Coexistence and Energy Efficiency in Wireless Networks

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Abstract

Dynamic spectrum access has been recently proposed to increase the utilization of the licensed spectrum bands, and support the constantly growing volumes of mobile traffic in the modern society. At the same time, the increasing demand for wireless connectivity, as a result of the rapid emergence of innovative wireless and mobile services, has led to the deployment of various wireless technologies in the open ISM bands. This thesis addresses the effective coexistence among the diverse wireless technologies in the above scenarios, and the energy efficiency of the deployed wireless systems, both listed among the key challenges that wireless networking is facing today.

We discuss cooperative sensing, a fundamental mechanism for allowing unlicensed users perform opportunistic access in the licensed spectrum. Considering the scenario where the users perform both sensing and unlicensed spectrum access, we evaluate the efficiency of multi-channel cooperative sensing schemes with respect to the per user achievable capacity. We conclude that a careful optimization of both the number of sensed channels, and the allocation of sensing duties to the network users is necessary to achieve high capacity gains in large-scale networks of unlicensed users.

We address a number of energy efficient design issues for sensor networks and wireless LANs. We study how to improve the energy efficiency of low-power sensor networks operating under the interference from a coexisting WLAN. We propose a cognitive, cross-layer access control mechanism that minimizes the energy cost for multi-hop WSN communication, by deriving energy-optimal packet lengths and single-hop transmission distances, based on the knowledge of the stochastic channel activity patterns of the interfering WLAN. We show that the proposed mechanism leads to significant performance improvements on both energy efficiency, as well as end-to-end latency in multi-hop WSN communication, under different levels of interference. Additionally, we develop and validate the considered WLAN channel activity model and implement efficient, lightweight, real-time parameter estimation methods.

We investigate how to enhance the multi-hop communication performance in ad hoc WLANs, when 802.11 stations operate under a power saving duty-cycle scheme. We extend the traffic announcement scheme of the 802.11 power saving mode, allowing the stations to propagate pending frame notifications to all nodes in the end-to-end forwarding path of a network flow. We study the performance of the proposed scheme with respect to end-to-end packet delay and signaling overhead, while we investigate the impact on the achievable duty-cycle ratios of the wireless stations. For the purpose of the evaluation, and for the comparison with the standard 802.11 power saving mechanism, we implement the protocol extension in a development platform.

Finally, we study how the combination of the objectives for energy efficiency and a high quality of service impacts the topology stability of self-organized ad hoc networks comprised of individual agents. Based on a non-cooperative game theoretic model for topology formation, we identify key extensions in the nodes' strategy profile space that guarantees a stable network formation under multi-objective player utility functions.

Sammanfattning

Dynamic spectrum access har nyligen föreslagits som ett sätt att öka utnyttjandet av licensierade frekvensband, och på så vis stödja det moderna samhällets ständigt växande volym av mobiltrafik. Samtidigt har den ökade efterfrågan på trådlös anslutning, till följd av snabbt framväxande, innovativa trådlösa och mobila tjänster, lett till utbyggnaden av diverse trådlösa tekniker i de öppna ISM-banden. Denna avhandling behandlar effektiv samexistens bland de olika trådlösa teknikerna i ovanstående scenarier och energieffektiviteten hos de utplacerade trådlösa systemen, två av de nyckelutmaningar som trådlösa nätverk står inför idag.

Vi diskuterar kooperativ avkänning, en grundläggande mekanism för att olicensierade användare opportunistiskt ska kunna få åtkomst till licensierade spektrum. Utifrån scenariot där användarna utför både avkänning och olicensierad spektrumtillgång utvärderar vi effektiviteten med avseende på varje användares uppnåeliga kapacitet. Vi drar slutsatsen att en noggrann optimering av både antalet avkända kanaler och tilldelningen av avkänningsuppgifter till nätanvändare är nödvändiga för att uppnå höga kapacitetsvinster i storskaliga nätverk av olicensierade användare.

Vi tar upp ett antal frågor om energieffektiv design för trådlös sensornätverk (WSN) och WLAN. Vi studerar hur man kan förbättra energieffektiviteten hos ett sensornätverk som verkar under störningar från ett samexisterande WLAN. Vi föreslår en kognitiv, lageröverskridande mekanism för åtkomstkontroll som minimerar energikostnaden för multi-hop kommunikation i WSN. Framtagningen av åtkomstkontrollen sker genom härledning av energioptimerade paketlängder och överföringsavstånd, baserat på kunskap om stokastiska kanalaktivitetsmönster i störande WLAN. Vi visar att den föreslagna mekanismen leder till betydande prestandaförbättringar både avseende energieffektivitet, och end-to-end latens i multi-hop WSN kommunikation under olika nivåer av störningar. Dessutom utvecklar vi och validera den föreslagna kanalaktivitetsmodellen för WLAN och implementerar effektiva och lätta realtidsmetoder för skattning av parametrar.

Vi undersöker hur man kan förbättra prestandan för multi-hop kommunikation i ad hoc WLANs då 802.11 stationer verkar enligt energisparande duty-cycle system. Vi utvidgar tekniken för trafikmeddelande hos 802.11 i energisparläge, och studerar prestanda i det föreslagna systemet med avseende på end-to-end fördröjning och behovet av ytterligare signalering. Samtidigt undersöker vi effekten av de uppnåeliga duty-cycle förhållandena hos de trådlösa stationerna. För utvärdering och jämförelse med standardmekanismen för energisparande i 802.11 implementerar vi det utvidgade protokollet i en utvecklingsplattform.

Slutligen studerar vi hur kombinationen av mål för energieffektivitet och hög kvalitet av tjänster påverkar stabiliteten i topologin hos självorganiserade ad hoc nätverk bestående av enskilda aktörer. Baserat på en modell för icke-kooperativa spel vid topologi-bildning, identifierar vi viktiga tillägg till nodernas strategiska profil som garanterar en stabil nätverksbildning enligt spelarnas multi-objektiv nyttofunktioner.

