Journal of Theoretical and Applied Information Technology
15st July 2026. Vol.104. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A CROSS-DISCIPLINARY APPROACH TO OPPORTUNISTIC RESOURCE ALLOCATION IN MULTICELLULAR SYSTEMS: INSIGHTS FROM GIS AND BIOINFORMATICS

MOHAMED ATIFI[1], JAMILA DAHMANI[2], LAHCEN ZIDANE[3], AZIZ BOUJEDDAINE[4], SARA RIAHI[5], HAMID KHALIFI[6]

[1, 2, 3] Faculty of Sciences, Ibn Tofail University of Kenitra, Morocco
[4] Laboratory IA, Moulay Ismail University of Meknes, Morocco
[5] National School of Architecture of Rabat, Morocco
[6] Faculty of Sciences, Mohammed V University in Rabat, Morocco
E-mails: [1]mohamed.atifi@uit.ac.ma, [2]jamila.dahmani@uit.ac.ma, [3]lahcen.zidane@uit.ac.ma, [4]a.boujeddaine@edu.umi.ac.ma, [5]s.riahi@enarabat.ac.ma, [6]h.khalifi@um5r.ac.ma

ABSTRACT

GIS and Bioinformatics concepts are increasingly relevant in the analysis and modeling of complex systems. The rapid evolution of wireless and mobile systems has made the optimal allocation of radio resources an increasingly critical challenge. The growth of telecommunications networks relies on the efficient deployment of wireless technologies such as Wireless Fidelity (Wi-Fi) and mobile systems such as Long-Term Evolution (LTE). In this article, we propose an algorithm that improves overall radio resource allocation within a heterogeneous wireless and mobile network environment, using dynamic programming and the Bellman principle of optimality. User mobility is explicitly taken into account to enhance performance, and the proposed approach is validated through numerical testing. This optimization framework, grounded in dynamic programming, also echoes methodologies shared with bioinformatics (e.g., sequence alignment algorithms) and relies on a spatial zoning model that can be represented and analyzed through Geographic Information Systems (GIS).

Keywords: *Resource allocation; Optimization; GIS; Cellular systems; QoS; Bioinformatics*

1. INTRODUCTION

Wireless and mobile communication systems are evolving at a very fast pace, driven by continuous technological advancements and growing connectivity demands. This evolution has resulted in the emergence and large-scale deployment of multiple network technologies such as Wi-Fi, WiMAX, GSM, UMTS, and more recently LTE. These technologies have significantly improved user communication, while users themselves have become increasingly demanding in terms of Quality of Service (QoS). In this work, we account for both user mobility and the type of service to which users are connected, in order to ensure their satisfaction. Specifically, we consider a mobility model in which users move in all directions within the service area with equal probability—a model commonly used to represent traffic patterns on major routes and other scenarios involving a constant flow of mobile terminals [1].

We now review several radio resource scheduling algorithms [2]. Classical algorithms, such as Round Robin and Random Access, are simple approaches inherited from wired networks. Round Robin, widely used in wireless networks, allocates an equal amount of resource units to each user in turn. Random Access (RA) allocates radio resources randomly among users.

Fair algorithms were introduced to address the limitations of classical approaches by incorporating the notion of fairness among users with differing service requirements. These include Fair Queuing (FQ), Max-Min Fair, and Weighted Fair Queuing (WFQ). In FQ, for a given transmission rate, each of the active users is served at an equal share of that rate, making it fairer than Round Robin. Max-Min Fair allocates resource units iteratively, gradually and equally increasing the throughput available to each user until no further units can be assigned to users who have already reached their requested rate.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

WFQ improves upon FQ by introducing a weighting system that allocates additional resource units to certain transmissions [3].

Opportunistic algorithms were developed to exploit frequency diversity and multi-user variability, allocating resource units based on the most favorable transmission and reception conditions. These include Maximum Signal-to-Noise Ratio (MaxSNR), also known as Maximum Carrier-to-Interference Ratio (MaxC/I), and Proportional Fair (PF). MaxSNR prioritizes the transmission with the highest signal-to-noise ratio, while PF allocates a subcarrier's time slot to the user with the most favorable transmission conditions relative to the average across that subcarrier. Under this principle, mobile users are scheduled only when their radio conditions are favorable, ensuring optimal use of available resource units.

The contribution of this work lies in our proposed model for radio resource allocation. Unlike prior approaches, we adopt dynamic programming as a key technique for solving the optimization problem associated with optimal resource allocation to users. Dynamic programming, particularly Bellman's principle of optimality, is a fundamental optimization framework that extends far beyond a single application domain [4]. It forms the basis of numerous classical algorithms, including those used in bioinformatics for sequence alignment and RNA structure prediction, highlighting the broad applicability and interdisciplinary significance of this optimization paradigm [5], [6].

