User Bandwidth Usage - Driven HNN Neuron Excitation Method for Maximum Resource Utilization within Packet - Switched Communication Networks

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***Abstract*—Mobile and wireless systems beyond 3G are being designed under the *user-centric paradigm*. Dynamic Resource Allocation (DRA) is a topic on intensive research to address efficiently such paradigm. Hopfield Neural Networks (HNN) have proved useful in the past to solve this kind of complex optimization problems. Recently, various approaches have been proposed to realize HNN-based user-centric DRA. However, the initial algorithms suffer from severe instability problems impacting the overall performance. This letter analyses the source of the existing limitations and proposes an enhanced formulation, ensuring maximum resource utilization while optimizing the convergence of the neural network. The letter highlights the improved performance in terms of optimum convergence and bandwidth utilization.**

***Index Terms*—Hopfield Neural Networks, Dynamic Resource Allocation, Wireless Networks.**

I. Introduction

Dynamic Resource Allocation (DRA) is a key process within radio resource management which ensures a fair distribution of the scarce available resources in order to guarantee the required Quality of Service (QoS). When the system capacity is limited by the interference level as happens in CDMA-based systems, the resource allocation optimization is especially complex, and is currently a very active field of research, see e.g., [1]-[2]. However, most of the techniques reported so far are either incapable of achieving optimum resource allocation or cannot operate in real time, since DRA is an NP-complete optimization problem. On the other hand, Ahn and Ramakrishna [3] proposed a Hopfield Neural Network (HNN) as an effective real-time solution to fair resource use maximization, thereby demonstrating the utility of HNN as a tool for resource usage optimization. This seminal work has further inspired the recent application of user-centric HNN-DRA algorithms within UMTS [4]. However, the HNN-DRA in [3] suffers from important limitations, such as the instability of the neural network, which may hamper their practical implementation. Hence, this letter aims at presenting an optimum user-centric resource allocation technique based on an enhanced HNN formulation.

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II. Analysis of the HNN-based DRA Algorithm

At the essence of a HNN is an energy function which gradient describes the time evolution of the neurons, where the equilibrium points of the HNN correspond with the minima of the energy [5]. This feature has been extensively used to accommodate the specification and solution of complex optimization problems defining an energy function which global minimum corresponds with the optimum solution. The HNN-DRA proposed by Ahn and Ramakrishna in [3] guarantees a fair distribution of the total system bandwidth and maximizes the use of the available bandwidth. To this effect, a 2D-HNN (with $N \times M$ neurons, N users and M bit rates) is presented. $\mathbf{V}$ stands for the outputs of this neuron matrix, which represent the bit rates allocated to each user, being $V_{ij} = 1$ if the j-th bit rate is assigned to the i-th user and $V_{ij} = 0$ otherwise. The energy function proposed is as follows [3]:

$$\begin{aligned} E =& \frac{\mu_1}{2}\sum_{i=1}^{N}\sum_{j=1}^{M} C_{ij}V_{ij} + \frac{\eta^{\zeta}\mu_2}{2}\left|1 - \sum_{i=1}^{N}\sum_{j=1}^{M}\frac{B_{ij}}{B_T}V_{ij}\right| + \\ &+ \frac{\mu_3}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\psi_{ij}V_{ij} + \frac{\mu_4}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}V_{ij}\left(1 - V_{ij}\right) + \\ &+ \frac{\mu_5}{2}\sum_{i=1}^{N}\left(1 - \sum_{j=1}^{M}V_{ij}\right)^2 \end{aligned} \quad (1)$$

This energy function is composed by five terms. The first one ensures a fair resource allocation among connections. The second term aims at maximizing the allocated bit rate to each user without exceeding the maximum system capacity B_T. Note that with η^{ζ}, where $\zeta = u\left(\sum_{i=1}^{N}\sum_{j=1}^{M}\frac{B_{ij}}{B_T}V_{ij} - 1\right)$ and η is a constant, a high penalty is imposed once the maximum system capacity is exceeded. The third term prevents particular bit rates from being allocated to specific users. Matrix Ψ hence represents a service bit rate permission table, being $\psi_{ij} = 0$ if the j-th bit rate is allowed to the i-th user and $\psi_{ij} = 1$ otherwise. The fourth term is intended for reaching an stable solution where $V_{ij} \in \{0, 1\}$. Finally, the fifth term guarantees that only one bit rate among the available is suggested for each user.