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In 2008 I joined LCN, a small laboratory in KTH with six PhD students, and saw it growing today into a large group with more than twenty researchers. I am grateful to the "old" LCNers, Rolf, György, Fetahi, Ian, Vladimir, Ognjen, Sylvia and Ljubica for an enjoyable working environment, great social events and our inspiring Friday-"fika" sessions! Special thanks to my long-term office-mates, Olafur, Ilias, Liping and Valentino, for breaking the routine of the everyday life at the office with unforgettable scientific (and non-scientific) discussions. To all the younger members of LCN: I wish you good luck with your PhD studies!

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Contents

Chapter 1

Introduction

1.1 Motivation

In the recent decades our society has witnessed a dramatic increase in the demand for wireless connectivity in industrial and residential areas, as well as an exponential growth in the volumes of data traffic as a result of the proliferation of mobile broadband services, such as video telephony, personal communication, and mobile multimedia streaming services. At the same time, rapidly emerging application scenarios in the context of Wireless Sensor Networks (WSN) and the Internet of Things (IoT), such as smart homes, building automation, surveillance, and complex industrial control systems, increase the need for wireless connectivity, in both machine-to-machine and machine-to-cloud communication scenarios.

Having to rely on limited spectrum, allocated by regulatory bodies, mobile operators have addressed the exponentially increasing demand for mobile data traffic by, both, expanding the coverage and the deployment density of mobile networks, as well as by investigating ways to increase the efficiency of the allocated licensed spectrum. Dynamic spectrum access, based on the innovative concept of software-defined radio, constitutes an *hierarchical* spectrum sharing paradigm, enabling a more efficient use of the radio spectrum by allowing the co-deployment of wireless systems that can exploit the burstiness of mobile traffic and, thus, make use of temporarily non-utilized licensed spectrum.

Wireless Local Area Networks (WLAN) have addressed the need for wireless connectivity by promoting a *flat*, un-coordinated, unlicensed deployment of WLAN access points in the open industrial, scientific and medical (ISM) spectrum bands, offering cheap, broadband, wireless internet access to machines and individuals. Beside WLANs, mesh radio technologies, such as 802.15.4-based 6LoWPAN, as well as ultra low power wireless Personal Area Network (WPAN) solutions, such as Bluetooth and ZigBee, make use of the unlicensed ISM bands, in an effort to provide cost-efficient machine-to-machine (M2M) communication, for both consumer and large-scale industry quality IoT applications.

The *coexistence* of diverse network technologies in the same spectral bands introduces two significant challenges. First, it requires interference management mechanisms that will effectively restrict the interference to licensed networks in scenarios of hierarchical coexistence. This advance may allow for spectrum regulation changes, which will permit unlicensed access within D-TV, UMTS and LTE spectral resources. Second, it requires access protocol mechanisms that will ensure a fair sharing of spectral resources in case of *flat*, or *heterogeneous* coexistence, that is the co-deployment of *secondary* wireless systems with diverse characteristics in terms of transmission power, coverage and data rates. Instead of being optimized for standalone operation, wireless protocols need to be designed in a way that guarantees efficient access in the shared spectrum bands.

The tremendous expansion in the deployment of wireless systems, in an effort to satisfy the increasing demands for wireless connectivity, has turned energy efficiency into one of the most important considerations in wireless networking. Energy efficient communication can lower the operational costs of wireless systems, allowing for large-scale infrastructure deployments, or permit the realization of environmentally sustainable solutions, such as energy harvesting. Being energy efficient, battery-operating wireless devices with finite power supplies can maximize their operational lifetime, which is a desired feature in scenarios where mobility and portability are crucial application requirements. Lifetime maximization can, additionally, lower the required frequency of human intervention for network re-configuration, and, in general, decrease network maintenance costs. At the same time, energy efficiency should not be guaranteed at the cost of low network performance. Therefore, energy efficient design comprises of mechanisms – spanning, possibly, multiple layers of the wireless protocol stack – that ensure both a low-power operation for the wireless devices, and a high quality of performance.

1.2 Scope and Outline of this Thesis

This thesis focuses on a number of design issues related to efficient wireless coexistence and low-power wireless network operation. The first part of the thesis concentrates on performance modeling and analysis of cognitive access control mechanisms that can guarantee an efficient coexistence between heterogeneous wireless networks. The thesis contributes to the following topics:

- Hierarchical coexistence: we investigate the efficiency of cooperative spectum sensing schemes in cognitive radio networks, with respect to the achievable capacity of the unlicensed users. We study the case of dense ad hoc congnitive networks, evaluating the fundamental limits of secondary capacity under constraints on the interference to the coexisting primary network.

- Flat heterogeneous coexistence: we design a cognitive access control scheme for wireless sensor networks that operate under WLAN interference. The scheme is based on a stochastic characterization of the WLAN channel activity and employs cross-layer optimizations to increase the energy efficiency in WSN communication.

- Stochastic WLAN modeling: we introduce and analyze stochastic models for WLAN channel activity and develop efficient methods for real-time model parameterization to support interference-aware cognitive access control.

The second part of the thesis addresses issues related to energy efficiency in wireless networks. We focus on the following topics:

- We address the challenge of optimizing the WLAN power saving mechanism to alleviate the negative effects of radio duty-cycling on the communication performance in multi-hop 802.11 ad hoc networks.
- We study topology control in energy-constrained self-organized wireless sensor networks under a game-theoretic formulation with multi-objective player utility functions, reflecting both lifetime and QoS performance objectives.

The thesis is structured as follows: In Chapter 2 we discuss challenges and solution approaches regarding efficient heterogeneous wireless coexistence. Chapter 3 surveys network design approaches towards enhancing the energy efficiency in wireless networks. In Chapter 4 we give a more detailed description of the main analytic and simulation tools that were used in this thesis. Chapter 5 includes a summary of the original contibutions, while Chapter 6 presents the main conclusions derived in this thesis, along with possible directions for future research.

Chapter 2

Wireless Coexistence

Wireless coexistence defines the scenario when various communication networks – often operating on different radio technologies – coexist in the same geographical area and spectrum space. Wireless coexistence can be the result of the deployment of unlicensed, dynamic spectrum access-based networks operating within a licensed spectrum space [1]. Alternatively, it can be the natural outcome of the uncoordinated deployment of several networks inside the same open spectrum band [2]. In both scenarios, however, the spectrum resources must be shared among multiple networks.