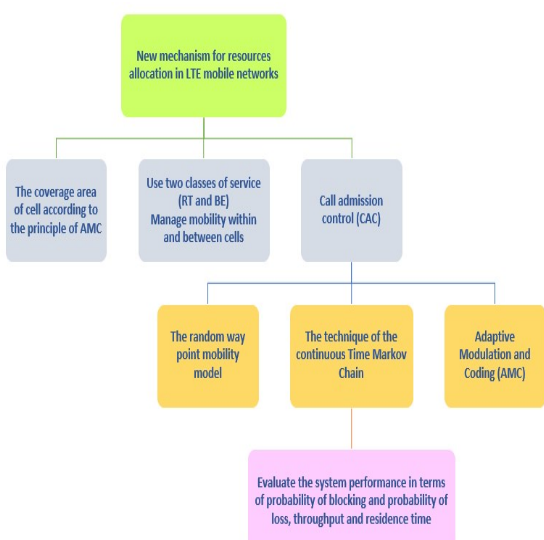

Figure 1. Resource allocation scheme for LTE

In view of its different classes of algorithms that we just mentioned above a comparison would be possible but given the intrinsic characteristics that each has, it would be more or less difficult. Including the rate offered, quality of service, it offers equity between different users, and the simplicity of its implementation [7]. The table below attempts to summarize the performance level schedulers presented in this section. The performance criteria are shown in the table as follows: By putting on a scale of 0 to 2 with 0: representing the lower level and 2 representing the maximum target to reach where it is desirable to tender. From all the above we can afford to build this table below. It should be noted that these data are indicative [8]. Their purpose is not to compare algorithms but to get an idea of the schedulers to implement faster. Differentiation service: according to its service yes / no.

Table 1. Qualitative classification of schedulers

Schedulers	RR	RA	FQ	WF	MMF	Max SNR	PF	EXP-PF	M-LDWF
Rate	0	0	0	0	0	2	2	2	2
Fairness	1	1	2	2	2	0	1	1	1
Service differentiation	No	No	No	No	Yes	No	No	Yes	Yes
Simplicity	2	2	1	1	2	1	1	1	1

The rest of the paper is organized as follows: Section 2 reviews related work on radio resource allocation. Section 3 introduces the model of the heterogeneous system studied where all system parameters are defined. The mathematical model of resource allocation is established in Section 4. The optimality principle and its resolution method are presented in Section 5. Section 6 is reserved for the allocation of cellular systems resources. The results are simulated and analyzed in Section 7. Section 8 discusses cross-disciplinary perspectives in bioinformatics and GIS. We finished our study in section 9 by a conclusion.

2. RELATED WORK

Resource allocation in heterogeneous wireless and mobile networks has been studied through several complementary methodological families. A first body of work relies on classical and fair scheduling rules, Round Robin, Fair Queuing, Max-Min Fair, and Weighted Fair Queuing, which prioritize simplicity and fairness but do not exploit channel-state diversity [9], [10]. A second family, opportunistic scheduling (MaxSNR, Proportional Fair), improves spectral efficiency by favoring users with the most favorable instantaneous radio conditions, at the cost of long-term fairness guarantees [11], [12].

Beyond these heuristic approaches, game-theoretic formulations have been proposed to model the competitive or cooperative interaction between users and networks in heterogeneous environments [2], [8], [13], [14], [15], [16]. These works cast resource sharing as a non-cooperative or evolutionary game and derive equilibrium allocations, but generally assume static or quasi-static network states and do not explicitly account for the sequential, state-dependent nature of user mobility and handover.

Dynamic programming, by contrast, is naturally suited to sequential decision problems in which the system evolves through discrete states over time. Earlier applications of dynamic and stochastic optimization to radio resource management have addressed subcarrier-and-bit allocation [17] and cross-layer scheduling [1], [18], but, to the best of our knowledge, few works combine Bellman's principle of optimality with an explicit, mobility-aware, multi-zone model of a heterogeneous LTE/WIMAX system as proposed here.

It is worth noting that Bellman's principle of optimality is not specific to telecommunications. The same recursive decomposition underlies foundational algorithms in bioinformatics, most notably the Needleman–Wunsch global sequence alignment algorithm and the Smith–Waterman local alignment algorithm, both of which solve sequence-comparison problems by decomposing them into optimal sub-alignments [5], [6]. This methodological kinship suggests that solution techniques developed in one domain, including the approximation strategy proposed in Section 7, may be transferable to allocation problems formulated in other fields.

On the spatial side, the zone-based representation of network coverage used in this work (Section 3) is conceptually close to the spatial data models employed in Geographic Information Systems (GIS) for radio network planning, where coverage areas and overlapping zones are represented as geo-referenced layers to support site selection and capacity planning [19]. Section 8 discusses this connection further.

3. MODEL OF WIRELESS SYSTEMS

The probability distribution of received packets in a heterogeneous network system is illustrated in Figure 1. The service area Z_1 is modeled as a circular region fully covered by a mobile network [13]. This area is further partitioned into several homogeneous circular sub-zones $\left(Z_i\right)_{2\leq i\leq m}$, each covered by a wireless network.

This spatial partitioning of the service area into zones is well suited to representation through Geographic Information Systems (GIS), which provide the tools commonly used in network planning to map coverage zones, visualize overlapping sub-areas, and support spatial decision-making for resource deployment [19]. As a result, mobile and wireless networks overlap within the sub-regions Z_i, while the wireless networks remain mutually disjoint. The region Z_0 corresponds to the portion of the service area that is not covered by any wireless network [14]. Users equipped with multi-access devices are able to switch between networks in overlapping zones by automatically selecting the one offering the highest available resources.

