ActMesh- A Cognitive Resource Management paradigm for dynamic mobile Internet Access with Reliability Guarantees

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Abstract

Wireless Mesh Networks (WMNs) are going increasing attention as a flexible low-cost networking architecture to provide media Internet access over metropolitan areas to mobile clients requiring multimedia services [2]. In WMNs, Mesh Routers (MRs) from the mesh backbone and accomplish the twofold task of traffic forwarding, as well as providing multimedia access to mobile Mesh Clients (MCs). Due to the intensive bandwidth-resource requested for supporting QoS-demanding multimedia services, performance of the current WMNs is mainly limited by spectrum-crowding and traffic-congestion, as only scarce spectrum-resources is currently licensed for the MCs' access [2]. In principle, this problem could be mitigated by exploiting in a media-friendly (e.g., content-aware) way the context-aware capabilities offered by the Cognitive Radio (CR) paradigm. As integrated exploitation of both content and context-aware system's capabilities is at the basis of our proposed Active Mesh (ActMesh) networking paradigm. This last aims at defining a network-wide architecture for realizing media-friendly Cognitive Mesh nets (e.g., context-

aware Cognitive Mesh nets). Hence, main contribution of this work is four fold:

1. After introducing main functional blocks of our ActMesh architecture, suitable self-adaptive Belief Propagation and Soft Data Fusion algorithms are designed to provide context-awareness. This is done under both cooperative and noncooperative sensing frameworks.

2. The resulting network-wide resource management problem is modelled as a constrained stochastic Network Utility Maximization (NUM) problem [3], with the dual (contrasting) objective to maximize spectrum efficiency at the network level, while accounting for the perceived quality of the delivered media flows at the client level.

3. A fully distributed, scalable and self-adaptive implementation of the resulting Active Resource Manager (ARM) is deployed, that explicitly accounts for the energy limits of the battery powered MCs and the effects induced by both fading and client mobility. Due to informationally decentralized architecture of the ActMesh net, the complexity of (possibly, optimal) centralized solutions for resource management becomes prohibitive when number of MCs accessing ActMesh net grow. Furthermore, centralized resource management solutions could required large amounts of time to collect and process the required network information, which, in turn, induce delay that can be unacceptable for delay

> sensitive media applications, e.g., multimedia streaming [4]. Hence, it is important to develop network-wide ARM policies that are both distributed and scalable by exploiting the radio MCs capabilities to sense, adapt and coordinate themselves.

We validate our analytical models via simulation based numerical tests, that support actual effectiveness of the overall ActMesh paradigm, both in terms of objective and subjective performance metrics. In particular, the basic trade-off among backbone traffic-vs-access traffic arising in the ActMesh net from the bandwidth-efficient opportunistic resource allocation policy pursued by the deployed ARM is numerically characterized.

The standardization framework we inspire to is the emerging IEEE 802.16h one [5].

"Oggi sono finalmente arrivata alla realizzazione del mio desiderio più grande. Ripercorrendo questo viaggio il pensiero più importante va ai miei genitori, a mio fratello, ai miei nonni, a Davide e a tutti imiei amici più cari i quali mi hanno sempre sostenuta e sopportata con molta pazienza.

Ringrazio, con affetto sincero, tutti coloro che mi sono stati vicini e che mi hanno seguita da lontano. Un ringraziamento particolare va a tutti coloro che, con pazienza, mi hanno seguita nella realizzazione di questa tesi. Infine, ma non per questo meno importanti, grazie a tutti gli amici persi e poi ritrovati."

"Finally, today, I realize one of my greater desire. Going back over this tour, my more important thought goes to my parents, my brother, my grandparents, Davide and all my closest friends.

Thank you, with deep affection, to all those that in this years have been close to me and that have been followed me. An especially thanks goes out to all those that, with patience, have followed me in the realization of this thesis. Finally, but not least important, thanks to all my lost and then found friends."

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”Questo lavoro di tesi lo dedico alle persone più importanti della mia vita senza le quali non ce l’avrei mai fatta a raggiungere questo ulteriore traguardo. Un pensiero speciale va alla mia nonna che dall’alto mi osserverà per tutta la mia vita.”

”I dedicate this work to most important people of my life, without them I would not never achieve this further goal. An especially thought I dedicate to my grandmother that, for all my life, will observe me from the heaven.”

Introduction

0.1 The Active Mesh paradigm: Motivation, Architecture and Tackled Problem

(WMNs) offer a promising networking architecture to provide multimedia services to mobile users and represent an attractive solution to extend the broadband Internet access in the local-area and metropolitan area networks [2]. As a matter of this fact, WMNs are undergoing a rapid growth around the world. However, as the network density and traffic increase, the spectrum resource available for WMN applications is quickly becoming over crowded [6]. Cognitive Radio (CR) is a promise radio access paradigm suitable for mitigating the spectrum crowding problem [7]. It is suitable for *opportunistic* access (under reliability guarantees) to licensed or even unlicensed spectrum bands [6], so to be specifically applicable to the heavy spectrum accessing requirement characterizing the Wireless Mesh Network environment.

In this contribution, we focus our emphasis on the Cognitive Wireless Mesh networking scenario envisioned in [8] and referred to as Cognitive Mesh. Cognitive Mesh is featured as a self-organized and self-configured network architecture that aims at combining Cognitive Radio technology with the distributed mesh structure, in order to provide an integrated service platform over a wide range of converged *heterogeneous* networks realizing Opportunistic Spectrum Access under Reliability Guarantees (OSA-RG) [6],[8]. Basically, the Cognitive Mesh network is formed by interconnecting several clusters of (mobile) Mesh Clients (MCs) via a wireless backbone composed by (static) Mesh Routers (MRs) that also act as a cluster-head [8].[0.1]. The Cognitive Mesh paradigm leverages the context and content-aware capabilities of the supported MCs for improving utilization of the available access frequency bands.

0.2 A first Sketch of the Considered Cognitive Mesh Network

In the Cognitive Mesh architecture we go to consider, for supporting bandwidth demanding multimedia applications run by MCs (see Fig.2.1.1), the bandwidth available for implementing the underlying wireless mesh backbone is the main system resource whose usage is to be capitalized [8],[9]. MCs are battery-powered (e.g., energy-limited) mobile nodes equipped by

[0.1]At last one MR plays the additional role of Gateway from/to the wired Internet (see Fig.2.1.1) *single-interface* (e.g., single carrier) tunable CRs that enable efficient (e.g., opportunistic and dynamic) spectrum access to the wireless mesh backbone (see Fig.2.1.1). Each MC runs (possibly, heterogeneous) multimedia application programs that generate rate and delay-sensitive Variable Bit Rate (VBR) bursty traffic flows to be routed by the mesh backbone towards the Internet (see Fig.2.1.1). At the same time, the mesh backbone must also deliver to the MCs the corresponding traffic generated in downlink by the Internet (see Fig.2.1.1). So, according to the backbone architecture envisioned in [9] for broadband applications, each MR composing the multi-hop backbone of Fig.2.1.1 is assumed to be equipped by two non-interferring radio interfaces, so to be capable to receive (from the clustered MCs and the upstream MR, see Fig.2.1.1) and transmit data (to the downstream MR, see Fig.2.1.1) *in parallel* (e.g., in a full-duplex way). So doing, the resulting multi-hop backbone may route higher throughput from/to the Internet by exploiting *orthogonal* (e.g., noninterferring) wireless links over the successive hops (see [9, Sect.III.A] for a in-deep discussion about this point).

0.3 Opportunistic Spectrum Access under Reliability Guarantees in Energy and Bandwidth limited Cognitive Mesh Networks

The Cognitive Mesh architecture we go to consider must support high-throughput multimedia flows from/to battery-powered mobile MCs, so that it operates in an energy and bandwidth-limited regime. Thus, in order to maximize the network spectrum efficiency, we assume that each MR of Fig.2.1.1 makes available *only one* frequency band (e.g., only one radio interface) for receiving data. This (single) band must be shared by both:

i) MCs falling into the cluster controlled by the MR for accessing in uplink to the Internet; and,

ii) the upstream MR over the backbone for forwarding traffic in downlink from the Internet (see Fig.2.1.1)

Furthermore, due to the delay and delay-jitter sensitive features of the traffic typically generated by multimedia applications [4], in order to capitalize the usage of switching-resources required to route in downlink (e.g., from the Internet to the clusters)[0.2] over the mesh backbone must retain higher prior-

[0.2] Obviously, the same considerations hold when backbone traffic must be forwarded in uplink (e.g., from the MRs to the Internet), while the cluster traffic must be broadcast in downlink (e.g., from each MR to the MCs falling into the corresponding cluster, see Fig.2.1.1).

ity than the access traffic generated in uplink by the clustered MCs toward the Internet. Thus, in the bandwidth-limited Cognitive Mesh scenario we go to consider, the i-th MR (e.g., the header MR(i) of the i-th cluster) handles the traffic received over the backbone from the $(i + 1)$-th upstream MR as the *primary traffic*, while it treats the aggregate access traffic received from the MCs falling into the i-th cluster as a *secondary traffic*. In turn, this means that, in the considered Cognitive Mesh architecture, the $(i + 1)$-th MR (i.e., MR(i+1)) is the Primary User (PU) of the i-th cluster (see Fig.2.1.1); and the i-th MR) is the corresponding cluster-head (i.e., i-th access point); and, finally, all MCs currently falling into the i-th cluster are the Secondary User (SU) of the i-th cluster. Thus, in order to capitalize on the usage of the available spectrum resource, the SUs (i.e., MCs) of each cluster exploit their cognitive capabilities (namely, spectrum sensing, spectrum decision and spectrum sharing capabilities [7],[10]) to access in uplink their cluster-head in an *opportunistic way with Reliability Guarantees* (OSA-RG). Specifically, according to the CORVUS paradigm in [6], in our framework we assume *fixed in a deterministic* (i.e., no probabilistic) way the maximum (e.g., worst-case) number of packet collisions allowed by the PU of each cluster in any time interval. This means, that, *unlike* [11], our Cognitive Mesh guarantees that, slot-by-slot, the time-average worst-case number of collisions experienced by each PU is *always* below a fixed upper-bound value that is independent from the actual operating conditions of the network. Thus, in each cluster, SUs must perform

OSA under deterministic *hard* Reliability Guarantees in terms of worst-case number of collisions suffered by the corresponding PU in any time interval.

In additional, since each MC is battery-powered and the uplink channels available to MCs for the access the cluster-heads are fading affected, the Cognitive Mesh we go to consider is also energy-limited. Specifically, we assume that the OSA-RG performed by each MC must meet constraints on *both* the corresponding allowed average and peak energies. Furthermore, we require that these energy constraints are to be full filled *regardless from* the mobility pattern actually followed by each MC.

0.4 Towards Content-aware Cognitive Mesh architectures: The Proposed Active Mesh Paradigm for Multimedia Applications

Since each MC of Fig.2.1.1 runs multimedia programs, it is reasonable to require that the overall Cognitive Mesh must provide a minimum level of perceptive satisfaction to its clients.

As in [12],[4], in the considered mesh network the satisfaction level perceived by each MC is assumed to be measured by a (suitably defined) *media distortion-function* that, in turn, depends on the actual media application and media encoder utilized by each MC [4, Chap.4].

A distinguishing feature of the Cognitive Mesh scenario we aim at considering is, indeed, that each MC in Fig.2.1.1:

i) is *aware* of both type (audio, video, multimedia,etc.) of processed media content and corresponding user subjective distortion-function adopted to measure the media quality lastly perceived by the end-users;

ii) selects the (feasible) OSA-RG policy that *minimizes* the perceived media distortion, so to attempt to attain the satisfaction level required by the end-user.

Thus, being the Wireless Mesh Network paradigm envisioned in our work both context-aware (e.g., cognitive) and also content-aware (e.g., media aware), it is a step beyond legacy Cognitive Mesh architecture [8]. We coin the *Active Mesh (ActMesh)* term to refer to WMNs that are both Cognitive and Content-aware. Hence, being aware of the media distortion actually perceived by the clients of the provided networking service, the ActMesh paradigm is an instance of next-generation user-friendly networking architecture [12],
[4, Chap.14].

Hence, according to the media-oriented services to be supported by the ActMesh network, we assume that each MC of Fig.2.1.1 is equipped by a scalable media encoder[0.3] that generates a *VBR bursty* traffic flow. In order to both smooth the resulting delay-jitter and also perform an energy-saving *opportunistic* exploitation of the fluctuations of the access channel quality induced

[0.3] As, for example, a Fine-Granularity Scalable (FGS) MPEG-4 video encoder [12], or, more in general, an adaptive vector quantizer with adaptive quantization-step [4].

by fading and client mobility, we also assume that each MC is equipped by a finite-capacity buffer, where a number of packets lastly output by the media encoder is queued before being uploaded towards the Internet (see Fig.4.0.1 and related text for more details about the adopted queueing model).

0.5 The Tackled Network-wide Resource Management Problem

After considering a slotted Active Mesh architecture, the constrained optimization problem we aim at tackled consists in the *cross-layer adaptive joint control* of the:

i) set of media flows and transmit-energies generated by MCs under (possibly) imperfect spectrum sensing and/or access channel state estimation;

ii) access opportunities (e.g. access scheduling) in each cluster.

The objective is to:

i) *maximize* the aggregate access goodput conveyed to the Internet by the overall Active Mesh network.

The (main) sets of considered system *constraints* are hard upper bounds on the:

i) peak-energy allowed each MC;

ii) average-energy allowed each MC;

iii) worst-case number of packet collisions allowed in each cluster among primary and secondary traffic flows over time intervals of any desired duration (e.g., long time-intervals as well as short time-intervals);

iv) maximum *finite* queue length allowed each MC.

About the considered optimization problem, five main explication remarks are, indeed, in order.

First, since the above constraints must to be met regardless from the randomly time-variant fluctuations in the network state induced by fading, bursty traffic behavior, and client mobility, thus, the nature of the considered optimization problem is dynamic and stochastic.

Second, due to the (possibly) high number od MCs and clusters served by the considered ActMesh of Fig.2.1.1, we explicitly require that the solution of the tackled optimization problem is both *distributed* and *scalable*. This means that the implementation of the resulting resource allocation policies at each MC and cluster-head must rely on only locally acquired measurements, while their implementation-complexity must be active over the net of Fig.2.1.1.

Third, the tackled optimization problem simultaneously involves the behavior of MCs, cluster-head and mesh backbone. Thus, it requires resources allocation at the *system level*, and, then, it represents an instance of *Resource Management Problem* in Cognitive and Content-aware Mesh Networks (CC-

RMP).

Fourth, due to both the context (i.e., cognitive) and content-aware nature of the ActMesh net of Fig.2.1.1, we anticipate that the above defined optimization problem jointly embraces the Application (APP), MAC and Physical (PHY) layers of the protocol stack of each MC, together with the PHY and MAC layers of the protocol stack of each cluster-head (see Fig.4.0.1). So, in order to gain in performance by the exploitation of the interactions among these different layers, in this work we pursue a cross-layer approach leads to the joint optimal design of the flow-control and transmit-energy policies pursued by each MC, combined with the access policy implemented by each cluster-head.

Fifth, the effects of both imperfect spectrum sensing and imperfect access channel measurements performed by each MC are explicitly modelled and taken into account by the tackled optimization problem.

0.6 Why Cross-Layer Design in Active Mesh Networks

Several characteristic arising from the cognitive and content-aware nature of the proposed Active Mesh paradigm may cross-layer design more useful for ActMesh nets than (multi-hop) wireless networks, such as cellular, ad hoc or sensor networks.

Some of these characteristics more relevant for the goals of this work are listed in the following a), b), c), d) items.

a) Mixed Traffic types with Heterogeneous QoS

ActMesh nets are introduced to support a large variety of media services that give arise to many traffic types with *heterogeneous* features, QoS requirements and user expectations. In order to deliver such services in ActMesh nets, application layer, routing and MAC protocols need to cooperate in an *active* way; otherwise (e.g., without *active cooperation*), either user level of perceived satisfaction is not met, or the network resource is wasted. For example, in the ActMesh scenario of Fig.2.1.1, variation of bandwidth demand advanced by a MC can trigger reallocation of time slots planned for the access, reconfiguration of access channels, reallocation of access rates etc. on all access links available at the corresponding cluster (see Fig.2.1.1).

b) Cognitive MAC and Imperfect Spectrum Sensing

MAC plays a critical role in the Active Mesh architecture of Fig.2.1.1. Although many MAC solutions are, in principle, available however, none of them is, indeed, ideal because of the following two major factors:

1. the spectrum sensing and access channel estimation carried out by MCs are, in practice, always affected by errors and
2. the adopted MAC protocol itself may not offer guaranteed performance.

In the second factor, a typical example is CDMA/CA, which is a best effort MAC protocol and cannot provide any guarantee for delay, collisions, etc.

Thus, it is reasonable to conclude that the ActMesh paradigm demands for cross-layer design of the MAC and PHY layers that is able to exploit the cognitive capabilities offered by PHY layer so to capitalize the use of the available spectrum under hard Reliability Guarantees, even in the presence of error measurements in both spectrum sensing and access channel estimation.

c) Advanced PHY Layer Technologies

It is expected that several advanced PHY layer technologies must be adopted by the Active Mesh paradigm for providing the QoS levels requested by the clients in the envisioned energy and bandwidth limited application scenario. These technologies fall into the following main categories:

c.1) Rate-Adaptive Transmission Technology- this is achieved by equipping the network nodes (i.e., both MCs and MRs) with multiple options of modulation and coding, possibly combined with adaptive power-control schemes. With rate-adaptive technology, a same physical layer may support different access rate, depending on the access channel quality and energy-constraints to be met. In turn, this requires design of suitable MAC-adaptation (e.g., link adaptation) protocols, which are an instance of cross-layer schemes aiming at maximizing the data-link throughput.

c.2) Multi-Antenna Technology- Multi-Antenna technology can significantly reduce the interference between colliding nodes, as well as improve (via spatial multiplexing) the access capacity of the overall network [7, Chap.9]. However, it is expected that taking full advantage of Multi-Antenna in ActMesh nets will require network wide-scheduling schemes involving upper layers of the protocol stack to coordinate spatial signal shaping. Some (preliminary) results along this direction are presented by Authors in [7, Chap.9].

c.3) Cognitive Radios- Obviously, equipping MCs of the ActMesh of Fig.2.1.1 with cognitive radios is the key to both: *i)* reduce packet collisions among primary and secondary users; and *ii)* improve spectrum usage via opportunistic access [7]. However, to effectively exploit the PHY layer capabilities offered by Cognitive Radios, additional algorithm for accessing to the spectrum in an opportunistic way must be developed (in cross-layer way) at the MAC layer [7].

It must be expected that all the above three class of the physical layer technologies will be integrated in emerging ActMesh nets, which further demands for a cross-design of multiple layers of the protocol stack.

No clean-slate protocol architecture

By resolving an optimization problem that directly involves the functionalities covered by multiple distinct layers in the conventional ISO/OSI protocol stack model, new protocol architectures even totally different from the legacy ISO/OSI model may arise. Up to now, the well known TCP/IP protocol stack has been mainly adopted for most applications of WMNs (see, for example,

[2]). Thus, in order to further improve the bandwidth performance of the proposed ActMesh paradigm without fully abandoning the TCP/IP protocol stack, a suitable cross-layers design able to capitalize the cooperation between different layers seems to be mandatory.

Based on the above considerations, we conclude that cross-layer design is imperative for ActMesh nets.

0.7 Related Works on Network-wide Resource Management in Cognitive Systems

The basic paradigm of CRs has been introduced by J.Mitola III less than a decade ago [13], essentially as an extension of the previous Software Defined Radio (SDR) concept. Although the Mitola's vision assumes that every possible parameter observable by a wireless node should be taken into account to make it adaptive and context-aware, nevertheless, up to now, the most of the published work has essentially focused on considering the cognitive radio as a physical layer technology for spectrum sensing/sharing, and the cognitive radio term has been sometimes used also with more limited goal to denote spectrum agile radios [7, Chap.1].

However, the cognitive radios themselves are only a component (e.g., building block) of a larger network-wide system, when we go to consider the optimization of spectrum capacity of an overall access network under reliability guarantees and QoS constraints [7, Chap.14]. In fact, as also stressed, for example, in [7, Chap.14], a single-node radio-centric point of view is not longer enough to describe multi terminal systems where cognitive and active (i.e., intelligent) methods are used to improve network-wide performance indices, such as the aggregate client-traffic conveyable by the overall network. Only a few of works have recently started to consider some issues related to the architecture performance of general Cognitive Wireless Networks (CWNs) (see, for example, [7, Chaps.9,14] for recent overview on this largely unexplored topic). Very few works focused on resource management aspects in Cognitive Mesh networks (see, for example,[14],[15],[16],[17] and references therein) and virtually no works explicitly consider network-wide resource management issues in context and content-aware WMNs.

In the following two subsections, we summarize some main results recent appeared in the literature on the network-wide resource management for CWNs and, then, for CogMesh nets. In overview these results, we also point out main differences with respect to the contributions offered by our work.

A) Related results on Network-wide Resources Management in Cognitive Wireless Networks

Resource management has so far mainly pursued a radio-centric approach and, then, it has mainly focused on spectrum sensing at the PHY layer, as well as MAC layer resource allocation on a particular radio terminal [7]. In this (limited) context, the problem of the optimal spectrum assignment to SUs in static CWNs is treated in [18],[19], under the (optimistic) assumption of perfect spectrum sensing (e.g., error-free detection of PUs' activity). Scheduling of SUs under *imperfect* spectrum sensing is considered, for example, in [20],[21],[22],[23], where probabilistic maximum collision constraints are introduced to provide soft (i.e., not deterministic) reliability guarantee to PU. In [24], the stability region of a basic point-to-point dual-transmit single-receive queueing system composed by a (single) PU transmitter and a (single) SU transmitter is addressed. Specifically, the performance gain arising from the cooperation (possibly) offered by the SU transmitter is characterized in [24] by focusing on a bandwidth-unconstrained static application scenario, where no bounds on the average transmit power are present.

After this radio-centric phase, some first developments in network oriented resource management of spectrum opportunities in CWNs are becoming available. According to [7, Chap.14], from a formal point of view, network-wide resource management may be stated as the general problem to maintain a specified QoS level in a CWN by performing resource re-allocation and also adaptive admission control. The ultimate goal of network-wide resource management in CWNs is to maximize network utility without compromising QoS of already present clients. To attain this quite broad goal, several heterogeneous formal approaches mainly exploiting:

i) Learning Theory;

ii) Graph Theory;

iii) Game Theory;

iv) Stochastic Network Utility Maximization (NUM),

are currently pursued in the literature [7, Chap.14], as detailed in the following.

i) Moving from the biologically inspired Cognitive Engine previously presented in [25] for modelling the self-adaptive behavior of a Cognitive Radio terminal, in [26], the architecture of a Cognitive Resource Manager (CRM) is firstly introduced for enabling cross-layer optimization via artificial-intelligence-based learning and adaptation. Afterwards, this CRM architecture is refined in [27], where a cross-layer implementation is developed that relies on genetic algorithms for adaptively processing the stimuli acquired by the surrounding radio environment in form of (suitable) ACK/NACK feedbacks. Although this CRM architecture retains the appealing feature to may be implemented without requiring explicit network-state information, however, the therein employed genetic algorithms do not guarantee convergence to the optimum. Furthermore, nor energy constraints neither client mobility aspects are considered in [27].

ii) Graph-theoretic models are utilized in [17],[19],[28],[29],[30] for managing the interference present in (possibly, multihop) CWNs. Specifically,

[19] develops a graph-based model to manage the spectrum access problem in interference limited CWNs and proposed several (heuristic) algorithms for attempting to attain fair and high throughput operating points. In [29], a multichannel contention graph is introduced to account for the impact of the interference, and, then, it is proposed joint scheduling and spectrum allocation algorithms for fair spectrum-sharing. In [28], the concept of time spectrum block is introduced to model spectrum preservation and, then, distributed protocols are presented to allocate such blocks for cognitive radio clients in an interface-free fashion. A quite innovative layered graph model is proposed in [30] to characterize spectrum access opportunities in multihop CWNs and, then, it is used to perform joint spectrum scheduling and routing. By pursuing a similar approach, a mixed-integer nonlinear program is devised in [17] to tackle with a joint spectrum allocation, scheduling and routing problem.

Overall, the somewhat common features of these graph-based contributions are that no fading-induced energy constraints are accounted for and, in general, perfect spectrum-sensing is also assumed.

iii) A first set of Game Theory based works rely on economic-inspired incentives to regulate the competition among CRs in resource-limited CWNs [31],[32],[33],
[34]. Specifically, in [31], a distributed spectrum allocation scheme based on local bargaining is proposed for cognitive *ad hoc* wireless networks.

Afterwards, in [32], five spectrum access rules are proposed and a spectrum management broken is also developed for allowing radios to fairly share the available bandwidth by following the proposed rules. Recently, the authors of [33] have proposed the (so called) VERITAS paradigm, which relies on a truthful and computationally efficient spectrum auction to support eBay-oriented dynamic spectrum markets. [34] proposes a joint power and channel allocation scheme that exploits a distributed pricing policy to improve network utility.

A second set of works utilizes the concept of Nash equilibrium to self-drive the operating point of the underlying CWN toward an optimized state. Specifically, in [35], a information-theoretic-based characterization of the throughput region sustained by competitive cognitive access nets is developed that accounts for both the spatial-multiplexing and interference-mitigation capabilities offered by the Multi-Antenna physical platform equipping each CR. Interestingly enough, in [35], the topic of the self-convergence of the overall competitive access network toward the most-performing feasible working point is also addressed, and actual effectiveness of the therein deployed competitive access-platform is supported via numerical performance comparisons against CSMA/CA-based access networks.

The recent contributions in [36],[37],[7, Chap.15] explicitly consider the delay-sensitive feature of real-time multimedia traffic in modelling the competitive interaction of media CRs in both single hop [36],[7, Chap.15] and multi-hop [37] networking architectures. Specifically, in these works, each player (e.g.,cognitive radio) is modelled as an M/G/1 autonomous queueing system with priority that plays a noncooperative game. The target pursued by each player is the maximization of the (average) value of a locally defined objective function that is proportional to the min-deadline probability experienced by each player. Although the multimedia feature of the carried out traffic is explicitly addressed in [36],[37], [7, Chap.15], these contributions *do not* explicitly consider fading effects and client mobility. Furthermore, they *do not* take into account for energy constraints, *neither* perform energy control. Finally, all these contributions assume *perfect* spectrum-sensing and, thus, do not consider the degrading effects arising from (possible) collisions among primary and secondary transmissions.

iv) A last research line resorts to the framework of *Network Utility Maximization* (NUM) for modelling network-wide resource management problems and, then, it exploits the analytical tool offered by the (possibly, stochastic and nonlinear) optimization for solving them [3]. The contributions in [10],[7, Chap.14] present good overviews of state of art of this NUM-inspired research line. Specifically, a distributed algorithm is proposed in [18] for solving a joint power-control scheduling and routing problem, with the objective to maximize the aggregate conveyed data rates for a set of long-live communication sessions. In [38], the authors develop a distributed algorithm for joint spectrum allocation, power control, routing and congestion control for collision-free and interference-free static wireless networks.

More recently, the authors of [39] present a distributed scheduling and resource allocation scheme for OFDMA-based CWNs which allocates power to the clients so as to maximize a (suitable) weighted average rate of individual clients. Although, the proposed scheme could represent a good starting framework for multi-carrier CWNs, nevertheless, some specific assumptions made in [39] (namely, fairness being defined as guaranteeing minimum requirements for primary users and extensive utilization of OFDMA architecture) limit the application area of the therein proposed resource management scheme. Furthermore, the bursty feature typically retained by coded media flows is not considered in [39], where no queueing aspects are accounted for.

At least in principle, [11] is the work adopting a development line more similar to that pursued in our contribution. In fact, in [11] the framework of the adaptive queueing and stochastic optimization is employed to design online flow-control, scheduling and resource allocation algorithms for single-hop CWNs. The target pursued in [11] is the maximization of the aggregate average throughput conveyed by the secondary users under a constraint on the maximum collision rate with primary users. The resulting resource manager of [11] operates without a priori knowing the mobility patterns of secondary users and it provides deterministic upper-bounds on the worst-case number of collisions suffered by any primary users over any time-interval. Although these last two properties are also retained by the resource manager go to develop, however, our contribution differentiates from [11] under the following main aspects. First, the application scenario considered in [11] is fading-free. As a consequence, nor any energy-constraints are considered in [11], neither the problem of energy-control and access rate control are therein address. Second, unlike our model, [11] assumes each mobile equipped by an *infinite*-capacity buffer. Third, we anticipate that our ActMesh networking architecture firmly guarantees deterministic (i.e., hard) upper-bounds on the maximum number of collisions suffered by any primary user over any time-interval, whose values are *fully independent* from these assumed by the underlying objective functions. On the other hand, the corresponding worst-case collision number guaranteed in [11] is always *strictly larger* than that guaranteed by our framework (see the additive term X_{max} at [11, pp.771]). In addition, the limit on the worst-case collision number guaranteed in [11] *grows unbounded* when the corresponding objective function of [11, Sect.3] approaches its optimum value (see [11, eqs.(4),(5)]).

B) Related Results on Network-wide Resource Management in Cognitive Mesh Wireless Networks

An updated overview of the (few of) works tackling with resource management in CogMesh wireless nets is presented in [7, Chap.14]. Specifically, a first set of previous works related to bandwidth-allocation using opportunistic spectrum access in single-hop CogMesh is [40],[41],[6],[42],[43],[44]. In [40], authors propose a greedy heuristic algorithm to maximize the total number of channels by opportunistically allocating unused licensed links to cognitive static base stations. Although a similar framework is also considered in [41], authors of [40] introduce a reward function proportional to both the base stations coverage and induced inter-cell interference. Both works in [40],[41] consider static access networks and relay on an inter-cell interference model that demands for overlapping among adjacent cells. In [6], authors present the CORVUS paradigm, that envisions a CR approach for usage of unlicensed spectrum via the generation of collision-free virtual unlicensed bands. However, [6] only provides system requirements and the general architecture of the CORVUS platform, but no problem formulation or results are presented to support CORVUS effectiveness. On the other hand, in [42], authors formulate, indeed, the channel allocation and power control problems in CogMesh nets as a mixed-linear integer optimization problem. However, the bursty nature of the client traffic and the resulting client bandwidth requirements are not taken into account. In [43],[44], a distributed channel assignment algorithm is presented and numerically tested to select the channel experiencing both least primary-induced interference and maximum transmission e.g. Shannon's capacity. However, no energy constraints or queueing aspects are considered in these two contributions.

