) algorithm for WCDMA systems for non-real time data services using a Hopfield Neural Network (HNN). Previous works have demonstrated the utility of HNN to implement DRA algorithms in the uplink due to the high computational speed of its hardware implementation and the maximization of the total allocated bandwidth. This paper presents an enhanced version of these algorithms by introducing a packet delay control technique, guaranteeing a better QoS and taking into account both uplink and downlink.**

I. INTRODUCTION

Nowadays mobile wireless communication systems are characterized by offering a wide range of services (speech, video conference, data download, video streaming, etc.). Services are characterized by different user profiles with distinct Quality of Service (QoS) parameters (minimum bit rate, maximum packet delay, etc.), and differ in the amount of resources required. In these increasingly complex scenarios, the need of an efficient Radio Resource Management (RRM) becomes crucial to maximize the utilization of the radio resources while assuring a minimum QoS. Within this context, Dynamic Resource Allocation (DRA) algorithms arise as a key element in the system, since they determine the amount of radio resources allocated to each user at each instant.

The DRA problem has been widely studied in the literature, e.g. [1]-[5] and references therein. Hopfield Neural Networks (HNN) have been successfully employed to implement DRA algorithms in the uplink [2]-[4]. The main benefit of the HNN is the high computational speed of its hardware implementation, which permits real-time running of the algorithm, what is not possible with other analytical solutions [6].

Previous works as [3] and [4] have tried to solve the DRA problem with the main aim of maximizing the total allocated uplink bandwidth, by means of a HNN. However, they only solve the DRA partially, not guaranteeing a global QoS, since packet delay was not considered. This paper proposes a new DRA HNN-based algorithm, based on [3] and [4], for the uplink and downlink taking into account both bit rate and delay constraints, providing services with controlled bit rate and delay. The delay control technique adopted is based on [7], and prioritizes users by their average bit rate.

The proposed algorithm follows a user-centric approach, since bit rates are not only allocated by network constraints, but also by users' expectations and requirements. This feature allows the system to maximize the utilization of the radio resources as a function of the user service profile.

The rest of the paper is organized as follows. Section II presents the WCDMA constraints that the DRA algorithm should take into account. Section III presents the solution adopted for the DRA problem based on a HNN. Section IV presents the proposed DRA algorithm. Section V shows some numerical results obtained by simulation. Finally, the most important conclusions are drawn in section VI.

II. DRA CONSTRAINTS

This paper considers a WCDMA system where a set of possible bit rates are allowed. Each user is characterized by a subset of these bit rates, defined by the type of service he is subscribed to. If N is the number of users demanding for resources, and M is the number of possible bit rates, the DRA algorithm shall find the optimal bit rate $R_{b,i}$, i=1,…,N, for each user satisfying the following constraints.

A. Load Constraint

Being the WCDMA systems interference-limited, the total load is controlled by means of the call admission control to avoid exceeding a predefined maximum value $\eta_{UL\max}$ in the uplink and $\eta_{DL\max}$ in the downlink.

There are different ways to estimate the load factor. A very good overview can be found in [5]. In this paper it is used the throughput-based uplink load estimation and the power-based downlink load estimation. These estimations can be calculated as:

$$\eta_{UL} = (1+\upsilon)\sum_{i=1}^{N}\frac{1}{1+\dfrac{W}{(E_b/N_0)_{UL,i}\,R_{bUL,i}}} \le \eta_{UL\max} \qquad (1)$$

$$\eta_{DL} = \frac{P_{DL}}{P_{DL\max}} \le \eta_{DL\max} \qquad (2)$$

where υ is the other-to-own cell interference ratio, W is the total transmission bandwidth, $(E_b/N_0)_{UL,i}$ is the uplink energy per bit to spectral density noise power ratio of the i-th user, $R_{bUL,i}$ is the uplink bit rate of the i-th user, P_{DL} is the total downlink power needed for the base station and $P_{DL\max}$ is the maximum available power of the base station. The total downlink power can be calculated as:

$$P_{DL} = \frac{\sum_{i=1}^{N} L_{PDL,i} \frac{P_{NDL} + \chi_i}{\rho + \frac{W}{\left(E_b/N_0\right)_{DL,i} R_{bDL,i}}}}{1 - \sum_{i=1}^{N} \frac{\rho}{\rho + \frac{W}{\left(E_b/N_0\right)_{DL,i} R_{bDL,i}}}} \quad (3)$$

where $L_{PDL,i}$ is the downlink path loss between the *i*-th user and the base station, P_{NDL} is the downlink thermal noise, χ_i is the intercell interference observed by the *i*-th user and ρ is the orthogonality factor.