$$Zo = Z_1 - \bigcup_{j=1}^{m} Z_j \qquad (1)$$

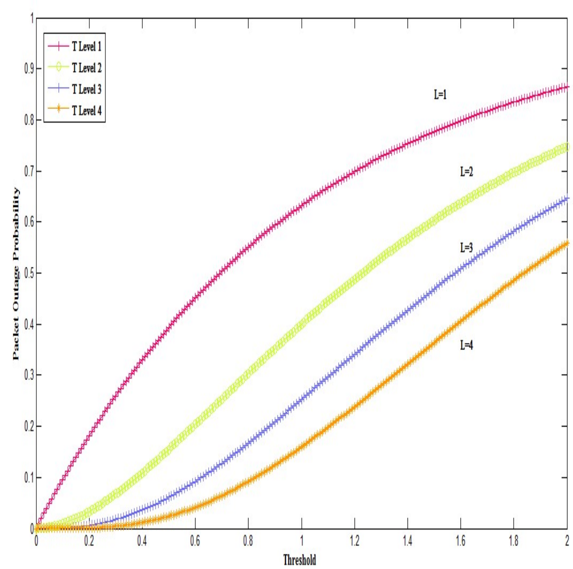

Figure 2. Probability distribution of received packet

4. MATHEMATICAL MODEL OF RESOURCE ALLOCATION

If a user is in a zone Z_i where both mobile and wireless networks coexist then he has the possibility to connect either newly or by handover to the mobile or wireless network [20]. If the number of resources is higher for the mobile network then the user will

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

connect to it otherwise the resources are blocked to connect to the wireless network [8].

The mathematical model and subsequent expressions presented below are derived from the framework established in [21].

Z : All zones, $z \in Z$; I : All users, $i \in I$; K : All services, $k \in K$; R : All networks, $r \in R$; $\tau_{z,z'}$: Release rates of the z zone to the cell z' ; $\tau_z^{i,k}$: Average rate of request for access to a service k by a user i in the zone z ; IP_z^i : Probability of finding a user i in z zone; $x_{z,r}^t$: Available resources of the network r in the zone z in step t ; The optimization problem variable used is the number of resource units that must be allocated to allow a user to connect. $y_{z,r}^{i,t}$: Resources allocated to the user i by the network r in the zone z in step t . These resources are directly dependent on those available, the probability of a user and the average rate of handover [15].

Calculated by the formula [2]:

$$y_{z,r}^{i,t} = \sum_{k \in K} x_{z,r}^t \left(IP_z^i + \tau_z^H \right) \tau_z^{i,k} \qquad (2)$$

Where the average rate of handover (H) is given by:

$$\tau_z^H = U_z^k \times \tau_{z,z'} \qquad (3)$$

Depending on the mobility model, the output rate of Z service area to the Z_i cell is defined by:

$$\tau_{z,z'} = \frac{E(\upsilon) \times L_{Z_i}}{\pi \times A(z)} \qquad (4)$$

$E(\upsilon)$ is the average speed of mobile users in the service area, L_{Z_i} is the length of the perimeter of the cell Z_i and $A(z)$ is the area of the service area. The probability of finding a user in a sub area $A(z)$:

$$IP_z^i = \frac{A(z)}{A(z_{tot})} \qquad (5)$$

With: $A(z)$: Area of sub-area z and $A(z_{tot})$: Area of the total service area. The request rate for access to a service $k\tau_z^{i,k}$ is given by:

$$\tau_{z_i}^{i,k} = IP_z^i \times \tau_z^{i,k} \qquad (6)$$

As resource units are limited, they depend on both the number of subcarriers and their spacing within the overall bandwidth division. Orthogonal Frequency Division Multiplexing (OFDM) spreads radio transmissions across all available subcarriers [11]. In this way, the transmitted signal is distributed over the entire set of subcarriers in the network, which helps improve overall throughput. Moreover, OFDM modulation addresses the issue of distant users, as it takes the distance parameter into account [17]. It also enables adaptive control of transmission power according to propagation distance. In this sense, it acts as a protective layer that enhances the robustness of signal delivery [9].

Table 2. Modulation parameters

$N_{of,r}^{i,t}$	The number of OFDM symbol of the network r occupied by the user i in step t.
$N_{bit,r}^{i,t}$	The number of bits of the modulation network r occupied by user i in step t
K_r	Number of subcarriers of a network r

4.1 Constraints and performances

The available resources are limited; we allocate taking into account the maximum to reach. This inequality shows that we can't allocate radio resource units to a user beyond what is available. We have the parameters that allow us to determine the occupancy function of a user in heterogeneous networks [22].

$$g^{i,t}\left(y_{z,r}^{i,t}\right) = max\left(f_1^{i,t}\left(y_{z,r}^{i,t}\right), f_2^{i,t}\left(y_{z,r}^{i,t}\right), \ldots, f_r^{i,t}\left(y_{z,r}^{i,t}\right)\right) \qquad (7)$$

Under the following constraints:

$$\sum_{i \in I} y_{z,r}^{i,t} \le x_{z,r}^t \qquad (8) \qquad ,$$

$$y_{z,r}^{i,t} \ge 0 \qquad (9) \qquad , \qquad x_{z,r}^t \ge 0 \qquad (10)$$

Where we have:

$$f_r^{i,t}\left(y_{z,r}^{i,t}\right) = K_r \times N_{of,r}^{i,t} \times N_{bit,r}^{i,t} \times y_{z,r}^{i,t}$$

We assume that the numbers of subcarriers $\left(K_r\right)_{r \in IN}$ networks follow an increasing sequence, $\left(K_r \le K_{r+1}\right)$.