A second set [14],[16],[45],[46],[47] of more recent contributions makes more intensive use of the NUM framework [3], for deploying optimized resource management policies for (possibly, multihop) CogMesh nets. Specifically, the COMNET paradigm recently introduced in [14], aims at realizing an intelligent frequency-agile self-managed mesh network. For this purpose, in [14], an analytical model is proposed for allowing MRs to estimate the power-level present in a give frequency-band and location induced by primary LAN traffic, thus creating a virtual map of white spaces in space and frequency domains. Hence, this virtual map is used in [14] to formulate a suitable network-wide channel-assignment optimization problem which, in turn, is solved in a decentralized fashion. Although [14] and our contribution both focus on the spectrally-efficient opportunistic access in CogMesh, however some architectural (non minor) differences are present. Firstly, the COMNET paradigm requires reliable location-information of the mesh nodes before performing channel assignment. Secondly, *no issues* induced by fading phenomena, energy-constraints, queueing management and nodes mobility are tackled by [14].

In [45], authors formulate, at first, a nonlinear integer optimization problem aiming at maximizing the number of served MCs, while suitable protecting the primary mesh users from harmful interference. Afterwards, in [45, Sect.III], they present low-complexity greedy-type heuristic algorithms for approximating the optimal solution of the stated problem. Nor fading effects neither energy-constraints or client mobilities issues are accounted for in [45], while perfect spectrum-sensing is considered. In [47], an iterative algorithm is developed to efficiently compute optimal link-scheduling in multi-hop multi-channel multi-radio wireless CogMesh nets. Specifically, in [47], the overall network-wide scheduling problem is decomposed into a sequence of smaller optimization sub-problems and suitably defined Maximum Weighted Independent Set (MWIS) sub-problems. Although inter-node interference is modelled in [47] via a conflict-based graph, no fading effects or mobility issues are therein considered. In [46], authors propose two optimal policies (namely, the Optimal Deterministic Spectrum Scheduling and the Optimal Randomized Spectrum Scheduling) for performing two-hop collision-free spectrum scheduling and minimal-cost routing over two-hop CogMesh nets. The solving approach followed in [46] relies on a graph-theoretic approach and does not consider energy-control issues or mobility-induced effects.

Main focus of the (very recent) contribution in [16] is on the end-to-end bandwidth- allocation to the hops composing the CogMesh backbone, with the objective to attain a suitable level of fairness among all non gateway MRs. For this purpose, fairness concepts based both max-min and lexicographical models are considered. The concept of feasible transmission mode is introduced in [16], for assuring feasible end-to-end routes over the communication graph describing the considered mash backbone. Being the focus on the design of the mesh Backbone, [16] does not explicitly address issues related to client access or energy and mobility-induced constraints.

0.8 Main Contributions and Outline of the Work

From the outset, we conclude that a still open problem in CogMesh based content aware access nets concerns the media friendly jointly optimal adaptive control of the traffic flows and access rate at the MCs with reliability guarantees for the backbone traffic when energy constraints induced by fading and mobility are also active.

Hence, according to this conclusion, main contributions of this work may be so summarized.

- First, we develop *closed-form* expressions for the optimal control policies solution of the tackled *cross-layer* stochastic optimization problem. These last policies allow a *scalable and distributed* implementation of the network-wide Resources Manager of the underlying Active Mesh net (i.e., the Active Resource Manager (ARM)).

- Second, for allowing an adaptive implementation of the deployed Resource Manager, we design suitable distribute *Belief Propagation* and *Soft Data Fusion* algorithms that enable the overall ActMesh net to quickly *self-adapt* to both context and content time variations. According to the learning based paradigms [48], the adaptation strategies pursued by these algorithms *explicitly account* for the errors possibly impairing both the spectrum sensing and access channel measurement operations performed by each MC.

- Third, we provide explicit evidence that Active Mesh paradigm allows both *cooperative and noncooperative* implementations of the Belief Propagation and Soft Data Fusion algorithms under a common sensing architecture.

- Fourth, we numerically test actual performance of the deployed ARM by considering Rayleigh faded ActMesh nets, where MCs randomly move following mutually independent Markovian random walks [49], while the joint activity of the MRs (i.e., primary users) composing the mesh backbone of Fig.2.1.1 randomly evolves according to a (general) multistate Markovian chain. Three metric we use to measure the attained performance, that are: *i)* the aggregate average access goodput uploaded to the Internet;and, *ii)* the maximum number of the MCs served by the Active Mesh access network (i.e., the network capacity).

- Finally, the optimized tradeoff among the conflicting requirements of reliable spectrum sensing and access channel measurement versus high network-wide spectral efficiency is also investigated.

The rest of this work is organized as follows:

- in Chapter 1, we describe the background and paradigms of Cognitive Radio Networks;

- in Chapter 2, the considered application scenario and the network model are described. After, the access frame Structure and the Mesh Client signalling protocol is defined. Furthermore, Mesh Router traffic model and Mesh Client mobility model are envisioned.

- In Chapter 3, we see the Mesh Client and Mesh Router functionalities in detailed way, and, finally, we supply the basic definitions of collision probability and primary user collision, respectively.

- In Chapter 4, specifically, we modelled the wireless access channel and explain the queue model that we used for the formulation of the global optimization problem.

- In this Chapter 5, we define the global resource allocation problem and demonstrate that this last centralized problem can be splitted into different distributed and scalable sub-problems. Moreover, each sub-problem can be splitted in three problems: *i)* Access Rate Allocation Problem; *ii)* Access Windows Allocation Problem, and *iii)* Flow Control problem.

The solutions of this last problem are determined by Mesh Client, Mesh Router and Mesh Client, respectively.

- In Chapter 6, we describe the simulated scenario and the ultimate target, in Chapter 7, is to evaluate the performance of the Active Mesh Network in terms of aggregate access goodput varying different parameters.

About the adopted notation, underlined letters denote vectors, capital letters embraced by squared brackets $[\cdots]$ denote matrices, scalar random variables (r.vs.) are denote by bold characters, while their outcomes are indicated by the corresponding not bold symbols. $E\{\cdots\}$ is the expectation operator, $\mathbb{R}^+$ is the field of the nonnegative real numbers, $\mathbb{C}$ denotes the complex field, $\triangleq$ means equal by definition, while $[x]^+$ is $\max\{x, 0\}$ and $p_s(s)$ is the pdf of the r.v. **s**. Finally, $E_s\{\varphi(\mathbf{s}; x)\} \triangleq \int \varphi(s; x)p_s(s)ds$ is the expectation of the bi-argumental function $\varphi(s; x)$ done only over the pdf of the r.v. **s**, while $[f(x)]_a^b$ indicates $\max\{a; \min\{f(x); b\}\}$.

CAPITOLO 1

Cognitive Radio Networks: Background and Paradigms

1.1 Introduction

With the increasing demand of wireless application, the insufficiency of spectrum is more and more serious; on the contrary, the utilization of some licensed spectrum is always low [50]. In order to increase the spectrum utilization, cognitive radio makes it possible for unlicensed users to access the spectrum unoccupied by licensed users.

The concept of the cognitive radio is proposed by Mitola [51], and the language for cognitive function is investigate in [52]. In [53], the detailed expositions of signal processing and adaptive procedures are presented. In [54], the major characteristics of cognitive radio networks are presented from physics layer to transport layer, as well as cross-layer design.

The spectrum agility of cognitive radio brings new challenges. The following sections illustrate the wide variety of new problems for cognitive radio. The state of the art strategies are presented in this chapter.

1.2 Cognitive Radio Models

Cognitive radio is a hot research topic in recent years. The wireless communication systems with cognitive radio are modelled as different models. Until now, there have been many research works on cognitive radio. Most of the works can be conclude as one of the following four kinds of cognitive radio models.

1.2.1 Initial Cognitive Cycle

When cognitive radio is proposed, an intelligent communication technology is expected, including observe, orient, plan, learn, decide and act [51],[53]. The basic idea of the initial cognitive cycle is concluded as Fig.1.2.1. The receivers obtain the channel quality information and the interference information from the surrounding radio environment by observing. After the transmitters receive the necessary feedback information from their corresponding receivers, they determine the strategies, which read to the radio environment. For more intelligent function, machine learning is adopted for estimating the utilities of possible strategies to improve system performance.

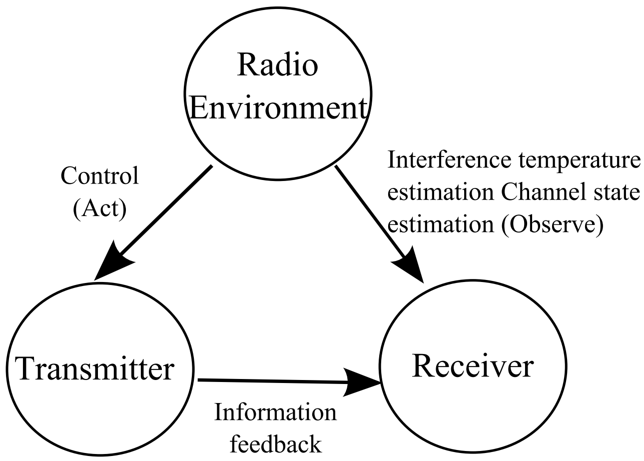


Figure 1.2.1: Basic cognitive cycle

1.2.2 Dynamic Spectrum Model

Based on the initial cognitive cycle model, cognitive radio is studied to be utilized further for spectrum sharing between licensed/primary users and unlicensed/secondary users in licensed spectrum. In that case, the secondary user are not allowed to cause too large interference that may interrupt the communication or decrease the service quality of primary users.

In the dynamic spectrum model [55], it is assumed that the primary users may not always use the spectrum. Hence, the secondary users can opportunistically utilize the spectrum when it is not being occupied by the primary users, as shown in Fig.1.2.2. According to the primary users' spectrum usage pattern,

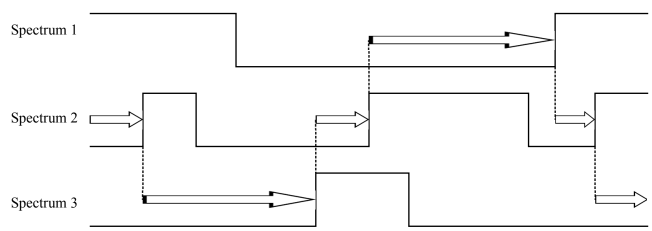


Figure 1.2.2: Dynamic spectrum model

based on the experimental results in [56] and [57], the spectrum usage can be modelled as an ON-OFF process: ON (OFF) state represents when the spectrum is occupied (unoccupied) by primary users. The spectrum dynamics can be modelled as s semi-Markov process as in [58].

In this model, with perfect spectrum sensing, which means that the secondary users detect the spectrum status error-freely and justify the status in time if some primary user comes back, the secondary users and primary users do not interfere with each other. The research challenge focuses on how to discover and utilize the spectrum opportunities more efficiently. Considering the error of spectrum sensing, the possible interrupt to primary users should be investigated. The schemes need to achieve a balance of the tradeoff between the utility of secondary users and the influence to primary users.

1.2.3 Interference Temperature Model

In the interference temperature model [59], both primary and secondary users can be co-exist on the same spectrum. The secondary users' interference to the primary receivers should not exceed a threshold. Interference temperature is introduced into cognitive radio by Federal Communications Commission (FCC) as a metric for the measurement of interference in a radio environment. In order to prevent the negative impact to the primary users, the interference temperature limit is used to indicate the allowed worst RF environment. In order to protect the primary users' communications, the interference caused by secondary users must be kept below the interference temperature limit at the primary receivers. That is, the primary users' Quality of Service (QoS) is considered acceptable if the secondary users' interference is kept below a given interference temperature limit. The maximum interference tolerance can be calculate as:

$$Q_{max} = \xi T_{max} \tag{1.2.1}$$

where ξ is Boltzmann's constant and T_{max} is the interference temperature limit. [60] analyzes the capacity of cognitive user with the assumption that the cognitive user estimates the statistic results of its interference to the primary through various fading channels. The average and peak interference constraints are considered respectively in [60]. With this model, an extra interference temperature constraint is added into the problems compared with conventional wireless communication systems, as shown in Fig.1.2.3.

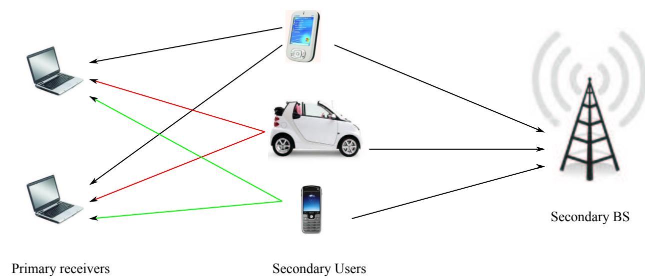


Figure 1.2.3: Interference temperature model

1.2.4 Cognitive Cooperation

In [61] and [62], it is assumed that the cognitive user can obtain and transmit the messages that the primary user will send. The capacities of both primary users and secondary users are obtained. Based on these, [63] analyzes the capacity of a cognitive user who transmits simultaneously with a primary user in the condition that the primary user can achieve the data rate just as it would in the absence of the cognitive radio user. [64] extends the results of [63] to Multiple Access Channel (MAC) and gives a heuristic scheme to achieve the maximum sum-rate. In this model, there exists a tradeoff that the secondary transmitter sends primary data or secondary data, as shown in Fig.1.2.4. Transmitting primary data can increase the primary throughput and improve the capability of interference tolerance of primary users. On the other hand, transmitting secondary data can increase the secondary throughput and decrease the interference to primary users.

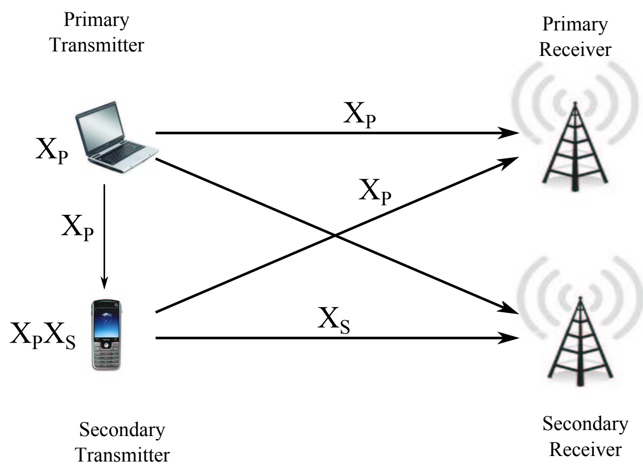


Figure 1.2.4: Cognitive cooperation model

1.3 Cognitive Radio Network Paradigms

Since its introduction in [63], the definition of cognitive radio has evolved over the years. Consequently, different interpretations of cognitive radio and different visions for its future exist today. In this section we describe a few communication models that have been proposed for cognitive radio. We broadly classify them into *overlay or known interference* models, *underlay or interference avoidance* models.

Underlay Paradigm:

The underlay paradigm encompasses techniques that allow communication by the cognitive radio assuming it has knowledge of the interference caused by its transmitter to the receiver of all noncognitive users [65]. In this setting the cognitive radio is often called a *secondary user* which cannot significantly interfere with the communication of existing (typically licensed) users, who are referred to as *primary users*. Specifically, the underlay paradigm mandates that concurrent noncognitive and cognitive transmissions may occur only if the interference generated by the cognitive devices at the noncognitive receivers is below some acceptable threshold. The interference constraint for the noncognitive users may be met by using multiple antennas to guide the cognitive signals away from the noncognitive receivers, or by using a wide bandwidth over which the cognitive signal can be spread below the noise floor, then despread at the cognitive receiver. The latter technique is the basis of both spread spectrum and ultrawideband (UWB) communications. The interference caused by a cognitive transmitter to a noncognitive receiver can be approximated via reciprocity if the cognitive transmitter can overhear a transmission from the cognitive receiver's location. Alternatively, the cognitive transmitter can be very conservative in its output power to ensure that its signal remains below the prescribed interference threshold. In this case, since the interference constraints in underlay systems are typically quite restrictive, this limits the cognitive users to short range communications. While the underlay paradigm is most common in the licensed spectrum (e.g., UWB underlays many licensed spectral bands), it can also be used in unlicensed bands to provide different classes of service to different users.

Overlay Paradigm:

The enabling premise for overlay systems is that the cognitive transmitter has knowledge of noncognitive users' codebooks and its messages as well [65]. The codebook information could be obtained, for example, if the noncognitive users follow a uniform standard for communication based on a publicized codebook. Alternatively, they could broadcast their codebooks periodically. A noncognitive user message might be obtained by decoding the message at the cognitive receiver. However, the overlay model assumes the noncognitive massage is known at the cognitive transmitter user begins its transmission. While this is impractical for an initial transmission, the assumption holds for a message retransmission where the cognitive user hears the first transmission and decodes it, while the intended receiver cannot decode the initial transmission due to fading or interference. Alternatively, the noncognitive user mays end its message to the cognitive user (assumed to be close by) prior to its transmission. Knowledge of a noncognitive user's message and/or codebook can be exploited in a variety of ways to either cancel or mitigate the interference seen at the cognitive and noncognitive receivers. On the one hand, this information can be used to completely cancel the interference due to the noncognitive signals at the cognitive receiver by sophisticated techniques like dirty paper coding [66]. On the other hand, the cognitive users can utilize this knowledge and assign part of their power for their own communication and the remainder of the power to assist (relay) the noncognitive transmissions. By careful choice of the power split, the increase in the noncognitive user's signal-to-noise power ratio (SNR) due to the assistance from cognitive relaying can be exactly offset by the decrease in the noncognitive user's SNR due to the interference caused by the remainder of the cognitive user's transmit power used for its own communication. This guarantees that the noncognitive user's rate remains unchanged while the cognitive user allocates part its power for its own transmissions. Note that the overlay paradigm can be applied to either licensed or unlicensed band communications. In licensed bands, cognitive users would be allowed to share the band with the licensed users since they would not interfere with, and might even improve, their communications. In unlicensed bands cognitive users would enable a higher spectral efficiency by exploiting message and codebook knowledge to reduce interference.

Interweave Paradigm:

The ”interweave” paradigm os based on the idea of *opportunistic communication*, and was the original motivation for cognitive radio [52]. The idea came about after studies conducted by the FCC [63] and industry [67] showed that a major part of the spectrum is not utilized most of the time. In other words, there exist temporary space-time frequency voids, referred to as *spectrum holes*, that are not in constant use in both the licensed and unlicensed bands.

These gaps change with time and geographic location, and can be exploited by cognitive users for their communication. Thus, the utilization of spectrum is improved by opportunistic frequency reuse over the spectrum holes. The interweave technique requires knowledge of the activity information of the noncognitive (licensed or unlicensed) users in the spectrum. One could also consider that all the users in a given band are cognitive, but existing users become primary users, and new users become secondary users that cannot interfere with communications already taking place between existing users.

To summarize, an interweave cognitive radio is an intelligent wireless communication system that periodically monitors the radio spectrum, intelligently detects occupancy in the different parts of the spectrum and then opportunistically communicates over spectrum holes with minimal interference to the active users. For a fascinating motivation and discussion of the signal processing challenges faced in interweave cognitive radio, we refer the reader to [68].

Table 1 [69] summarizes the differences between the underlay, overlay and interweave cognitive radio approaches. While underlay and overlay techniques permit concurrent cognitive and noncognitive communication, avoiding simultaneous transmissions with noncognitive or existing users is the main goal in the interweave technique. We also point out that the cognitive radio approaches require different amounts of side information: underlay systems require knowledge of the interference caused by the cognitive transmitter to the noncognitive receiver(s), interweave systems require considerable side information about the noncognitive or existing user activity (which can be obtained from robust primary use sensing) and overlay systems require a large amount of side information (non-causa knowledge of the noncognitive user's codebook and possibly its message). Apart from device level power limits, the cognitive user's transmit power in the underlay and interweave approaches is decided by the interference constraint and range od sensing, respectively. While underlay, overlay and interweave are three distinct approaches to cognitive radio, hybrid schemes can also be constructed that combine the advantages of different approaches. For example, the overlay and interweave approaches are combined in [65]

Before launching into capacity results for these three cognitive radio networks, we will first review capacity results for the interference channel. Since cognitive radio networks are based on the notion of minimal interference, the interference channel provides fundamental building block to the capacity as well as encoding and decoding strategies for these networks.

UNDERLAY	OVERLAY	INTERWEAVE
Channel Side Information: Cognitive transmitter knows the channel strengths to noncognitive receiver.	Codebook Side Information: Cognitive nodes know channel gains, codebooks and the messages of the noncognitive users.	Activity Side Information: Cognitive user knows the spectral holes in space, in time, or frequency when the noncognitive user is not using these holes.
Cognitive user can transmit simultaneously with noncognitive user as long as interference caused is below an acceptable limit.	Cognitive user can transmit simultaneously with noncognitive user; the interference to noncognitive user can be offset by using part of the cognitive user's power to relay the noncognitive user's message.	Cognitive user transmits simultaneously with a noncognitive user only in the event of a false spectral hole detection.

UNDERLAY	OVERLAY	INTERWEAVE
Cognitive user's transmit power is limited by the interference constraint	Cognitive user can transmit at any power, the interference to noncognitive users can be offset by relaying the noncognitive user's message	Cognitive user's transmit power is limited by the range of its spectral hole sensing.

Table 1.3.3: Comparison of underlay, overlay and interweave cognitive radio techniques.

1.4 Research on Cognitive Radio Systems

1.4.1 PHY-layer Spectrum Sensing

Spectrum sensing is a necessary technology of cognitive radio. With efficient spectrum sensing, the spectrum opportunities could be discovered. From PHY-layer view, the spectrum sensing can be divided into three categories, non-coherent detection, coherent detection and feature detection [70].

The most usual non-coherent detection method is energy detection. The advantages of energy detection are short sensing time and low complexity. in addition, it does not need any a priori. However, because of the uncertainty of noise, there exists a SNR wall. The signal can not be detected if its SNR is lower than the SNR wall. As the signal is detected according to the signal strength, it can not distinguish different kinds of signal.

When the signal has the corresponding pilot, the coherent detection can be adopted. The matched filter is one of the coherent detection methods, but the performance is affected by high complexity, unstable time clock and the length of pilot. Because of these factors, the implement is limited in practice.

feature detection utilizes the properties of signal to detect whether there is any primary user nearby. As the signal has periodic features because of frame structures but the noise does not have any period, cyclostationary detection can be used to distinguish the signal and the noise. Using pattern recognition, different kinds of signal can be distinguished by comparing the cyclostationary properties of the detected signal with a priori known signal properties. Although the performance is better than energy detection, the SNR wall still exists. If the signal strength is not too low, the signal can be recognized from the unstable noise.

1.4.2 MAC-layer Spectrum Sensing

On spectrum sensing, there exists a tradeoff between sensing time and sensing reliability. The sensing methods which have high reliability always need long sensing time. A two-level spectrum structure is proposed in [71] to balance the tradeoff between these two aspects. Energy detection is adopted to discover primary users cursorily. Then, if it is possible that there exists any primary user, more elaborate spectrum sensing is deployed.

Because of the fading effect, the spectrum sensing results of one user is not always accurate. Therefore, the cooperation between secondary users is necessary [72]. There are two kinds of cooperation, centralized cooperative spectrum sensing and distributed cooperative spectrum sensing.

The centralized cooperative spectrum sensing, a centralized controller collects the sensing observations results from different users, and fuses the collected data altogether to obtain a table for available spectra. The results obtained by centralized cooperative spectrum sensing are accurate relatively, but it needs long sensing time, large computational capability and heave overhead.

Distributed cooperative spectrum sensing lets each user detect the presence/absence of primary signal and obtain the table of available spectrum respectively. By communicating with the neighbor users, the chosen spectrum is determined. How the sense the spectrum accurately by exchanging limited information is still an open problem.

The our approach is hybrid, because each user detects the signal and after sends the result of its decision along with the level of the corresponding reliability at the access point.

1.5 Radio Resource Allocation

Dynamic spectrum management is an efficient method to avoid the interference between primary users and secondary users. When some spectrum is idle, the cognitive radio system choose the spectra which have low interference. If the primary users come back to use the spectrum occupied by secondary users, the cognitive radio systems should obtain the information in time. Based on the information, the secondary user choose another spectrum from the candidate spectrum set, or decrease the transmit power to avoid too large interference to primary user if there is no other candidate spectra.

In cognitive radio networks, the power control schemes need to consider not only their own utilities, but also the influence to primary users. Game theory is an efficient method for distributed power control [73],[74]. Spectrum allocation and power control affect each other, so joint spectrum allocation and power control investigated [75]. For multi-hop networks, routing is also an important issue. The performance of cognitive radio networks can be optimized by designing appropriate routing, spectrum allocation and power control schemes.

1.6 Spectrum Marketing

On spectrum pricing, in [76], a framework for coordinating dynamic spectrum is proposed. In [77], the dynamic pricing strategy is proposed for competitive agile spectrum access markets. Sharply value in cooperative game is used for evaluate the contribution of each system in spectrum marketing [78]. The investigation on spectrum pricing is also introduced into IEEE 802.22 standardization [79].

On the contrary of spectrum pricing, spectrum auction [80],[81] is also a practical way for spectrum marketing. Each system announces a price to other systems according to the utilities and costs if it can win the auction and get the spectrum. Based the economic theory, the systems can approach the optimal performance for maximizing their own profits.

1.7 Application and Standardization

Cognitive radio is used widely in several areas of wireless communication. In [82], the application of cognitive radio in wireless emergence networks is investigated combined with relaying to enhance the coverage performance in the disasters. In [83], cognitive radio is employed for military application.

IEEE 802.22 is the first wireless standard applying cognitive radio. The secondary users use TV spectrum to improve the spectrum utilization, when it is unoccupied by nearby TV transmitters. Besides IEEE 802.22, other wireless standardization, such as IEEE 802.11n and IEEE 802.16h (this last represent the standard used in this work), also adopt cognitive radio for interference coordination among users in the some system, rather than between two systems. Many researchers are trying to use the idea of cognitive radio LTE networks.

The IEEE 802.11h standard is the cognitive mesh network.

1.8 A Perspective of Future Research on Cognitive Radio

Cognitive radio is one of the research frontiers in wireless communication field. Both academic and industry researchers have large interest to cognitive radio and gained many achievements. However, there are still some research challenges as follows [84].

1. Cooperative Sensing: distributed cooperative sensing needs further research to balance the tradeoff between accurateness and overhead better.

2. Cognitive MIMO: MIMO can decrease the interference by adjusting the signal orthogonal to the interference channel to primary users [85]. Therefore, using multiple antennas is helpful in cognitive radio networks to increase the throughput of secondary users and decrease the interference to primary users.

3. Robust Cognitive Radio: In most of the exist research works, the radio resource allocation is investigated based on perfect spectrum sensing results. Considering the error of spectrum sensing, the resource allocation schemes should restrict the outage probability that secondary users interrupt the communication of primary users.

4. Cognitive Mesh: Application of cognitive paradigm to Wireless Mesh Network

CAPITOLO 2

Considered application Scenario and Network Model

In this Chapter 2, we describe the Active Mesh Network architecture and define the first general assumptions. After, we characterize and define the main features of the functional blocks of the system. Specifically, first we are going to see the access frame structure, second we develop the Mesh Routers activities traffic model and the Mesh Clients mobility model. This last two developments are very important for characterize the Active Mesh Network behavior.

2.1 The Considered Active Mesh Network Architecture

The considered Active Mesh Network architecture, depicted in Fig.2.1.1, is formed by interconnecting several cluster of mobile Mesh Clients (MCs) and each cluster is coordinated by a Wireless Mesh Router (MR) that acts as access point of the corresponding IEEE 802.11x type WLAN. In this context, the Wireless Mesh backbone (continuous red line) transfer downlink traffic from the Internet to mobile clients and, simultaneously, the mobile clients generate uplink traffic addressed to Internet. Furthermore, the downlink traffic is assumed to be strongly delay-sensitive and no peer-to-peer communication between clients, falling into different clusters, is allowed.

In the Fig.2.1.1, $MC_{i.j}$ is the j-th client of the i-th cluster and $f_i,\ i = 1, 2, 3$ represents the (a priori known) center-frequency of the (single) channel available to MR(i). MR(i) is able to receive from *both* MR(i+1) and its mesh clients $MC_{i.1}$, $MC_{i.2}$, $\cdots$. The set of frequencies $\{f_1, f_2, \cdots\}$ are assumed mutually orthogonal; MR(i+1) is assumed to be the *primary user* of the i-th cluster, while mobile clients $\{MC_{i.1}, MC_{i.2}, \cdots\}$ are the *secondary users* of the i-th cluster .