B. Power Constraint

The power constraint takes into account the maximum power that mobile terminals can transmit, P_{ULmax}, and limits the maximum power that the base station can allocate to a single user session, P_{uDLmax}. The transmitted terminal power can be approximated by:

$$P_{UL,i} = \left(E_b/N_0\right)_{UL,i}\Big|_{\text{target}} \frac{R_{bUL,i} L_{PUL,i} P_{NUL}}{W\left(1-\eta_{UL}\right)} \leq P_{UL\max} \quad (4)$$

whereas the allocated power to a user:

$$P_{uDL,i} = L_{PDL,i} \frac{P_{NDL} + \chi_i + \rho \frac{P_{DL}}{L_{PDL,i}}}{\rho + \frac{W}{\left(E_b/N_0\right)_{DL,i}\Big|_{\text{target}} R_{bDL,i}}} \leq P_{uDL\max} \quad (5)$$

When more power than the maximum is needed in order to guarantee the corresponding $(E_b/N_0)_i$ target, the user is considered to be out of coverage at this bit rate $R_{b,i}$. In that case, the algorithm will allocate a lower bit rate if it is available in the subset. Otherwise the terminal starts a handover process.

C. Bit Rate Constraint

The DRA algorithm only allocates to each user one of the bit rates predefined in the associated subset. Each user profile has also a minimum ensured bit rate. This bit rate will not be always reachable, depending on the load of the system, but the algorithm forces the system to guarantee an average bit rate higher than the minimum defined in user QoS. The Service Credits (SCr) [7] are a good tool to control the average bit rates since they extend the idea of tokens from the leaky bucket algorithm to WCDMA systems. The SCr are a measurement of the amount of service the system owes to the users. The SCr of each user is updated every frame following:

$$SCr_i\left(r\right) = SCr_i\left(r-1\right) + R_{bm,i} - R_{b,i}\left(r\right) \quad (6)$$

where $SCr_i(r)$ is the credit of the *i*-th user in the *r*-th frame, $R_{bm,i}$ is the minimum ensured bit rate for the *i*-th user and $R_{b,i}(r)$ is the allocated bit rate for the *i*-th user in the *r*-th frame.

D. Delay Constraint

In order to control the packet delay, a certain delay threshold is defined. When the delay of a user exceeds it, the algorithm will temporally eliminate the lower bit rates of his subset to guarantee a higher transmission speed and a better QoS.

III. HNN-BASED OPTIMIZATION

The DRA is a NP (Non-deterministic Polynomial time) problem that makes impossible finding an analytical solution. As mentioned in the introduction, the main reason to use a HNN is its hardware implementation speed that makes possible a real-time running of the algorithm.

A. HNN Model

A HNN is constituted by a set of interconnected neurons. Neuron outputs change dynamically until reaching an equilibrium point. Hopfield stated that an energy function E can represent the dynamics of the HNN, and that the problem of finding an equilibrium point of the neural network can be solved by finding a local minimum of the energy function [8]. The dynamics of the HNN can be expressed as:

$$\frac{dU_i}{dt} = -\frac{U_i}{\tau} - \frac{\partial E}{\partial V_i} \quad (7)$$

where U_i and V_i are the input and output of the *i*-th neuron, and τ is the time constant of the circuit. The relationship between the outputs and the inputs of the neurons is non-linear, and is given by the sigmoid function:

$$V_i = f\left(U_i\right) = \frac{1}{1+e^{-\alpha U_i}} \quad (8)$$

where α is the gain of the neurons.

B. Problem Formulation

The DRA problem can be formulated in terms of a 2D-HNN with $L=N \cdot M$ neurons. Users are then represented in the first dimension of the neural network (by rows), whereas the second dimension represents the set of possible bit rates (by columns). Only two state neurons are taken into account: OFF or 0, and ON or 1. A neuron (*i*,*j*) is ON if the *i*-th user has the *j*-th bit rate allocated. Note that the rest of the neurons corresponding to user *i*, (*i*,*l*), $l \neq j$, must be OFF.