The increasing number of wireless and mobile applications and services emerging in the modern society, and the inherent problem of spectrum scarcity make wireless coexistence the ruling scenario, rather than the exception, and, therefore, demand for a rethinking of the mechanisms that regulate shared spectrum access.

Under wireless coexistence the spectrum access mechanisms should be designed for addressing two fundamental issues. In general, they should ensure that the available spectrum is shared, among the different network entities, as efficiently as possible. This implies that the coexisting networks should effectively discover opportunities to utilize their spectrum resources in a way that maximizes their performance. In the particular scenarios involving dynamic spectrum access, the access mechanisms should guarantee that the unlicensed networks are able to adapt their transmission schemes in a way that the resulting interference to the co-deployed licensed networks is controlled.

Efficient spectrum access design should, therefore, be *cognitive*, i.e. aware of the activity of the coexisting networks. In this Chapter we look into the key components of cognitive access mechanisms (Fig. 2.1) that enable an efficient wireless coexistence. We then introduce the most common performance metrics, with respect to which the efficiency of these access mechanisms is evaluated. Finally, we discuss the design and optimization of cognitive access mechanisms under both the aforementioned scenarios of wireless coexistence, focusing on the challenges and the solutions for regulating effectively the utilization of the shared radio spectrum.

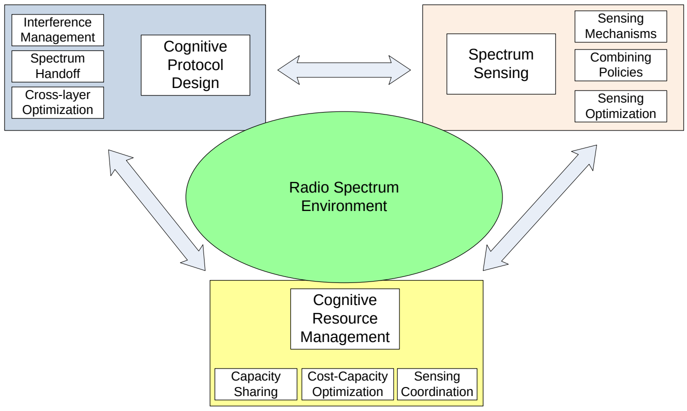

Figure 2.1: Interactions among the key components of a cognitive access scheme.

2.1 Cognitive Spectrum Access

Spectrum sensing

The first challenge in the case of wireless coexistence is how to effectively detect the presence of the co-deployed networks. *Spectrum* or *channel sensing* refers to the mechanism of detecting the presence of transmitted signals within a particular frequency band by listening to the channel. Spectrum sensing offers instantaneous spatio-temporal information about the status of the sensed channel (or spectrum band). Wireless terminals utilize this information to assess both the opportunity of performing a successful transmission within the particular band, as well as the probability of causing harmful interference to a coexisting wireless transmission [3]. In addition to that, spectrum sensing – performed over longer periods – can be used to characterize the statistical properties of spectrum occupancy in the neighborhood of a wireless user [4]. Based on this statistical information that user can adapt its long-term channel access behavior in order to avoid communication impairments due to the coexisting networks and, thus, maximize its communication performance.

Wireless terminals may perform spectrum sensing based on energy detection schemes [5][6] when the nature and the format of the transmitted signals are unknown. Alternatively, they utilize more sophisticated schemes, like match-filter, or cyclo-stationarity-based detectors [7], when a-priori knowledge of the particular signal characteristics is available.

Due to channel noise and signal attenuation phenomena, spectrum sensing is in general imperfect, leading to frequent erroneous channel activity assessments by the sensing devices. The performance of spectrum sensing degrades rapidly with the distance between the transmitter and the sensing device, which decreases the *signal-to-noise-ratio* over the sensing link. In addition, channel fading and shadowing on the sensing *link* limit the reliability of spectrum sensing mechanisms; this reliability can be increased by enforcing *cooperation* among several sensing devices [8], exploiting the spatial diversity over the sensing links [9][10][11][12]. The cooperative decision can be either *hard*, that is, based on combining individual decisions at each sensing device [13], or *soft* when it combines raw channel sensing measurements at each device [14][15]. Optimal soft decision combining [14] is shown to outperform hard combining schemes as the decision is made exploiting all the knowledge obtained through spectrum sensing.

The *cost* of sensing reflects the *resources* allocated to spectrum sensing, namely the sensing *time* or the sensing *energy* that are spent by the sensing devices, or the signalling and processing *overhead* of exchanging sensing results, in order to perform the collaborative decision. Sensing *optimization* aims at maximizing the achievable sensing performance, subject to certain constrains on the sensing cost [16].

Cognitive network protocol design

Cognitive network control refers to the design of wireless medium access, link-layer and routing control schemes aiming at achieving an efficient utilization of the transmission opportunities within the shared spectrum, discovered via sensing. Cognitive network control addresses two fundamental issues. It enables *interference management*, that is, it regulates the interference among the coexisting networks, and optimizes MAC and routing schemes for communication performance enhancement in coexistence scenarios.

Interference management builds on the information provided by channel sensing. To control the interference to a licensed network, an unlicensed user may need to immediately evacuate a spectrum band on which a signal originating from the licensed system has been detected. Alternatively, the user may apply an effective *power control* scheme, that is adapt its transmission power at a level that it does not cause harmful interference to the ongoing detected transmission [17]. Interference management may additionally involve *channel hopping* [18][19] mechanisms, where wireless users migrate to a different channel in order to mitigate the interference with the detected signals, thus, protecting both their own and the detected wireless transmissions.

Spectrum sensing and frequency hopping can be combined into efficient *spectrum sensing and handoff* schemes [20][21][22], where users dynamically modify their sensing and channel access policies based on the obtained sensing results, in order to limit the interference to and from the coexisting networks.