$$x_{z,r}^{t+1} = \begin{array}{c} x_{z,r}^t - \sum_{i \in I} y_{z,r}^{i,t} = x_{z,r}^t - \sum_{i \in I} \sum_{k \in K} x_{z,r}^t \left(IP_z^i + \tau_z^H\right) \tau_z^{i,k} \\ x_{z,r}^t \left(1 - \sum_{i \in I} \sum_{k \in K} \left(IP_z^i + \tau_z^H\right) \tau_z^{i,k}\right) = x_{z,r}^0 \left[1 - \sum_{i \in I} \sum_{k \in K} \left(IP_z^i + \tau_z^H\right) \tau_z^{i,k}\right]^{t+1} \end{array} \qquad (11)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5. OPTIMIZATION AND PRINCIPLE OF OPTIMALITY

Considering the time-varying nature of resource allocation in heterogeneous networks, the optimization model developed in the previous section is addressed using dynamic programming. Dynamic programming is a rigorous optimization technique that guarantees exact solutions under the defined model assumptions [23]. The approach relies on the sequential determination of optimal decisions across multiple stages. Its fundamental principle consists of decomposing a complex optimization problem into a set of interconnected sub-problems, each of which can be solved independently and recursively. This hierarchical decomposition continues until elementary sub-problems are obtained, whose solutions are straightforward to compute. The overall optimal solution is then constructed from these intermediate results, making dynamic programming particularly effective for solving large-scale and structured optimization problems [16]. This decomposition into sub-problems is the same principle exploited in bioinformatics dynamic programming algorithms (e.g., Needleman-Wunsch for global sequence alignment), confirming the generality of the method beyond radio resource management [5].

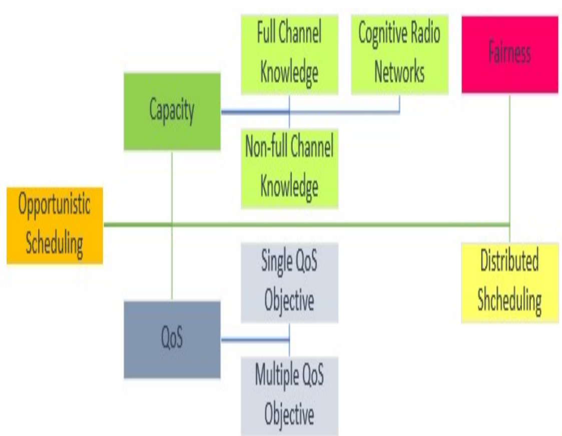

Figure 3. Opportunistic Scheduler Classification

The sequential structure of the considered optimization problem makes dynamic programming a particularly suitable solution approach. In this framework, the problem is formulated as a sequence of decisions associated with the different states of the system. For each state, resource allocation decisions are made by considering both the available resources and the specific requirements of users. Since the allocation process evolves according to the system state and the decisions taken at previous stages, dynamic programming provides an effective mechanism for determining optimal allocation policies over time [18].

5.1 Optimality principle

In dynamic programming, the solution to the original optimization problem is obtained by recursively combining the solutions of smaller sub-problems. This approach is founded on Bellman's Principle of Optimality, which states that an optimal policy is composed of optimal decisions at every stage. More precisely, regardless of the initial state and the decision taken, the sequence of subsequent decisions must remain optimal with respect to the state resulting from that initial decision [24]. This principle enables the decomposition of complex optimization problems into manageable stages while ensuring that the overall solution remains globally optimal.

The Bellman equation governs a dynamic system on discrete time $t = 0,1,....,T-1,T$ in a finite horizon T, as presented in [21].

E_t: State of the system at time t; $\Gamma(E_t)$: All actions in the state E_t ; $a_t \in \Gamma(E_t)$: Action among those possible when the system is in the state E_t. If Φ is the transfer function then we have:

$$E_{t+1} = \Phi(E_t, a_t) \quad (12)$$

Let $F(E_t, a_t)$ be the cost function to choose the action a_t if the system is in state E_t [25]; the overall cost after T step when arriving at state E_{T+1} is thus given by:

$$Z_T^*(E_{T+1}) = \min_{a_t} \left\{ \sum_{t=0}^{T} F(E_t, a_t) \right\} \quad (13)$$

Then

$$Z_T^*(E_{T+1}) = \min_{a_t \in \Gamma(E_t); E_{t+1} = \Phi(E_t, a_t)} \left\{ \sum_{t=0}^{T} F(E_T, a_T) + Z_T^*(E_{T-1}) \right\} (14)$$

5.2 Resource allocation model

Note by t: A discrete step of the finite-horizon dynamic system $T, t = 0,1,....,T$; $x_{z,r}^t$: System status at the beginning of the stage t . The set of $\Gamma(x_{z,r}^t)$ actions if the system is in state $x_{z,r}^t$ is defined by [26]:

$$\Gamma(x_{z,r}^t) = \left\{ \omega^t : \omega^t = \left(IP_z^i + \tau_z^H \right) \tau_z^{i,k} \right\} \quad (15)$$

Noting by Φ the transfer function then we have:

$$x_{z,r}^{t+1} = \Phi\left(x_{z,r}^{t}, \omega^{t}\right) \quad (16),$$

$$\Phi\left(x_{z,r}^{t},\omega^{t}\right)=x_{z,r}^{t}-\sum_{i\in I}y_{z,r}^{i,t}=x_{z,r}^{t}-x_{z,r}^{t}\omega^{t}=x_{z,r}^{t}\left(1-\omega^{t}\right) \quad (17)$$

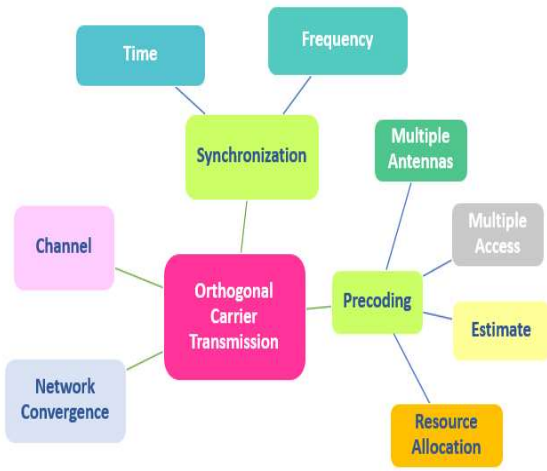

Figure 4. Resource allocation as an optimization problem under constraints.