With these conditions, the absolute energy function minimum occurs in one of the 2^L corners (since each neuron has two different states, $V_{ij} \in \{0,1\}$) of the *L*-dimensional hypercube. After solving (7) numerically by the Euler technique and reaching a stable state, each neuron (*i*,*j*) is set to ON if $V_{ij} \geq 0.5$, or to OFF if $V_{ij} < 0.5$. The energy functions proposed in this paper is based on the proposal made for the uplink in [3] and [4]. In uplink

$$E_{UL} = \frac{\mu_{UL1}}{2} \sum_{i=1}^{N} \sum_{j=1}^{M_{UL}} C_{ULij} V_{ULij} + \frac{\beta^{\zeta} \mu_{UL2}}{2} \left| 1 - \frac{\eta_{UL}}{\eta_{UL\max}} \right| + \\ + \frac{\mu_{UL3}}{2} \sum_{i=1}^{N} \sum_{j=1}^{M_{UL}} \psi_{ULij} V_{ULij} + \frac{\mu_{UL4}}{2} \sum_{i=1}^{N} \sum_{j=1}^{M_{UL}} V_{ULij} \left(1 - V_{ULij}\right) + \\ + \frac{\mu_{UL5}}{2} \sum_{i=1}^{N} \left(1 - \sum_{j=1}^{M_{UL}} V_{ULij}\right)^2 \quad (9)$$

The constraints μ_{UL1} to μ_{UL5} (and μ_{DL1} to μ_{DL6} in the downlink) weight the terms of the energy functions and are selected to obtain a rapid approach to the desired solution.

First term of the uplink energy function. It introduces the cost function C_{ULij}. This function takes into account the prioritization made by the Service Credits of (6) as follows:

$$C_{ULij} = \frac{\Gamma_{ULij}}{\max\limits_{x,y}\left\{\left|\Gamma_{ULxy}\right|\right\}} \tag{10}$$

$$\Gamma_{ULij} = SCr_{ULi}\left(r-1\right) + R_{bULm,i} - R_{bUL,i}^{(j)} \tag{11}$$

here $R_{bUL,i}^{(j)}$ represents the j-th bit rate of the i-th user for the uplink. The term Γ_{ULij} is the SCr of the next frame s if the j-th bit rate is allocated to the i-th user at the end of the algorithm. The value of the cost function increases with the credits, increasing thus the energy function as well. The dynamics of the HNN will tend to minimize the cost function value and hence to minimize the number of credits.

Second term of the uplink energy function. The μ_{UL2} term forces the system to allocate the maximum resources that can be utilized. The β^{ζ} factor, with:

$$\zeta = u\left(\frac{\eta_{UL}}{\eta_{UL\max}} - 1\right) \tag{12}$$

is introduced to penalize the situations where $\eta_{UL}>\eta_{UL\max}$. The load expression in (1) has been modified to introduce the voltage of the neurons as follows:

$$\eta_{UL} = \left(1+\upsilon\right)\sum_{i=1}^{N}\sum_{j=1}^{M}\frac{V_{ij}}{1+\dfrac{W}{\left(E_b/N_0\right)_i R_{b,i}^{(j)}}} \tag{13}$$

Third term of the uplink energy function. This term uses the ψ_{UL} matrix. This matrix represents the uplink bit rate subset of each user, where ψ_{ULij}=0 if the j-th bit rate is usable by the i-th user and ψ_{ULij}=1 otherwise, to penalize the energy function if the allocated bit rate is not in the user subset. As stated in section II.D, if one user exceeds a certain service delay threshold, the ψ_{UL} matrix is temporarily changed to suppress the minimum bit rates of that user.

Fourth and fifth term of the uplink energy function. The last two terms ensure a rapid convergence to correct and stable states of neurons. The first one forces the minimum to be in the corners of the hypercube, and the second one forces users to have only one bit rate allocated.