As it can be observed from (1), in the gradient of the second term two variables depend on V_{ij}, namely ζ and the absolute value. The derivative of the absolute value is not defined at 0 and the lateral limits differ and have opposite signs. Consequently, the system in [3] will oscillate. This oscillation has severe consequences for the HNN performance, since it prevents the network from reaching a stable solution. The formulation in [3] forces the system to change abruptly its evolution (i.e., its gradient), since ζ is activated to reduce drastically the outputs of **all neurons** each time B_T is exceeded; subsequently increasing them in the next iteration, when the total bit rate is below B_T.

III. User Bandwidth Usage-Driven HNN-DRA Algorithms (UB-HNN-DRA)

This section presents an enhanced HNN-DRA formulation, UB-HNN-DRA, which proposes a new second term in (1), to effectively address the HNN dynamics drawback identified in the previous section. The UB-HNN-DRA follows the same objective as the HNN-DRA algorithm. However, for the reasons detailed below, the second term has been redefined as follows:

$$-\frac{\mu_{2a}}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\frac{B_{ij}}{B_T}V_{ij} + \frac{\mu_{2b}}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\xi_{ij}V_{ij} \qquad (2)$$

$$\xi_{ij} = u\left(\frac{H_{ij}}{B_T} - 1\right)$$

$$H_{ij} = B_{ij} + \sum_{\substack{n=1\\n\neq i}}^{N}\sum_{m=1}^{M}B_{nm}V_{nm}$$

where H_{ij} is the system total bit rate if the j-th bit rate is allocated to the i-th user and the rest of users are assigned the current bit rate status. The first component, weighted by μ_{2a}, always maximizes the overall allocated resources. The second component, weighted by μ_{2b}, now permits that only the users whose bit rate demands make H_{ij} exceed B_T are penalized for such behavior as opposed to [3], where such penalty affects all users.

In the gradient of the new proposed term it is also necessary to calculate the derivative of ξ_{ij} and consequently the derivative of the step function. A similar discontinuity appears as in (1) but in this case the effect - penalty - is isolated to each individual neuron (i.e., it is only applied to the neurons that change their ξ_{ij}). This improvement allows some of the neurons to retain its natural stable evolution and also the overall HNN to reach a stable state whereas beforehand oscillation was mandatory and optimum solution could not be reached.

In consequence, this simple change reduces the neurons oscillation probability, increasing the stability of the solutions reached and ultimately, improving the overall system performance.

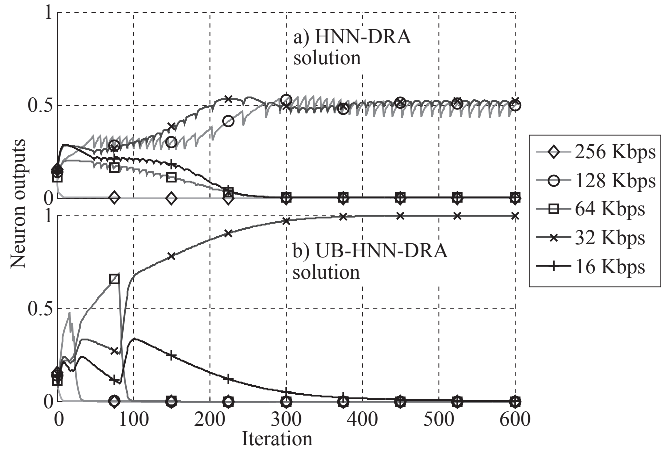

Fig. 1. Simulation example of the two energy functions studied in this letter.

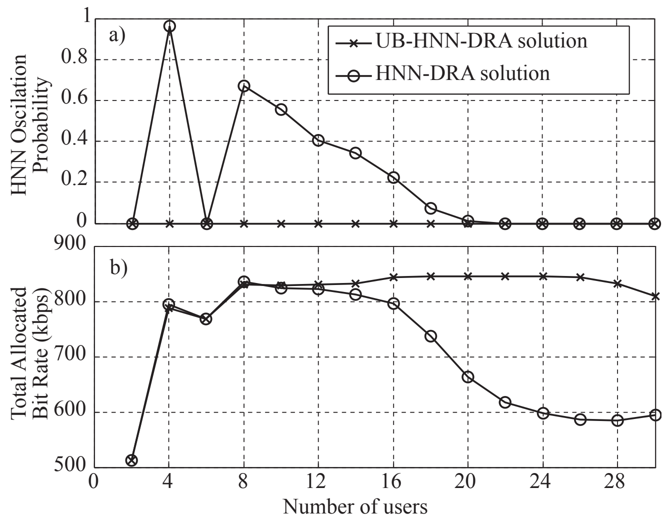

Fig. 2. a) HNN oscillation probability. b) Total allocated bandwidth.