In addition to the instantaneous information provided by spectrum sensing, a cognitive network control scheme may utilize a-priori statistical knowledge of the transmission patterns of the users of the coexisting networks. Such schemes involve the optimization of a set of *cross-layer* transmission parameters. As far as *Medium Access Control* (MAC) is concerned, cognitive access schemes optimize the frame transmissions lengths to avoid collisions with the users of the co-deployed networks [23]. Cognitive *routing* schemes involve routing traffic dynamically, avoiding network nodes with limited spectrum resources. Under multi-hop communication cognitive access control may optimize the next-hop selection, with the objective of maximizing the performance of the end-to-end communication under the interference of the coexisting networks [24]. For such solutions it is crucial that the a-priori knowledge of the aforementioned transmission behavior is sufficiently accurate, while, at the same time, it can be obtained at minimal cost.

Finally, cognitive network control may employ medium access protocol techniques that enhance the robustness of single-hop communication, such as enforcing enhanced link-layer transmission handshake mechanisms, thus, improving collision detection and interference mitigation. Alternatively, it may involve mechanisms for smooth inter-operation between the coexisting networks, for example, by a-priori assuming [25], or by identifying the tranmission patterns of the co-deployed networks – decoding link-layer management transmissions [26] – to enable in this way a more efficient spectrum sharing.

Cognitive resource management

In wireless coexistence scenarios *cognitive resource management* refers, to the process of determining the amount of network resources that needs to be spent for discovering transmission opportunities. In addition, it manages the allocation of the resulting transmission opportunities to the network users.

Spectrum resource management models the inherent tradeoff between the resources allocated for spectrum sensing and the resulting sensing performance, that reflects the *cognitive capacity*, that is the amount of spectrum resources available for the network users. This modeling enables the derivation of the sensing parameters that result in a target *cost-capacity* operational point for the cognitive system. As a representative example of cognitive resource management, [27] addresses the problem of sensing efficiency maximization in cognitive radio networks. Considering that the time spent for sensing reflects a capacity loss for the users, the work aims at optimizing the lengths of the spectrum sensing periods.

In the context of collaborative sensing, and since discovering spectrum opportunities requires effort from a set of cooperating users, these users need to decide how large part of the spectrum space they intend to sense and utilize. On one side, a large space may increase the number of channels to sense, so that there are more transmission opportunities to share. On the other side, this requires more sensing efforts from the users, revealing that there is an optimal spectrum space to be sensed that depends, additionally, on the *capacity* requirements of the existing users [28].

An important challenge is how the discovered transmission opportunities will be allocated among the existing wireless users. Optimally, a fair spectrum resource sharing scheme is desired, which implies that the sensing cost of each wireless user quantitatively reflects its achievable transmission capacity [29]. In addition to that, wireless users may, in general, have different capacity requirements; this diversity among the individual user requirements or objectives needs to be taken into consideration when distributing the cost of spectrum sensing so as to provide strong inscentives for cooperation to the wireless users [30].

2.2 Performance Metrics in Cognitive Coexistence

Sensing and interference control

The *cross-network interference*, defined as the interference between the coexisting networks, can be viewed from two different perspectives: from the transmitter's, or the interferer's, and from the receiver's perspective. From the interferer's point of view we aim at evaluating the ability of a network to detect and effectively *avoid* to cause interference to the co-existing systems. From the perspective of a receiver, we aim at quantifying the ability of a system to efficiently operate in the presence of interfering networks.

Interference avoidance

The ability of wireless system to effectively detect and avoid interfering with a co-deployed network is quantitatively captured by the probabilities of *missed detection*, p_{MD}, and *false alarm*, p_{FA}. p_{MD} denotes the probability that a transmitted signal at an arbitrary point in time is not detected by the users of a coexisting network who aim at simultaneously utilizing the same transmission band in the neighborhood of the transmitted signal. On the other side, p_{FA} defines the probability that channel sensing results in a false detection of signal presence due to channel noise. *Local* missed detection refers to the sensing performance at individual sensing devices, while *global* or *cooperative* missed detection refers to the collaborative detection process by a set of devices. Regardless of the exact spectrum sensing model that is applied,

$$p_{\mathrm{MD}} \triangleq p_{\mathrm{MD}} \left(\mathit{SNR(d)}, T_s \right)$$

is a decreasing function of the instantaneous *signal to noise ratio* at the sensing device, while it decreases with the duration of the sensing time allocated for sensing, T_s. As SNR is a decreasing function of the distance separation, d, missed detection probability increases with the length of the sensing link.

Missed detection events, however, do not necessarily result in cross-network interference, unless multiple users from different networks simultaneously attempt to utilize the same channel in the neighborhood of each other. Therefore, a network that intends to operate without causing harmful interference to a coexisting wireless system calculates the *probability of interference*, P_I, on a channel as the joint probability of two events: *i)* a missed detection of an ongoing transmission from a user of the coexisting network in the particular channel, and *ii)* a channel access attempt by a network user that collides with the ongoing transmission, resulting in transmission error:

$$P_I \triangleq \Pr\{\text{missed detection}, \text{collision}\}.$$

Under wireless coexistence interference can not be completely avoided, due to the imperfections in spectrum sensing and the stochastic nature of the channel access. Instead, coexistence is regulated based on practical non-zero interference *constraints*, i.e. $P_I \leq P_I^{\max}$, which, if met, guarantee an acceptable system performance.

Surviving cross-network interference

From the receiver's point of view we are interested in assessing the ability of a wireless device to communicate successfully under the interference of the co-deployed networks [31]. We quantitatively capture the efficiency of coexistence by evaluating for a transmitter-receiver pair the probability of *successful communication*,

$$\Pr\{\text{success}|d_{\text{t-r}}\},$$

in the presence of cross-network interference. Communication success decreases with the transmitter-receiver spatial separation, $d_{\text{t-r}}$, [24], since a higher distance decreases the receiver signal power, and, consequently, exposes the transmission to potential interference from a larger area,

$$\frac{\partial \Pr\{\text{success}|d_{\text{t-r}}\}}{\partial d_{\text{t-r}}} \leq 0, \quad d_{\text{t-r}} > 0.$$

In addition to that, communication success depends heavily on the transmission properties of the coexisting networks, which, in turn, depend predominantly on the traffic patterns of their users. In general, the duration of the communication, t, decreases $\Pr\{\text{success}|d_{\text{t-r}}, t\}$, since it increases the time interval within which this transmission is exposed to cross-network interference,

$$\frac{\partial \Pr\{\text{success}|d_{\text{t-r}}, t\}}{\partial t} \leq 0, \quad t > 0.$$

Cross-network interference estimation

Efficient wireless coexistence is facilitated if the networks configure their communication mechanisms based on the knowledge of the stochastic spatio-temporal channel access patterns of the co-deployed systems [23]. An accurate modeling and parameter estimation of the channel usage is, therefore, desired under wireless coexistence.