In case of downlink the energy function is as follows:

$$\begin{aligned} E_{DL} = {} & \frac{\mu_{DL1}}{2}\sum_{i=1}^{N}\sum_{j=1}^{M_{DL}} C_{DLij}V_{DLij} - \frac{\mu_{DL2}}{2}\frac{\sum_{i=1}^{N}\sum_{j=1}^{M_{DL}} R_{bDL,i}^{(j)}V_{DLij}}{R_{bDL\max}} + \\ & + \frac{\mu_{DL3}}{2}\sum_{i=1}^{N}\sum_{j=1}^{M_{DL}}\xi_{ij}V_{DLij} + \frac{\mu_{DL4}}{2}\sum_{i=1}^{N}\sum_{j=1}^{M_{DL}}\psi_{DLij}V_{DLij} + \\ & + \frac{\mu_{DL5}}{2}\sum_{i=1}^{N}\sum_{j=1}^{M_{DL}} V_{DLij}\left(1-V_{DLij}\right) + \frac{\mu_{DL6}}{2}\sum_{i=1}^{N}\left(1-\sum_{j=1}^{M_{DL}}V_{DLij}\right)^2 \end{aligned} \tag{14}$$

First term of the downlink energy function. Similar to the first term of the uplink energy function

Second term of the downlink energy function. This term forces the algorithm to maximize the total allocated bandwidth in terms of bit rate. $R_{bDL\max}$ is the maximum allocable bit rate.

Third term of the downlink energy function. This term penalizes the energy function if a user rate allocation implies an excess of the maximum available power. The downlink total power is calculated, for each user i and each bit rate j, assuming the rest of users, $k\neq i$, with the allocation of the current neuron state (with the real values of the neurons, $V_{kl}\in[0,1]$). If more power than the maximum allowed is needed to allocate the j-th bit rate to the i-th user, then this term forces the output of the V_{ij} neuron to be reduced. The formulation of this term is:

$$\xi_{ij} = u\left(\frac{H_{ij}}{\eta_{DL\max}P_{DL\max}} - 1\right) + u\left(-H_{ij}\right) \tag{15}$$

$$H_{ij} = \frac{\sum\limits_{\substack{k=1\\k\neq i}}^{N}\sum\limits_{l=1}^{M} L_{PDL,k}\dfrac{P_{NDL}+\chi_k}{D_{kl}}V_{DLkl} + L_{PDL,i}\dfrac{P_{NDL}+\chi_i}{D_{ij}}}{1-\sum\limits_{\substack{k=1\\k\neq i}}^{N}\sum\limits_{j=1}^{M}\dfrac{\rho}{D_{kl}}V_{DLkl} - \dfrac{\rho}{D_{ij}}} \tag{16}$$

$$D_{ij} = \rho + \frac{W}{\left(E_b/N_0\right)_{DLi} R_{bDL,i}^{(j)}} \tag{17}$$

H_{ij} represents the total required power which should be reserved by the base station to users $k\neq i$ to transmit at the bit rates of the current neuron state, and to allocate the j-th bit rate to the i-th user.

Fourth, fifth and sixth terms of the downlink energy function. They act similarly to the third, fourth and fifth terms of the uplink energy function.

IV. DRA HNN-BASED ALGORITHM

The proposed DRA algorithm consists in three parts: the delay state check, the Connection Admission Control (CAC) algorithm and the HNN optimization.

A. Delay state check.

First the DRA algorithm checks the delay status of all users. The algorithm increases the minimal bit rate of those users whose maximum delay threshold was exceeded. The new minimal bit rate is calculated to ensure the transmission of the entire buffer in time, but it must never exceed the user's maximal bit rate. With these restrictions, the new minimal bit rate for the i-th user can be expressed as:

$$R_{b\min,i} = \min\left\{\max_j\left(R_{b,i}^{(j)}\right), \max_b\left(\frac{\sum_{p=b}^{L_{B,i}} B_i\left(p\right)}{t_i\left(b\right)}\right)\right\} \tag{18}$$

where $L_{s,i}$ is the buffer length, $B_i(b)$ is the number of bits stored in the b-th position of the buffer and $t_i(b)$ is the deadline for the data in the b-th position.

B. CAC algorithm.

The CAC algorithm decides, at the beginning of each frame, whether new service requirements are accepted in the system or not. For new connections their service credits are initialized to zero.