Remark 2.1 Some considerations about the use of the Mesh Router with two radio interfaces - Before proceeding, some remarks about the use of a Mesh Router with two radio interfaces. According to WMN architecture [9, Sect.III A], in Fig.2.1.1 each MR has two radio interfaces operating simultaneously and not interfering. The first interface of MR(i) works at f_i frequency and it is used to receive traffic from both MR(i+1) and MCs belong to i-th cluster. The second interface (i.e., f_{i+1} frequency) is exploited by MR(i) only for forwarding uplink traffic (i.e., from MR(i) to MR(i+1)). Hence, according

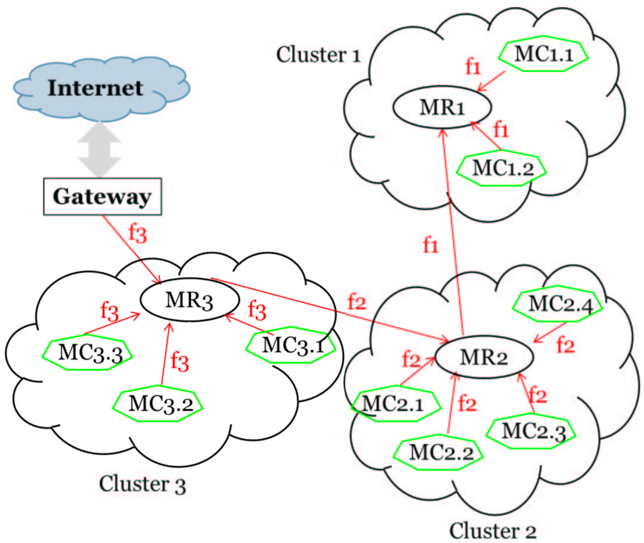


Figure 2.1.1: A snapshot of single-carrier single-radio Wireless Mesh Network (WMN) organized into multiple non-overlapping non-interfering clusters.

to [9, Sect.III A], the traffic sent over the backbone of Fig:2.1.1, is not subject to self-interference. In this work, this architecture (see for more details [9, Sect.III a]) use different orthogonal channels and two radio interface, that grant higher drain traffic compared to an architecture with only one radio interface (see, for example, [9, Fig.3]).

General assumptions

Before proceeding to the analysis of the resulting Active Mesh Network of Fig.2.1.1, we introduce general operating conditions as follows:

ASSUMPTION 2.1 Both MRs and MCs are single-carrier and single-radio. This means that a single frequency (channel) f_i is available to i-th Mesh Router in order to receive both $(i+1)$-th Mesh Router (via backbone) and all clients $\{MC_{i.1}, MC_{i.2}, \cdots\}$ that belong to i-th cluster and that generate uplink traffic addressed to Internet (see Fig.2.1.1);

ASSUMPTION 2.2 time is slotted, with slot-duration of T_s (sec) and the transmissions can start only at the beginning of slot;

ASSUMPTION 2.3 the available set of frequencies $\{f_1, f_2, \cdots\}$ are a priori known by Mesh Clients. Furthermore, these frequencies are taken orthogonal so that there is not inter-cluster interference.

ASSUMPTION 2.4 Mesh Clients are considered *mobile* and they may move from one cluster to another *only* at the end of slot, thus in a slot-time the MCs are assumed *statics*.

ASSUMPTION 2.5 If, in a slot-time, the i-th Mesh Router receive packets by $(i+1)$-th Mesh Router, then the MR(i) should not receive from any MCs in the i-th cluster for the duration of the considered slot.

Hence, in agreement with this last consideration, we denote by MR(i+1) the primary user (i.e., the primary transmitting node), with MR(i) the receiving node and with MCs the secondary users (i.e., the secondary transmitting nodes) of the i-th cluster.

Furthermore, on the basis of above assumptions, we may have two type of possible collisions at the receiving node namely Primary-Secondary and Secondary-Secondary collisions.

The *Primary-Secondary collisions* occur when the primary user and one or more secondary users transmit simultaneously. In the following, we consider the Channel Detection operation in order to minimize the occurrence of primary-secondary collision events. Instead, the term Secondary-Secondary collisions indicates the collisions that occur when, simultaneously, two or more Mesh Clients send Information Units to MR(i). In order to achieve the minimization of the occurrence of secondary-secondary collision events, we adopt, for example, an IEEE 802.11x access policy (see in the sequel).

In order to go on with our work, we also assume that:

ASSUMPTION 2.6 No peer-to-peer communication between clients belonging to different clusters is possible.

On the basis of what we have shown so far, we consider the application scenario depicted in Fig.2.1.2 going to describe the *cognitive access* problem of the considered *slotted and single carrier* system. Specifically, we stress that

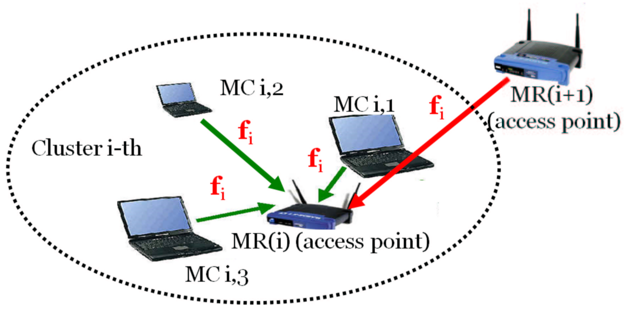


Figure 2.1.2: Cognitive access in the i-th cluster.

we will deal with the cognitive routing problem.

Referring to the Fig.2.1.2, we can continue with the following general assumptions:

ASSUMPTION 2.7 the MCs $\{MC_{i.j}\}$ are battery powered (i.e., energy constrained), hence, if the link $MC_{i.j}$ →MR(i) is affected by fast fading, the (general) client cannot transmit even if there is not primary transmission and/or secondary transmission;

ASSUMPTION 2.8 the secondary wireless links, of Fig.2.1.2, are affected by fading phenomena. Specifically, the fading phenomena are assumed constant over each slot-time (i.e. we assume a "block fading" channel), but they may vary in an independent and identically distributed (i.i.d.) way on a per slot basis;

ASSUMPTION 2.9 at the beginning of each slot, any Mesh Clients carry out Channel Sensing and Channel Estimation operations. The goal of Channel Sensing is to detect the presence or absence of primary transmissions, while Channel Estimation has the objective to provide an estimate $\widehat{h}_{ji}(t)$ of channel gain at each node $\{MC_{i.j}\}$ (see Fig.2.1.2). In the following, we assume that both Channel Sensing and Channel Estimation operations are made by each MCs at the beginning of slot period and these may be affected by (no ideal) errors. These errors are motivated by the fact that *i)* the primary user of Fig.2.1.2 (i.e., MR(i+1) node) cannot belong to the i-th cluster and, then, in this last case, the primary signal can arrive very attenuated to the secondary users; *ii)* at the beginning of each slot MR(i) generate a priori known sequence of pilot and in according to this sequence each MCs estimate the gain of the secondary link. Furthermore, we assume that the power and duration of the sequence is limited, hence, we can take that the corresponding estimate $\widehat{h}_{ji}(t)$ is error affected.

2.2 Access Frame Structure and Mesh Client Signalling Protocol

Before proceeding to description to the intra-cluster slot structure, we remember that the network depicted in figure Fig. 2.1.1 works in synchronous way (i.e. each MR or MC can starts its transmission only at the beginning of slot).

Remark 2.2 Some considerations about the secondary users synchronization - The secondary users $\{MC_{i.j}, j = 1, ..., N_{t_0}\}$, belonging to at same cluster, can synchronize their slot structure through the knowledge of the slot duration T_s (s) and through the Channel Detection operation (see the following Fig.2.2.1). Moreover, in order to allow Channel Estimation, the mesh router transmits to secondary users a known pilot's sequence. Each secondary user know this sequence and based on this it calculates both Channel Estimation and obtains synchronization.

Fig.2.2.1 reports the basic slot structure used by each secondary users to transmit to access point MR(i) of Fig2.1.2. Specifically, the slot duration T_s $(sec.)$ is splitted into $L_t \geq 1$ mini-slot with duration $T_c \triangleq T_s/L_t$. Furthermore, in order to better understand the slot structure, we have represented the MC functionalities (blue color) and the MR functionalities (green color).

Therefore, we can say that the j-th MC employ the first $L_D \geq 1$ mini-slot for Channel Detection phase; the second $L_E \geq 0$ mini-slot for Channel Estimation; the third $L_S \geq 1$ for Resource Allocation and Clients' Scheduling (also exploit by MR(i)); the fourth $L_P \geq 1$ mini-slot to transmit (possibly) data to MR(i) and, the last $L_A \geq 1$ mini-slot to receive Ack message. Specifically, during the $L_D \geq 1$ mini-slot, all secondary users and the MR(i) are listening the channel. Each MCs collect information and on the basis of these pre-decide about the primary users' activity. During the second mini-slot the node MR(i), of Fig.2.1.2, transmits a known pilot's sequence and on the basis of the received sequence each MC computed the Channel Estimation. In the $L_P \geq 1$ mini-slot, each MC ($MC_{i.j},\ j = 1, \cdots$) decides if to transmit or not transmit toward the MR(i) according to: *i)* presence or absence to the primary user; *ii)* the value of Channel Estimation; *iii)* queue length $q_i(t)$ in the node $MC_{i.j}$; *iv)* average and peak energy, $\varepsilon_{ave}(j)$ and $\varepsilon_p(j)$, respectively and, *v)* Quality of Service (QoS) requests.

Regarding to MR's functionalities, we may state that it exploit $L_B \geq 1$ mini-slot for Belief Propagation and $L_F \geq 1$ mini-slot for Soft Data Fusion phase, respectively. In addition, both MC(j) and MR(i) use the L_S mini-slot for Resource Allocation and Clients' Scheduling, while the last $L_A \geq 1$ mini-slot are used MR(i) to sent Ack messages. Specifically, in the following, we adopt that the Ack message is a priori know and its format is a priori fixed and it is independent both noticed packet and MAC/IP address. Furthermore, MR(i) generates the Ack message when there are not secondary-secondary and/or primary-secondary collisions, while MR(i) does not generate the Ack message when *i)* it has not received data from MC(j); *ii)* there was primary-secondary collision (Nack message); and *iii)* MR(i) received data from MR(i+1). If MR(i) generate Ack message, this last is sent, in broadcast, to all MC(j) present on the i-th cluster and each MC(j) receives the Ack message without delay.

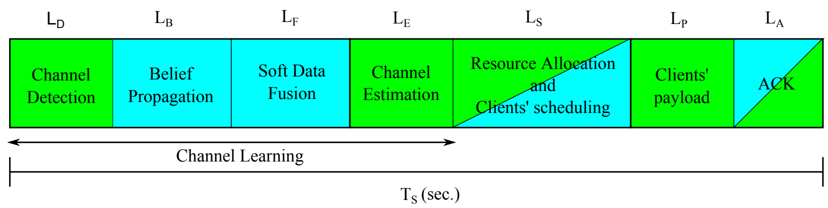


Figure 2.2.1: The considered intra-cluster slot structure.

At this point, we may conclude that:

$$L_t \equiv L_D + L_B + L_F + L_E + L_S + L_P + L_A, \qquad (2.2.1)$$

with $L_B = L_F = 0$ because the Belief Propagation and Soft Data Fusion operations request exchange of short signalling message and they may be, simultaneously, undertaken with the Channel Estimation phase. Furthermore, let

$$1 - \left(\frac{L_D + L_E + L_S + L_A}{L_t}\right) \equiv \frac{L_P}{L_t} \in [0,1], \qquad (2.2.2)$$

be the fraction of slot t dedicated to the transmission of the data.

In the following of work, we will denote by k the index of mini-slot, so that $0 \leq k \leq (L_t - 1)$.

Remark 2.3 Some considerations about the Ack message - Before proceeding, some remarks about the information transferred from the Ack message is in order. Assuming that all mesh clients receive an Ack message, this means that the primary users MR(i+1) is not active; one and only one secondary user is active; and, the (only) mesh client, which transmit the packet, acquires the (additional) information about the correct receipt of the packet and, hence, the latter can be removed from the queue.

Now, on the contrary, we suppose that any mesh client does not receive the Ack message. In this case, all mesh clients obtain the information about one on the other event occurred in the current slot namely there was secondary-secondary collision or primary and one or more secondary users collision or no mesh clients have sent data to the Mesh Router.

Specifically, the mesh clients belonging to i-th cluster, in the slot t employ the following signalling protocol.

Signalling protocol

1) During the $L_D \geq 1$ mini-slot (i.e., for $0 \leq k \leq L_D - 1$), all secondary users $\{C_{i,j},\ j = 1, ...\}$ and the MR(i) are listening the channel. Each MCs collect L_D information and on the basis of these pre-decide (in Cooperative or Noncooperative way) about the primary users' activity.

2) During the second $L_E \geq 0$ mini-slot (i.e., for $L_D \leq k \leq L_D + L_E - 1$), the node MR(i), of Fig.2.1.2, transmits a known pilot's sequence and on the basis of the received sequence each MC computed the Channel Estimation.

3) In the $L_P \geq 1$ mini-slot (i.e., for $L_D + L_E \leq k \leq L_D + L_E + L_P - 1$), each MC ($MC_{i.j},\ j = 1, \cdots$) take the decision to transmit or not transmit toward the MR(i) according to: *i)* presence or absence to the primary user activity; *ii)* the value $\widehat{h}_{ji}(t)$ of Channel Estimation; *iii)* queue length $q_i(t)$ in the node $MC_{i.j}$; *iv)* average and peak energy, $\mathcal{E}_{ave}^{j}$ and $\mathcal{E}_{p}^{j}$, respectively and, *v)* Quality of Service (QoS) requests.

4) The last L_A mini-slot (i.e., for $L_D+L_E+L_P \leq k \leq L_t-1)$) are dedicated to MR(i) for transmit the ACK message. Specifically, we assume that:

4.1) *i)* Ack message is a priori known and its length is L_A mini-slot; *ii)* its structure is a priori fixed and it does not depend neither discovered packet nor MAC/IP address of the mesh client;

4.2) MR(i)generates the Ack message when there are not collisions neither between secondary users nor between primary-secondary user;

4.3) Ack message is sent to all MC(j) in broadcast way;

4.4) it is correctly received and without delay;

4.5) MR(i) of Fig:2.1.2 does not generate Ack message when:

- It has not received data from MC(j);
- there was primary-secondary collision;
- there was secondary-secondary collision;
- MR(i) received data from MR(i+1).

Remark 2.4 Some considerations about the signalling protocol - The described signalling protocol handle the communication between secondary users belonging to the same cluster and mesh router when collisions are present. So, the goal of this protocol does not address the communication between the primary user MR(i+1) and the receive node MR(i) and for this reason this last node does not sent the Akc message when receive data by primary user.

2.3 Mesh Router Traffic Model and Mesh Client Mobility Model

Before proceeding with the definition of Mesh Routers activity traffic model, Mesh Clients mobility model and the tackled constrained optimization problem, we introduce other two assumption and after the main taxonomy of this work.

ASSUMPTION 2.10 The overall mesh network is considered to operate under stationary and ergodic conditions.

ASSUMPTION 2.11 The cluster, where the Mesh Client MC(j) is a member, is assumed to be known at the beginning of slot t. On the contrary, each Mesh Client does not know the cluster of the other clients which are in the considered network.

For example, this last assumption is verified when the MR(i) generate a pilot sequence that hold (in coded form) the serial number i (see Figs.2.1.2,2.2.1).

The main taxonomy of this work is the following:

$$\mathcal{I} \geq 1 \triangleq \text{number of clusters in the network (in the Fig.2.1.1, } \mathcal{I} = 3\text{);} \quad (2.3.1)$$

$$N_{t_0} \geq 1 \triangleq \text{total number of the mesh clients in the considered network}$$
$$\text{(in the case of Fig.2.1.1, } N_{t_0} = 9\text{);} \quad (2.3.2)$$

$$MC(j) \triangleq j - th\text{Mesh Client}, \quad j = 1, \cdots, N_{t_0}; \quad (2.3.3)$$

$$N_i(t) \triangleq \text{number of mesh clients belonging to } i\text{-th cluster in the considered slot}$$
$$\text{(in Fig:2.1.1, } N_1(t) = 4,\ N_2(t) = 2 \text{ and } N_3(t) = 3\text{);} \quad (2.3.4)$$

$$MR(i) \triangleq \text{the } i\text{-th Mesh Router} \quad i = 1, \cdots, \mathcal{I}; \quad (2.3.5)$$

$$\mathcal{C}_i(t) \triangleq \text{set of the mesh clients belonging to } i\text{-th cluster}, \quad i = 1, \cdots, \mathcal{I} \quad (2.3.6)$$

According to previous definition follows that:

$$N_{t_0} = \sum_{i=1}^{\mathcal{I}} N_i(t) \equiv \sum_{i=1}^{\mathcal{I}} |\mathcal{C}_i(t)| \quad \forall t \geq 0$$

Given the assumption of stationary As.2.10, we assume N_{t_0} and $\mathcal{I}$ to be known constants, while $N_i(t)$ may change, slot-by-slot, with mobility of mesh clients.

2.3.1 Mesh Router Traffic Model

In agreement with Fig.2.1.1, it is plain that each cluster is controlled by a primary user MR(i+1), $i = 1, \cdots, \mathcal{I}$ and by definition we have that MR(i+1)$\triangleq$

Gateway Node (see Fig.2.1.1). By definition, the binary vector of the primary activities assuming $2^{\mathcal{I}}$ configurations in a slot t is:

$$\vec{a}(t) \triangleq \begin{bmatrix} a_1(t) \\ \vdots \\ a_{\mathcal{I}}(t) \end{bmatrix}, \in \{0,1\}^{\mathcal{I}} \tag{2.3.7}$$

where, by definition, $a_i(t)$ in (2.3.7) is equal to:

$$a_i(t) \triangleq \begin{cases} 1, & \text{if the primary user is active;} \\ 0, & \text{if the primary user is not active.} \end{cases} \tag{2.3.8}$$

In the following, we will consider also the herein assumptions:

ASSUMPTION 2.12 in agreement with the Fig:2.1.1, the mesh router MR(i+1) send to MR(i) an exogenous traffic equal to $\rho_i\ (IU/slot),\ i = 1, \cdots, \mathcal{I}$. Each MR(i) tolerate a maximum fraction of collisions with the secondary users and, by definition, all N_{t_0} mesh clients know the set of maximum collisions probability (primary-secondary) $\{\nu_i \in (0,1), i = 1, \cdots, (\mathcal{I}+1)\}$ supported by MR(i). Thus, the maximum average rate of information unit (IU) tolerated by primary user, is equal to:

$$\nu_i \rho_i \quad (IU/sec.), \quad i = 1, \cdots, \mathcal{I} \tag{2.3.9}$$

Moreover, we also assume that:

ASSUMPTION 2.13 the value of $\vec{a}(t)$ (see eq.(2.3.7)) is independent of the adopted mesh clients scheduling policy.

In agreement with the As.2.12, we assume that if there are primary secondary collisions the primary user (MR(i+1)) does not retransmit the packets. For example, this fact happens: *i)* the primary users adopt FEC mechanisms that allow to recover the transmitted packet; *ii)* the primary users generate delay-sensitive, but loss-tolerant traffic (e.g, Voice Over IP (VoIP) traffic) where the re-transmissions are not permitted but part of the transmitted packet may be lost.

2.3.2 Mesh Client Mobility Model

In agreement with the Fig.2.1.2 and successively going to consider the Fig.2.1.1, we can declare that, the j-th mesh client (MC(j), $j = 1, \cdots, N_{t_0}$) is a member of one and only one i-th cluster ($i = 1, \cdots, \mathcal{I}$) in each slot t. Hence, according to this consideration, the MC(j) transmit its IUs only through the corresponding channel $f_i,\ i = 1, \cdots, \mathcal{I}$. By definition, the position information of all mesh clients is represented by the Mobility Matrix that it is defined as follows:

$$[M](t) \triangleq \begin{bmatrix} m_{11}(t) & m_{12}(t) & \cdots & m_{i\mathcal{I}}(t) \\ m_{21}(t) & m_{22}(t) & \cdots & m_{2\mathcal{I}}(t) \\ \vdots & \vdots & \vdots & \vdots \\ m_{N_{t_0}1}(t) & m_{N_{t_0}2}(t) & \cdots & m_{N_{t_0}\mathcal{I}}(t) \end{bmatrix} \qquad (N_{t_0} \times \mathcal{I}) \tag{2.3.10}$$

where $m_{ji}(t)$ represents the binary variable and it can assume the value one, only if the j-th secondary users is member of i-th cluster in the slot t, or zero otherwise.

$$m_{ji}(t) \triangleq \begin{cases} 1, & \text{if MC(j) belong to } i\text{-th cluster in a slot } t \\ 0, & \text{otherwise} \end{cases} \tag{2.3.11}$$

$1 \leq j \leq N_{t_0}, 1 \leq i \leq \mathcal{I}$.

Remark 2.5 **Mobility Matrix properties -** Before proceeding to the analysis of the principal functional blocks of Fig.2.2.1, we list some properties of the Mobility Matrix. The matrix $[M](t)$ is binary of size $(N_{t_0} \times \mathcal{I})$ and, in each row, only one element is equal to one. As a consequence of this fact, $[M](t)$ may sign up $\mathcal{I}^{N_{t_0}}$ different configurations. Hence, together, these last form the admissible set of the mobility matrix corresponding to:

$$[M](t) \in \{[\mathcal{M}_n], \quad 0 \leq n \leq (\mathcal{I}^{N_{t_0}} - 1)\}. \tag{2.3.12}$$

where, in eq.(2.3.12), the size matrix $[\mathcal{M}_n]$ is $(N_{t_0} \times \mathcal{I})$ and each row has one and only one element equal to one. In agreement with the eqs.(2.3.10),(2.3.11) follow this other two properties:

- $$\sum_{j=1}^{N_{t_0}} m_{ji}(t) \equiv N_i(t) \triangleq |\mathcal{C}_i(t)|, \quad \forall i,\ \forall t; \tag{2.3.13}$$
- the $\mathcal{C}_i(t)$ of eq.(2.3.6) is formed by the elements of index one of i-th column of $[M](t)$

Since the system is considered to operate under stationary and ergodic conditions (As.2.10), in the following, we assume valid this other assumption:

ASSUMPTION 2.14 the random sequences $\{\vec{a}(t),\ t \geq 0\}$, $\{[M](t),\ t \geq 0\}$, are jointly independent and identically distributed in t. Hence, the probabilities are defined as follow:

$$\{P(\vec{a}(t) = \vec{a}_m),\ [M](t) \equiv [\mathcal{M}_n],\ 0 \leq m \leq (2^{\mathcal{I}} - 1),\ 0 \leq n \leq (\mathcal{I}^{N_{t_0}} - 1)\} \tag{2.3.14}$$

With regard to the last assumption, we can note that the probabilities in eq.(2.3.14) are not a priori known to the MCs. Therefore, the 'on-the-fly' version of the scheduler, will allow to MC(j) to compute on-line the statistics in eq.(2.3.14) necessary to implement the scheduler. Moreover, assuming the sequences $\{\vec{a}(t)\}$ and $\{[M](t)\}$ i.i.d. will loosen where we will extend to all scheduler structure at the case of sequences $\{\vec{a}(t)\}$ and $\{[M](t)\}$ jointly stationary and ergodics. At last, we can note that the condition As.14 allow that the random variables $\{\vec{a}(t)\}$ and $\{[M](t)\}$ may be correlated (i.e., statistically independent) at a same t. In the application scenario of Fig.2.1.1, the possible statistical dependence between $\{\vec{a}(t)\}$ and $\{[M](t)\}$ could start by fact that the downlink traffic sent to backbone of Fig.2.1.1 can derive to MCs position. Hence, the mesh router MR(i+1) activity can due by the corresponding MCs position. Before proceeding with our work, we can conclude that the matrix in eq.(2.3.10) permit to give a description of the mesh clients mobility without to introduce the model about the motion of the mesh clients.

2.3.3 Downlink Traffic: Descriptor Parameters

In this section, we give a description of the downlink traffic in the backbone of Fig.2.1.1. In order to this aim, we model the node MR(i+1) as a G/G/1 queue that operate under stationary and ergodic conditions (see Fig.2.3.1). After denoting by ρ_i , $i = 1, \cdots, \mathcal{I}$ $(IU/slot)$, according to As.13, the av-

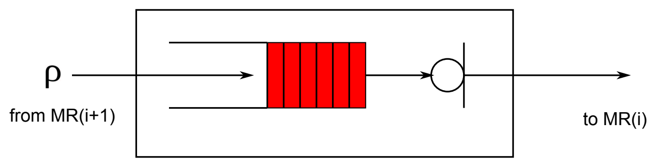


Figure 2.3.1: G/G/1 queue model.

erage traffic forwarded by i-th hop of the backbone, we define by $\mu_i,\ i = 2, 3, \cdots, (\mathcal{I}+1),\ (IU/slot)$ the service rate of the MR(i). Then, by definition, the ratio between ρ_i and μ_{i+1} is the utilization factor $\bar{\eta}_i \in [0, 1],\ i = 1, \cdots, \mathcal{I}$.

Since the backbone of Fig.2.1.1 operate under stationary and ergodic conditions, an application of the Little's formula [86, pp.157] leads to the following relationship:

$$P(a_i(t) = 1) = \bar{\eta}_i, \quad i = 1, \cdots, \mathcal{I}. \tag{2.3.15}$$

The equation 2.3.15 is very important because it states that the probability $P(a_i(t) = 1)$ that the primary user MR(i+1) has to transmit is equal to the utilization factor. Moreover, by definition, this last depend on the traffic load of the backbone.

CAPITOLO 3

Mesh Client and Mesh Router Functionalities

In the first part of this Chapter 3, we develop the MC functionalities, specifically, Channel Detection and Channel Estimation phases. In order to obtain this target, we assume that the mesh client MC(j) is a member to i-th cluster at the beginning slot t (i.e., $m_{ji}(t) \equiv 1$, see eq.(2.3.11)). Going to analyze, the first $L_D \geq 1$ mini-slot and the second $L_E \geq 0$ mini-slot of Fig.2.2.1, we can state that the MC(j) collects two information (eventually errors affected), respectively. The first one concerns about the presence ($a_i(t) = 1$) or absence ($a_i(t) = 0$) of the primary user activity. The second one about the corresponding access channel coefficient $h_{ji}(t)$. Separately, in the following subsections, the two phases (Channel Detection and Channel Estimation) and the corresponding binary detection and parameter estimation algorithms are described.

In the second part, we develop the MR functionalities, Belief Propagation and Optimal Data Fusion, respectively. Furthermore, Belief Propagation can be Noncooperative and Cooperative and in the following we discern the difference.

3.1 Mesh Client Functionality-Channel Detection Phase

Referring to Fig.2.1.2, after denoting by $\zeta_j(k;t)$ the MC(j)'s observation in the k-th mini-slot of the t-th slot, $s_{i+1}(k;t)$ the sample (deterministic or aleatory) generated by MR(i+1) in the k-th mini-slot, $g_{ji}(k;t)$ the channel coefficient MR(i+1)$\rightarrow$MC(j) in the mini-slot k-th and $n_j(k;t)$ the observation noise. Then, MC(j) determines the presence or absence of the primary user MR(i+1) according to the following problem:

$$\begin{cases} \zeta_j(k;t) \equiv n_j(k;t), & \text{if} \quad a_i(t) = 0, \\ \zeta_j(k;t) \equiv g_{ji}(k;t)s_{i+1}(k;t) + n_j(k;t), & \text{if} \quad a_i(t) = 1 \end{cases} \tag{3.1.1}$$

where $0 \leq k \leq (L_D - 1)$. If the MC(j) decides that the primary user is present, we set $\hat{a}_{ji}(t) = 1$, otherwise $\hat{a}_{ji}(t) = 0$. These decisions are taken according to:

$$y_j(t) \begin{cases} > \tau_j & \text{when} \quad \hat{a}_{ji}(t) = 1, \\ < \tau_j & \text{when} \quad \hat{a}_{ji}(t) = 0 \end{cases} \tag{3.1.2}$$

Referring to the last decision rule, $\tau_j \geq 0$ represent the decision threshold implemented by MC(j) while $y_j(t) \triangleq \varphi_j(\zeta_j(0;t), \cdots, \zeta_j(L_D-1);t)$ the corresponding statistical decision and $\varphi_j(\cdots)$ is the decision function. We may conclude that different mesh client can implement several decision rules.

The MC(j) determines the presence or absence of the primary user on the basis of the corresponding miss detection probability P_{MD}^{ji} and false alarm probability P_{FA}^{j} defined as follows:

$$P_{MD}^{ji} \triangleq P(y_j < \tau_j | a_i = 1, m_{ji} = 1) \equiv P(\hat{a}_{ji} = 0 | a_i = 1, m_{ji} = 1), \tag{3.1.3}$$

$$P_{FA}^{j} \triangleq P(y_j > \tau_j | a_i = 0, m_{ji} = 1) \equiv P(\hat{a}_{ji} = 1 | a_i = 0, m_{ji} = 1) \tag{3.1.4}$$

In previous equations (3.1.3),(3.1.4), we may note that while P_{MD} is (ji)-indices dependent, P_{FA} is only j-index dependent. Particularly, P_{FA} in (3.1.4) is independent from both the fading of the channel and signal s_{i+1} generated by primary user. Hence, obtaining τ_j in function of P_{FA} by (3.1.4) and replacing this last in (3.1.3), we can rewrite the miss detection probability as follows:

$$P_{MD}^{ji} \equiv \Phi_{ji}(P_{FA}^{j}; L_D), \tag{3.1.5}$$

where $\Phi_{ji}(\cdot)$ represents the Complementary Receiver Operating Characteristic (CROC) of j-th mesh client. Specifically, $\Phi_{ji}(\cdot)$ in (3.1.5) depends on: *i)* number of observations for Channel Detection; *ii)* type of MC(j) implemented detection; and *iii)* fading and primary user's signal statistics, respectively. Henceforth, we consider valid the following analytical properties about the CROC considered in this work.