Channel usage patterns – including the durations and the autocorrelation properties of the *active* and *idle* channel periods – depend on the traffic workload of the network users, on the network topology, and on the underlying medium access mechanisms [32][33]. These factors must be considered when introducing a tractable wireless *channel occupancy* modeling [34]. The *applicability* of the channel occupancy model is assessed applying a *goodness-of-fit* tests, of a set of measurements or observations, against the expected observations under the model in question.

Following the model validation, an efficient parameter estimation algorithm must be designed. The estimation efficiency is assessed by the resulting *accuracy* of the estimated parameters, evaluated by the *parameter estimation errors* as a function of the resources spent for channel occupancy estimation. As the channel occupancy parameterization is performed by the users collecting active and idle period duration samples, with the help of their own channel sensing infrastructure, we evaluate the efficiency of the parameter estimation as the minimum required number of collected samples that guarantee that the parameter estimation error drops below a predefined threshold.

Communication performance

Achievable capacity

Under wireless coexistence, we define a network's *achievable capacity* [35] as the total amount of the shared spectrum resources available for communication. The achievable capacity, C, is a function of the spectrum sensing performance of a network, quantified through the missed detection and false alarm probabilities, the total number of sensed bands, M, as well as the aggregate cross-network channel *load*, ρ, within the sensed spectrum space.

$$C \triangleq C\left(M, \rho, p_{\mathrm{MD}}, p_{\mathrm{FA}}\right). \tag{2.1}$$

The network achievable capacity is then shared among the users, N, of the network, leading to the *per-user* average achievable capacity,

$$C(N) = \frac{C\left(M, \rho, p_{\mathrm{MD}}, p_{\mathrm{FA}}\right)}{N}. \tag{2.2}$$

QoS-related metrics

$C(N)$ indicates the per-user spectrum resources that are available for communication, reflecting nominal user communication performance. Additionally, we may want to evaluate the impact of wireless coexistence on the practically experienced communication quality. For that we introduce a set of user QoS-related performance metrics.

We introduce the *end-to-end transmission delay*, to evaluate the communication delays in multi-hop wireless networks as a result of cross-network interference. The end-to-end delay depends on the experienced interference along the multi-hop transmission paths, which affects the expected number of retransmissions, ETX_r, on each link of the path, where ETX_r is inversely proportional to the probability

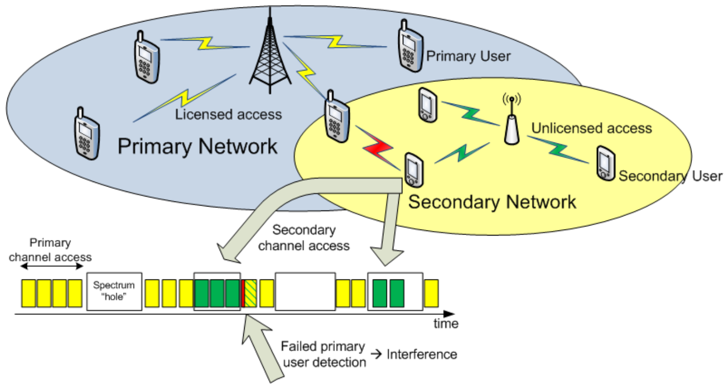

Figure 2.2: Hirearchical primary-secondary network coexistence with the secondary network performing dynamic, unlicensed spectrum access.

of successful transmission,

$$ETX_r = \frac{1}{\Pr\{\text{success}|r\}}.$$

Similarly, in multi-hop wireless networks *end-to-end throughput* defines the information delivery rate – in bits per time unit – between a source and the respective destination node under cross-network interference. Multi-hop paths experiencing high cross-network interference should normally be avoided, in order to maintain high throughput, and to limit the experienced end-to-end delays [36].

Energy efficiency is a commonly set objective for communication networks formed by energy-constrained wireless devices. Designing an energy efficient protocol stack is a fundamental prerequisite, in order to guarantee a sufficiently long network lifetime. Protocol design is energy efficient, when it minimizes the energy cost per transmitted unit of information. Considering, in general, multihop communication scenarios, we quantify energy efficiency by defining the *normalized energy cost* metric [24], which gives the total energy required for transmitting a unit of information over a unit of distance towards the final destination node.

2.3 Design Challenges for Coexistence Scenarios

Hierarchical coexistence: The case of primary-secondary network coexistence

Traditional regulatory access mechanisms in cellular networks, such as exclusive spectrum licensing and spatial frequency reuse often fail to guarantee an efficient usage of the available spectrum [37]. Spectrum may remain highly underutilized as a result of low instantaneous demand for wireless traffic exchange within the licensed networks [38][3], caused by high spatio-temporal burstiness in user traffic demand. Licensed spectrum underutilization has been experimentally proven in a broad set of scenarios [39], and in particular for cellular – UMTS and LTE – communication networks [37][40].

Parallel to this, we have witnessed the emergence of broadband wireless internet services with lower requirements in terms of user-experience QoS, including data delivery delay, jittering, or packet loss rates. Such services can be supported by unlicenced, low-priority, *dynamic spectrum access*-based networks [41] [1] [42] that coexist with the licensed (or primary) networks and make use of the temporarily non-utilized licensed spectrum (Fig. 2.3).

Wireless coexistence, however, introduces the need for interference control between the licensed, and the unlicensed – or *secondary* – users (SU), since licensed users should not experience any communication performance degradation due to the operation of the unlicensed network. In other words, *interference management*, based on spectrum sensing [43], is the key component behind the deployment of unlicensed (or secondary) communication networks.