The cost function $F\left(x_{z,r}^{t}, \omega^{t}\right)$ to choose the action ω^{t} if the system is in the state $x_{z,r}^{t}$ which corresponds to the occupation function of the user i is thus defined:

$$F\left(x_{z,r}^{t},\omega^{t}\right)=\begin{matrix}K_r\times N_{of,r}^{i,t}\times N_{bit,r}^{i,t}\times y_{z,r}^{i,t}=K_r\times N_{of,r}^{i,t}\times N_{bit,r}^{i,t}\times\left(x_{z,r}^{t}-x_{z,r}^{t+1}\right)\\ K_r\times N_{of,r}^{i,t}\times N_{bit,r}^{i,t}\times\left(x_{z,r}^{t}\omega^{t}\right)\end{matrix} \quad (18)$$

The global number of resource units allocated a user after T step when arriving at the state x^{T+1} is thus given by: $Z_T^{*}\left(x^{T+1}\right)=\max_{\omega^{t}}\left\{\sum_{t=0}^{T}F\left(x^{t},\omega^{t}\right)\right\}$ (19) , Then

$$Z_T^{*}\left(x^{T+1}\right)=\max_{\omega^{t}\in\Gamma\left(x^{t}\right);x^{t+1}=\Phi\left(x^{t},\omega^{t}\right)}\left\{\sum_{t=0}^{T}F\left(x^{T},\omega^{T}\right)+Z_T^{*}\left(x^{T-1}\right)\right\} \quad (20)$$

The quantity of assigned resource units corresponds to the maximum required to sustain the user's data stream. Each resource unit carries a specific amount of information, determined by dividing the available bandwidth over the considered time interval [27].

6. ALLOCATION OF CELLULAR SYSTEMS RESOURCES

Orthogonal Frequency Division Multiplexing (OFDM) is a modulation scheme designed to support user mobility and robust wireless communication. A key extension of this technique is Orthogonal Frequency Division Multiple Access (OFDMA), a radio access technology that enables multiple users to share the available frequency spectrum through division of subcarriers. OFDMA is particularly implemented in Long-Term Evolution (LTE) networks to enhance spectral efficiency and support simultaneous transmissions from multiple users. It is used in other networks such as UMTS [12].

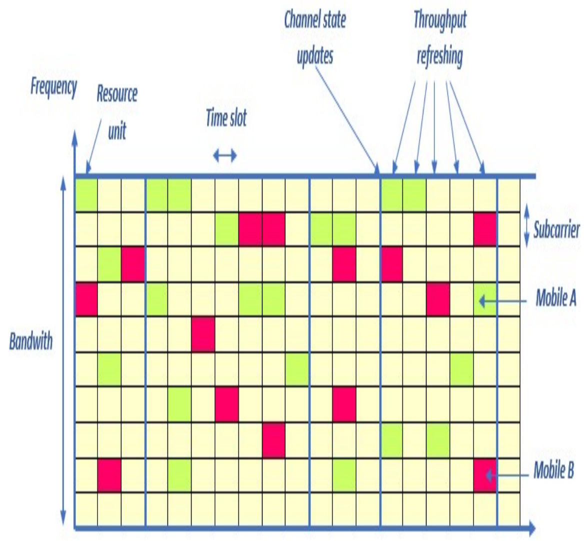

Figure 5. LTE resource block

The objective is to efficiently share the available radio spectrum among multiple users by dynamically allocating portions of the resource according to their requirements. In an OFDMA-based system, the transmitted digital signal is divided and mapped onto a large set of orthogonal subcarriers. This multiple-access technique enables flexible and efficient resource allocation, allowing the network to accommodate a large number of users with diverse and varying Quality of Service (QoS) demands while maintaining high spectral efficiency.

Table 3. Simulation parameters

Parameter	Value
Channel Model	Attenuation with fading
Cell Diameter	1 km
MCS User	16 QAM, 64 QAM
Number of Users	10 Users
Number of TTI	2000

The occupation function of a user i located only in the LTE network to which $y_{z,1}^{i,t}$ resources have been allocated in a zone z in step t is given by [8]:

$$g_1^{i,t}\left(y_{z,1}^{i,t}\right)=K_1\times N_{of,1}^{i,t}\times N_{bit,1}^{i,t}\times y_{z,1}^{i,t} \quad (21)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

If the user is connected to the wireless network WIMAX then the occupancy function becomes:

$$h_2^{i,t}\left(y_{z,2}^{i,t}\right) = K_2 \times N_{of,2}^{i,t} \times N_{bit,2}^{i,t} \times y_{z,2}^{i,t} \quad (22)$$