ASSUMPTION 3.1 **Complementary Receiver Operating Characteristic general properties -** CROC general properties are listed in the following:

1. Fixing L_D (i.e., the number of mini-slot dedicated to Channel Detection phase), the miss detection probability decreases with increasing of the false alarm probability:

$$\partial\Phi_{ji}(P_{FA}^{j}, L_D)/\partial P_{MD}^{j} < 0, \quad \forall P_{MD}^{j} \in [0,1]; \tag{3.1.6}$$

2. Fixing the false alarm probability, the miss detection probability decreases with L_D:

$$\partial\Phi_{ji}(P_{FA}^{j}, L_D)/\partial L_D < 0; \tag{3.1.7}$$

3. fixing false alarm probability and increasing L_D value, the miss detection probability decreases in exponential way. This last happens when the channel coefficients $\{g_{ji}(k,t)\}$ in (3.1.1) are i.i.d. random variables (see also [7],[1],[87]):

$$\Phi_{ji}(P_{FA}^{j}, L_D) \approxeq \Phi_{ji}(P_{FA}^{j}, L_D = 1), \quad \text{i.i.d. fading} \tag{3.1.8}$$

4. fixing the false alarm probability and increasing L_D, the miss detection probability decreases as:

$$\Phi_{ji}(P_{FA}^{j}, L_D) \approxeq \frac{1}{L_D}\Phi_{ji}(P_{FA}^{j}, L_D = 1), \quad \text{constant fading} \tag{3.1.9}$$

when the L_D coefficients are all the same (i.e., perfectly correlated fading).

3.1.1 Noncooperative/Cooperative Spectrum sensing

We have cooperative Spectrum sensing when all Mesh Client, in the same cluster, operate in cooperative way and, in this case, the fading, in eq.(3.1.8), may be independent and identically distributed (i.i.d.). Each mesh client measure its channel gain $g_{ji}(t)$ in independent and equidistributed way and before proceeding with the decision about the presence or absence of the primary user, they exchange these measures.

On the contrary, correlated fading (3.1.9) may occurs if each mesh client carry out channel sensing in noncooperative way, so that, each mesh client processes its observations in independent way (no space/time diversity).

Before proceeding with the description of the other functional blocks, we define the Ideal Spectrum Sensing.

DEFINITION 3.1 **Ideal Sensing Spectrum -** The Channel Detection algorithm is defined ideal when the false alarm and miss detection probabilities, (P_{FA}^{j}, P_{MD}) are zero, respectively. ¡in this case, we have: $\check{a}_{ji}(t) \equiv a_i(t)$, $\forall i \in \mathcal{I}$.

For Channel Detection algorithm, we cam make this assumptions:

ASSUMPTION 3.2 Spectrum Sensing procedure

i) each mesh client know both own false alarm probability P_{FA}^{j} in (3.1.4) and the set of miss detection probabilities $\{P_{MD}^{ji},\ i \in \mathcal{I}\}$;

ii) at the beginning of each slot (see Fig.2.1.2) each mesh client MC(j $\in \mathcal{C}_i(t)$) make Channel Detection;

iii) each access point MR(i) has not Channel sensor and for this reason, at the beginning of each slot, it can not perform channel sensing.

Before proceeding, we note that an updated detailed overview about spectrum sensing architecture algorithms for wireless CRNs is presented in [7, Chap.4], where several aspects concerning centralized-vs-distributed data fusion, cooperative-vs-noncooperative sensing and hard-vs-soft data fusion are debated. In the sequel, we directly focus on the development of the (somewhat novel and ActMesh-oriented) Belief Propagation and Data Fusion algorithms specifically required by the ActMesh networking architecture of Fig.2.1.1.

3.2 Mesh Client Functionality-Channel Estimation Phase

Assuming the access channel mutual (i.e., the same in uplink and in downlink), let $h_{ji}(t) \in \mathbb{C}$: MC(j)$\rightleftarrows$MR(i) be the access channel gain at the frequency f_i (see Fig.2.1.2). During Channel Estimation phase, the access point of the i-th cluster generate a pilot sequence $p \in \mathbb{C}$ (constant) a priori known to all mesh client of the overall network. On the basis of this sequence, the MC(j) calculates the channel estimation according to:

$$\xi_{ji}(k,t) \equiv h_{ji}(t)p + v_j(k,t), \quad L_D \leq k \leq L_D + L_E - 1. \tag{3.2.1}$$

where $\{v_j(k,t) \in \mathbb{C},\ L_D \leq k \leq L_D + L_E - 1\}$ is a zero-mean, stationary noise sequence and with variance equal to:

$$N_v(j) \triangleq E\{||v_j(k,t)||^2\}, \quad j = 1, \cdots, N_{t_0}, \quad (Watt/Hz). \tag{3.2.2}$$

ASSUMPTION 3.3 The variance $N_v(j)$ considers both the noise generated by receiver to be used by MC(j) and the interference caused by the simultaneously transmission of the primary user of the i-th cluster.

The resulting channel state $s_{ji}(t) \in \mathbb{C}^1$ at the t-th slot is application dependent and it is modelled as a deterministic function, a priori known, t-invariant and continues:

$$s_{ji}(t) \triangleq \chi(h_{ji}(t)) \tag{3.2.3}$$

where $\chi : \mathbb{C}^1 \to \mathbb{C}^1$ is continuous function of $h_{ji}(t)$

According to eqs.(3.2.1) and (3.2.2), during to the Channel Estimation phase, the MC(j) calculates an access channel estimate $\hat{s}_{ji}(t)$. The estimator and its performance can change from mesh client by mesh client.

Let $\hat{s}_{ji}(t) \triangleq \omega_j(\{r_{ji}(k,t),\ 0 \leq k \leq L_D + L_E - 1\})$ be the channel state estimate, let $\varepsilon_{ji}(t) \triangleq s_{ji}(t) - \hat{s}_{ji}(t)$ be the error in estimating channel, indicating with $\bar{\varepsilon}_{j,i} \triangleq E\{\varepsilon_{ji}(t)\}$ the average estimate error, with $\sigma^2_{\varepsilon}(ji) \triangleq$

$E\{(s_{ji}(t)-\hat{s}_{ji}(t))^2\}$ the mean-square error and with $p_{ji}(\varepsilon_{ji}) \in \mathbb{R}^+$ the probability density function (pdf). In the following, we will assume that:

ASSUMPTION 3.4 MC(j) knows the set of pdf $\{p_{ji}(\varepsilon_{ji}),\ \forall i = 1,\cdots,\mathcal{I}\}$. Specifically, the sets $\{\bar{\varepsilon}_{ji}\},\ i = 1,\cdots,\mathcal{I}\}$ and $\{\sigma_\varepsilon^2(ji),\ i = 1,\cdots,\mathcal{I}\}$ are noted to MC(j). Moreover, $\omega_j(\cdots),\ j = 1,\cdots,N_{t_0}$ can be different by Mesh Client to Mesh Client, but at same time they must be all asymptotically consistent, non-polarized and with mean square estimate error strictly decreasing with increasing the observations number, or rather:

$$\lim_{L_E\to\infty} E\{(s_{ji}(t)-\hat{s}_{ji}(t))\} \equiv 0, \quad \forall(j,i,t), \tag{3.2.4}$$

and

$$\lim_{L_E\to\infty} \hat{s}_{ji}(t) \stackrel{(m.q.)}{=} s_{ji}(t), \quad \forall(j,i,t), \tag{3.2.5}$$

DEFINITION 3.2 **Ideal Estimator -** The estimator $\omega_j(\cdots)$ is state to be ideal if $p_{ji}(\varepsilon_{ji}) \equiv \delta(\varepsilon_{ji}),\ \forall i = 1,\ldots,\mathcal{I}$, that is for $\bar{\varepsilon}_{ji} \equiv \sigma_\varepsilon^2(ji) \equiv 0,\ \forall i = 1,\ldots,\mathcal{I}$

EXAMPLE 3.1

Before proceeding with the formulation of the work, we develop an example of channel estimator. We suppose that the channel state is defined as the corresponding SINR $s_{ji} \triangleq \|h_{ji}\|^2/N_v(j)$ and the channel estimate $\hat{s}_{ji}$ is obtained from the estimate $\hat{h}_{ji}$ of h_{ji} as follows:

$$\hat{s}_{ji} \triangleq \|\hat{h}_{ji}\|^2/N_v(j) \in \mathbb{R}_0^+. \tag{3.2.6}$$

In addition, we suppose also that the sequence $\{v(k,t)\}$ in (3.2.1) is Gaussian, white, (possibly) roundly complex and with mean zero. Then, the ML estimate $\hat{h}_{ji}$ is the following:

$$\hat{h}_{ji} \triangleq \hat{h}_{ji}(ML) \triangleq arg \max_{h_{ji}} \{p(\xi_{ji}(k,t)),\ L_D \leq k \leq L_E + L_D - 1,\ |h_{ji}\} \equiv$$
$$\equiv \frac{1}{L_E p} \left(\sum_{k=L_D}^{L_D+L_E-1} \xi_{ji}(k,t) \right) \tag{3.2.7}$$

and its performance are as follows:

$$E\{(\hat{h}_{ji} - h_{ji}|h_{ji})\} \equiv 0, \quad \forall h_{ji} \in \mathbb{C}^1; \tag{3.2.8}$$

$$E\{(\|\hat{h}_{ji} - h_{ji}\|^2|h_{ji})\} = \frac{N_v(j)}{\|p\|^2 L_E}. \tag{3.2.9}$$

Hence, from (3.2.8) and from the (3.2.6) follows that: $\lim_{L_E \to \infty} \hat{h}_{ji} \overset{(m.q.)}{=} h_{ji}$, $\lim_{L_E \to \infty} \hat{s}_{ji} \overset{(m.q.)}{=} s_{ji}$ respectively.

On the basis of this last limit expression, we may conclude that the channel estimate $\hat{s}_{ji}$ accomplish the Assumption 3.4.

3.3 Mesh Router Functionality-Belief Propagation

Let $\Gamma_i(t)$ to be the set (empty or not empty) of the information about the MR(i+1) activity in the previous (t-1) slot that the MR(i) knows at the beginning of t-th slot, we can write the following Belief Propagation definition:

DEFINITION 3.3 **Belief Propagation -** Belief Propagation is the algorithm by which, each access point MR(i) estimates and/or update the following conditional probability $P(a_i(t) = 1|\Gamma_i(t))$ at the beginning of t-th slot.

According to Definition 3.3, the corresponding probability depends on the set $\Gamma_i(t)$, hence, on the basis of this fact, we can distinguish between Noncooperative and Cooperative Belief Propagation.

DEFINITION 3.4 Noncooperative and Cooperative Belief Propagation - The Belief Propagation is called *Noncooperative* when the set $\Gamma_i(i)$ is empty or contains information about *only* the MR(i+1) past activities of the i-th cluster .

The Belief Propagation is called *Cooperative* when the set $\Gamma_i(t)$ is nonempty and it contains information about the previous activities of all primary users of the overall mesh network of Fig.2.1.1.

Before proceeding with the Data Fusion definition, in the following subsections 3.3.1,3.3.2, we develop three examples of Belief Propagation for three different sets $\Gamma_i(t)$. Specifically, the first and the second example correspond to Noncooperative Belief Propagation (see subsection3.3.1), while the last represents an example of Cooperative Belief Propagation (see subsection 3.3.2).

3.3.1 Noncooperative Belief Propagation

Case A: $\Gamma_i(t)$ ***empty set*** In this case, the MR(i) updates the probability $P(a_i(t) = 1|\Gamma_i(t))$ measuring and updating the occurrence frequency of the event $a_i(t) = 1$, for $\tau \leq (t-1)$. Specifically, on the basis of the As. 3.7, MR(i) knows the values $a_i(\tau)$ until the instant $\tau = t-1$, hence, at the beginning of slot, MR(i) calculates or updates the occurrence frequency, on the basis of the following expression:

$$F_i(t) \triangleq \frac{1}{(t-1)}\left(\sum_{\tau=1} t-1 a_i(\tau)\right), \quad t \geq 2. \qquad (3.3.1)$$

Obviously, since the network in Fig.2.1.1 work in stationary and ergodic way, we have:

$$\lim_{t\to\infty} F_i(t) \equiv P(a_i(t)=1|\Gamma_i(t)) \equiv 1-P(a_i(t)=0|\Gamma_i(t)). \qquad (3.3.2)$$

We may conclude saying that the equation (3.3.1) and (3.3.2) represent an example of Noncooperative Belief Propagation.

CASE B: $\Gamma_i(t)$ ***does not empty set*** In this second case, we assume that the activity state of the primary user is modelled with a Markov's homogeneous chain depicted in Fig.3.3.1. Referring to Fig.3.3.1, we define the

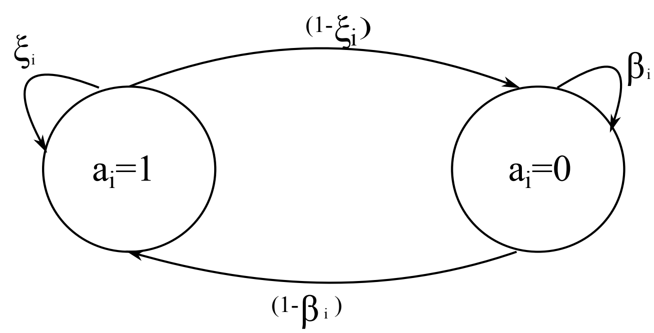


Figure 3.3.1: Two-state Markov chain for the activity process of the i-th primary user MR(i+1)

transaction probabilities as follows:

$$\beta_i \triangleq P(a_i(t) = 0 | a_i(t-1) = 0); \tag{3.3.3}$$

$$\xi_i \triangleq P(a_i(t) = 1 | a_i(t-1) = 1) \tag{3.3.4}$$

and we assume that this probabilities are known at the access point MR(i) of the i-th cluster. Furthermore, we assume that at the beginning of t-th slot, the access point knows $a_i(t-\Delta)$ for a fixed and strictly positive value of delay $\Delta \geq 1$. To be more precise:

$$\Gamma_i(t) \equiv \{a_i(t-\Delta)\}. \tag{3.3.5}$$

The above equation (3.3.5) is equivalent to assuming that the access point MR(i) has exact knowledge about the primary user activity belonging to its cluster in the $(t-\Delta)$ slot.

Hence, MR(i) calculate the probability $P(a_i(t) = 1|\Gamma_i(t)) = 1 - P(a_i(t) = 0|\Gamma_i(t))$ by applying the following prediction equation:

$$\begin{bmatrix} P(a_i(t) = 0|\Gamma_i(t)) \\ P(a_i(t) = 1|\Gamma_i(t)) \end{bmatrix} \equiv \left(\begin{bmatrix} \xi_i & (1-\beta_i) \\ (1-\xi_i) & \beta_i \end{bmatrix} \right)^{\Delta} \times \\ \times \begin{bmatrix} a_i(t-\Delta) \\ 1 - a_i(t-\Delta) \end{bmatrix}, \quad \forall i \in \mathcal{I}, t \geq 1 \tag{3.3.6}$$

(3.3.5) and (3.3.6) represent an example of Noncooperative Belief Propagation.

3.3.2 Cooperative Belief Propagation

$\Gamma_i(t)$ **contains information about the previous activities all primary users:** Let $\overrightarrow{a}(t) \triangleq [a_1(t) \cdots a_{\mathcal{I}}(t)]^T$ to be the column vector of the primary user activities belonging to the Mesh network depicted in Fig.2.1.1; let to be $\overrightarrow{a}_m \triangleq [a_m(1), a_m(2), \cdots, a_m(\mathcal{I})]^T$ the m-th determination assuming by $\overrightarrow{a}(t)$ and let to be $\overrightarrow{e}(m)$, $0 \leq m \leq (2^{\mathcal{I}} - 1)$, the column vector with dimension $(2^{\mathcal{I}} - 1)$, we assume that:

i) the sequence $\{\overrightarrow{a}_i(t),\, t \geq 1\}$ describes all $\mathcal{I}$ primary activities and represents a Markov's homogeneous chain with $2^{\mathcal{I}}$ states;

ii) let to be $p(m|m') \triangleq P(\overrightarrow{a}(t) = \overrightarrow{a}_m | \overrightarrow{a}(t-1) = \overrightarrow{a}_m)$, $0 \leq m \lesseqgtr m' \leq (2^{\mathcal{I}} - 1)$ the corresponding transaction probability is define as follows:

$$[P_A] \triangleq \begin{bmatrix} p(0|0) & p(0|1) & \cdots & p(0|2^{\mathcal{I}}-1) \\ \vdots & \vdots & \vdots & \vdots \\ p(2^{\mathcal{I}}-1|0) & p(2^{\mathcal{I}}-1|1) & \cdots & p(2^{\mathcal{I}}-1|2^{\mathcal{I}}-1) \end{bmatrix}$$

and it is a priori known to all access points MR(i), $i \in \mathcal{I}$ of the network in Fig.2.1.1;

iii) at the beginning of slot, each mesh router knows the set $\{a_i(t-\Delta)\}$,

$\forall i \in \mathcal{I}$ of the all primary user states at the $(t-\Delta)$ slot, that is:

$$\Gamma_i(t) \equiv \begin{bmatrix} a_1(t-\Delta) \\ a_2(t-\Delta) \\ \vdots \\ a_{\mathcal{I}}(t-\Delta) \end{bmatrix}, \quad \forall i \in \mathcal{I}. \tag{3.3.7}$$

The (3.3.7) is equivalent to assume that, at the beginning of slot, each MR(i) broadcast the following information $a_i(t-\Delta)$ to all other access points via the backbone of Fig.2.1.1. According to this last statement, all MR(i) have the same set $\Gamma_i(t)$ and this represents the cooperative Belief Propagation.

In the considered example, the Belief Propagation algorithm implemented by each MR(i) proceed as follows:

i) independently and individually, each MR(i) calculates

$$\overrightarrow{\pi} \triangleq [P(\overrightarrow{a}(t) = \overrightarrow{a}_0|\Gamma_i(t)), \cdots, P(\overrightarrow{a} \equiv \overrightarrow{a}_{(2^{\mathcal{I}}-1)}|\Gamma_i(t))]^T$$

the probability vector according to:

$$\overrightarrow{\pi}(t) \equiv [P_A]^{\Delta}\overrightarrow{e}(\overline{m}); \tag{3.3.8}$$

ii) independently and individually, each MR(i) calculates the own probability $P(a_i(t) = 1|\Gamma_i(t))$ according to the following expression:

$$P(a_i(t) = 1|\Gamma_i(t)) \equiv \sum_{m=0}^{(2^{\mathcal{I}}-1)} P(\overrightarrow{a}(t) = \overrightarrow{a}_m|\Gamma_i(t)). \tag{3.3.9}$$

3.4 Mesh Router Functionality-Optimal Data Fusion

Each MR(i) knows the primary's activity only at the end of the t-th slot (i.e., during the Ack phase of Fig.2.2.1) but MR(i) must know the state of MR(i+1) at the beginning of the phase Resource Allocation. Hence, during the latter part of Channel Detection of Fig.2.2.1 and after Belief Propagation phase, each access point MR(i) carries on the Data Fusion. Specifically, the mesh router MR(i) merges (Data Fusion) decisions $\{\hat{a}_{j,i}(t),\ j \in \mathcal{C}_i(i)\}$ already took by MC(j) in the first part of Channel Detection.

By definition, the set of the information about the MR(i+1) activity is $\mathcal{V}_i(t),\ i \in \mathcal{I},\ t \geq 1$ and these information are available at access point MR(i) at the end of the Channel Detection phase. According to this last definition, we introduce the following assumption:

ASSUMPTION 3.5 Available information to Data Fusion - $\mathcal{V}_i(t) \supseteq \Gamma_i(t)$ and $\mathcal{V}_i(t)$ does not contain useful information about the optimization problem solutions, specifically, the optimal access rate and optimal access time solution[3.1].

Let

$$\widetilde{P}_L^i(t) \triangleq P(a_i(t) = 0 | \mathcal{V}_i(t)),\ i \in \mathcal{I},\ t \geq 1 \tag{3.4.1}$$

[3.1] These optimizations are calculated during the next Resource Allocation and Client's Scheduling phase of Fig.2.2.1.

to be the posteriori probability (i.e., conditioned on $\mathcal{V}_i(t)$) that the i-th channel is transmission free, we introduce the following Data Fusion definition:

DEFINITION 3.5 Data Fusion definition - The Data Fusion is algorithm that computes the above conditional probability. This last is computed by each MR(i), at the end of Channel Detection phase of Fig.2.2.1 and on the basis of the set information $\mathcal{V}_i(t)$.

Now, since, the Channel Detection phase is not carried out by MR(i), but it is carried out by all mesh clients (MC(j)) in overall network, we assume that:

$$\mathcal{V}_i(t) \equiv \{\{\hat{a}_{j,i}(t),\ \forall j \in \mathcal{C}_i(t)\},\ \Gamma_i(t)\}, \quad i \in \mathcal{I}, \quad t \geq 1. \tag{3.4.2}$$

Specifically, for Data Fusion phase, each MR(i) uses the decisions $\breve{a}_{ji}(t)$, $j \in \mathcal{C}_i(t)$ of eq.(3.1.2), already calculated by MC(j), and the set $\Gamma_i(t)$ (eventually empty) already known to the MR(i).

Specifically, the assumption:

$$P(\hat{a}_{j,i}(t), j \in \mathcal{C}_i(t)|a_i(t), \Gamma_i(t)) \equiv \prod_{j \in \mathcal{C}_i(t)} P(\hat{a}_{j,i}(t)|a_i(t), \Gamma_i(t)), \tag{3.4.3}$$

leads to the following result about the Optimal Soft Data Fusion.

Proposition 3.1 Optimal Soft Data Fusion - Under the above reported assumptions in eqs.(3.4.2),(3.4.3), for the solution of the conditional probability the following relationship hold:

$$\begin{aligned}\widetilde{P}_L^i(t) &= P(a_i(t)=0|\Gamma_i(t))[\prod_{j\in\mathcal{C}_i(t)} P(\hat{a}_{j,i}(t)|a_i(t)=0)]/ \\ &\Bigg[P(a_i(t)=0|\Gamma_i(t))[\prod_{j\in\mathcal{C}_i(t)} P(\hat{a}_{j,i}(t)|a_i(t)=0)] \\ &+ P(a_i(t)=1|\Gamma_i(t))\prod_{j\in\mathcal{C}_i(t)} P(\hat{a}_{j,i}(t)|a_i(t)=1)\Bigg], \quad t\geq 1, \quad i\in\mathcal{I}.\end{aligned} \tag{3.4.4}$$

Proof. Applying the Bayes' Rule and using (3.4.3), we may demonstrate the validity of (3.4.4).

The probabilities $P(a_i(t)|\Gamma_i(t))$ are known to the MR(i) via the Belief Propagation (see (3.3.2),(3.3.6),(3.3.9)). Specifically, inserting (3.4.2) into (3.4.1) and applying the Bayes' Rule, we obtain the following expression about the posteriori probability defined in (3.4.1).

$$\begin{aligned}\widetilde{P}_L^i(t) &= P(\hat{a}_{ji}(t), j\in\mathcal{C}_i(t)|a_i(t)=0,\Gamma_i(t))P(a_i(t)=0|\Gamma_i(t))/ \\ &\Bigg[P(\hat{a}_{ji}(t), j\in\mathcal{C}_i(t)|a_i(t)=0,\Gamma_i(t))P(a_i(t)=0|\Gamma_i(t)) \\ &+ P(\hat{a}_{ji}(t), j\in\mathcal{C}_i(t)|a_i(t)=1,\Gamma_i(t))P(a_i(t)=1|\Gamma_i(t))\Bigg].\end{aligned} \tag{3.4.5}$$

By definition, the set $\Gamma_i(t)$ contains the information about $a_i(t)$, therefore, conditioned on $a_i(t)$, $\Gamma_i(t)$ is not significant and it can be remove from the conditioning. Then, we can rewrite (3.4.3) as follows:

$$P(\breve{a}_{ji}(t), j \in \mathcal{C}_i(t)|a_i(t), \Gamma_i(t)) \equiv P(\breve{a}_{ji}(t), j \in \mathcal{C}_i(t)|a_i(t)) \equiv \\ \equiv \prod_{j \in \mathcal{C}_i(t)} P(\hat{a}_{ji}|a_i(t)). \tag{3.4.6}$$

Introducing, eq.(3.4.8) into (3.4.5), we obtain (3.4.4). □

The eq.(3.4.4) define the Optimal Soft Data Fusion algorithm that each MR(i) delivers at the end of the Channel Detection phase. At this regard, we may note that (see eq.(3.1.3),(3.1.4)):

$$P(\hat{a}_{ji}(t)|a_i(t) = 0) \equiv \begin{cases} P_{FA}^{j}, & \text{for} \quad \hat{a}_{ji} = 1, \\ 1 - P_{FA}^{j}, & \text{for} \quad \hat{a}_{ji} = 0, \end{cases} \tag{3.4.7}$$

and

$$P(\hat{a}_{ji}(t)|a_i(t) = 1) \equiv \begin{cases} P_{MD}^{ji}, & \text{for} \quad \hat{a}_{ji} = 0, \\ 1 - P_{MD}^{ji}, & \text{for} \quad \hat{a}_{ji} = 1. \end{cases} \tag{3.4.8}$$

We may assert: *i)* first, each mesh client calculates the decision $\hat{a}_{ji}(t)$; *ii)* second, on the basis of this decision, it knows the value of the eqs.(3.4.5),(3.4.8) and it sends this last probabilities at the access point which calculates the value of the eq.(3.4.4).

At this point of the work, we ask ourselves if our Data Fusion algorithm is hard or soft. Before proceeding to answer to this question, we go to see what can be retrieve in the current literature. Specifically, in the remark, we see which are the soft and hard Data Fusion definitions.

Remark 3.1 **Some considerations about the Data Fusion -** According to [48], the Data Fusion algorithm is defined 'hard' when the mesh clients, in overall network, provide hard information (i.e., binary decisions) to the corresponding mesh router and the access point provides hard information. On the contrary, in [48], the Data Fusion algorithm is defined 'soft' if, directly, the mesh clients provide the observations (see eq.(3.1.1)) to the mesh router, this last processes the set of the observations and provides hard decisions.

Hence, our Data Fusion in eq.(3.4.4) is neither hard nor soft. In fact, the mesh clients provide the soft information (in form of probability) to the access point. In turn, the mesh router processes the soft information and provides a soft information (in form of probability, see eq.(3.4.4)).

Before proceeding with the joint constrain problem description, we note that each mesh client, belonging to the Active Mesh Network of Fig.2.1.1, has its own priority level as regards other mesh client. Specifically, the mesh client priority level is defined by $\theta_j \in]0,1]$ value. In this regard, we suppose verified the following assumption:

ASSUMPTION 3.6 **The MC priority level: DiffServ model -** Each mesh client knows only the own value θ_j while each access point MR(i), $i \in \mathcal{I}$, knows the complete priority level set $\{\theta_j \in]0,1],; j = 1, \cdots, N_{t_0}\}$.

3.4.1 Mesh Router Functionality-ACK Message Definition

The access point MR(i) sends, at the end of t-th slot, to MC, belonging to its cluster, an ACK/NACK message. The ACK message is defined as follows:

$$Z_A^i(t) \triangleq \begin{cases} 1, & \text{if MR(i) sends the Ack message,} \\ 0, & \text{otherwise.} \end{cases} \tag{3.4.9}$$

If the mesh client receives $Z_A^i(t) = 1$, it learns the following two information: *i)* the primary user was not active in the current t-th slot (i.e., $a_i(t) = 0$); and *ii)* one or more mesh clients transmitted and all their transmissions have been successful. On the other hand, when the mesh client receives $Z_A^i(t) = 0$, it acquires these other information which are mutually exclusive: *i)* none secondary user has transmitted in the current slot; or *ii)* there were collisions between secondary user; or *iii)* there was primary-secondary collision. We may conclude that:

$$\begin{cases} Z_A^i(t) = 1 \\ Z_A^i(t) = 0 \end{cases} \tag{3.4.10}$$

When $Z_A^i(t) = 1$, each MC(j) learns the information $a_i(t) = 0$ **and** the secondary transmissions have been successful, while when $Z_A^i(t) = 0$, each MC(j) learns the information: there was collision or any secondary user has transmitted.

Hence, the event $Z_A^i(t) = 1$ brings information on the primary user activity, while the event $Z_A^i(t) = 0$ does not provided, in general, any information on the presence or absence activity of the primary user. Notable exception when, in each cluster, the access point MR(i) adopts a orthogonal MAC policy for regular the transmissions of the secondary user. In order to obtain this target, we introduce the following definition (see [7, Chap.14,Sect.5]):

DEFINITION 3.6 **Orthogonal-vs-non orthogonal secondary-user scheduling -** We assume that each access point, in the own cluster, adopts a same MAC policy for to regular the mesh clients access. Then, the MAC policy is orthogonal if it avoids the secondary user collisions belonging to the same cluster, otherwise, the MAC policy is non orthogonal if two or more secondary user transmitted in the same cluster, simultaneously.

An orthogonal MAC policy guarantees that there are never any collisions between secondary user, but it does not guarantee the absence of the primary-secondary collisions. The most important consequence, that we have when the MAC is orthogonal, is as follows:

i) the Ack message can be defined as: $Z_A^i(t) = 1 - a_i(t)$

ii) $Z_A^i(t) = 0$ indicates that the primary user was not active in the current slot.

On the basis of the above factors, we introduce the following fundamental assumption:

ASSUMPTION 3.7 **Orthogonal MAC and Ack message -** Each access point MR(i) has a perfect knowledge of the state $a_i(t)$ of the primary user only at the end of t-th slot (i.e., in the Ack phase of Fig.2.1.2). Moreover, the orthogonal MAC is employed in each cluster (i.e., there are never any collisions between secondary users). In addition, in order to this above factors, we may define the Ack message as follows:

$$Z_A^i(t) \triangleq 1 - a_i(t). \tag{3.4.11}$$

Before proceeding, we list some important properties that to descend from the above As.3.7.

Property 3.1 ***i)*** MC(j)$\in \mathcal{C}_i(t)$ receives $Z_A^i(i) = 1$ if and only if the primary user MR(i+1) is not active, otherwise it receives $Z_A^i(t) = 0$ ($Z_A^i(i) = 1 \leftrightarrows a_i(t) = 0$ and $Z_A^i(i) = 0 \leftrightarrows a_i(t) = 1$, respectively);

ii) if $Z_A^i(t) = 1$, each mesh client MC(j)$\in \mathcal{C}_i(t)$ drains all the IUs presents in its queue, otherwise the mesh client does not remove the IUs.

iii) $E\{Z_A^i(t)\} = 1 - P(a_i(t) = 1) \equiv 1 - E\{a_i(t)\}$

Specifically, we note that the above property *ii)* is no valid in the case of non-orthogonal MAC, hence, we can not define the Ack message as in equation (3.4.11). In the rest of the work, we assume always confirmed the As.3.7.