Spectrum sensing & capacity maximization

Spectrum sensing is the fundamental mechanism for identifying appropriate transmission opportunities and for protecting the licensed or *primary* user operation. The efficient design of spectrum sensing involves optimizations at both local and global (cooperative) level.

Local sensing optimization: At local level, cognitive users must first optimize the length of their sensing measurements [20][44]. Short-period sensing measurements increase the probability of missed-detecting an active primary user, while longer sensing periods reduce the time available for secondary communication and increase the energy consumption of sensing. As typically there are more than one channels available for secondary access, sensing is often perform sequentially over a set of multiple channels. An important challenge here is how to optimize the order in which sensing is carried out in each of the bands. The work in [45] optimizes the sensing order taking the long term occupancy statistics of the respective channels and minimizes the required sensing energy cost while maintaining a target missed detection probability at each sensed band. To increase energy efficiency sensing order optimization can be combined with dynamically adjusting the sensing time duration [46], upon achieving a target performance. Spectrum sensing can, additionally, employ learning techniques for deriving the optimal sensing order [47], to maximize reliability. Optimal sensing policies may be applied in order to select a particular subset of channels to sense, for example, based on long-term channel availability [48] or short-term band occupancy along with channel quality statistics [49].

Sensing resource allocation: At cooperative level, sensing performance increases with optimal combining of individual sensing measurements, based on the experienced SNR levels at the sensing devices [14], the individual measurement reporting reliability [50], or the correlation among sensing results [51].

In addition, efficient cooperative sensing involves the optimization of the total sensed bandwidth [52] and the extent of cooperation among sensing devices. As discovering spectrum opportunities requires effort from the cognitive users, the users need to decide, first, how large part of the spectrum space, dedicated for unlicensed operation, they want to utilize, and, second, how many of them should cooperate for sensing each band in the spectrum space. On one side, the users may increase the number of channels to sense, so that there are more transmission opportunities to share. On the other side, this requires more sensing efforts from each SU. Similarly, increasing the number of cooperative users lowers the resulting missed detection probability [53], at the expense of linearly increased sensing resource requirement for detecting channel availability. In Paper A, we address the above joint optimization aiming at maximizing the achievable per-user cognitive capacity, as it was defined in Section 2.2 and show how the density of the secondary network, and the desired coexisting licensed network interference constraint are important design factors.

Sensing coordination: After determining the number of users to participate in the cooperative decisions, a remaining issue is how to decide on the exact sensing duties to be allocated to the existing secondary users. This problem is often defined as *sensing coordination* [54]. Correlation-aware sensing cordination schemes [55] aim at guaranteeing that the users sensing the same bands experience uncorrelated channel gains on the sensed links. Sensing coordination may rely on a centralized mechanism that distributes sensing coordination information to the secondary users, ensuring a similar missed detection rate over each of the sensed bands. Alternatively, a distributed approach lets the existing secondary users individually select a set of bands to sense. Clearly the first approach achieves a higher capacity due to balanced detection performance in each sensed band, at the expense of a significant signalling overhead that is required to distribute the coordination information to the users. Such overhead may be prohibited in scenarios where energy efficiency is desired or in cases where time constraints require fast cooperative sensing decisions. In Paper A we define and analyze sensing allocation mechanisms, spanning from fully randomized to fully centralized sensing coordination schemes, and conclude that there exists a constant performance gap between the centralized and distributed approaches that is independent of the network density and the remaining design factors. We achieve this by analytically deriving the asymptotic performance limits for the aforementioned sensing coordination schemes.

Heterogeneous flat coexistence: The case of WSN and WiFi

Flat wireless coexistence is the result of uncoordinated co-deployment of networks operating in overlapping subsets of the open spectrum ISM bands. As opposed to

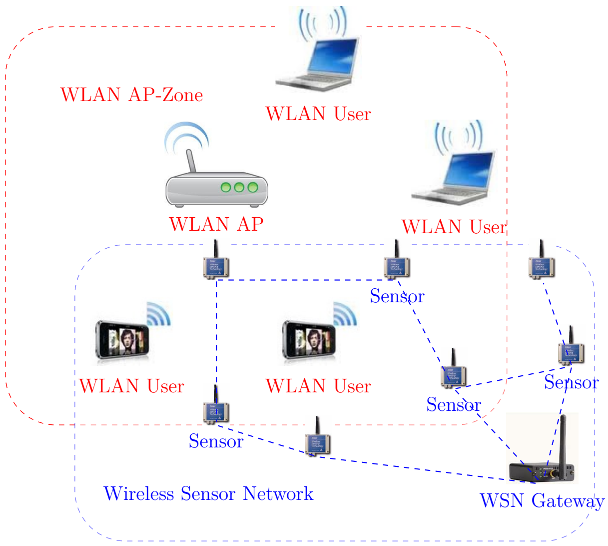

Figure 2.3: Heterogeneous coexistence of 802.11 and 802.15.4 networks in the 2.4GHz ISM band.

the case of hierarchical coexistence, where exclusive spectrum ownership demands efficient interference avoidance mechanisms, flat coexistence focuses on developing protocols that, instead, guarantee an efficient operation for all systems.

In recent years we have witnessed a rapid increase in the technologies operating in the 2.4GHz ISM band, with the common characteristics of being license-free networks, employing random medium access schemes, and supporting error and delay-tolerant communication services. Among the most popular systems we list the wireless sensor networks with customized communication standards, IEEE 802.15.4-based personal area networks (WPAN), IEEE 802.11-based wireless LANs, as well as Bluetooth networks, cordless phones and RFID communication systems.

Due to the different transmission characteristics of the aforementioned systems, flat coexistence is, defined as heterogeneous [24], and imposes different challenges in the design of the different network players. Systems with relatively high transmission power levels, combining, additionally, efficient broadband physical layer, enhanced radio hardware and moderate communication ranges, often do not experience any performance degradation due to the operation of coexisting networks. The protocol stack of such systems can, therefore, be designed and optimized considering standalone operation.