IV. Performance Evaluation

The performance of the proposed formulation has been studied in terms of convergence capability and system bandwidth utilization. The system is bandwidth-limited and the maximum capacity is set to 850 kbps, a common value for WCDMA UMTS deployment [4]. A number of valid bit rates 256, 128, 64, 32, 16 kbps are available to provide a single service. Thus, the QoS observed by the users is directly related to the bit rates allocated. Consequently the HNN target is set to maximize the allocated bandwidth serving each user with a bit rate as high as possible. Since only one service is provided, the ψ matrix is set to all zeros, allowing all bit rates to all users. The simulations are carried out with increasing number of active users in a single cell.

In order to decouple performance degradation due to wireless phenomena, such as path loss, noise or interference, from performance degradation due to spurious HNN dynamics behavior, such issues are not taken into consideration. The HNN-DRA parameters are taken from [3] and the UB-HNN-

DRA parameters are set to:

$$\mu_1 = 1000 \quad \mu_{2a} = 4000 \quad \mu_{2b} = 10000$$
$$\mu_3 = 8000 \quad \mu_4 = 200 \quad \mu_5 = 6000$$

The algorithms are said to reach stability when all neuron variations decrease under a tolerance, which has been set to 10^{-4}.

Initially, the dynamics of the HNN-DRA and the UB-HNN-DRA algorithms are studied. Fig. 1 shows a typical evolution of the neuron outputs for a particular user. This result has been obtained in a simulation with 16 users demanding for resources. As it can be observed, the HNN-DRA is unable to decide between 32 and 128 kbps. On the other hand, with the UB-HNN-DRA, the oscillations disappear and the system is able to reach the equilibrium point allocating 32 kbps to the user.

It can be argued that this evolution is rather seldom, without real impact on the long-term average system performance. To this effect, the oscillation probability, $P_{oscillation}$ - probability that the system get at the maximum number of iterations without reaching stability - has been defined and evaluated. The maximum number of iterations has been set to 10000, a sufficient large value to detect oscillations since the average number of iterations in the simulations is 579. As depicted in Fig. 2a), HNN-DRA exhibits a significant oscillation probability. It is only for two special cases that such probability is zero. A system with two users has enough resources to deliver the maximum bit rate, 256 kbps. In the case that 6 users are present such probability is also zero since the fair allocation, 850/6=141, is higher and close to 128 kbps therefore the HNN-DRA is stable with all the users allocated with 128 kbps. On the contrary, fair allocation for 4 users, 850/4=212, is now lower and close to 256 kbps and hence the HNN-DRA tries to allocate 256 kbps to all users. Since this allocation exceeds B_T, all the neuron outputs are reduced and consequently the absolute value avoids the HNN-DRA to reach a stable state. This behavior explains the high oscillation probability. The case with 8 users is similar but now the fair allocation is lower and close to 128 kbps. On the contrary, UB-HNN-DRA exhibits no oscillation and quick system convergence is achieved.

Finally, the average total allocated bit rate when no oscillation is detected was studied. As illustrated in Fig. 2b) a worse bandwidth utilization is exhibited by HNN-DRA for increased number of users. However, such behavior improves the stability of HNN-DRA since the maximum bandwidth is not exceeded. Consequently the reduction in the oscillation probability is at the expense of a low utilization of the free bandwidth. On the other hand, UB-HNN-DRA maximizes the bandwidth usage and couples that resource allocation optimization with fast convergence due to the oscillation avoidance mechanism embedded in the enhanced formulation.

V. Conclusion

This letter has underlined main drawbacks identified in existing user-centric HNN-DRA formulation for packet-switched communication systems and has presented an enhanced formulation, the UB-HNN-DRA algorithm. The letter has shown that the resulting DRA algorithm can improve substantially performance compared to precedent schemes, maximizing the allocated resources and reducing the oscillation probability to negligible values, critical aspect for effective real-time provision of user-centric multimedia services in future wireless systems to a large number of users with varying QoS requirements.

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