3.5 Collision Probability and Primary User Collisions: Basic Definitions

Remembering that each primary user MR(i+1) tolerates no more than ν collisions with the simultaneously secondary transmissions in each slot, each access point MR(i) must adjust the mesh client transmission in order to respect the maximum average collision constraint.

Hence, we define the following binary variable to achieve this goal as follows:

$$c_i(t) \triangleq \begin{cases} 1, & \text{if } a_i(t) = 1 \text{ and its transmission has collided} \\ 0, & \text{otherwise.} \end{cases} \qquad (3.5.1)$$

Directly on the basis of (3.5.1) follows that:

$$P(c_i(t) = 1) \equiv P((a_i(t) = 1) \textbf{\textit{ and }} (\text{there is collision})); \qquad (3.5.2)$$

$$P(c_i(t) = 0) \equiv P((a_i(t) = 0)) + P((a_i(t) = 1) \textbf{\textit{ and }} (\text{there is not collision})) \qquad (3.5.3)$$

Furthermore, we introduce also the definitions of collision probability and collision occurrence frequency, respectively:

$$P_c(i) \triangleq E\{c_i(t)\} \equiv \lim_{t\to\infty} \frac{1}{(t-1)} \left(\sum_{\tau=1}^{(t-1)} c_i(\tau) \right), \qquad (3.5.4)$$

$$x_i(t) \triangleq \frac{1}{(t-1)} \left(\sum_{\tau=1}^{(t-1)} c_i(\tau) \right), \quad t \geq 1 \qquad (3.5.5)$$

where $x_i(t)$ is measured by the access point MR(i) at the beginning of slot t.

Directly by definitions in (3.5.4), (3.5.5) follows the two more important property:

$$P_c(i) = \lim_{t\to\infty} x_i(t), \quad t \geq 1 \tag{3.5.6}$$

$$x_i(t+1) = \frac{1}{t}[c_i(t) + x_i(t)(t-1)], \quad t \geq 1 \tag{3.5.7}$$

where $(x_i(1) = 0)$.

Before proceeding, we introduce the additional assumption:

ASSUMPTION 3.8 **Collisions management -** Autonomously, each access point MR(i) knows the $c_i(t)$ value at the end of t-th slot (i.e, in the Ack phase of Fig.2.1.2) and uses the $x_i(t)$ value in (3.5.5) at the beginning of slot (i.e., in the Channel Learning of Fig.2.1.2). Moreover, according to (3.5.7), the access point calculates the $x_i(t+1)$ value at the end of slot (i.e., in the Ack phase)

Property 3.2 Assuming valid the condition $x_i(t) \leq \nu_i, \quad \forall t \geq 1$, at the same time are valid also the following assertions:

i) the condition $P_c(i) \leq \nu_i$ is guaranteed;

ii) the condition $x_i(t) \leq \nu_i$, for $t \to \infty$ is equivalent to the above condition.

Proof. Since $x_i(t) \leq \nu_i, \ \forall t \geq 1$, then it is valid also for $t \to \infty$. Hence, $\lim_{t\to\infty} x_i(t)$ is equivalent to $P_c(i) \leq \nu_i$ (see (3.5.6)). □

In order to understand the importance and the utility of the above constraint $x_i(t) \leq \nu_i$, we indicate the random collision numbers tolerated by primary user in the first $\Delta \geq 1$ slots as follows:

$$N_c^i(\Delta) \triangleq \left[\sum_{\tau=1}^{\Delta} c_i(\tau) \right], \quad \Delta \geq 1. \tag{3.5.8}$$

Directly by (3.5.5) we have the following property about the QoS guaranteed to the primary user MR(i+1).

Property 3.3 **Hard guaranteed QoS -** We suppose verified the condition $x_i(t) \leq \nu_i$, for all $t \geq 1$. Then, the random variable $N_c^i(\Delta)$ in (3.5.8) is upper bound (i.e., probability equal one):

$$N_c^i(\Delta) \leq \nu_i \Delta, \quad \forall \Delta \geq 1 \tag{3.5.9}$$

Proof. Since $x_i(\Delta + 1) \equiv \frac{1}{\Delta} N_c^i(\Delta) \leq \nu_i, \forall \Delta \geq 1$, follows (3.5.9). □

The above equation (3.5.9) may be rewrite in the equivalent way as follows:

$$P(N_c^i(\Delta) > \Delta \nu_i) \equiv 0 \tag{3.5.10}$$

and it represents an hard guaranteed QoS on the primary user performance. This hard QoS is very attractive in cognitive applications, where a fundamental requirement is not worse the primary users performance. Hence, in the following, we assume always verified the condition:

$$x_i(t) \leq \nu_i, \quad \forall t \geq 1, \forall i \in \mathcal{I}. \tag{3.5.11}$$

Before proceeding with the work, we complete this section comparing our guaranteed QoS with that in [11].

Remark 3.2 Comparison with [11] - The condition in (3.5.11) is stronger respect to the stability condition in [11]. Hence, our condition in (3.5.11) and the stability virtual queue in [11] are equivalent for $t \to \infty$, but for finite t (3.5.11) is stronger respect to condition in [11]. Then, we conclude that our hard guaranteed QoS is strictly better. Moreover, the authors of [11] achieved the maximum aggregate average goodput when $V \to \infty$, but if the last parameter is equal ∞, the maximum collisions number tolerated by primary user become ∞. Hence, the optimal value of objective function requires infinity queue length.

CAPITOLO 4

Wireless Access Channel and Queue Model

In this Chapter 4, fist we describe the wireless access channel between the j-th mesh client and the its access point in detailed way and after the queueing model of a general mesh client. Specifically, as shown in Fig.4.0.1, we model the j-th mesh client as a time slotted fluid G/G/1 queue fed by a j-th Variable Bit Rate (VBR) media encoder whose output rate may be controlled. In this operating context, the problem we go to tackle deals with closed-form cross-layer design of the controllers that jointly, and in distributed way, performs optimal management of the access rate, access window and client-flow. Time is slotted, with slot duration of T_s $(sec.)$ (see Fig.2.2.1) and the t-th slot spans the interval $[t, (t+1)),\ t \in \mathbb{N}_0^+$. The Information Units (IUs) to be sent over the wireless access channel of Fig.4.0.1 are delivered by the media encoder at the end of each slot. At first, they are buffered into the playin buffer of finite capacity N_j^{max} and, then, they are transferred to the current access point over the available wireless access channel. By definition, the number of IUs arriving at the input of the j-th playin buffer at the end of slot t is the j-th client-flow $\lambda_j(t) \in \mathbb{R}_0^+$ $(IU/slot)$ at slot t. As already indicated in the previous Chapter, the wireless access channel is affected by fading phenomena that we assume constant over each slot.

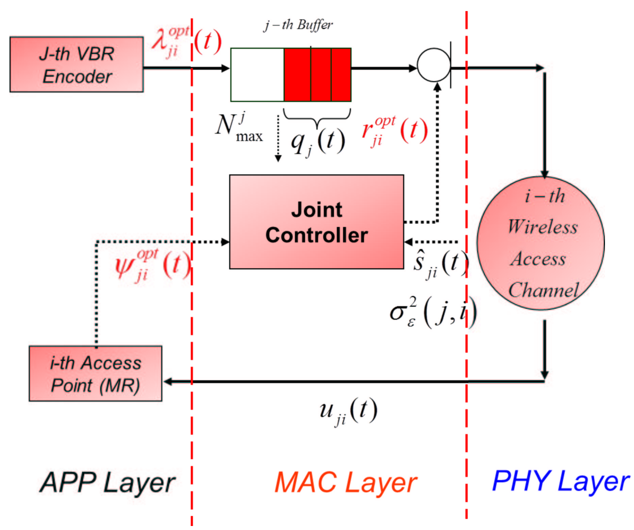


Figure 4.0.1: Queue model and access channel for MC(j) in t-th slot

In the next sections, we see more details the specific about the wireless access channel and the queueing model, respectively.

4.1 Wireless Access Channel

As already indicated in Chapter 2, the j-th mesh client may walk to another only at the end of slot and the fading phenomena in different clusters may have different statistical. Thus, in order to take in account of the effects of mesh clients mobility over the measured channel, we introduce the follows relationships about the access channel state and the estimation access channel state, respectively.

$$s_j(t) \triangleq \sum_{k=1}^{\mathcal{I}} m_{jk}(t) s_{jk}(t) \tag{4.1.1}$$

$$\hat{s} \triangleq \sum_{k=1}^{\mathcal{I}} m_{jk}(t) \hat{s}_{jk}(t) \tag{4.1.2}$$

The resulting estimation access channel state at the t-th slot (see eq.(4.1.2)) is modelled as a random variable (r.v.) with pdf $p(\hat{s}_j)$. This last pdf is computable from the corresponding pdfs $\{p(\hat{s}_{jk}),\ k = 1, \cdots, \mathcal{I}$ according to the following relationship:

$$p(\hat{s}_j(t) = a) \equiv \sum_{k=1}^{\mathcal{I}} P(m_{jk}(t) = 1) p(\hat{s}_{jk}(t) = a), \quad \forall a \in \mathbb{R} \tag{4.1.3}$$

where $P(m_{jk}(t) = 1)$ is the probability that MC(j) has to be in the k-th cluster in a (generic) slot t. The above probability depends on the MC(j)'s Motion Law. We assume that, at most, each j-th mesh client knows (or accurately estimates) the probabilities $\{P(m_{jk}(t) = 1),\ k = 1, \cdots, \mathcal{I}\}$, but the access point MR(i), $i \in \mathcal{I}$ does not know the MC(j) Motion Law.

By eqs.(4.1.1),(4.1.2) and (4.1.3) arise from the elementary properties, as detailed by following Proposition 4.1:

Proposition 4.1 **Estimator property -** Directly from eqs.(4.1.1),(4.1.2) and (4.1.3), for the properties of the estimator follows that:

1. the error estimation is dictated by:

$$E\{(s_j - \hat{s}_j)\} = \sum_{k=1}^{\mathcal{I}} P(m_{jk} = 1)\bar{\varepsilon}_{jk}, \tag{4.1.4}$$

   where $\bar{\varepsilon}_{jk} \triangleq E\{(s_{jk} - \hat{s}_{jk})\}$.

2. The error estimation variance is given by the following relationship:

$$\sigma_{\varepsilon}^2(j) \triangleq E\{(s_j - \hat{s}_j)^2\} \equiv \sum_{k=1}^{\mathcal{I}} P(m_{jk} = 1)\sigma_{\varepsilon}^2(j,k) \tag{4.1.5}$$

3. According to As.3.4, the corresponding estimate $\hat{s}_j$ of eq.(4.1.2) is asymptotically consistent and non-polarized, to be more precise:

$$\lim_{L_E \to \infty} \hat{s}_j(t) = s_j(t), \quad \forall j = 1, \cdots, N_{t_0}, \quad \forall t \tag{4.1.6}$$

   and

$$\lim_{L_E \to \infty} E\{(s_j(t) - \hat{s}_j)^2\} \equiv 0; \quad \forall j = 1, \cdots, N_{t_0}, \quad \forall t. \tag{4.1.7}$$

In the following, we assume that:

ASSUMPTION 4.1 Each mesh client knows the ratio $\overline{s}_j^2/\sigma_{\varepsilon}^2(j)$, where $\sigma_{\varepsilon}^2(j)$ is defined in eq.(4.1.5), while $\overline{s}_j^2 \triangleq E\{s_j^2\}$

4.2 Queue Model and Per-Client Goodput

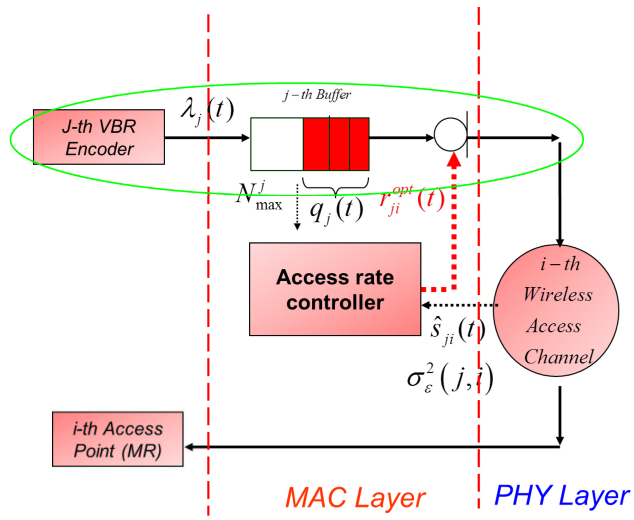
Referring to the Fig.4.0.1, with more detail we describe the mesh client and mesh router behavior. We proceed to describe the queueing model of the j-th MC(j) (see Fig.4.1(a)) and its ultimate target.

Before proceeding, let us assume that the queueing system of Fig.4.0.1 works in the steady-state. Let $T_P \triangleq (L_P/L_t)T_s$ $(sec.)$ and $\eta_0 \triangleq L_p/L_t \leq 1$ be the Payload phase duration and the fraction of the slot-time dedicated to Payload phase of Fig.2.2.1, respectively. Furthermore, let us assume that, in each slot t, the access point MR(i) assigns a fraction of the slot time $\Psi_{ji}(t) \in [0, 1]$ at the MC(j) to transmit uplink data. Furthermore, let us post also the following assumption about the orthogonal access by mesh clients belonging to the overall network.

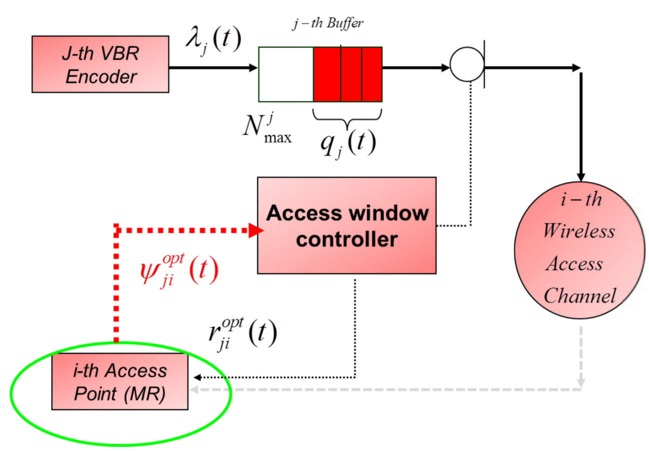
ASSUMPTION 4.2 **Orthogonal Access -** Each mesh client is member to i-th cluster in a time slot t. Hence, according to orthogonal access, MC(j) can get to only access point MR(i) so that $\Psi_{jk}(t) \equiv 0$ for all $k = 1, \cdots, \mathcal{I}$ such that $j \notin \mathcal{C}_k(t)$. Furthermore, there must be secondary-secondary collisions in the i-th cluster. Therefore, this last statement requires that the following relationship has occurred:

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \leq 1, \quad \forall t, \quad \forall i = 1, \cdots, \mathcal{I} \tag{4.2.1}$$

As we can see in Fig.4.1(a) (green circle), the j-th Mesh Client is equipped

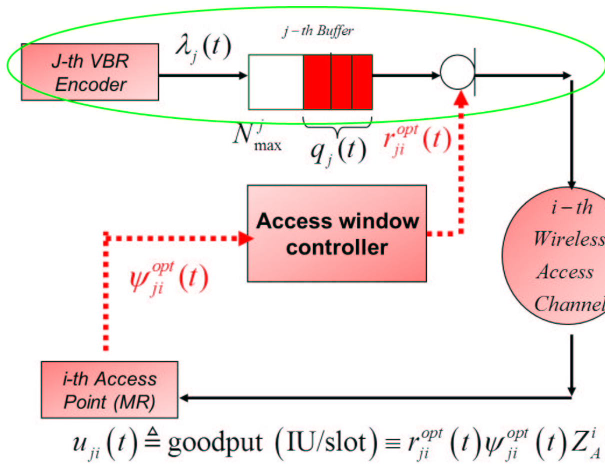


(a)

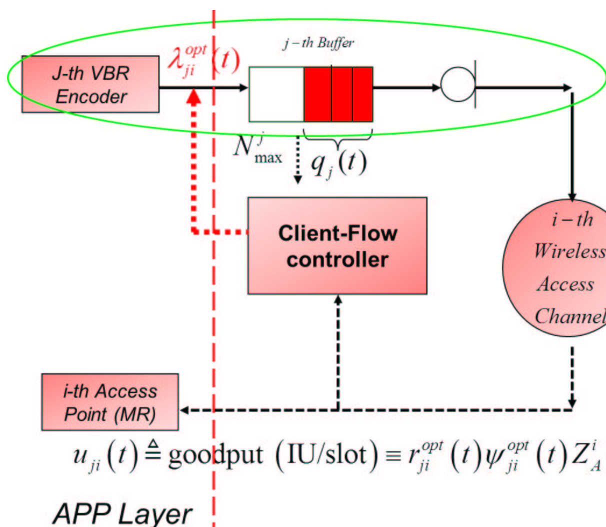


(b)

Figure 4.2.1: Queueing Model of j-th Mesh Client: (a) MC(j) components (green circle) and its ultimate target; (b) optimal access windows.



(a)



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(b)

Figure 4.2.2: Queueing Model of j-th Client: (a) Per-client goodput

with a buffer of finite capacity N^j_{max}. The IUs to be send over the i-th wireless access channel are delivered by VBR encoder at the end of each slot, and they are buffered into a queue. The first ultimate target of the j-th MC is to design an access rate controller, that on the basis of the channel estimation ($\widehat{s}_{ji}(t)$) and the queue length, maximizes the access rate $r_j(t)$ $(IU/slot)$ respecting MAC and PHY layer constraints.

When the MC(j) has determined its optimal access rate, the control passes to i-th Mesh Router (see Fig.4.1(b)), that designs the optimal access window, on the basis of the optimal access rates sent from the j-th MC. Once determined the optimal access windows the MR(i) communicate to MCs the values (in the following chapter, we see that the total transmission window is assigned to Mesh Client with maximum access rate).

At this point, the control passes back to the authorized MC that sends to MR(i) its IUs and if there is any collision with the primary user, it drains the IUs (see Fig.4.2(a)). Hence, having denoted by $r_j(t)$ $(IU/slot)$ the MC(j) access rate during t-th slot, the number of IUs (uplink traffic) that the j-th mesh client sends over the wireless access channel is equal to:

$$\eta_0 r_j(t)\left[\sum_{k=1}^{\mathcal{I}} m_{jk}(t)\Psi_{jk}(t)\right]\ (IUs) \tag{4.2.2}$$

Moreover, let $q_j(t)$ to be the number of IUs present in the j-th mesh client buffer at the beginning of slot t. Hence, after denoting by $u_j(t)$ (IU) the per-client goodput in the t-th slot, the evolution of the j-th queue is described by the corresponding Lindley's equation:

$$q_j(t+1) = [q_j(t) - u_j(t) + \lambda_j(t)]^+, \quad t \geq 0 \tag{4.2.3}$$

where for the per-client goodput the following relationship is valid:

$$\begin{aligned} u_j(t) = \eta_0 r_j(t) \left[\sum_{i=1}^{\mathcal{I}} m_{ji}(t) \Psi_{ji}(t) Z_A^i(t) \right] \overset{(a)}{\equiv} \\ \overset{(a)}{\equiv} \eta_0 r_j(t) \left[\sum_{i=1}^{\mathcal{I}} m_{ji}(t) \Psi_{ji}(t) (1 - a_i(t)) \right], \quad (IU). \end{aligned} \tag{4.2.4}$$

where (a) in (4.2.4) follows from eq.(3.4.11).

Afterwards, on the basis of the drained traffic and the information units in the queue, the MC(j) determines the optimal client-flow $\lambda^{opt}(t)$ (see the following Chapter 5).

Before proceeding with the formulation of the optimization problems, we can see that the cost of sending $r_j(t)$ IUs over slot t depends on the energy $\mathcal{E}_j(t)$ (measure in Joule) that the MC(j) requires for transmit. Thus, we assume that $r_j(t)$ depends on $\mathcal{E}_j(t)$, $\hat{s}_j(t)$, $\widetilde{P}_L^j(t)$ and $\sigma_\varepsilon^2(j)$ via the Rate-Energy Function $\mathcal{R}(\cdot,\cdot;\cdot,\cdot)$, so that we can write:

$$r_j(t) \triangleq \mathcal{R}_j(\mathcal{E}_j(t), \hat{s}_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) \tag{4.2.5}$$

where $\widetilde{P}_L^j(t) \triangleq \sum_{i=1}^{\mathcal{I}} \widetilde{P}_L^i(t)$ represents the probability that j-th channel is available.

From an analytic point of view, $\mathcal{R}_j(\cdot,\cdot;\cdot,\cdot) : \mathbb{R}_0^+ \times \mathbb{R}_0^+ \times [0,1] \times \mathbb{R}_0^+ \rightarrow \mathbb{R}_0^+$ in (4.2.5) (measured in (IU/slot)) is 4-argumental function, with values in $\mathbb{R}_0^+$ and t-invariant.

Therefore, at the present, we limit to introduce few assumptions on $\mathcal{R}_j(\cdot,\cdot;\cdot,\cdot)$. First, the rate-energy function $\mathcal{R}(\cdot,\cdot;\cdot,\cdot)$ is continuous with respect to its 4 arguments and admits up to second-order continuous derivatives with respect to $\mathcal{E}$ and $\hat{s}_j$. Second, it vanishes when either $\mathcal{E}_j = 0$ or $\hat{s}_j = 0$ (i.e., $\mathcal{R}_j(0,\cdot;\cdot,\cdot) = \mathcal{R}_j(\cdot,0;\cdot,\cdot) \equiv 0$). Third, it is strictly decreasing with the increase of $\sigma^2_\varepsilon(j),\ \forall\mathcal{E}_j > 0,\ \hat{s}_j > 0,\ \widetilde{P}_L(j) \geq 0$. Fourth, it is increasing for $\mathcal{E}_j \geq 0$ and $\hat{s}_j \geq 0$, while it is nonincreasing for $\widetilde{P}_L(j)$. Finally, for any assigned $\hat{s}_j > 0$, $\widetilde{P}_L(j) > 0$ and $\sigma^2_\varepsilon(j) \geq 0$, the rate-energy function is strictly concave in the $\mathcal{E}_j$-variable, that is, $\partial^2\mathcal{R}_j(\mathcal{E}_j,\hat{s}_j;\widetilde{P}_L(j),\sigma^2_\varepsilon(j))/\partial\mathcal{E}_j^2 < 0$, for $\mathcal{E}_j > 0$, $\hat{s}_j > 0$, $\widetilde{P}_L(j) > 0$ and $\sigma^2_\varepsilon \geq 0$.

According to $\mathcal{R}_j(\cdot,\cdot;\cdot,\cdot)$, let

$$\mathcal{E}_j(t) \equiv \varepsilon_j(r_j(t),\hat{s}_j(t);\widetilde{P}^j_L(t),\sigma^2_\varepsilon(j)) \triangleq \mathcal{R}_j^{-1}(r_j(t),\hat{s}_j(t);\widetilde{P}^j_L(t),\sigma^2_\varepsilon(j)) \tag{4.2.6}$$

be the energy to be radiated by the mesh client, in a slot time, to sent $r_j(t)$ $(IU/slot)$ in the available access channel.

EXAMPLE 4.1

We remember that the Gap-analysis the system goodput is measured by the following formula:

$$\log(1 + \mathcal{E}\hat{s}/\mathcal{G})$$

where $\mathcal{G} \geq 1$ represents the performance gap. Hence, if $\mathcal{G}$ increases, the system performance decreases. On the basis of this considerations, we may consider the following

Rate-Energy Function as an example:

$$\mathcal{R}(\mathcal{E}_j, \hat{s}_j, \widetilde{P}_L(j), \sigma_\varepsilon^2(j)) \equiv \log\left[1 + \frac{\mathcal{E}_j \hat{s}_j \widetilde{P}_L(j)}{\left(1 + \frac{\sigma_\varepsilon^2(j)}{\overline{s}_j^2}\right)}\right] \quad (IU/slot). \tag{4.2.7}$$

Inverting (4.2.7) respect to $\mathcal{E}_j$ we obtain the following Energy-Rate function:

$$\mathcal{E}_j(r_j, \hat{s}_j, \widetilde{P}_L(j), \sigma_\varepsilon^2(j)) \equiv \frac{\exp(r_j) - 1}{\hat{s}_j \widetilde{P}_L(j)}\left(1 + \frac{\sigma_\varepsilon^2(j)}{\overline{s}_j^2}\right) \quad (Joule) \tag{4.2.8}$$

CAPITOLO 5

Optimization Problem

In this Chapter 5, first we describe the system constraints that we have adopted in this work for formulate our network problem. After, in Section 5.2 we define the Global Resource Allocation Problem and attempt that the constrained joint optimization problem can be recast as $\mathcal{I}$ distributed and scalable subproblems. Furthermore, in Section 5.3 we stress that the i-th subproblem can be separated into other three subproblem without loss optimality.

5.1 System Constraints

In this section, referring to the application scenario previously written, before proceeding to the constrained joint optimization problem definition, we define the constraints of the tackled optimization problem.

$$x_i(t+1) \le \nu_i, \quad \forall t \ge 1, \quad \forall i \in \mathcal{I} \tag{5.1.1}$$

$$E_{\hat{s}_j}\{\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))\} \le \mathcal{E}_{ave}, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.1.2}$$

$$\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) \le \mathcal{E}_P^j, \quad \forall t \ge 1, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.1.3}$$

$$0 \le q_j(t+1) \le N_{max}^j, \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.1.4}$$

$$0 \le \lambda_j(t) \le \lambda_{max}^j, \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.1.5}$$

$$0 \le \eta_0 r_j(t) \le q_j(t), \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.1.6}$$

$$0 \le \Psi_{ji}(t) \le m_{ji} \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.1.7}$$

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \equiv \sum_{j=1}^{N_{t_0}} m_{ji}(t)\Psi_{ji}(t) \le 1, \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.1.8}$$

where

$$x_i(t+1) = \frac{1}{t}[c_i(t) + (t-1)x_i(t)], \quad t \ge 1, \quad x_i(1) \equiv 0, \quad i \in \mathcal{I} \tag{5.1.9}$$

dictates the evolution of the average collisions fraction in the t-th cluster. Moreover, by definition, the maximum quantity of IUs arriving at the input of the j-th playin buffer at the end of slot t is the maximum client-flow λ^j_{max} $(IU/slot)$; the maximum primary-secondary collision probability tolerated in i-th cluster is $\nu_i \in]0,1[$; the available average energy and the available peak energy at the MC(j) are $\mathcal{E}^j_{ave}\ (j)$ and $\mathcal{E}^j_p\ (J)$, respectively.

Therefore, the decisions (i.e., the variables to optimized) to be taken in each time slot, are $3N_{t_0}$, where, N_{t_0} represents the mesh client's total number. In fact, the variables $\{\lambda_j(t),\ j = 1, \cdots, N_{t_0}\}$ $(IU/slot)$ (i.e., j-th client-flow control) and $\{r_j(t),\ j = 1, \cdots, N_{t_0}\}$ $(IU/slot)$ (i.e., j-th access rate) are $2N_{t_0}$. Furthermore, the variables $\Psi_{ji}(t)$ (i.e., the access windows) are $(\mathcal{I} \times N_{t_0})$, but only N_{t_0} can be different from zero because the j-th mesh client is a member of only one cluster.

With regard the expected value in (5.2.12), we have that:

$$E_{\hat{s}_j}\{\mathcal{E}(\hat{s}_j(t), r_j(t), \widetilde{P}^j_L(t), \sigma^2_\varepsilon(j))\} \overset{(a)}{\equiv} \int_{\hat{s}_j} \mathcal{E}(\cdot,\cdot,\cdot,\cdot) p_{\hat{s}_j} d\hat{s}_j \equiv$$
$$\overset{(a)}{\equiv} E_{\hat{s}_j}\{\mathcal{E}(\hat{s}_j(t), r_j(t), \widetilde{P}^j_L(t), \sigma^2_\varepsilon(j) | q_j(t), \widetilde{P}_L(t))\}, \quad t \geq 1$$

where (a) represents the expected value of the irradiate energy $\mathcal{E}_j(t)$ of the MC(j). The expected values is regarding to the channel estimate and conditioned on both queue state $q_j(t)$ and available channel probability $\widetilde{P}^j_L(t)$ computed in the Soft Data Fusion phase.

However, regarding to the constraint (5.2.11), we remember that at the beginning of slot the access point knows $x_i(t)$ value, then, MR(i) takes this last value to calculate the optimal access windows $\{\Psi_{ji}(t), j \in \mathcal{C}(t)\}$. Furthermore, on the basis of both (5.1.9) and collision variable $c_i(t)$, each MR(i) update $x_i(t)$ at the end of slot t.

In the matter of constraint (5.2.11), the following necessary condition is valid:

Proposition 5.1 Necessary condition for the constraint in (5.2.11) **-** A necessary condition in order that the constraint $x_i(t) \leq \nu_i$ is meet, it is that there are no collisions intra cluster until the instant $\lceil \nu_i \rceil - 1$, then the following condition is verified:

$$c_i(t) \equiv 0, \quad \forall t = 1, 2, \cdots, (\lceil 1/\nu_i \rceil - 1). \tag{5.1.10}$$

Proof. We suppose that $c_i(1) = c_i(2) = \cdots = c_i(t-1) = 0$, thus $x_i(t) = 0$ and $x_i(t+1) \equiv (1/t)[c_i(t) + (t-1)x_i(t)] \equiv (1/t)c_i(t)$.