On the opposite side, the performance of systems operating within narrow-band channels and with relatively low transmission power may be severely affected by the presence of high-powered systems. For such networks, the performance of the channel access control mechanisms can be significantly improved, if their design is *cognitive*, i.e. aware of the radio environment, including the presence and channel occupancy patterns of the coexisting networks.

In this thesis we focus on the popular scenario of a low-power WSN that operates under the interference of a coexisting WLAN (Fig. 2.3). Heterogeneous coexistence is justified by the relatively high difference in the transmission power of the two network technologies. Due to this difference, WLAN terminals are *blind* towards the WSN transmissions [4], and do not back off when a transmission is initiated that overlaps with that of a WSN packet. As a result of such packet collisions, WSN communication performance degrades, while WLAN througput is hardly affected by WSN interference, a scenario that is often defined as *asymmetric* interference.

The negative impact of the cross-network WLAN interference on the WSN performance has been underlined in a plethora of experimental studies [56], while similar studies have been conducted for Bluetooth systems [57] [58]. In order to survive the WLAN interference and, thus, guarantee a high communication performance, WSNs must employ smart channel access mechanisms, i.e. avoid using the wireless channel simultaneously with the WLAN terminals. We review here the basic principles of cognitive coexistence in the case of flat-hierarchy, asymmetric interference scenarios.

WLAN white space characterization

Model design and validation: Identifying and capturing the statistical properties of the spatio-temporal WLAN channel occupancy enables the WSN users to assess accurately the transmission opportunities under WLAN coexistence [34]. The first step towards this direction is the adoption of an appropriate stochastic model that can describe WLAN occupancy in a broad range of WLAN networking scenarios. To be attractive for analytic performance studies and cognitive access control design, a good model candidate must be relatively simple. It must, additionally, bare the structure and the required degrees of freedom that ensure a good potential of capturing the behavior of WLAN channel occupancy at a *microscopic* level [59], that is, modeling directly the short term temporal behavior of the channel status in WLAN networks.

Related work in this area includes the seminal approach in [33] that derives an analytic model for the impact of IEEE 802.11 MAC protocol on channel occupancy assuming saturated traffic. WLAN traffic, however, is far from saturated; consequently, channel usage models are usually developed based on a-priori considered traffic generation patterns [60] [61], or workload models derived from measurement studies [62] [63] [2]. In this thesis we adopt the interesting approach introduced in [23], where an ON-FF semi-Markovian model is employed to characterize the WLAN channel usage. A significant challenge in WLAN activity characterization is to assess the generality of the proposed model; this may be conducted based on real traces of WLAN channel usage collected from public WLAN hotspot measurements [64], or generated in testbed experiments [2]. Instead, Paper D validates the model applicability over a broaded range of traffic workload scenarios, generated based on experimentally driven high-layer 802.11 traffic statistics [65], in an effort to close the gap between *macroscopic* WLAN traffic workload modeling [65]–[73] and microscopic channel usage models. Focusing primarily on modeling the idle channel periods, we show that the proposed model exhibits excellent fitting under diverse WLAN scenarios, due to its inherent *mixture* distribution for the idle period lengths, consisting of a right truncated term that models the short 802.11 DCF back-off periods, and a heavy-tailed [74] term for the longer periods of WLAN terminals' inactivity.

Model parameterization: WSN terminals rely on channel sensing, in order to collect a sequence of channel occupancy samples – active and idle period lengths – and to parameterize the WLAN channel usage model [2]. The challenge rises due to the sensing limitations of the WSN terminals, which may only partially detect the WLAN channel activity. Thus, in [75] we enhance the adopted WLAN model considering the WSN limited sensing range, and prove the existence of a closed-form expression for the model stochastic distribution functions on the Laplace transform domain [76].

Estimation algorithms are required to be computationally efficient, in order to be able to run on constrained-resource devices, such as sensor nodes. CPU constraints impose limits on the complexity of the estimation algorithms, while memory constrains require *on-the-fly* computation of the model parameters, without the need for storing the collected WLAN *empirical* channel occupancy traceset. In [75] we describe a estimation algorithm based on maximum-likelihood maximization and show that for a target estimation accuracy, as defined in Section 2.2, the convergence speed – in number of samples – depends on the percentage of the observable WLAN activity. In an attempt to satisfy potential memory limitations, in Paper C [77] we develop an estimation algorithm that allows WSN terminals to dynamically re-compute the model parameters based on a real-time sample collection mechanism. The algorithm structure is based on a modified version of an iterative *discrete stochastic optimization* scheme [78]. In Paper C we prove the algorithm convergence stability based on the properties of the WLAN channel occupancy functions.

Interference-aware protocol design

Under WLAN coexistence WSN terminals need to control channel access in a way that it alleviates the harmful WLAN interference and ensure an effective use of the shared ISM spectrum band. Traditional interference mitigation schemes include *channel hopping* mechanisms, where WSN nodes measure and tune to the best available band for communication [79] [80] [81]. However, the effectiveness of these schemes is debatable, particularly in cases where all considered bands exhibit similar statistical interference. Alternative approaches focus on mitigating the cross-network interference by adding information redundancy [31][82] or by partial intervention with the WLAN MAC operation [26]. The efficiency of these approaches is accompanied by either significant transmission overhead, or hardware extensions in WSN design.

Effort has therefore been put on exloiting the knowledge of 802.11 channel activity patterns leading to cognitive access control, alternatively denoted as *interference-aware* MAC design. Approaches similar to the seminal work in [83] attempt to jointly optimize polices for channel access and discovery of transmission opportunities, based on a-priori known traffic statistics of the interfering network. A requirement for a wide system-optimization approach is to efficiently couple the cognitive access mechanism with the WLAN channel occupancy model derivation [4] [23]. Our work in Paper B addresses the challenges of model estimation, and cognitive access optimization over partially observable WLAN activity. It shows that the WLAN occupancy statistics serve as input for both the design of the channel sensing scheme, as well as for the optimization of the WSN transmission policies and can, therefore, maximize the probability of transmission success, as defined in Section 2.2 under cross-network interference.