C. HNN optimization.

Next, the HNN algorithm is called and the new resource allocation is obtained. This algorithm solves (7) with the numerical Euler's technique. The gradients of the energy functions can be calculated as:

$$\frac{\partial E_{UL}}{\partial V_{ULij}} = \frac{\mu_{UL1}}{2} C_{ULij} - \frac{(-\beta)^{\zeta} \mu_{UL2}}{2\eta_{UL\max}} \frac{1+\upsilon}{1+\frac{W}{(E_b/N_0)_{UL,i} R_{bUL,i}^{(j)}}} + + \frac{\mu_{UL3}}{2}\psi_{ULij} + \frac{\mu_{UL4}}{2}(1-2V_{ULij}) - \mu_{UL5}\left(1-\sum_{l=1}^{M_{UL}} V_{ULil}\right) \quad (19)$$

$$\frac{\partial E_{DL}}{\partial V_{DLij}} = \frac{\mu_{DL1}}{2} C_{DLij} - \frac{\mu_{DL2}}{2} \frac{R_{bDL,i}^{(j)}}{R_{bDL\max}} + \frac{\mu_{DL3}}{2}\xi_{ij} + + \frac{\mu_{DL4}}{2}\psi_{DLij} + \frac{\mu_{DL5}}{2}(1-2V_{DLij}) - \mu_{DL6}\left(1-\sum_{l=1}^{M_{DL}} V_{DLil}\right) \quad (20)$$

Finally the SCr for all the users are updated.

V. Numerical results

A. Simulation Scenario

This section presents some results obtained with the proposed DRA algorithm considering web browsing users. The scenario consists in seven cells with radius 0.5 km, with the cell under study in the center. The maximum available power is 40 dBm, and the transmitted power of the interfering cells is 37 dBm. The other-to-own cell interference ratio considered in the uplink is 0.55. The path loss for the i-th user is calculated using [5]:

$$L_{PUL,i}(\text{dB}) = 129.4 + 35.2\log_{10}(d_i) \quad (21)$$

$$L_{PDL,i}(\text{dB}) = 137.4 + 35.2\log_{10}(d_i) \quad (22)$$

where d_i is the distance in km between the i-th user and the center cell. Users are on the move with a random speed uniformly distributed between 0 and 60 km/h. The thermal noise power level is -102 dBm. The total transmission bandwidth, W, is 3.84 Mchips/s. The frame period is equal to 0.1 s.

The maximum load factors, $\eta_{UL\max}$ and $\eta_{DL\max}$, are set to 0.7 and 0.6 respectively. The allowed bit rates in the uplink and downlink are {256 kb/s, 128 kb/s, 64 kb/s, 32 kb/s, 16 kb/s} and the corresponding E_b/N_0 ratios are {2.2 dB, 2.3 dB, 2.4 dB, 2.7 dB, 3.1 dB} for the uplink and {5.3 dB, 4.2 dB, 4.25 dB, 4.3 dB, 4.35 dB} for the downlink. The delay threshold is set to 50%.

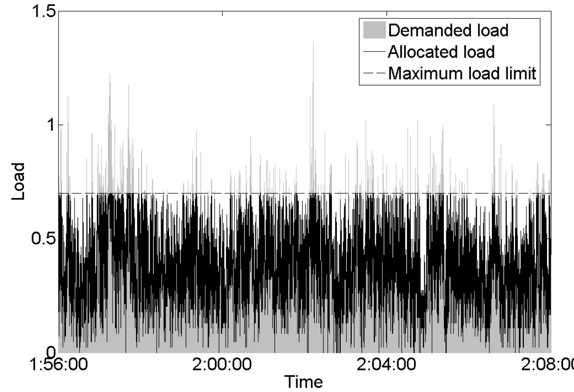

Figure 1. Comparison of the demanded and allocated uplink load in a simulation time interval.

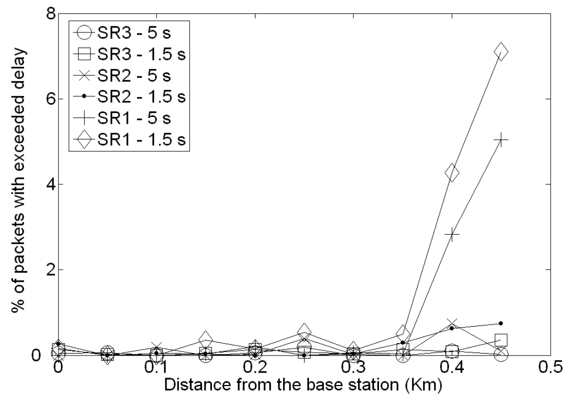

Figure 2. Percentage of downlink packets with exceeded delay by type of service vs. distance between the terminal and the base station.