Imposing the constraint $x_i(t+1) \leq \nu_i = (1/t)c_i(t) \leq \nu_i \rightarrow t \geq c_i(t)/\nu_i$. Hence, if $c_i(t) = 0$, the last condition is always accomplished, while if $c_i(t) = 1$, the condition is satisfied only for $t \geq 1/\nu_i$. □

Before proceeding with the optimization problem formulation, in each cluster, we assume valid the condition (5.1.10). Specifically, we introduce the parameter:

$$\widetilde{T} \triangleq \max_{i \in \mathcal{I}} \{\lceil 1/\nu_i \rceil\}, \tag{5.1.11}$$

and also the following assumption:

ASSUMPTION 5.1 **Transitory Phase of the system: Definition -** Each access point guarantees that:

$$c_i(t) \equiv 0, \quad \forall t = 1, \cdots, (\widetilde{T} - 1), \quad \forall i \in \mathcal{I}. \qquad (5.1.12)$$

According to the previous assumption of stationarity and ergodicity condition, the parameter $\widetilde{T}$ in (5.1.11) can be performed as the start of the Steady-state of the network depicted in Fig.2.1.1. Furthermore, (5.1.12) guarantees that:

$$x_i(t) = 0, \quad \forall t = 1, 2, \cdots, \widetilde{T}, \quad \forall i \in \mathcal{I}. \qquad (5.1.13)$$

Sufficient condition to guarantee (5.1.12) is that the client-flow sequences $\{\lambda_j(t),\ t \geq 1\}$ are identically null. Specifically, we assume that $\lambda_j(t) = 0,\ \forall t = 1, 2, \cdots, (\widetilde{T} - 2)$ and $\forall j = 1, 2, \cdots, N_{t_0}$. According to this last assumption follows that:

$$u_j(t) = 0, \quad \forall t = 1, 2, \cdots, (\widetilde{T} - 1) \quad \text{and} \quad \forall j = 1, \cdots, N_{t_0}; \qquad (5.1.14)$$

$$q_j(t) \equiv r_j(t) = 0, \quad \forall t = 1, 2, \cdots, (\widetilde{T} - 1) \quad \text{and} \quad \forall j = 1, \cdots, N_{t_0}; \qquad (5.1.15)$$

$$\Psi_{ji}(t) = 0, \quad \forall t = 1, 2, \cdots, (\widetilde{T} - 1) \quad \text{and} \quad \forall j = 1, \cdots, N_{t_0} \quad \text{and} \quad \forall i \in \mathcal{I}; \qquad (5.1.16)$$

In addition, the conditions in (5.1.10) and (5.1.13) are automatically satisfied.

5.1.1 Objective Function and Distributed, Scalable Optimization

In the previous section, we saw that the number of the variables to optimized are $3N_{t_0}$, thus, we can conclude that this number is linearly increasing with the number of mesh clients presented in the network of Fig.2.1.1. The target of the mesh networks is to allow the Internet access to users which are not directly connect to the corresponding Internet Gateway. Hence, the constrained joint optimization problem must be distributed and scalable scheduling.

DEFINITION 5.1 **Distributed and Scalable Scheduling -** In our application scenario, by definition, the term distributed and scalable scheduling indicates that: *i)* the optimal access rate $r_j^{opt}(t)$ and optimal client-flow control $\lambda_j^{opt}(t)$ do not require the knowledge of the access rate $r_k(t),\ k \neq j$ and/or of the client-flow control $\lambda_k(t)$ neither in the same time nor in different time, and *ii)* optimal set of the access windows $\{\Psi_{ji}^{opt}(t),\ j \in \mathcal{C}_i(t)\}$ depends on the set of access rates $\{r_j(t),\ j \in \mathcal{C}_i(t)\}$

Specifically, the carried properties, in the above Definition 5.1, are equivalent to the following conditions:

$$E\{r_j(t)|Z_A^i, \Psi ji(t), q_j(t), \hat{s}_j(t),\ i \in \mathcal{I}\} \equiv E\{r_j(t)|q_j(t), \hat{s}_j(t)\},$$
$$\forall t \geq \widetilde{T}, \quad \forall j = 1, \cdots, N_{t_0}; \tag{5.1.17}$$

$$E\{\Psi_{ji}(t)|r_j(t), q_j(t), \hat{s}_j(t),\ i \in \mathcal{I}\} \equiv E\{\Psi_{ji}(t)|r_j(t)\},\\ \forall t \geq \widetilde{T}, \quad \forall j = 1, \cdots, N_{t_0}. \tag{5.1.18}$$

About these last conditions, we can see that from the condition in (5.1.17), each MC(j) computes in a fully distributed way (i.e., autonomously) the optimal access rate conditioned to the current queue length and the current estimated channel. Moreover, the computational complexity of the optimal access rate $r_j^{opt}(t)$ is independent by the total number of the mesh clients N_{t_0} and by the number of clusters in the considered network of Fig.2.1.1 (fully scalable system). The ultimate target of j-th mesh client is the constrained maximization of its own objective function, specifically, different mesh client may adopt different objective function for compute the optimal access rate. Furthermore, each access point MR(i) compute the optimal access windows $\{\Psi_{ji}^{opt}(t),\ j \in \mathcal{C}_i(t)\}$ on the basis on the only knowledge of the optimal access rates (previously computed by the mesh client and after sent to the MR(i) at the beginning of Resource Allocation phase) via the condition in eq.(5.1.18).

5.2 Global Resource Allocation Problem

In this work, the ultimate target is the (constrained) maximization of the sum of the aggregate average goodput by all mesh client: $\sum_{j=1}^{N_{t_0}} \theta_j E\{u_j(t)|r_k^{opt}(t),\ k = 1, \cdots, N_{t_0}\}$ conditioned on the set of optimal access rates independently computed by the mesh client in overall network of Fig.2.1.1. To formally state the mentioned constrained joint optimization problem, for convenience, we remember the definition of Energy-Rate function in eq.(4.2.6):

$$\mathcal{E}_j(t) \equiv \varepsilon_j(r_j(t), \hat{s}_j(t); \widetilde{P}_L(t;j), \sigma_\varepsilon^2(j)) \triangleq \mathcal{R}_j^{-1}(r_j(t), \hat{s}_j(t); \widetilde{P}_L(t;j), \sigma_\varepsilon^2(j))$$

Hence, the tackled joint optimization problem may be stated as follows:

$$\max_{[\lambda_j(t), \Psi_j(t)]} \left\{ \sum_{j=1}^{N_{t_0}} \theta_j E\{u_j(t) | r_k^{opt}(t), k = 1, \cdots, N_{t_0}\} \right\}, \tag{5.2.1}$$

$$s.t. : x_i(t+1) \leq \nu_i, \quad \forall t \geq 1, \quad \forall i \in \mathcal{I} \tag{5.2.2}$$

$$E_{\hat{s}_j}\{\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))\} \leq \mathcal{E}_{ave}, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.2.3}$$

$$\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) \leq \mathcal{E}_P^j, \quad \forall t \geq 1, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.2.4}$$

$$0 \leq q_j(t+1) \leq N_{max}^j, \quad \forall t \geq 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.5}$$

$$0 \leq \lambda_j(t) \leq \lambda_{max}^j, \quad \forall t \geq 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.6}$$

$$0 \leq \eta_0 r_j(t) \leq q_j(t), \quad \forall t \geq 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.7}$$

$$0 \leq \Psi_{ji}(t) \leq m_{ji} \quad \forall t \geq 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.8}$$

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \equiv \sum_{j=1}^{N_{t_0}} m_{ji}(t) \Psi_{ji}(t) \leq 1, \quad \forall t \geq 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.9}$$

Remark 5.1 Some considerations about the considered optimization problem - Eq.(5.2.1) points out that we maximize the expected goodput conditioned on the optimal access rates.

From an analytical point of view, the reason for considering the conditional expectation in (5.2.1) in place of the following unconditional optimization problem:

$$\max_{[r_j(t),\lambda_j(t),\Psi_j(t)]} \left\{ \sum_{j=1}^{N_{t_0}} \theta_j E\{u_j(t)\} \right\}, \tag{5.2.10}$$

$$s.t.: x_i(t+1) \le \nu_i, \quad \forall t \ge 1, \quad \forall i \in \mathcal{I} \tag{5.2.11}$$

$$E_{\hat{s}_j}\{\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))\} \le \mathcal{E}_{ave}, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.2.12}$$

$$\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) \le \mathcal{E}_P^j, \quad \forall t \ge 1, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.2.13}$$

$$0 \le q_j(t+1) \le N_{max}^j, \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.14}$$

$$0 \le \lambda_j(t) \le \lambda_{max}^j, \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.15}$$

$$0 \le \eta_0 r_j(t) \le q_j(t), \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.16}$$

$$0 \le \Psi_{ji}(t) \le m_{ji} \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.17}$$

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \equiv \sum_{j=1}^{N_{t_0}} m_{ji}(t) \Psi_{ji}(t) \le 1, \quad \forall t \ge 1, \quad j = 1, \cdots, N_{t_0}, \tag{5.2.18}$$

is that this last does not admit distributed solution. In fact, in order to obtain the joint maximization in (5.2.10) subject to the constraint (5.2.12), in each slot t is required that the access points (of the overall network) know the pdf $\{p_{\hat{s}_j}(\hat{s}_j),\ j = 1, \cdots, N_{t_0}\}$ of all mesh client belonging to the i-th cluster. In turn, since the mesh client's mobility, this last requires that each access point know the mesh client's walking rule. Hence, we can conclude that the reason for considering the conditional expectation in (5.2.1) is necessary and sufficient condition for distributed solution of the considered problem.

Proposition 5.2 The corresponding objective function in (5.2.1) can equivalently rewritten as follows:

$$\sum_{i=1}^{\mathcal{I}} \left\{ \max_{[\lambda_j,\Psi_{ji}]} \left\{ \sum_{j\in\mathcal{C}_i(t)} \theta_j E\{u_j(t)|r_k^{opt}(t), k\in\mathcal{C}_i(t)\} \right\} \right\}, \quad t \geq \widetilde{T} \tag{5.2.19}$$

Proof. As previously mentioned, each MC(j) belongs to one and only one cluster, thus we can rewrite the eq.(5.2.1) as follows:

$$\begin{aligned} &\max_{[\Psi_{ji},\lambda_j]} \left\{ \sum_{j=1}^{N_{t_0}} \theta_j E\{u_j(t)|r_k^{opt}, k=1,\cdots,N_{t_0}\} \right\} \equiv \\ &\equiv \max_{[\Psi_{ji},\lambda_j]} \left\{ \sum_{i=1}^{\mathcal{I}} \sum_{j\in\mathcal{C}_i(t)} \theta_j E\{u_j(t)|r_k^{opt}, k=1,\cdots,N_{t_0}\} \right\}, \\ &\quad \forall j=1,\cdots,N_{t_0}, \forall i\in\mathcal{I}. \end{aligned} \tag{5.2.20}$$

Assuming that there is not inter-cluster interference and there are not peer-to-peer communications between mesh clients belonging to different cluster, following that:

i) the conditioned expected value in (5.2.20) can be rewrite $E\{u_j(t)|r_k^{opt}, k = 1,\cdots,N_{t_0}\} \equiv E\{u_j(t)|r_k^{opt}, k\in\mathcal{C}_i(t)\}$;

ii) for each $i\in\mathcal{I}$, the access windows $\{\Psi_{ji}(t), j\in\mathcal{C}_i(t)\}$ are inter-dependent.

Hence, on the basis of *i)* and *ii)* the second member of eq.(5.2.20) can be rewrite in the equivalent form (5.2.19). □

Hence, according to the Proposition 5.2, the corresponding constrained joint optimization problem may be rewritten in $\mathcal{I}$ parallel and independent subproblems.

5.3 i-th Per-Cluster Constrained Optimization Problem

In detail, the i-th joint constraint optimization subproblem may be formulated as detailed by the following Proposition 5.3.

Proposition 5.3 **(i-th PCOP) -** On the basis of the previously stated, the i-th Per-Cluster Constrained Optimization Problem that the MR(i) must solve, in each slot t, may be stated as follows:

$$\max_{[\lambda_j(t), \Psi_{ji}(t)]} \left\{ \sum_{j \in \mathcal{C}_i(t)} \theta_j E\{u_j(t) | r_k^{opt}(t), k \in \mathcal{C}_i(t)\} \right\}, \tag{5.3.1}$$

$$s.t. : x_i(t+1) \leq \nu_i, \tag{5.3.2}$$

$$0 \leq q_j(t+1) \leq N_{max}^j, \tag{5.3.3}$$

$$0 \leq \lambda_j(t) \leq \lambda_{max}^j, \tag{5.3.4}$$

$$0 \leq \Psi_{ji}(t) \leq 1, \tag{5.3.5}$$

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \equiv \sum_{j=1}^{N_{t_0}} m_{ji}(t) \Psi_{ji}(t) \leq 1, \tag{5.3.6}$$

where $r_k^{opt}(t),\ k \in \mathcal{C}_i(t)$, in eq.(5.3.1), is the optimal access rate independently computed by k-th mesh client at the beginning to Resource Allocation phase of Fig.2.2.1, while eqs.(5.3.4)-(5.3.6) represent instantaneous constraints.

In the following, we indicate with $\{\lambda_j^{opt}(t)\}$ and $\{\Psi_{ji}^{opt}(t)\}$ the solution of optimal client-flow control and optimal access windows, respectively.

5.4 Mesh Client Problem-Access Rate Allocation Problem

Slot by slot, at beginning of Resource Allocation phase (see Fig.2.2.1), each mesh client computes optimal access rate $r_k^{opt}(t),\ k \in \mathcal{C}_i(t)$ maximizing its own objective function. Hence, the tackled optimization problem may be stated as detailed by the following Proposition 5.12.

Proposition 5.4 By definition, the j-th Access-Rate Allocation Problem that, slot by slot, the mesh client must solve, without the knowledge of both the access windows and the primary activity, may be formulated in this way:

$$\max_{[r_j(t)]} E_{\hat{s}_j}\{w_j(r_j(t))|q_j(t)\}, \tag{5.4.1}$$

$$s.t. : E_{\hat{s}_j}\{\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))|q_j(t), \widetilde{P}_L^j(t)\} \leq \mathcal{E}_{ave}^j, \tag{5.4.2}$$

$$\varepsilon_j(\hat{s}_j(t), r_j(t); \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) \leq \mathcal{E}_P^j, \quad \forall t \geq 1, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.4.3}$$

$$0 \leq \eta_0 r_j(t) \leq q_j(t),, \tag{5.4.4}$$

$$0 \leq q_j(t+1) \leq N_{max}^j,, \tag{5.4.5}$$

$$\sum_{i=1}^{\mathcal{I}} m_{ji}\Psi_{ji}(t) \equiv 1, \tag{5.4.6}$$

$$\sum_{i=1}^{\mathcal{I}} m_{ji}(t)Z_A^i(t) \equiv 1 \tag{5.4.7}$$

where the objective function in (5.4.1) can be arbitrary or it variant from mesh client to mesh client. Therefore, at the present, we limit to introduce few assumptions on $w_j(r_j)$. First, the utility function $w_j(r_j)$ is a real nonnegative, independent of t and depending on the access rate r_j $(IU/slot)$. Second, the first-order derivative $\partial w_j/\partial r_j > 0$ done with respect to the r_j is strictly non-decreasing in r_j for $r_j \geq 0$. Third, for any assigned $r_j \geq 0$, the utility function is concave in r_j, that is, $\partial^2 w_j/\partial r_j^2$

Before proceeding to the optimization problem solution, remarks about the choice of $w_j(\cdots)$ for multimedia applications.

Remark 5.2 **Choice of objective function in** (5.4.1) **-** In general, the function varies according to video coding scheme used. In this work, we use the MPEG-4 fine-granularity scalable (FGS) coding scheme as the scalable video coding technology of reference. FGS video stream can be dynamically adapted to the varying condition of the network. In this case, an appropriate choice is to adopt the rate-distortion function as follows [12]:

$$w_j(r_j) \equiv -exp((\lg_2)[a_j r_j + b_j \sqrt{r_j} + c_j]), \quad r_j \geq 0; \tag{5.4.8}$$

where $a_j < 0$, $b_j \leq 0$ and c_j are constant parameters and they vary depending on the source video stream present at the input of the mesh client MPEG-4 encoder.

Now, after recognizing that the optimization problem ARAP of eqs.(5.4.1)-(5.4.7) is convex in r_j, the resulting optimal solution $r_j^{opt}(t)$ may be evaluated in closed-form, as detailed by the following Proposition 5.5 (see Appendix A for the proof).

Proposition 5.5 Under the above reported assumptions for the optimal solution of the constrained optimization problem in (5.4.1)-(5.4.7) we have that:

***i*)** the j-th optimal access rate is optimally scheduled according to

$$r_j^{opt}(t) = \left[\varepsilon_r^{-1}(\widehat{s}_j(t), \widetilde{P}_L^j, \sigma_\varepsilon^2(j), \frac{1}{\mu(t)})\right]_0^{r_P^j(t)} \tag{5.4.9}$$

where $\varepsilon_r^{-1}(\cdot,\cdot,\cdot,\cdot)$ denotes the inverse function of $\varepsilon_r(\cdot,\cdot,\cdot,\cdot)$ with respect to the $\mathcal{E}$-variable, while

$$r_p^j(t) \triangleq \min\left\{\frac{q_j(t)}{\eta_0}, \mathcal{R}_j(\widehat{s}_j(t), \mathcal{E}_p^j, \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))\right\}$$

is the peak-value of the access rate allowed at slot-t. Furthermore, $\mu(t)$ in (5.4.9) is the optimal value of the dual variable of the tackled optimization problem, and it may be computed using the stochastic approximation $\mu(t+1) = \mu(t-1) + (k/t)(\mathcal{E}_{ave} - \overline{\mathcal{E}}(t))$ where $\overline{\mathcal{E}}(t)$ represents the instantaneous average energy up to the current slot.

Remark 5.3 Some consideration about the ARAP problem - Eq.(5.4.1) point out that we maximize (slot-by-slot) the expected utility function given (i.e., conditioned on) the j-th current queue length $q_j(t)$ of the playin buffer.

From an analytical point of view, the reason for considering the conditional expectation in (5.4.1) is that closed-form computation of this last requires to solve the corresponding Lindley's equation $p_{q_j}(a) = \int_{b=0}^{\infty}\int_{\hat{s}=0}^{\infty} p_\lambda(\lambda_j = a - b + r_j(\hat{s}; b))p_{\hat{s}}(\hat{s})p_{q_j}(b)d\hat{s}db$. However, this resist closed-form solution, even when the pdf $p_{\lambda_j}(\lambda_j)$ of the flow generated by the media encoder of Fig.4.0.1 is known in advance and preassigned. For the same reason, in (5.4.2) we consider a constraint on the available average energy conditioned on the current queue length $q_j(t)$, in place of the unconditional average constraint.

The Access-Rate Allocation Problem (ARAP) solutions are distributed (i.e, computed on the basis of only knowledge $q_j(t)$, $\hat{s}_j(t)$ and $p_{\hat{s}_j}(\hat{s}_j)$) and scalable (i.e., with computational complexity independent of both the number of the mesh clients and the number of clusters in overall network of Fig.2.1.1). The mesh client computes $r_j^{opt}(t)$ assuming that: *i)* the access point MR(i) assigns it unitary window transmission $\Psi_{ji}(t) = 1$ and, *ii)* there will be no collisions between primary-secondary.

In determining optimal access rate, we assume that the j-th mesh client know the optimal client-flow control $\lambda_j^{opt}(t-1)$ in the previous $(t-1)$-th slot but does not know the current value of $\lambda_j^{opt}(t)$.

5.5 Mesh Router Problem-Access Window Optimization Problem

To complete the joint optimization problem solution in (5.3.1)-(5.3.6), we must shift the focus on the mesh router (i.e., the access point). The mesh router, in fact, must solve the following Access Window Optimization sub-problem that represents the inner maximization problem of the general joint optimization problem.

$$\max_{\{\Psi_{ji}(t), j \in \mathcal{C}_i\}} \left\{ \sum_{j \in \mathcal{C}_i(t)} \theta_j E\{u_j(t) | r_k^{opt}(t), k \in \mathcal{C}_i(t)\} \right\}, \quad t \geq \widetilde{T}, \tag{5.5.1}$$

$$s.t. : x_i(t+1) \leq \nu_i, \quad \forall t \geq \widetilde{T}, \tag{5.5.2}$$

$$0 \leq \Psi_{ji}(t) \leq 1, \quad \forall j \in \mathcal{C}_i(t), \forall t \geq \widetilde{T}, \tag{5.5.3}$$

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \equiv \sum_{j=1}^{N_{t_0}} m_{ji}(t) \Psi_{ji}(t) \leq 1, \forall t \geq \widetilde{T}, . \tag{5.5.4}$$

To determine the optimization problem solution, we start developing conditional expectation values in the objective function in (5.5.1), according to the following Proposition .

Proposition 5.6 **Per client Average Goodput -** The conditional expected value in (5.5.1) can be rewrite as follows:

$$E\{u_j(t)|r_k^{opt}(t), k \in \mathcal{C}_i(t)\} \equiv \eta_0 r_j^{opt}(t)\widetilde{P}_L^i(t)E\{\Psi_{ji}(t)|r_k^{opt}, k \in \mathcal{C}_i(t)\}, t \geq \widetilde{T} \tag{5.5.5}$$

where $\widetilde{P}_L^i(t) \triangleq P(a_i(t) = 0|\mathcal{V}_i(T))$ represents the conditional probability that i-th channel is primary free. On the basis of eq.(3.4.4), each mesh router calculates the above probability slot-by-slot.

Proof. According to the definition of $u_j(t)$, $j \in \mathcal{C}_i(t)$, we can recast the objective function in (5.5.1) as follows:

$$\begin{aligned}
&E\{u_j(t)|r_k^{opt}(t), k \in \mathcal{C}_i\} = E\{\eta_0 r_j^{opt}\Psi_{ji}(t)Z_A^i(t)|r_j^{opt}(t), k \in \mathcal{C}_i(t)\} \stackrel{(a)}{=} \\
&\stackrel{(a)}{=} \eta_0 r_j^{opt}(t)E\{\Psi_{ji}(t)(1-a_i(t))|r_k^{opt}(t, k \in \mathcal{C}_i(t))\} \stackrel{(b)}{=} \\
&\stackrel{(b)}{=} \eta_0 r_j^{opt}(t)E\{E\{\Psi_{ji}(t)(1-a_i(t))|V_i(t), r_k^{opt}, k \in \mathcal{C}_i(t)\}|r_k^{opt}, k \in \mathcal{C}_i(t)\} \stackrel{(c)}{=} \\
&\stackrel{(c)}{=} \eta_0 r_j^{opt}(t)E\{\Psi_{ji}(t)E\{(1-a_i(t))|V_i(t), r_k^{opt}, k \in \mathcal{C}_i(t)\}|r_k^{opt}, k \in \mathcal{C}_i(t)\} \stackrel{(d)}{=} \\
&\stackrel{(d)}{=} \eta_0 r_j^{opt}(t)E\{\Psi_{ji}(t)|r_k^{opt}, k \in \mathcal{C}_i(t)\}E\{(1-a_i(t))|\mathcal{V}_i(t)\}
\end{aligned} \tag{5.5.6}$$

where (a) follows from $Z_A^i(t) = 1 - a_i(t)$; (b) conditioning on the set $\mathcal{V}_i(t)$ defined in chapter 3; (c) by the assumption 3.8 and (d) follows from the fact that the primary activity state does not depend by the mesh clients access rates. Furthermore,

$$E\{(1 - a_i(t)|\mathcal{V}_i(t))\} = 1 - E\{a_i(t)|\mathcal{V}_i(t)\} = 1 - P(a_i(t) = 1|\mathcal{V}_i(t)) \equiv$$
$$\equiv P(a_i(t) = 0|\mathcal{V}_i(t)) = \text{by definition} = \widetilde{P}_L^i(t). \tag{5.5.7}$$

At this moment, introducing eq.(5.5.7) in (5.5.6), directly we obtain eq.(5.5.5)

□

According the above Proposition 5.6 we may introduce the following definition by Optimal Access Windows:

DEFINITION 5.2 **Optimal Access Windows -** The Optimal Access Windows $\{\Psi_{ji}^{opt}(t), j \in \mathcal{C}_i(t)\}$ are defined as solution of the constrained maximization problem in (5.5.1)-(5.5.4).

Before proceeding with the optimal access windows solution, in according to (5.5.5) we recast the Access Window Optimization Problem in this way:

Proposition 5.7 **Equivalent Access Window Optimization Problem -** The Access Window Optimization Problem in (5.5.1)-(5.5.4) can be recast as follows:

$$\max_{\{\Psi_{ji}(t), j\in\mathcal{C}_i\}} E\bigg\{ \sum_{j\in\mathcal{C}_i(t)} \theta_j r_j^{opt}(t)\widetilde{P}_L^i(t)\Psi_{ji}(t)\bigg\}, \quad t \geq \widetilde{T}, \tag{5.5.8}$$

$$s.t. : x_i(t+1) \leq \nu_i, \quad \forall t \geq \widetilde{T}, \tag{5.5.9}$$

$$0 \leq \Psi_{ji}(t) \leq 1, \quad \forall j \in \mathcal{C}_i(t), \forall t \geq \widetilde{T}, \tag{5.5.10}$$

$$\sum_{j\in\mathcal{C}_i(t)} \Psi_{ji}(t) \equiv \sum_{j=1}^{N_{t_0}} m_{ji}(t)\Psi_{ji}(t) \leq 1, \forall t \geq \widetilde{T}, . \tag{5.5.11}$$

5.6 Access Window Optimization Problem Solution

Before proceeding with the solution, we can decompose the Access Window Optimization Problem (AWOP) in two problems, hard and soft problem respectively.

5.6.1 Hard and Soft Problem

Supposing the available channel probability, computed via (3.4.4) in the Soft Data Fusion phase, is $\widetilde{P}_L^i(t) = 1$ and the primary-secondary collision event is $c_i(t) = 1$, we can assert that the per-client goodput is zero. Following that the traffic, in the queue's mesh client, is not drained because the primary-secondary collision event is occurred. In case of no collisions, we have the secondary utility equivalent to $u_j(t) = \sum_{j\in\mathcal{C}_i(t)} \theta_j(t) r_j^{opt}(t)\Psi_{ji}(t)$. According to this above assumption, we recast the Access window optimization problem in

(5.5.8)-(5.5.11) as detailed in the following proposition:

Proposition 5.8 Hard and Soft Access Window Optimization Problem-Definition - The hard access window optimization problem can be recast as follows:

$$\max_{\{\Psi_{ji}(t), j\in\mathcal{C}_i(t)\}} E\left\{(1-c_i(t))\sum_{j\in\mathcal{C}_i(t)}\theta_j(t)r_j^{opt}(t)\Psi_{ji}(t)\right\}, \quad t\geq\widetilde{T} \tag{5.6.1}$$

$$s.t.: x(t)\triangleq\frac{1}{t-1}\sum_{k=1}^{t-1}c(k)\leq\nu, \quad \forall t\geq\widetilde{T} \tag{5.6.2}$$

$$0\leq\Psi_{ji}(t)\leq 1, \quad \forall j\in\mathcal{C}_i(t), \quad \forall t\geq\widetilde{T} \tag{5.6.3}$$

$$\sum_{j\in\mathcal{C}_i(t)}\Psi_{ji}(t)\leq 1, \quad \forall t\geq\widetilde{T} \tag{5.6.4}$$

while the Soft access window optimization problem is equivalent to the problem (5.6.1)-(5.6.3), where the (5.6.2) constraint is replace with:

$$P_c\leq\nu_i, \quad \forall t\geq\widetilde{T}, \tag{5.6.5}$$

where P_c represents the primary-secondary collision probability.

It stands to reason the constraint (5.6.2) involves (5.6.5), thus, generally, the Soft problem is a relaxation of the Hard problem.

According to what has been said so far, the optimization problem that we must resolve are the hard and soft access window optimization problem, respectively. We find the optimal policies that maximize the average per-cluster goodput and to evaluate if between the soft and hard solutions there is performance loss in terms of aggregate access goodput.

Before proceeding with the solution of the problem, we develop the optimal policy that is able to maximize the average per client goodput in the case of no primary user is present.

5.6.2 Optimal Policy without Primary User Transmission

Let us indicate by Secondary Allocation Problem (SAP) the Access window optimization problem when any primary user is present (i.e, $P_L^i(t) = 1$).