We observe that the main difference lies in the number of subcarriers. Indeed, the LTE network, having a larger bandwidth than WiMAX, satisfies $K_1 \le K_2$. The occupation function depends on both the distance and the amount of data transmitted through the modulation scheme. Consequently, it varies depending on whether the connection is established via an LTE mobile network or a WiMAX wireless network [10]. The heterogeneity between LTE and WiMAX networks allows users to select the most appropriate network based on their location and the availability of resources. Accordingly, for a given user, we define the occupation function in a heterogeneous system comprising WiMAX and LTE networks as follows:

$$f_r^{i,t}\left(y_{z,r}^{i,t}\right) = max\left(g_i\left(y_{z,1}^{i,t}\right), h_i\left(y_{z,2}^{i,t}\right)\right) \quad (23)$$

As we seek to allocate $y_{z,r}^{i,t}$ radio resources to maximize the occupancy function then we establish the following optimization problem [24]:

$$max\sum_{i=1}^{n} f_i\left(y_{z,r}^{i,t}\right) \quad (24) \quad ,$$

$$\sum_{i\in I} y_{z,r}^{i,t} \le x_{z,r}^{t}, y_{z,r}^{i,t} \ge 0, x_{z,r}^{t} \ge 0, r \in \{1,2\} \quad (25)$$

7. SIMULATION AND ANALYSIS OF THE RESULTS

The main simulation parameters are given in Table 3. The number of users is intentionally limited due to the exponential computational complexity of the optimal algorithm $\left(O(U^N)\right)$.

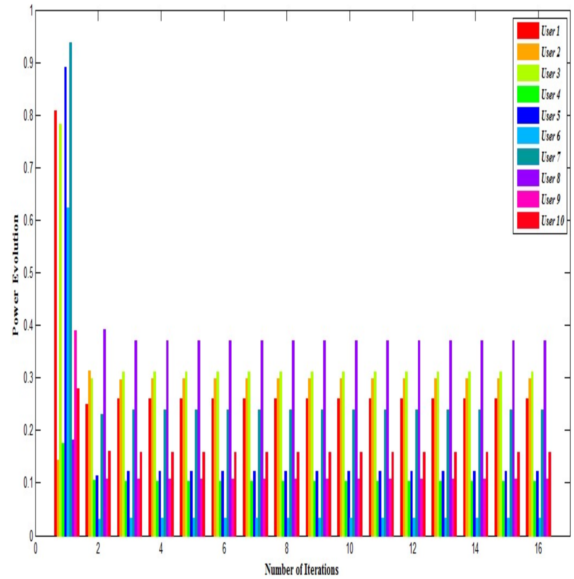

Figure 6. Evolution of the power vs. number of iterations, SINR optimization.

However, results with similar trends for an instance of 50 users were also observed. To assess the fairness among users, we use the index Jain defined by: $F(\Delta t) = \left(\sum_{u\in U} \bar{D}_u(\Delta t)\right)^2 \Big/ U \sum_{u\in U}\left(\bar{D}_u(\Delta t)\right)^2$ (26)

With $\bar{D}_u(\Delta t)$ the average rate of the user u calculated on windows of duration Δt.

Figure 6 presents a comparison between the proposed approximation algorithm (Approx), the optimal algorithm under the Single MCS constraint (25), and the classical optimal algorithm (22), which does not incorporate LTE-B specific characteristics in the resource allocation process. Nevertheless, the Single MCS constraint is still enforced after the execution of the algorithm.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

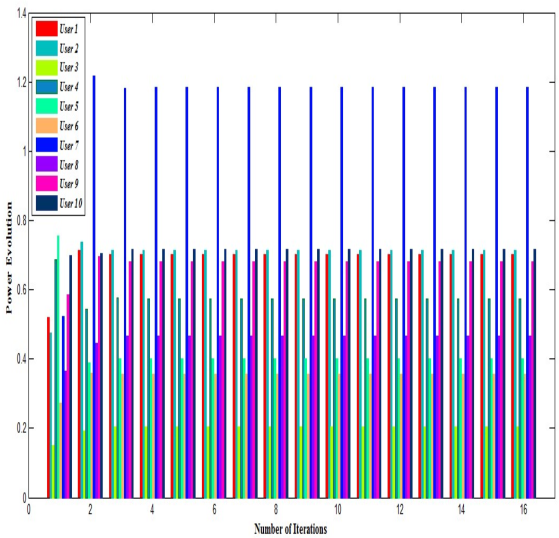

Figure 7. Evolution of the power vs. Number of iterations, fairness optimization.

Figure 7 illustrates the fairness index as a function of Δt in a system comprising 18 secondary users (SUs). It can be observed that the overall throughput achieved by the proposed algorithm remains very close to the optimal solution and significantly outperforms the classical approach. As expected, the optimal solution provides the best performance in terms of both throughput and fairness. However, the fairness level achieved by the proposed method remains highly satisfactory, reaching approximately 0.94. These results demonstrate that the proposed algorithm is effective and practical for real-world implementation.