TABLE I.
Uplink Delay Statistics

Bit rate class	Delay class	Average delay	% of packets with exceeded delay
*SR*1	1.5 s	0.28 s	0.015 %
	5 s	0.56 s	0.031 %
*SR*2	1.5 s	0.28 s	0.018 %
	5 s	0.62 s	0.013 %
*SR*3	1.5 s	0.28 s	0.011 %
	5 s	0.58 s	0.006 %

TABLE II.
Downlink Delay Statistics

Bit rate class	Delay class	Average delay	% of packets with exceeded delay
*SR*1	1.5 s	0.34 s	1.330 %
	5 s	0.81 s	0.801 %
*SR*2	1.5 s	0.32 s	0.201 %
	5 s	0.72 s	0.142 %
*SR*3	1.5 s	0.32 s	0.098 %
	5 s	0.70 s	0.049 %

The parameters of the considered HNN network have been calculated similarly to [2] and are the following:

$$\mu_{UL1}=1000 \quad \mu_{UL2}=5000 \quad \mu_{UL3}=8000 \quad \mu_{UL4}=100$$
$$\mu_{UL5}=6000 \quad \beta=10 \quad \Delta t=10^{-4} \quad \alpha=1$$
$$\mu_{DL1}=1000 \quad \mu_{DL2}=300 \quad \mu_{DL3}=5000 \quad \mu_{DL4}=8000$$
$$\mu_{DL5}=100 \quad \mu_{DL5}=8000$$

User's sessions have a Poisson arrival distribution with an arrival average rate of 1 call/s for the uplink and 5 calls/s for the downlink, and an exponential duration distribution with mean 60 s. Users' traffic is generated following the ON and OFF states concept to imitate the web traffic. The ON and OFF times, t_{ON} and t_{OFF}, are calculated from pareto distributions with shape parameter of 1.2 and average ON and OFF duration of 0.325 s and 0.315 s respectively. The length of the packet is calculated as:

$$t_{ON} R_{bAV,i} \tag{23}$$

where $R_{bAV,i}$ is the desirable average bit rate for the i-th user, computed in this work as the half of the maximum bit rate for that user. The next packet will be generated after $t_{ON}+t_{OFF}$ seconds.

Six types of service have been considered. Each service is characterized by a subset of allowed bit rates and a maximum delay. Specifically, three different subsets of bit rates are considered: $SR1\equiv$\{256 kb/s, 128 kb/s, 64 kb/s, 32 kb/s, 16 kb/s\} with the minimum ensured of 64 kb/s, $SR2\equiv$\{128 kb/s, 64 kb/s, 32 kb/s, 16 kb/s\} with the minimum ensured bit rate of 32 kb/s and $SR3\equiv$\{32 kb/s, 16 kb/s\} with the minimum ensured bit rate of 16 kb/s. Two maximum delays are studied for each subset: 1.5 s and 5 s.

B. Simulation Results

Fig. 1 shows the total uplink load demanded by users, assuming that they ask for their maximum bit rate, and the real system load after scheduling. It can be seen that the allocated and demanded loads are identical, except when the demanded exceeds the maximum load limit $\eta_{UL\max}$, i.e. 0.7. In that case the allocated approaches $\eta_{UL\max}$. The average allocated load when the demanded exceeds $\eta_{UL\max}$ is 0.686, very closed to the maximum allowed value. This study shows the utility of the HNN algorithm to allocate the maximum possible resources. The same comparison is not possible in downlink because users could not reach their maximum bit rate not because of the load but because of the power needed from the base station (5).

Tables I and II show the delay statistics for the DRA algorithm proposed in this paper. The average delay in the uplink and downlink for each delay class are very similar and lay very low from the maximum allowed. The uplink percentages of packets with exceeded delay remain also at very low values, what is also valid for the downlink services $SR2$ and $SR3$. The increase of service $SR1$ can be explained with fig. 2. Most of the delayed packets occur in the edge of the cell, where the highest bit rate is not reachable due to the channel interferences.

VI. CONCLUSIONS

This paper has presented an uplink and downlink Dynamic Resource Allocation approach for multi-service wireless WCDMA networks where different user profiles exist. User profiles are characterized by a subset of possible data rates and a maximum packet delay. A Hopfield Neural Network has been proposed to maximize the resource allocation, while guaranteeing a maximum service delay. The proposed algorithm is based on previous works where only the uplink rate allocation problem is addressed. Numerical results obtained show that a great delay performance can be achieved, even for high system loads, prioritizing users according to their average bit rates and solving the delay critical situations by increasing the user bit rate. Furthermore, the packet delay control objective has been reached while keeping an excellent rate allocation performance.

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