The SAP problem can be formulated as follows:

$$\max_{\{\Psi_{ji}(t), j \in \mathcal{C}_i(t)\}} E\left\{ \sum_{j \in \mathcal{C}_i(t)} \theta_j(t) r_j^{opt}(t) \Psi_{ji}(t) \right\}, \quad t \geq \widetilde{T} \tag{5.6.6}$$

$$s.t. : 0 \leq \Psi_{ji}(t) \leq 1, \quad \forall j \in \mathcal{C}_i(t), \quad \forall t \geq \widetilde{T} \tag{5.6.7}$$

$$\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t), \quad \forall t \geq \widetilde{T} \tag{5.6.8}$$

Proposition 5.9 Under the above reported assumptions, for the optimal access window controller solution of the constrained optimization problem in (5.6.6)-(5.6.8) we have that:

$$\Psi_{ji}^* = \begin{cases} 1, & \text{for} \quad j = j_{max}(t) \\ 0, & \text{otherwise} \end{cases} \tag{5.6.9}$$

where $j_{max}(t) \triangleq \text{argmax}_j\{\alpha_j(t)\}$ and $\alpha_{max}(t) = \alpha_{j_{max}}$, having denote by

$\alpha_j \triangleq (\theta_j r_j^{opt}(t))$. The optimal value of the total utility is the following:

$$E\left\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_j(t)\Psi_{ji}(t) \right\} = E\{\alpha_{max}\} \tag{5.6.10}$$

Proof. For each policy Ψ_{ji} that respects the constraints we have:

$$\begin{aligned} E\{u_j(t)\} =& E\left\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_j \Psi_{ji}(t) \right\} \leq \\ & \leq E\left\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_{max} \Psi_{ji}(t) \right\} \leq \\ & \leq E\left\{ \alpha_{max} \sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) \right\} \leq E\{\alpha_{max}\} \end{aligned} \tag{5.6.11}$$

From the above expression follows that the admissible policy is performance loss or equal to eq.(5.6.9). □

5.6.3 Statistics Properties and Average Utility

Let us indicate by $\mathcal{O}, C$ the events of secondary active and primary-secondary collision, respectively. $P_{ON}(t)$ is the secondary transmission probability in a t-th slot (i.e., $P_{ON}(t) = Prob(\mathcal{O})$) and $P_{OFF}(t) = (1 - P_{ON}(t))$ the probability of the complementary event. This last is tie up to the primary-secondary collision probability from the following relationship:

$$P_c(t) = P_{ON}(t)(1 - \widetilde{P}_L^i(t)) \tag{5.6.12}$$

Furthermore, let us indicate by $\mathcal{U} \equiv (\mathcal{O}, \overline{C})$ the joint event of secondary activity and no primary collision and $P_u(t)$ the corresponding probability, we have:

$$P_u(t) = P_{ON}(t)\widetilde{P}_L^i(t) \tag{5.6.13}$$

Proof.

$$\begin{aligned} P_c(t) = Prob(C) = Prob(C, \mathcal{O}) + Prob(C, \overline{\mathcal{O}}) = \\ = P_{ON}(t)Prob(C|\mathcal{O}) = P_{ON}(t)(1 - \widetilde{P}_L^i(t)); \end{aligned}$$

$$P_u(t) = Prob(\mathcal{O}, \overline{C}) = P_{ON}(t)Prob(\overline{C}, \mathcal{O}) = P_{ON}(t)\widetilde{P}_L^i(t)$$

□

Regarding to the optimal solution of the Hard/Soft AWOP problem is possible prove the following Proposition 5.10

Proposition 5.10 Under the above reported assumption, for the per client goodput we have that:

$$\begin{aligned} E\{u_j(t)\} \equiv E\Bigg\{(1 - c_i(t)) \sum_{j \in \mathcal{C}_i(t)} \alpha_j \Psi_{ji}(t)\Bigg\} = \\ = E\Bigg\{\sum_{j \in \mathcal{C}_i(t)} \alpha_j \Psi_{ji}(t) | (\mathcal{O}, C)\Bigg\} \widetilde{P}_L^i(t) P_{ON} \leq \\ \leq E\{\alpha_{max}(t) | \mathcal{O} \widetilde{P}_L^i(t) P_{ON}\}, \end{aligned} \tag{5.6.14}$$

where equality is obtained when the access windows $\Psi_{ji}(t)$ are choice according to (5.6.9). Following that the optimal policy is as follows:

$$\Psi_{ji}^{opt}(t) = \begin{cases} \Psi_{ji}^{*}, & \text{if in the current slot } t \text{ the transmission is determined} \\ 0, & \text{otherwise} \end{cases} \tag{5.6.15}$$

where the only degree of freedom in order to optimize is the choice of the criterion based on the decision of transmission or no transmission slot-by-slot.

Proof. Per cluster goodput we have that:

$$E\{u_j(t)\} = E\Big\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_{ji} \Psi_{ji}(t) | \mathcal{U} \Big\} P_u(t) =$$

$$= E\Big\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_{ji} \Psi_{ji}(t) | (\mathcal{O}, \overline{C}) \Big\} \widetilde{P}_L^i(t) P_{ON} \overset{(a)}{=} E\Big\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_{ji} \Psi_{ji}(t) | \mathcal{O} \Big\} \widetilde{P}_L^i P_{ON}$$

where (a) follows from the fact that the collision event C is independent to access rates $r_j(t)$ and access windows $\Psi_{ji}(t)$ conditionally to the event $\mathcal{O}$ of secondary transmission. Follows that, the variables set $(r_j(t), \Psi_{ji}(t))$, conditionally on the event $\mathcal{O}$ and their linear combination, is independent on the event C. Similarly to Proposition 5.9, each policy that meets the (5.6.4)-(5.6.3) constraints and $\sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) > 0$ constraint we have that:

$$E\Big\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_j(t) \Psi ji(t) | \mathcal{O} \Big\} \leq E\Big\{ \sum_{j \in \mathcal{C}_i(t)} \alpha_{max}(t) \Psi_{ji}(t) | \mathcal{O} \Big\} \leq$$

$$\leq E\Big\{ \alpha_{max}(t) \sum_{j \in \mathcal{C}_i(t)} \Psi_{ji}(t) | \mathcal{O} \Big\} \leq E\{\alpha_{max}(t) | \mathcal{O}\}$$

□

5.6.4 Optimal Access Window Controller

As mentioned the solution of the Access window optimization problem is based on two step. First, the mesh router must to determine the decision policy (i.e., it must to determine if the mesh client can transmit in the current slot), second, the mesh router must decide which mesh client is authorized to transmit.

Proposition 5.11 A policy $\mathcal{P}$ is admissible for the hard problem in (5.6.1)-(5.6.3) if it meets the (5.6.4)-(5.6.3) constraints slot-by-slot and also it decides to transmit only to t-th slot where the following condition is occurred:

$$x_i(t) \leq \frac{\nu_i t - 1}{t - 1}. \tag{5.6.16}$$

Hence, we can conclude that the admissible policy of the access window optimization problem is as follows:

$$\Psi_{ji}^{adm}(t) = \begin{cases} \Psi_{ji}^{*}(t), & \text{if} \quad x_i(t) \leq \frac{\nu_i t - 1}{t - 1} \\ 0, & \text{otherwise.} \end{cases} \tag{5.6.17}$$

and it is optimal for the hard problem.

5.7 Mesh Client Problem-Client Flow Control Problem

In the previous Chapter 4, we maintained that once the mesh client is selected to transmit and it received the Ack message containing the information of no primary activity, the Flow-Control problem must be solved.

Referring to the Per-Cluster Constrained Optimization Problem (PCOP) defined in (5.3.1)-(5.3.6) we demonstrate that the optimal client-flow policy $\lambda_j^{opt}(t)$ is totally distributed and solve the following problem:

$$\max_{[\lambda_j(t)]} E\{u_j(t)|r_k^{opt}, k \in \mathcal{C}_i(t)\}, \quad t \geq \widetilde{T}, \tag{5.7.1}$$

$$s.t.: 0 \leq \lambda_j(t) \leq \lambda_{max}^j, \quad \forall t \geq \widetilde{T}, \tag{5.7.2}$$

$$0 \leq q_j(t+1) \leq N_{max}^j, \quad \forall t \leq \widetilde{T}. \tag{5.7.3}$$

where the (5.7.2),(5.7.3) constraints are present also in the PCOP problem in (5.3.1)-(5.3.6). In fact, we can demonstrate that the client-flow problem in (5.7.1)-(5.7.3) is extract by the PCOP problem.

Proof. The following Lindley's equation:

$$q_j(t+1) = [q_j(t) - u_j(t) + \lambda_j(t)]^+, \quad t \geq \widetilde{T}, \tag{5.7.4}$$

dictates the evolution of the j-th queue-length (i.e., the queue state). From eq.(5.7.4) we can get the following expression for the j-th client-goodput:

$$u_j(t) = [q_j(t) - q_j(t+1) + \lambda_j(t)]^+, \quad t \geq \widetilde{T}. \tag{5.7.5}$$

The (5.7.4),(5.7.5) show that client-goodput and client-flow, $u_j(t)$ and $\lambda_j(t)$ respectively, are linked to a functional relationship (deterministic type). Hence, from (5.7.4),(5.7.5) follow the following property:

$$E\{u_j(t)|\lambda_k(t), k \in \mathcal{C}_i(t)\} \equiv E\{u_j(t)|\lambda_j(t)\}, \tag{5.7.6}$$

that is: given $\lambda_j(t)$, the client-goodput is independent on the other $\{\lambda_k(t), k \neq j\}$. By property in (5.7.6), we can rewrite (5.3.1) in the following equivalent form:

$$\max_{\{\Psi_{ji}(t), j\in\mathcal{C}_i(t)\}} \max_{\{\lambda_j(t), j\in\mathcal{C}_i(t)\}} \left\{ \sum_{j\in\mathcal{C}_i(t)} \theta_j E\{u_j(t)|r_k^{opt}(t), k \in \mathcal{C}_i(t)\} \right\} \equiv$$
$$\equiv \max_{\{\Psi_{ji}(t), j\in\mathcal{C}_i(t)\}} \left\{ \sum_{j\in\mathcal{C}_i(t)} \theta_j [\max_{[\lambda_j]} E\{u_j(t)|r_k^{opt}(t), k \in \mathcal{C}_i(t)\}] \right\} \tag{5.7.7}$$

Then, by (5.7.7), follow the client-flow problem in (5.7.1)-(5.7.2). □

Thus, after recognizing that the client-flow optimization problem in (5.7.1)-(5.7.3), is an instance of convex optimization problem, the Client-Flow control problem can be solved in distributed way and the resulting optimal client-flow $\lambda_j^{opt}(t)$ may be evaluated in closed-form, as detailed in the following Proposition 5.12.

Proposition 5.12 Under the above reported assumptions, for the optimal solution of the client-flow constrained optimization problem in (5.7.1)-(5.7.3), we have that the optimal client-flow is dictated by the following relationship:

$$\lambda_j^{opt}(t) \equiv \min\{(N_{max}^j - q_j(t) + u_j(t)); \lambda_{max}^j\}, \quad \forall t \geq \widetilde{T}, \quad \forall j = 1, \cdots, N_{t_0} \tag{5.7.8}$$

Proof. Let $E\{\lambda_j(t)|u_j(t), q_j(t)\}$ be the conditional expected value in $u_j(t)$, $q_j(t)$, and let $E\{\lambda_j(t)\} \triangleq E\{E\{\lambda_j(t)|u_j(t), q_j(t)\}\}$ be the corresponding unconditional expected value. Hence, $\lambda_j^{opt}(t)$ in (5.7.8) represents the controller policy that maximize the conditional expected value $E\{\lambda_j(t)|u_j(t), q_j(t)\}$, for all $t \geq \widetilde{T}$ and for all pair values $(u_j(t), q_j(t))$ respecting the (5.7.2),(5.7.3) constraints. Thus, the following property is valid:

$$\lambda_j^{opt}(t) = argmax_{\lambda_j(t)} E\{\lambda_j(t)|u_j(t), \lambda_j(t)\}, \quad \forall t \geq \widetilde{T}, \quad \forall (u_j(t), q_j(t)). \tag{5.7.9}$$

Furthermore, $\lambda_j^{opt}(t)$ in (5.7.8) is the only controller client-flow policy that respects the property in (5.7.9)[5.1]. Since that the property in (5.7.9) is valid for each t-slot and for each $(u_j(t), q_j(t))$, follow that $\lambda_j^{opt}(t)$ represents the only optimal client-flow policy.

Directly by the Lindley's equation $q_j(t+1) = [q_j(t) - u_j(t) + \lambda_j(t)]^+$

[5.1] In fact, for each pair of assigned values $(u_j(t), q_j(t))$, any other controller policy $\widetilde{\lambda}_j(t)$ working according to (5.7.8), satisfies the following relationship: $\widetilde{\lambda}_j(t) \leq \lambda_j^{opt}(t)$, $\forall t \geq \widetilde{T}$ and $\forall (u_j(t), q_j(t))$.

follows that the queue length $q_j(t+1)$ is bound as in the following development:

$$\lambda^j_{max} \leq q_j(t+1) \leq N^j_{max}, \quad \forall t \geq \widetilde{T} \tag{5.7.10}$$

.

Moreover, let $E\{u_j(t)\}$ be the corresponding unconditional expected value of the per-cluster goodput in (5.7.4), thus the following property is valid:

$$E\{u_j(t)\} \equiv E\{\lambda_j(t)\}. \tag{5.7.11}$$

Since as (5.7.3) constraint is valid, the j-th queue is steady, and, hence $E\{u_j(t)\}$ $\geq E\{\lambda_j(t)\}$. On the other hand if $E\{u_j(t)\} > E\{\lambda_j(t)\}$, then, the queue would be (average) empty (i.e., $E\{q_j(t+1)\} = 0$), but, since that this last relationship is contradictory with the lower bound in (5.7.10), follow that the equality in (5.7.11) must be true.

Since (5.7.11) and (5.7.9) are valid, we may say that $\lambda^{opt}_j(t)$ is the optimal client-flow policy solution of the optimization problem in (5.7.1)-(5.7.3).

Now, let $\widetilde{\lambda}_j(t)$ be the optimal client-flow policy, solution of the optimization problem:

$$argmax_{[\lambda_j(t)]} E\{u_j(t) | r^{opt}_k(t), k \in \mathcal{C}_i(t)\} \tag{5.7.12}$$

$$s.t. : 0 \leq \lambda_j(i) \leq \lambda^j_{max}, \quad \forall t \geq \widetilde{T}, \tag{5.7.13}$$

$$o \leq q_j(t+1) \leq N^j_{max}, \quad \forall t \geq \widetilde{T}, \tag{5.7.14}$$

by definition, $\widetilde{\lambda}_j(t)$ represents the problem solution (5.7.1)-(5.7.3). Moreover, always by definition, $\widetilde{\lambda}_j(t)$ maximize the conditional and unconditional expected value $E\{u_j(t)|r_k^{opt}(t), k \in \mathcal{C}_i(t)\}$ and $E\{u_j(t)\}$ respectively. We may conclude that both the policies $\lambda_j^{opt}(t)$ and $\widetilde{\lambda}_j(t)$ are optimal solutions of the client-flow optimization problem in (5.7.1)-(5.7.3), hence, necessary $\lambda_j^{opt}(t) \equiv \widetilde{\lambda}_j(t), \forall t \geq \widetilde{T}$. □

Remark 5.4 **Optimal client-flow controller -properties -** The optimal client-flow controller (5.7.1) enjoys of the following properties:

a) the optimal client-flow controller guarantees:

$$\lambda_{max}^{j} \leq q_j(t+1) \leq N_{max}^{j}, \quad \forall t \geq \widetilde{T}; \tag{5.7.15}$$

b) the optimal client-flow controller can be independently computed by each mesh client, slot-by-slot, on the basis of per-client goodput, at the end of t-th slot. Moreover, the client goodput is computed via the following analytical expression:

$$u_j(t) = \eta_0 r_j^{opt}(t) \left[\sum_{k=1}^{\mathcal{I}} \Psi_{jk}^{opt}(t) Z_A^k(t) m_{jk}(t) \right], \quad t \geq \widetilde{T}, \forall j = 1, \cdots, N_{t_0}.$$

CAPITOLO 6

Simulated Scenario

The purpose of this Chapter 6 is to define a Cognitive Wireless Mesh Network model which satisfies all the assumptions described earlier. Specifically, in the Section 6.1 we report the simulated Cognitive Wireless Mesh Network. In the following two Sections 6.2, 6.3 we describe the Mesh Clients mobility and the primary activity model, respectively. After, we pass to see the access channel statistics (Section 6.4) and, in the final Section 6.5 the Channel Sensing and primary user activity detection model.

6.1 Simulated Cognitive Wireless Mesh Network

In the simulation we consider a Cognitive Wireless Mesh Network constituted by $\mathcal{I} = 3$ clusters. Each cluster represents a circular cell with radius $R_0 = 1$ (see Fig.6.1.1). The wireless backbone in Fig.6.1.1 is formed by static

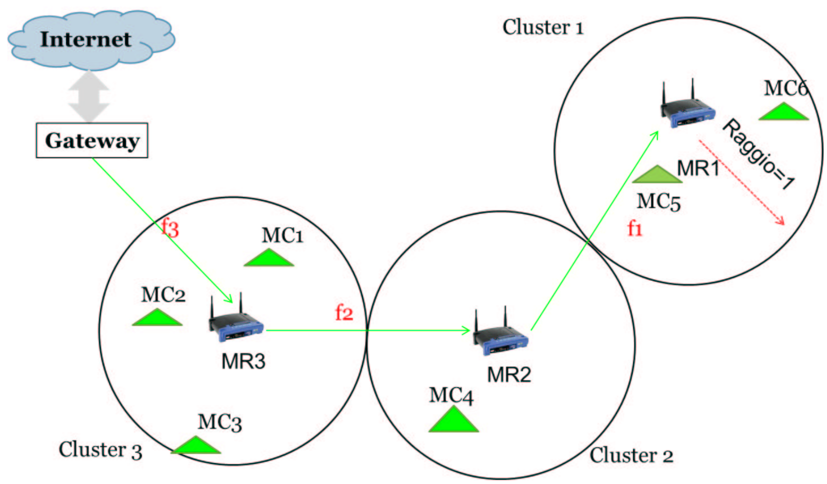

Figure 6.1.1: Example of cluster-partitioned Wireless Mesh Network used in simulation. $\mathcal{I} = 3$ and N_{t_0} ranges from $N_{t_0} = 3$ (lightly populated WMN) to $N_{t_0} = 30$ (densely populated WMN).

mesh router that may or may not aligned along the same direction. The spatial regions of coverage of each cluster may be tangent or less between them. Since each mesh client can access, slot by slot, only at the access point belonging to the cluster, we assume that the region of coverage are not overlapping each other.

6.2 Inter-cluster and Intra-cluster Mesh Client Mobility

According to the general model in [49, Sec.III D], we assume that the inter-cluster mesh client mobility model is controlled by a ”Markovian Random Walk with Discrete Random Directions”. Specifically, according to this inter-cluster mobility model (see for more details [49, Sec.III D]), the network in Fig.6.1.1 is simulated assuming that at the end of $(t-1)$ slot, each MC(j) chooses the cluster in which reside in the next t slot, independently of the other mesh client present in the network. Furthermore, each mesh client decides to stay in the current cluster with $(1-\beta)$ probability, while it decides to go in a different cluster (i.e., in the left or right cluster) with $\beta/2$ probability. The corresponding Markov's chain that describes the inter-cluster mesh client mobility is reported in the following Fig.6.2.1.

From the Fig.6.2.1 follow the properties below:

i) the corresponding mobility process $\{[M](t), t \geq 0\}$ is stationary and er-

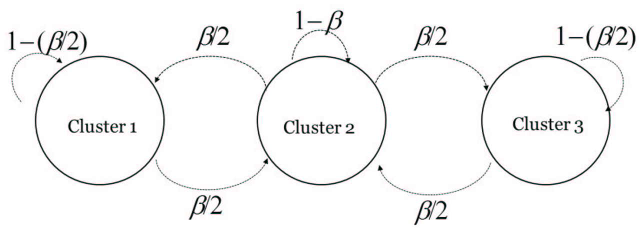

Figure 6.2.1: The Markovian Random walk describing the inter-cluster mobility of each mesh client of Fig.6.1.1.

godic;

ii) for each chosen β value, each mesh client has probability equal to $1/3$ to be in each of three clusters in Fig.6.2.1, in each slot t;

iii) in each slot, the average number of MCs present in each of the three cluster is equal to $(N_{t_0}/3)$.

Before proceeding with the intra-cluster mobility model description, we analyze how each client decides which position to occupy in the cluster at t-th slot. Independently of other mesh clients in the network, each MC chooses the cluster at the end of $(t-1)$ slot and determines the position in the chosen cluster. In the simulations, we assume that each MC(j), $j \in \mathcal{C}_i(t)$, selects randomly (i.e., with uniform pdf) and independently from the other MC the position in the i-th cluster of Fig.6.1.1. Once it has chosen the location, it remains for the whole duration of slot t. Specifically, we consider that each cluster is equipped with a reference system in polar coordinates. The origin of the system coincide with the access point MR (see Fig.6.2.2). In Fig.6.2.2, we point by $(d_j(t), \varphi_j(t))$ the mesh client distance and the angle by the access point, respectively. Obviously, we have that: $0 \leq d_j(t) \leq 1$ and $\varphi_j(t) \in [-\pi, \pi]$, $\forall j, \forall t$.

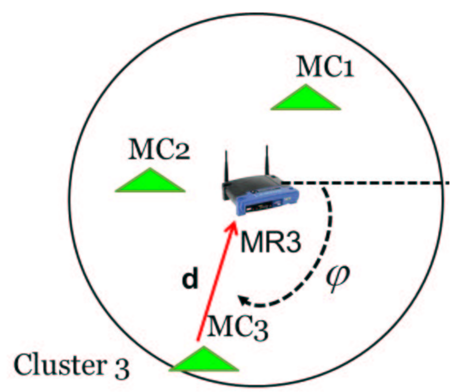

Figure 6.2.2: Mesh client position $\{\varphi, d\}$ in the cluster.

After each mesh client has chosen the position in the cluster [6.1], it determines the occupied position in the cluster for the slot t. According to the following intra-cluster mobility model, the position is chosen:

i) MC(j) generates the determinations $d_j(t), \varphi_j(t)$ of the random variables D, Φ with uniform pdf $[0, 1]$ and $[-\pi, \pi]$, respectively.

[6.1] We note that, in the slot t, the MC(j) can belong to the same cluster of the slot (t-1), but the position of the mesh client can change slot by slot

ii) MC(j) selects the position in the point of polar coordinates $\{d_j(t), \varphi_j(t)\}$ and it stays in that position for the total duration of the current slot t.

At this point, according to the last intra-cluster mobility model, we may conclude that each mesh client occupies a random position in the cluster, independently of each other mesh client.

6.3 Primary Activity Model

Referring to the Fig.6.1.1, the Gateway represents the primary user of the cluster number three; the mesh router three is the primary user of the cluster two and the access point two is the primary user of the cluster one.

Said this, the primary activity model may be described as a Markov's chain with $2^3 = 8$ states of a priori known transitions probabilities. In our simulations, we consider that the three primary users, in the network of Fig.6.1.1, choose their activity in independent way. Hence, the sequence of the states ON/OFF is independent and stationary. We adopt this simple model because it models the traffic forwarded by the backbone of a packet-switched network with a transfer mode to datagram.

Accordingly, the primary activity model is defined in the following way:

i) the activity states, of the three primary users in Fig.6.1.1, are independent (i.e., $P(a_1(t), a_2(t), a_3(t)) \equiv \prod_{i=1}^{3} P(a_i(i))$);

ii) the binary sequence $\{a_i(t) \in \{0, 1\}, t \geq 0\}$, $i = 1, 2, 3$, of the i-th primary activity states is stationary and i.i.d. in t, so that we can write:

$$P(a_i(t) = 0) = 1 - P(a_i(t) = 1 \equiv \gamma), \quad \forall t, \quad i = 1, 2, 3 \quad (6.3.1)$$

where $\gamma \in]0, 1[$ is the probability that the i-th primary user does not active in the t-th slot.

According to the previous assumptions we have that the each mesh client updates the following Belief Probabilities:

$$P(a_i(t) = 0|\Gamma_i(t)) \equiv 1 - P(a_i(t) = 1|\Gamma_i(t)) \equiv \gamma, \quad \forall t \geq 0, \quad i = 1, 2, 3, \quad (6.3.2)$$

and after calculates the eq.(3.4.4).

Moreover, the mesh client's priority levels $\{\theta_j, j = 1, \ldots, N_{t_0}\}$ and the maximum collision probabilities ν_i, $i = 1, 2, 3$, tolerated by the three primary users of Fig.6.1.1, are taken as follow:

$$\theta_j \equiv 1, \quad \forall j = 1, \ldots, N_{t_0}; \quad \nu_i \equiv \overline{\nu} \in]0, 1[, \quad \forall i = 1, 2, 3. \quad (6.3.3)$$

6.4 Wireless Access Channel

According to As.3.3 and As.3.4, in the Cognitive Wireless Mesh Network simulation, we assume that the access channel estimate $\widehat{h}_j(t) \in \mathbb{C}^1$ is affected by error $\varepsilon_j(t) \in \mathbb{C}^1$ and is related to the "true" value $h_j(t) \in \mathbb{C}^1$ according to the following relationship:

$$\widehat{h}_j(t) \equiv \sqrt{1-b_j^2}h_j(t) + \sqrt{b_j^2}\varepsilon_j(t), \quad t \geq 0, \quad j = 1, \ldots, N_{t_0}, \qquad (6.4.1)$$

where $b_j^2 \in [0,1]$ represents the estimate error variance; $h_j(t) \triangleq h_j^c(t) + jh_j^s(t)$ with $h_j^c(t), h_j^s(t)$ Gaussian real random variables with zero expected value, mutually independent and variance equal to $1/2$; $\varepsilon_j(t) \triangleq \varepsilon_j^c(t) + j\varepsilon_j^s(t)$ with $\varepsilon_j^c(t)$, $\varepsilon_j^s(t)$ Gaussian real random variables, zero mean, independent and variance $1/2$. Moreover, the random sequences $\{h_j(t) \in \mathbb{C}^1, t \geq 0\}$ and $\{\varepsilon_j(t) \in \mathbb{C}^1\}$ are stationary and i.i.d.; the N_{t_0} sequences $\{h_j(t)\}$, $j = 1, \ldots, N_{t_0}$, and $\{\varepsilon_j(t)\}$, $j = 1, \ldots, N_{t_0}$ are independent in index j.

By above assumptions, follow that the access channel is affected by fading with Rayleigh's pdf independent slot-by-slot and mesh client-by-mesh client. In addition, the first and second order statistics of $\widehat{h}_j(t), \varepsilon_j(t)$ and $h_j(t)$, in the (6.4.1), are valid the following properties:

Property 6.1 **Access Channel Properties -** The fading phenomena affecting the access channel are assumed constant over each slot (i.e., block fading model). Moreover, the b_j^2 parameter in (6.4.1) is related by $E\{||\widehat{h}_j - h_j||^2\}$ mean square error presents in the estimate access channel by following relationship:

$$b_j^2 = 1 - \left[1 - \frac{1}{2}E\{||\hat{h}_j - h_j||^2\}\right]^2. \qquad (6.4.2)$$

The first, second and fourth order moment of the random variables, present in the model, have the following expressions:

- $E\{||\hat{h}_j||^2\} \equiv E\{||h_j||^2\} \equiv E\{||\varepsilon_j||^2\} \equiv 1, \forall b_j^2 \in [0,1]$;
- $E\{(||\varepsilon_j||^2)^2\} \equiv E\{(||h_j||^2)^2\} \equiv 2$;
- $E\{(||\hat{h}_j||^2)^2\} \equiv 2(1 + b_j^2 - b_j^4)$;
- $E\{||h_j||^2||\hat{h}_j||^2\} \equiv (2 - b_j^2), \forall b_j^2 \in [0,1]$.

By definition, the state of the access channel $s_j(t)$ in the t-th slot is the corresponding instantaneous SNR, according to the following two relationships:

$$s_j(t) \triangleq \frac{1}{N_v(j)[1 + d_j(t)]^l}||h_j(t)||^2 \tag{6.4.3}$$

and

$$\hat{s}_j(t) \triangleq \frac{1}{N_v(j)[1 + d_j(t)]^l}||\hat{h}_j||^2, \tag{6.4.4}$$

where $N_v(j)$ $(Watt/Hz)$ indicates the spectrum noise presents in the j-th access channel (see the eq.(3.2.2)); $d_j(t)$ is the distance between the mesh client and the corresponding mesh router in the slot t; $2 \leq l \leq 4$ is the path loss exponent of the considered access channels.

Property 6.2 Estimator properties of (6.4.3)**,**(6.4.4) **-** In the following we list the estimator properties of the access channel defined in (6.4.4).

i) $\overline{s_j^2(t)} \triangleq E\{s_j^2(t)\} \equiv 2\left(\frac{1}{N_v(j)}\right)^2 E\left\{\frac{1}{(1+d_j)^{2l}}\right\} \equiv 2\left(\frac{1}{N_v(j)}\right)^2 \int_0^1 \frac{dy}{(1+y)^{2l}}$;

ii) $E\{s_j(t) - \hat{s}_j(t)\} \equiv 0, \quad \forall j, \quad \forall t$;

iii) the mean square error is defined as:

$$\sigma_\varepsilon^2(j) \triangleq E\{(s_j(t) - \hat{s}_j(t))^2\} \triangleq 2\left(\frac{1}{N_v(j)}\right)^2 E\left\{\frac{1}{(1+d_j)^{2l}}\right\} b_j^2(2-b_j^2)$$

From the above properties follow as:

$$\frac{\sigma_\varepsilon^2(j)}{s_j^2(t)} \equiv b_j^2(2-b_j^2). \tag{6.4.5}$$

From the (3.2.8) and assuming $N_v(j)/||p||^2 \equiv 1, \forall j = 1, \ldots, N_{t_0}$, we can write the (6.4.2) as follows:

$$b_j^2 = 1 - \left[1 - \frac{N_v(j)}{2||p||^2 L_E}\right] \equiv 1 - \left[1 - \frac{1}{2L_E}\right], \quad \text{for} \quad L_E \geq 1.$$

Finally, by inserting the above expression into (6.4.5), this last relationship can be written in this way:

$$\frac{\sigma_\varepsilon^2(j)}{s_j^2(t)} \equiv 1 - \left[1 - \frac{1}{2L_E}\right]^4, \quad \forall L_E \geq 1. \tag{6.4.6}$$

6.5 Channel Sensing and Primary User Activity Detection Model

According to said in the above Chapters, for each mesh client, we must specify the channel detection type (for example Energy Detector or Feature Extractor) used by MC(j). In a second moment, we must calculate the corresponding τ_j value in (3.1.2) and to implement (3.1.1), (3.1.2). In this way, the simulated setup depends on the Channel Detector now and again considered.

To have a general simulation setup, we develop an approach that allows to generate the $\check{a}_{ji}(t)$, ($j \in \mathcal{C}_i(t)$, $i \in \mathcal{I}$), guess starting decisions to the corresponding variable $a_i(t)$, ($i \in \mathcal{I}$) and considering the channel detector performance (i.e., false alarm and miss detection probabilities).

For this purpose, in this work the channel sensing adopted in the simulation setup is developed according to the following assumptions:

a.1) all the mesh clients in the simulated network adopt the same channel detector slot by slot and cluster by cluster;

a.2) the channel statistic features (i.e., fading phenomena and noise) in (3.1.1) do not depend on neither $j = 1, \ldots, N_{t_0}$ nor $i \in \mathcal{I}$ indices (in particular, $N_0(j)$ is the same for each mesh client).