8. CROSS-DISCIPLINARY PERSPECTIVES

8.1 Dynamic Programming Applications in Bioinformatics

The resolution method adopted in this work, recursive decomposition of a global optimization problem into elementary sub-problems via Bellman's principle of optimality (Section 5), is a general-purpose technique whose applicability extends well beyond radio resource management. In bioinformatics, the same recursive structure underlies some of the most widely used algorithms for biological sequence analysis. The Needleman–Wunsch algorithm computes the optimal global alignment between two sequences by defining, for each pair of prefixes, a cost function analogous to the occupation function defined in Equation (18), and by building the global solution from optimal sub-alignments [5]. Similarly, the Smith–Waterman algorithm applies the same recursive principle to local sequence alignment, and dynamic programming is also central to RNA secondary structure prediction [6]. The structural similarity between these problems and the resource-allocation problem addressed here, a finite-horizon decision process in which a state-dependent cost must be optimized step by step under capacity constraints, indicates that the approximation strategy introduced in Section 7 to control computational complexity could, in principle, be adapted to large-scale sequence-alignment problems where exact dynamic programming becomes computationally prohibitive. Figure 8 illustrates this structural analogy between the two recursive decomposition schemes.

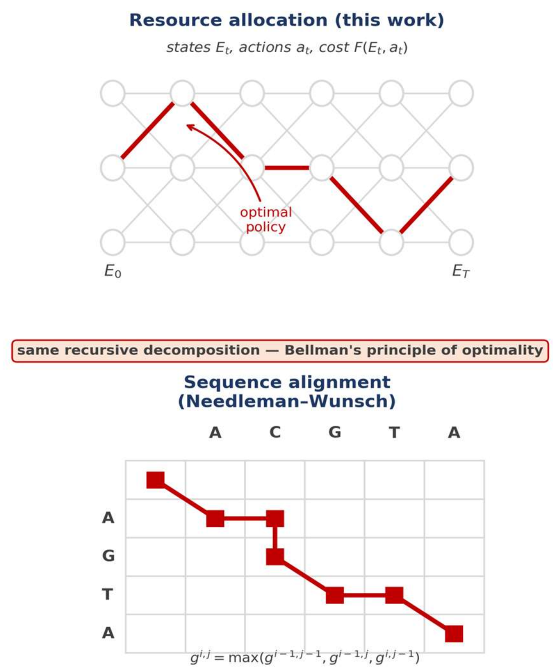

Figure 8. Structural analogy between dynamic programming for resource allocation and the Needleman–Wunsch algorithm.

8.2 Geographic Information Systems for Spatial Resource Modeling

The model introduced in Section 3 represents the service area as a set of geo-referenced circular zones, each characterized by its surface, its position relative to neighboring zones, and the resources available within it (Equation 5). This representation is structurally equivalent to the layered spatial data model used in Geographic Information Systems (GIS), where network coverage, cell boundaries, and overlapping service areas are stored and manipulated as geo-referenced vector or raster layers [19]. GIS tools are routinely used in cellular network planning to support site selection, propagation modeling, and visualization of coverage gaps, tasks that correspond

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

directly to the zone partition formalized in Equation (1) of this article. Integrating the proposed optimization model with a GIS environment would allow the spatial parameters used in the model (zone area, perimeter, user density) to be derived directly from geo-referenced data rather than from simplified analytical assumptions, and would enable a map-based visualization of the resulting resource allocation. This integration is identified as a promising direction for extending the present work. Figure 9 illustrates the correspondence between the zone-based model and its GIS layer representation.

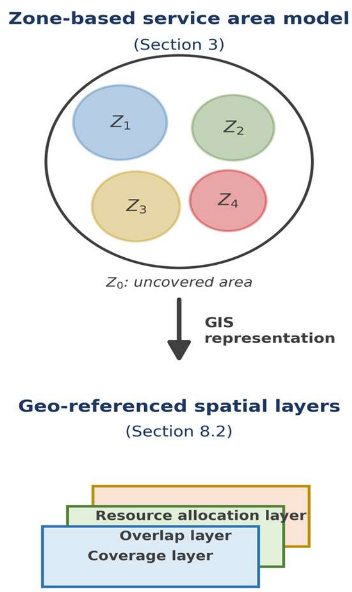

Figure 9. From zone-based service area model to geo-referenced GIS spatial layers representation.

9. CONCLUSIONS

The optimal allocation of radio resources can be formulated as an optimization problem, as it requires simultaneously accounting for resource availability and the maximization of user demands. To address this challenge, dynamic programming is adopted as the allocation approach. The proposed algorithm assumes that an ongoing connection remains active until the available resources are exhausted for incoming users. It also integrates users' actual requirements and aims to maximize throughput in the considered heterogeneous network, thereby improving both user satisfaction and operator performance, which is an important contribution in the field of telecommunications. Furthermore, factors such as communication duration, mobility-related signaling costs, cell geometry, and radio signal propagation conditions must be considered when designing an efficient resource management algorithm, representing promising directions for future research.

Furthermore, the spatial zoning model could be further enriched using GIS-based geospatial analysis tools, while the dynamic programming framework opens perspectives for cross-disciplinary application to optimization problems encountered in bioinformatics.

REFERENCES:

[1] Chen Feng, Xu Li, Zhen-Hui Tan, "Integrated Radio Resource Management Strategy for MIMO-OFDM System on Cross-Layer Architecture", Wireless Communications and Mobile Computing Conference 2008. IWCMC '08. International, pp. 255-260, 2008.

[2] A. B. MacKenzie and S. B. Wicker, "Selfish users in Aloha: a game-theoretic approach," IEEE 54th Vehicular Technology Conference. VTC Fall 2001. Proceedings, Atlantic City, pp. 1354-1357 vol.3.

[3] Sara RIAHI, Azzeddine RIAHI, ’’ resource allocation optimization based on channel quality for long term evolution systems (lte) ’’, Journal of Theoretical and Applied Information Technology, ISSN: 1992-8645, Vol.97. No 6 ,31st March 2019.