From above two assumptions follow that the false alarm and miss detection probabilities are independent both of the j and i indices and so we can write:

$$P_{MD} \triangleq P(\check{a}_{ji} = 0 | a_i = 1, m_{ji} = 1), \quad \forall j = 1, \ldots, N_{t_0}, \quad \forall i \in \mathcal{I}; \quad (6.5.1)$$

$$P_{FA} \triangleq P(\check{a}_{ji} = 1 | a_i = 0, m_{ji} = 1), \quad \forall j = 1, \ldots, N_{t_0}, \quad \forall i \in \mathcal{I}. \quad (6.5.2)$$

The false alarm and miss detection probabilities in (6.5.1), (6.5.2) depend on: *i)* the channel detector used by mesh clients; *ii)* fading phenomena and noise present in the considered channel for channel sensing; *iii)* the $L_D \geq 1$ observations number. According to this last considerations, we assume that:

a.3) the channel detector, the fading and noise statistics are known.

By the ***a.3*** assumption follows that the CROC is known. Moreover, for different Channel Detector (Energy Detector or Feature Extractor) and fading phenomena (Rayleigh, Nakagami, Log-Normal) the trends are in literature known (see, for example, [48], [1], [87], [22]). In the Table6.5.1,6.5.2 we report the values in the case of Energy Detector, with Rayleigh fading, and Energy Detector with Nakagami fading, respectively [1]. The corresponding value of

P_{FA}	P_{MD}
10^{-1}	4×10^{-2}
5×10^{-2}	6×10^{-2}
10^{-2}	8×10^{-2}
10^{-3}	10^{-1}

Table 6.5.1: P_{MD}-vs-P_{FA} for an Energy Detector operating in Rayleigh fading environment at SNR=20dB and $L_D = 1$ [1, Fig.3].

the miss detection probability for $L_D = 2$ can be obtained by (3.1.8) or (3.1.9) in the case of cooperative, noncooperative Channel Detection, respectively.

We can conclude this Chapter 6 saying that the primary user activity detection is composed by four steps. These last steps must be performed for each slot, mesh client and cluster. In the following we carry the four steps.

P_{FA}	P_{MD}
10^{-1}	9×10^{-4}
5×10^{-2}	1.2×10^{-3}
10^{-2}	3.5×10^{-3}
10^{-3}	6×10^{-3}

Table 6.5.2: P_{MD}-vs-P_{FA} for an Energy Detector operating in Nakagami fading environment (with Nakagami parameter $m = 3$) at SNR=20dB and $L_D = 1$ [1, Fig.2].

Primary User Activity Detection

1. According to the probabilistic model in (6.3.2), we generate the random variable $a_i(t) \in \{0, 1\}$ slot by slot and cluster by cluster.

2. For each slot, client and cluster, we produce the binary random variable $e_{ji} \in \{0, 1\}$. This variable represents the error and, specifically, it is generated according to three steps:

   2.1) the random variables $\{e_{ji}(t)\}$ are independent in t, i and j indices;

   2.2) if $a_i(t) = 1$ then $e_{ji}(t)$ is produced according to the following probabilistic model:

$$P(e_{ji}(t)|a_i(t) = 1, m_{ji}(t) = 1) \equiv 1 - P(e_{ji}(t) = 0|a_i(t) =$$
$$= 1, m_{ji}(t) = 1) \triangleq P_{MD},$$

where P_{MD} is the miss detection probability.

2.3) Otherwise, if $a_i(t) = 0$, then, the error is generated according to:

$$P(e_{ji}(t) = 1 | a_i(t) = 0, m_{ji}(t) = 1) =$$
$$= 1 - P(e_{ji}(t) = 0 | a_i(t) = 0, m_{ji}(t)) \triangleq P_{FA}$$

where P_{FA} is the false alarm probability.

3. Each mesh client generates the its decision $\breve{a}_{ji}(t)$ based on presence or absence of the primary activity according to the following relationship:

$$\breve{a}_{ji}(t) \triangleq e_{ji}(t) \oplus a_i(t), \quad \forall j \in \mathcal{C}_i(t), \quad \forall i \in \mathcal{I}, \quad \forall t \geq 1. \quad (6.5.3)$$

4. Each mesh client forwards at its access point (mesh router) the corresponding pair probability $\{P(\breve{a}_{ji}(t)|a_i(t) = 0), P(\breve{a}_{ji}(t)|a_i(t) = 1)\}$. The set of this last probabilities is merged by the access point, that, according to (3.4.4), generate the corresponding probability of available channel $\widetilde{P}_L^i(t)$. At the end, the mesh router communicates at all mesh client in the network the probability $\widetilde{P}_L^i(t)$ value.

CAPITOLO 7

Network-Wide Performance Evaluation

In this last Chapter 7, we show the obtained numerical results considering the Active Mesh Network described in the previous Chapter 6. In the Section 7.1, we carry the operation parameters of the mesh client employed in the simulations, while, in the next Sections, the obtained numerical results are reported.

7.1 Simulated Framework

In the simulated Active Mesh Network of Fig.6.1.1, we assume that the operating characteristics of the mesh clients in the network are homogeneous (i.e., $\mathcal{E}_p^j \equiv \mathcal{E}_p; \mathcal{E}_{ave}^j \equiv \mathcal{E}_{ave}; \lambda_{max}^j \equiv \lambda_{max}; N_{max}^j \equiv N_{max}, \forall j$). Furthermore, the rate function $\mathcal{R}(\mathcal{E}_j, \hat{s}_j, \widetilde{P}_L(j), \sigma_\varepsilon^2(j))$ of the mesh client adopted to evaluate the performance of the simulated system is the logarithmic one, e.g.,

$$\mathcal{R}(\mathcal{E}_j, \hat{s}_j, \widetilde{P}_L(j), \sigma_\varepsilon^2(j)) \equiv \log \left[1 + \frac{\mathcal{E}_j, \hat{s}_j \widetilde{P}_L(j)}{\left(1 + \frac{\sigma_\varepsilon^2(j)}{\overline{s_j^2}}\right)} \right], \ j = 1, \ldots, N_{t_0}, \ (IU/slot) \tag{7.1.1}$$

where $\sigma_\varepsilon^2 / \overline{s_j^2}$ is given by (6.4.6) and it is dependent on the channel estimation duration.

Referring to the Wireless Mesh Network simulation system, the average aggregate goodput represents the main magnitude and it is define in the following way:

$$\overline{gd} \triangleq \sum_{j=1}^{N_{t_0}} E\{u_j(t)\} \equiv \lim_{t \to \infty} \frac{1}{t} \{ \sum_{j=1}^{N_{t_0}} \sum_{\tau=1}^{t} u_j(\tau) \}, \quad (IU/slot). \tag{7.1.2}$$

Specifically, in this section, we test performance in terms of average aggregate goodput considering constant system parameters and variable parameters (see Table 7.1.1).

7.2 Optimal Data Fusion Performance Evaluation

Fig.7.2.1 reports the behavior of the average aggregate goodput for cognitive access and noncognitive access. An examination of this plot leads to the following main conclusion. The gap between average aggregate goodput with cognitive access (red curve) and noncognitive access (blue curve) increases about 70%. Furthermore, the gap is less pronounced for high values of energy.

CONSTANT PARAMETERS	**VARIABLE PARAMETERS**
$\mathcal{I} = 3$ cluster	N_{t_0}=total number of the mesh clients in the network
$r = 1\,(km)$= cluster's radius	L_D=minislots for channel detection phase
$\gamma = 0.5$ primary user activity probability	L_E=minislots for channel estimation phase
$N_max = 24\,(kbyte/slot)$	ν=maximum collision rate allowed by primary user
$\lambda_{max} = 10\,(kbyte/slot)$	$\mathcal{E}_ave$= average energy for mesh client

Table 7.1.1: Main simulated parameters

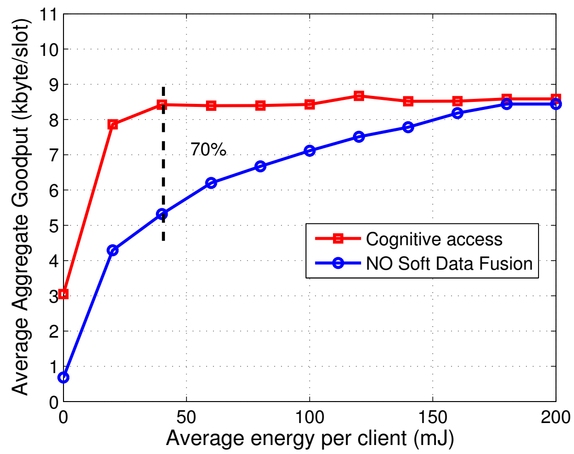

Figure 7.2.1: Behavior of average aggregate goodput for cognitive and noncognitive access.

7.3 Aggregate Access Goodput-vs-Channel Detection and Channel Estimation Reliability

The objective of this Section is to highlight the mechanism through which the constraint on the average energy for access mesh client influence the optimized tradeoff between the Channel Detection phase and Channel Estimation versus the average aggregate access goodput of Fig.2.1.1.

Before proceeding with the coverage, let $\overline{r}_j^{opt} \triangleq E\{r_j^{opt}(t)\}$ to be the unconditional average access rate and let $\overline{\Psi}_{ji}^{opt} \triangleq E\{\Psi_{ji}^{opt}(t)\}$ to be unconditional average access time. In additional, let $\overline{gd},\ (IU/slot)$ to be the average aggregate goodput of the network in Fig.2.1.1 and, by definition it is equal to:

$$\overline{gd} \triangleq \sum_{j=1}^{N_{t_0}} E\{u_j(t)\} \equiv \eta_0 \sum_{j=1}^{N_{t_0}} \overline{r}_j^{opt}[\sum_{1=1}^{I} P(m_{ji}=1)\overline{\Psi}_{ji}^{opt} P(a_i=0)] \equiv$$
$$\equiv \lim_{t\to\infty} \frac{1}{t}\{\sum_{j=1}^{N_{t_0}} \sum_{\tau=1}^{t} u_j(\tau)\}. \tag{7.3.1}$$

Let L_E and L_D to be the number of the L_t minislots in Fig.2.2.1 dedicated by the Channel Detection and Channel Estimation phases, respectively. Now, in order to test the behavior of the Active Mesh Network depicted in Fig. 6.1.1, we report in Fig.7.3.1 the average aggregate goodput versus L_D duration of the Channel Detection phase and the L_E duration of the Channel Estimation phase. For low L_E values (blue curve), regardless of the L_D value, we can see low values of the average aggregate goodput compared to the case in which we have L_E higher values (red curve). This last fact occur because for low L_D values we have high collision probabilities $E\{x_i(t)\}$ and, at the same time, low L_E values means less accuracy for channel estimation phase. Further, we can see that, increasing the duration of the channel estimation phase (i.e., improving the channel estimation), the average aggregate goodput increases up to certain L_D values, and after, it decreases with the increasing L_D values. Average aggregate goodput decreases because if the channel detection and channel estimation phases are very long, the payload phase is very short being the

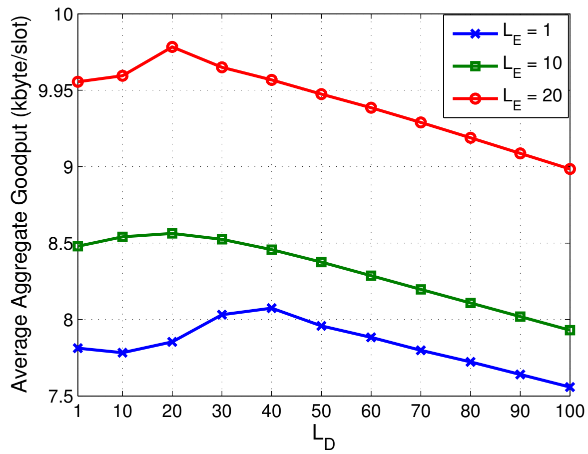

Figure 7.3.1: Behavior of average aggregate goodput for cognitive and noncognitive access.

slot duration constant. Hence, we achieve the maximum system performance in terms of average aggregate goodput when we identify the optimal tradeoff between the channel detection and channel estimation phases in order to maximize the average aggregate goodput. The optimal tradeoff between L_D and L_E duration represents a very important result.

7.4 Aggregate Access Goodput-vs-Average Energy

In this set of numerical results, we show the average aggregate goodput value for various mesh client's numbers in the two different cases. First, optimal tradeoff between channel detection and channel estimation phases ($L_D = L_E = 20$) and, second, no optimal tradeoff between channel detection and channels estimation phases. In Fig.7.4.1, 7.4.2, the average aggregate goodput increases with the increasing of the mesh client numbers in the network. In both cases, the maximum value of the average aggregate goodput is

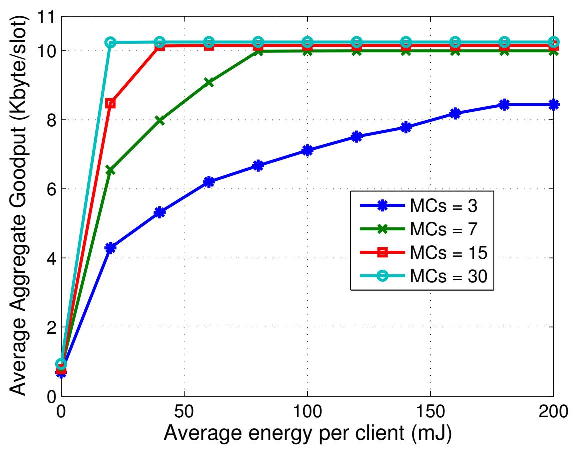

Figure 7.4.1: Average Aggregate Access Goodput-vs-Average Energy: Optimal tradeoff between Channel Detection and Channel Estimation.

little different, but with no optimal tradeoff the average energy for mesh client is greater. For example, we consider the green curve for seven mesh clients with optimal (Fig.7.4.1) and no optimal tradeoff (Fig.7.4.2), respectively. In Fig.7.4.1, the average aggregate goodput achieves the saturation value for energy about 80 (mJ), while in (Fig.7.4.2 the saturation value is achieved for

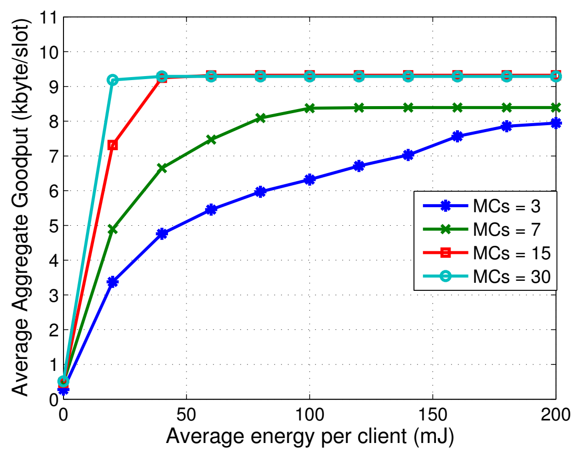

Figure 7.4.2: Average Aggregate Access goodput-vs-Average Energy: No optimal tradeoff between Channel Detection and Channel Estimation.

energy about 100 (mJ).

7.5 Aggregate Access Goodput-vs-Average Energy-vs-collision rates

Fig.7.5.1, 7.5.2 report the behavior of the average aggregate goodput in (7.1.2) for available mesh client average energy ($\mathcal{E}_{ave} > 0\ mJ$) and some values of the collision rates ν. Specifically, light loaded and highly loaded network are considered in Figs.7.5.1, 7.5.2, respectively. An examination of these

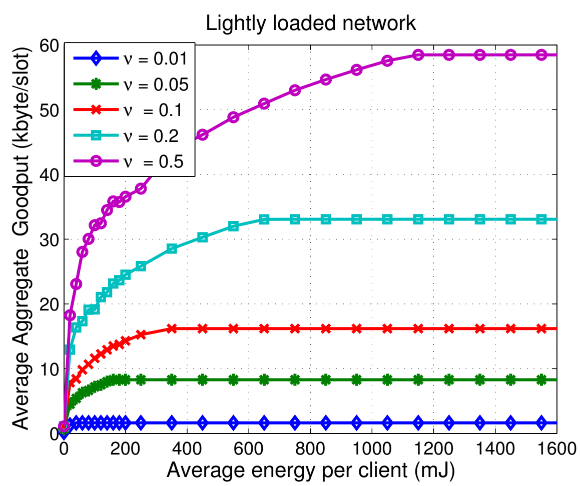

Figure 7.5.1: Average Aggregate Goodput-vs-Average Energy for different maximum rates: Lightly loaded network $\mathcal{I} = 3$, $N_{t_0} = 3$.

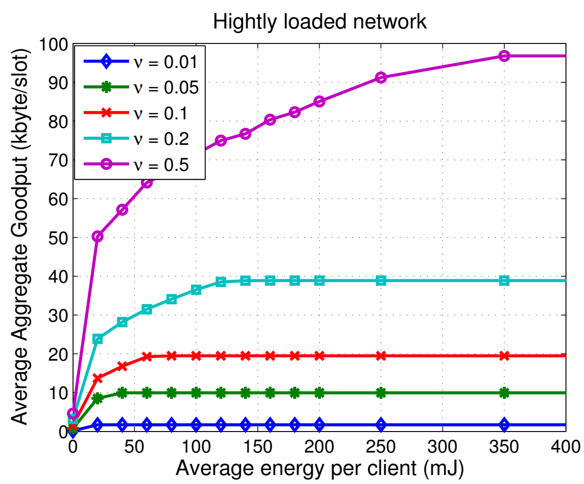

Figure 7.5.2: Average Aggregate Goodput-vs-Average Energy for different maximum rates: Highly loaded network $\mathcal{I} = 3$, $N_{t_0} = 30$.

plots leads to three main conclusions. First, the average aggregate goodput both in lightly and highly loaded network, increases with the average energy for client. In addition, the average aggregate goodput achieve the saturation value and over this last value it does not grow even if the $\mathcal{E}_{ave}$ increases. Second, the saturation value of the average aggregate goodput increases with the tolerated collision rates. Third, at fixed collision rate ν, the rate of increment of average aggregate goodput with average energy grows for increasing values of collision rate and of total number of mesh clients in the network.

7.6 Per Client-vs-Per Network Goodput

In this final Fig.7.6.1, we examine the per client goodput and the aggregate network goodput, in blue and red, respectively. Both plots are reported for different values of mesh client in the network of Fig. 6.1.1 (for example, MCs=3, 7, 15 and 30). The target of this last section is to show that increasing the total number of the mesh client, the aggregate network goodput increases while the per client goodput decreases.

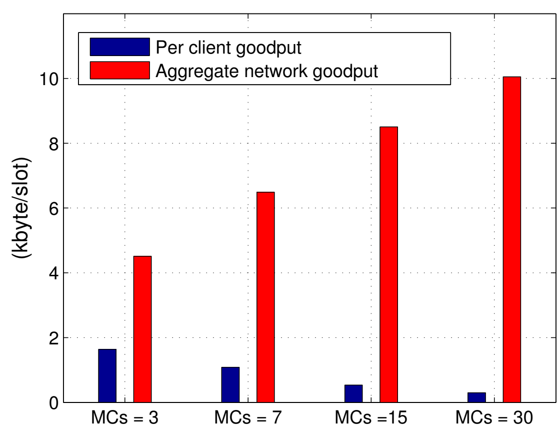

Figure 7.6.1: Per client-vs-Per network Goodput.

Conclusion

The importance of the proposed work lie in the fact that it constitutes the first approach to the optimal controller that jointly optimizes access rates, access windows and client-flows in a distributed way. The main contributions of the work may be so summarized. First, we have shown the application scenario and we have described the mesh client and mesh router functionality. Second, we have characterized the Global Resource Allocation problem. Afterwards, we have demonstrated that the constrained joint optimization problem may be recast as $\mathcal{I}$ distributed subproblems. Third, we have developed closed-form expressions for the optimal solution of the tackled cross-layer constrained global resource allocation problem. Fourth, we have described the simulation framework, and finally, we have characterized the corresponding average performance in terms of aggregate goodput. The presented solutions have shown to retain interesting properties concerning average aggregate goodput. In detail, in the previous Chapter 7, first the average aggregate goodput has been analyzed in the case of the cognitive access and noncognitive access; second the aggregate average goodput has been analyzed in different cases (for example in Sec.7.4).

Appendix A

Proof of the Proposition 5.5

Let $r_j(\cdot,\cdot,\cdot,\cdot)$ be any admissible scheduler for the problem (5.4.1)-(5.4.7) and let $r_j^{opt}(\cdot,\cdot,\cdot,\cdot)$ be the optimal one. After expressing the constraint in (5.4.3) on the peak-energy in terms of $r_j(\cdot,\cdot,\cdot,\cdot)$, from (5.4.3) and (5.4.4) we can see that any admissible scheduler $r_j(\cdot,\cdot,\cdot,\cdot)$ must satisfy the following inequality

$$r_j(\widehat{s}(t), \mathcal{E}_j(t), \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) \leq \min\left\{\frac{q_j(t)}{\eta_0}, \varepsilon^{-1}(\widehat{s}_j(t), \mathcal{E}_p^j, \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))\right\} \equiv$$

$$\equiv \min\{\frac{q_j(t)}{\eta_0}, \mathcal{R}_j(\mathcal{E}_j(t), \widehat{s}_j(t), \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j))\} \triangleq r_p^j(t).$$

Therefore, for any channel, buffer state, $\widetilde{P}_L^j(t)$ and $\sigma_\varepsilon^2(j)$, the resulting optimal access rate allowed at slot t, that is $r_j^{opt}(t) \leq r_p^j(t)$.

Thus, let us pass now to derive the expression of the optimal access rate policy $r_j^{opt}(t)$ of the ARAP problem. After recasting the constraint (5.4.5) in terms of the buffer equation $q_j(t+1) = [q_j(t) - u_j(t) + \lambda_j(t)]^+$,it may be recognized that the objective (5.4.1) and constraints (5.4.4),(5.4.5) are linear in $r_j(t)$, while constraints (5.4.2) and (5.4.3) on the available average and peak energies are strictly convex. In fact, the energy-function (4.2.6) can be obtained by inverting the rate-function in (4.2.5) with respect to the $\mathcal{E}$-variable, so that as a direct consequence of the properties assumed on $\mathcal{R}(\cdot,\cdot,\cdot,\cdot)$, it follows that the energy function is nondecreasing and convex in the r-variable. Furthermore, the ARAP problem (5.4.1)-(5.4.7) satisfies Slater's condition for constraint qualification, so that strong-duality holds and the optimal access rate may be obtained via an application of the Kurush-Khun-Tucker (KKT) conditions. Thus, the resulting Lagrangian function takes on the following form:

$$\mathcal{L}((r_j(t)),\mu(t)) \triangleq E_{\widehat{s}_j}\{r_j(t)\} - \mu(t)[E_{\widehat{s}_j}\{\mathcal{E}_j(r_j(t)\widehat{s}_j(t),\widetilde{P}_L^j(t),\sigma_\varepsilon^2(j))\} - \mathcal{E}_{ave}^j].$$

Hence, by imposing the gradient vanishing condition we obtain:
$\varepsilon_r(\widehat{s}_j(t), r_j(t), \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j)) = \frac{1}{\mu(t)}$, that allows us to arrive at the unconstrained solution:

$$r^*(t) = \varepsilon_r^{-1}\left(\widehat{s}_j(t), \widetilde{P}_l^j(t), \sigma_\varepsilon^2(j), \frac{1}{\mu(t)}\right)$$

of the tackled problem. Thus, since the Lagragian function is concave, it may be recognized that the solution of the following maximization problem:

$$\max_{0 \le r(t) \le r_p^j(t)} \mathcal{L}(r_j(t), \mu(t))$$

is the projection of $r^*(t)$ onto the underlying definition set, that is,

$$r_j^{opt}(t) \equiv \left[\varepsilon_r^{-1}(\widehat{s}_j(t), \widetilde{P}_L^j(t), \sigma_\varepsilon^2(j), \frac{1}{\mu(t)})\right]_0^{r_p^j(t)}.$$

This completes the proof of the optimal access rate solution of the ARAP problem.

Appendix B

Intra-cluster Access Protocol

Before proceeding to intra-cluster access protocol definition, we consider that, at the end of the Channel Detection phase of Fig.2.1.2, each mesh client sends to access point the pair probabilities $\{P(\hat{a}_{ji}(t)|a_i(t) = 0), P(\hat{a}_{ji}(t)|a_i(t) = 1)\}$ corresponding to decision. After receiving these probabilities, the mesh router, on the basis of the Belief Propagation phase, updates $P(a_i(t) = 0|\Gamma_i(t)) = 1 - P(a_i(t)|\Gamma_i(t))$, then, it computes the corresponding $\widetilde{P}_L^i(t)$ via (3.4.4) (see Data Fusion phase). Finally it transmits to each mesh client this last value.

According to above assumptions, we may define the Intra-cluster Access Protocol as follows (for general scheme of Reservation-based MAC in Cognitive Radio Networks, see [7, Chaps.14, Sect.5]):

1. **Channel Detection phase**: each MC(j), $j \in \mathcal{C}_i(t)$ autonomously calculates the decision $\hat{a}_{ji}(t) \in \{0, 1\}$ via eq.(3.1.2);

2. **Belief propagation phase**: according to the adopted Belief Propagation algorithm, the access point MR(i) updates $P(a_i(t) = 1|\Gamma_i(t))$;

3. **Soft Data Fusion phase**: each mesh client sends to its access point the pair of probability $\{P(\hat{a}_{ji}(t)|a_i(t) = 0, P(\hat{a}_{ji}(t)|a_i()t) = 1)\}$ of eqs.(3.4.5),(3.4.8); the access point calculates $\widetilde{P}_L^i(t)$ via eq.(3.4.4) and, then, sends to all mesh clients the value of $\widetilde{P}_L^i(t)$;

4. **Channel Estimation phase**: each MC(j), $j \in \mathcal{C}_i(t)$, calculates the channel state estimation $\hat{s}_{ji}(t)$;

5. **Resource Allocation phase**: first, each MC(j), $j \in \mathcal{C}_i(t)$, finds a solution of the ARAP problem (5.4.1)-(5.4.7) (i.e, the mesh client determines its optimal access rate $r_j^{opt}(t)$, $j \in \mathcal{C}_i(t)$) and conveys to the access point this last value. Second, MR(i) determines the optimal access windows $\{\Psi_{ji}^{opt}(t),\ j \in \mathcal{C}_i(t)\}$(see, the following eqs,(5.5.8)-(5.5.11)) and extends to all mesh client the information scheduling set $\{\Psi_{ji}^{opt}(t), j \in \mathcal{C}_i(t)\}$.

6. **Payload phase**: each MC(j), $j \in \mathcal{C}_i(t)$ sends to mesh router (i.e., access point) the following number of information unit in the reservation window:
$$\eta_0 r_j^{opt}(t)\Psi_{ji}^{opt}(t) \quad (IU). \tag{.0.1}$$

7. **Ack phase**: at the beginning of this phase, the access point MR(i) acquires the value of the collision variable $c_i(t)$ of eq.(3.5.1). On the basis

of this variable, the MR(i) carries out the following three operations:

(a) it calculates $x_i(t+1)$ via eq.(3.5.7);

(b) it computes the Ack variable $Z_a^i(t)$ via the following relationship:

$$Z_A^i(t) = 1 - c_i(t)$$

(c) it spreads the $Z_A^i(t)$ value to all mesh client.

The mesh client receive $Z_A^i(t)$ and it carries out the following three operations:

(a) it computes the goodput $u_j(t) = \eta_0 r_j^{opt}(t)\Psi_{ji}^{opt}(t)Z_A^i(t)$;

(b) it calculates the optimal client-flow λ_j^{opt} to the input of the j-th queue

(c) it calculates the new value of the queue length.

Remark .1 Before concluding this Appendix B about the assumed intra-cluster Reservation-Based MAC protocol, some additional remark are in order. As it is known, a MAC protocol may be reservation or Random-access based. For a Random-based MAC, no mechanism is available to match the MAC layer performance to the QoS requirements advanced by the upper layers (i.e., the application layer) of the protocol stacks of the mesh clients. Instead, a mesh client just attempts its best to access the spectrum. Such a MAC has a great advantage of simplicity and, furthermore, it works in a decoupled way from upper protocol layers. However, the drawback is that the MAC itself may exhibit poor performance that, in turn, cannot be improved (or, simply, controlled) via cross-layer interaction. Such a problem reflects one of the many issues of applying CSMA/CA MAC protocol to Cognitive Mesh Networks [2]. A good solution to this problem is to migrate toward Reservation-based MAC protocols [7, Chap.14],[2]. This is already (partially) done by the IEEE802.11e hybrid channel-access control, that includes mechanisms for scheduling and reservation which operate in parallel with CSMA/CA to improve the performance of 802.11 MAC. Thus, due to the mentioned limited capabilities of random access MACs, the Cognitive Mesh Networks architecture we consider directly relies on an adaptive (i.e., cognitive) Reservation-based MAC protocol for implementing intra-cluster access. In fact, although today's Wireless Mesh Networks are still mostly based on CSMA/CA-type Random-access MAC, the emerging WMNs (in particular, the envisioned CogMesh Networks) are migrating to use Reservation-based MAC. One reason for this migration is that many WMNs are being standardized under the framework of TDMA that offers sufficient flexibility for implementing Reservation-based MAC protocols [7, Chap.14]. Already envisioned examples include 802.16 mesh networks, UWB mesh networks and Wimedia mesh networks [2]. A second reason for migrating toward Reservation-based MAC protocols is that CSMA/CA MAC protocol cannot guarantees QoS levels and this limits its utilization in media application scenarios.

We may conclude that the our intra-cluster access protocol, is an example of access protocol Reservation-based and Polling. Furthermore, it allows the mesh clients to access according to Orthogonal-Time Division Multiple Access (O-TDMA) and it guarantees no secondary-secondary collisions. In addition, this access protocol is distributed in each i-th cluster (i.e, each mesh router acts as a Poller for its mesh clients). Moreover, it is adopted in each cluster slot-by-slot.

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