[4] Bellman, R. (1957). Dynamic Programming. Princeton University Press, Princeton, NJ.

[5] Needleman, S.B., Wunsch, C.D. (1970). A general method applicable to the search for similarities in the amino acid sequence of two proteins. Journal of Molecular Biology, 48(3), 443-453.

[6] Smith, T.F., Waterman, M.S. (1981). Identification of common molecular subsequences. Journal of Molecular Biology, 147(1), 195-197.

[7] Xin Ai , V. Srinivasan , Chen-khong Tham, Optimality and Complexity of Pure Nash Equilibria in the Coverage Game, IEEE Journal on Selected Areas in Communications, v.26 n.7, September 2008.

[8] Sara RIAHI, Azzeddine RIAHI, ’’ Game theory for resource sharing in large distributed systems ’’, International Journal of Electrical and Computer Engineering , IJECE, Vol. 9, No. 2, April 2019, pp. 1249~1257 ISSN: 2088-8708, DOI: 10.11591/ijece.v9i2.pp.1249-1257 .

[9] Chiapin Wang, Yuan-Chieh Huang, "Delay-scheduler coupled throughput-fairness resource allocation algorithm in the long-term evolution

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

wireless networks", Communications IET, vol. 8, no. 17.

[10] Cédric Gueguen and Malo Manini, « Fairness-Energy-Throughput Optimized Trade-off in Wireless Networks », in: ICNC 2018-International Conference on Computing, Networking and Communications, IEEE, 2018, pp. 1–8.

[11] Omer Faruk Gemici, Ibrahim Hokelek, Hakan Ali Çırpan, "GA based multi-objective LTE scheduler", Cognitive Cellular Systems (CCS) 2014 1st International Workshop on, pp. 1-5, 2014.

[12] Nicolas Guérin, Malo Manini, Rodolphe Legouable and Cédric Gueguen, « High system capacity pre-scheduler for multi-cell wireless networks », in: Wireless Networks (2020), pp. 1–13.

[13] Mkiramweni, M. E., Yang, C., Li, J., & Han, Z. (2018). Game-Theoretic Approaches for Wireless Communications with Unmanned Aerial Vehicles. IEEE Wireless Communications, 25(6), 104-112.

[14] Sara RIAHI, Azzeddine RIAHI,'' Applications of game theory to optimization of resource allocation of wireless systems: algorithmic solution'', International Journal of Online Engineering (iJOE), ISSN: 2626-849,Vol 14, No 12 (2018).

[15] Sara RIAHI, Azzeddine RIAHI,'' Optimization and evolutionary games, stochastic equilibrium application to cellular systems'', Advanced Intelligent Systems for Sustainable Development (AI2SD '2019), Marrakech 8 -11 July ,2019

[16] Sara RIAHI, A. RIAHI, ''The non-cooperative game theory applied to telecommunication systems'', International Journal of Information Science and Technology, iJIST, ISSN: 2550-5114 Vol.4-N.2 -2020.

[17] Y. J. Zhang and K. B. Letaief, "Multiuser adaptive subcarrier-and-bit allocation with adaptive cell selection for OFDM systems," IEEE Transactions on Wireless Communicaitons, 3(4):1566-1575, September 2004

[18] M.Y. Suraki, A.T. Haghighat, and M. Gholipour, "FCLCC: fuzzy cross-layer congestion control in mobile ad hoc networks," IJCSNS, vol.18, no.1, p.155, 2018.

[19] Chen, X., Wu, H., & Tri, T. M. (2012). Field strength prediction of mobile communication network based on GIS. Geo-Spatial Information Science, 15(3), 199-206.

[20] Zubair Md. Fadlullah, Chao Wei, Zhiguo Shi, Nei Kato, "Joint optimization of QoS and security for differentiated applications in heterogeneous networks", Wireless Communications IEEE, vol. 23, 2016, ISSN 1536-1284.

[21] Dione, D., ''Optimal performances of a global allocation of radio resources'', heterogeneous networks system, (2018).

[22] Sara RIAHI, Azzeddine RIAHI,''Resource allocation in Pre -5G cellular systems'' 2nd edition of the International Conference on Networking, Information Systems & Security (NISS 2019) RABAT Morocco March 27-28, 2019.

[23] Sara RIAHI, A. RIAHI, ''Performance evaluation of random access methods for wireless systems'', Journal of theoretical and applied information technology, ISSN: 1992-8645, Vol.99. No 7, (2021).

[24] S. A. Alghamdi, "Novel trust-aware intrusion detection and prevention system for 5G MANET–Cloud," Int. J. Inf. Secur., vol. 21, no. 3, pp. 469–488, 2022.

[25] S. Mohan1, dr. P. Vimala,'' enhancing congestion control and qos scheduling using novel rate aware-neurofuzzy algorithm in manet '', Journal of Theoretical and Applied Information Technology 15th June 2023. Vol.101. No 11

[26] Manuel Avila, Pedro Ponce, Arturo Molina, Katya Romo, Simulation Framework for Load Management and Behavioral Energy Efficiency Analysis in Smart Homes, Smart Multimedia, (2020) 497-508.

[27] Ritu nandal3, '' an evaluation of a resource allocation and scheduling model smart grid environment in different load and fault situations '' , Journal of Theoretical and Applied Information Technology 15th April 2023. Vol.101. No 7.