CHAPTER 3

Energy Efficiency

Energy efficiency is perceived as one of the most important concerns in wireless networking. In a wide range of network applications involving wireless devices with finite energy supplies, energy efficient operation is the key factor behind extending the lifetime of the devices to reasonable times. Typical examples of such application scenarios are battery-powered, radio-capable consumer electronics, such as wearable sport gadgets, health monitoring, or entertaintment electronics, where the requirement for energy efficiency is enforced by battery size limitations, driven by the consumers' demand for portability and minimal device design. In rapidly emerging networking applications within the context of the Internet of Things, such as smart home appliances, building automation, or smart cities, energy efficiency is, additionally, required for scaling up the deployed network infrastructures, while guaranteeing environmentally sustainable operation. Finally, the rapid proliferation of applications for wireless sensor networks, such as monitoring environmental conditions, or targeting surveillance, actuation and automation on complex industrial control systems [84], demands for energy efficient design in an effort to maintain low operational costs, thus, alleviate the concerns about the profitability of smart automation and monitoring solutions in large-scale industrial production.

Energy efficient design in wireless networking refers to two fundamental engineering tasks. The first task is to define appropriate metrics, based on which the energy efficiency of a network can be quantitatively evaluated. The second task is to come up with the required architectural changes in network design, and to engineer novel communication protocols, which will allow the wireless devices to utilize their energy resources as effectively as possible, while maintaining a high quality of service for the applications that use the networking infrastructure.

3.1 Evaluating the Communication Energy Efficiency

Metrics for energy efficiency

Transmission cost: As the major source of energy consumption of low-power wireless devices is associated with their radio operations, the primary mechanism for achieving energy efficiency is the minimization of the nodes' communication energy cost per unit of transmitted information. In general, communication protocol operations involve an inevitable transmission *overhead* – in the form of frame header extensions, link layer packet retransmissions to increase reliability, as well as medium access and routing protocol signalling – which may significantly increase the communication energy cost. We can quantify the cost of transmission overhead by normalizing the energy consumption with the amount of information transmitted by the wireless devices. In multi-hop networking scenarios, the protocol energy efficiency must account for the end-to-end energy cost of information delivery. Based on the above considerations, in this thesis we quantify the energy efficiency of communication protocols by defining the *normalized energy cost* metric [24], which gives the total energy required for transmitting a unit of information over a unit of distance towards the final destination node for a multi-hop end-to-end transmission.

Lifetime: One of the key directions towards energy efficient design is the maximization of the network lifetime, which is the amount of time when the wireless network can sustain the target operational performance. Network lifetime depends not only on the communication energy efficiency at the individual wireless devices, but, additionally, on the distribution of energy consumption among the nodes in the network. In multi-hop networks, exessive traffic relaying increases a node's energy consumption, and may lead to node failures, which impose a severe threat on the connectivity and the stability properties of the network topology. As a wireless node depends on relaying nodes so as to transmit and receive traffic over multiple hops, its lifetime is strongly correlated with the lifetime of the relaying nodes. Therefore, in this thesis we express the *lifetime* of a wireless device as a function of the lifetime of the nodes, on which this device relies, in order to achieve target connectivity properties. 'Energy efficient design' refers to efficient network formation, traffic routing, and topology control that increase the lifetime of the wireless devices.

Duty-cycle ratio: In addition to the energy consumption when transmitting or receiving data, the wireless devices may spend a significant amount of energy resources when they remain *idle*, that is, when they listen to the radio channel waiting to receive information. *Radio duty-cycling* is proposed as the straightforward approach towards mitigating the energy cost of idle listening [85]. Duty-cycling mechanisms are implemented on the *medium access control* (MAC) level [86]. Duty-cycling demands the wireless devices activate their radios only when they need to participate in data exchange; in the absence of relevant traffic, devices can transit to *sleep* [87] or *doze* state [88] to save energy. Energy savings are high when the devices remain in the doze state for long periods. Therefore, in this thesis we evaluate the efficiency of duty-cycling by the achievable *sleep ratio*, that is the percentage of time a wireless device can operate with its radio de-activated. 'Energy efficient' design concerns the optimization of duty-cycling parameters that maximize the sleep ratio of the devices in a network, under a given traffic workload.

Delay overhead: While it effectively decreases the cost of idle listening, duty-cycling may introduce significant delays in traffic exchange, as the devices are not able to receive data when they are in sleep state. Thus, data transmission needs to be buffered until the receiver wakes-up. In a multi-hop transmission, buffering delays may occur at each intermediate node introducing significant latency in traffic delivery, which, in turn, imposes concerns about the applicability of duty-cycling. A duty cycling-based protocol is efficient when the energy cost savings are achieved at the expence of low traffic exchange delays. Therefore, in this thesis we introduce the *delay overhead* metric to quantify the impact of duty-cycling on data delivery delays. In multi-hop networking scenarios the delay overhead denotes the end-to-end traffic exchange delays as a result of duty-cycling. Here, 'energy efficient design' refers to developing wireless duty cycle-based protocols that maintain a low multi-hop delay overhead.

Energy efficient protocol design in wireless networks

Energy efficiency in wireless networks can be viewed from two opposite perspectives: as a performance objective, or as a built-in constraint in network design. When constituting an objective, energy efficiency refers to the architecture and the optimization of network protocols, that decrease the energy cosumption of resource-constrained wireless devices. From the perspective of a constraint, energy efficient design refers to network architectural changes that allow network protocols to maintain high performance standards, while operating with limited energy resources. This chapter surveys recent developments related to energy efficient design, with the emphasis put on *cross-layer* approaches, where different protocol modules and building blocks, e.g. medium access, routing, or topology control are jointly designed for performance improvements, with respect to the aforementioned performance metrics.

We begin with energy efficient design approaches in wireless ad hoc and sensor networks, and close the discussion with novel advances and contributions towards energy efficiency in 802.11 (WLAN) networks.

3.2 Energy Efficient Design for Wireless Ad hoc and Sensor Networks

Cross-layer protocol optimizations for energy efficiency

Wireless sensors employ *power control* as a means of regulating their energy consumption level [89]. Power control covers a broad area of power conservation techniques that aim at increasing energy efficiency, while satisfying performance requirements, such as througphout, data-rates, and link reliability. Reducing transmission power at the devices decreases, in general, communication range and data-rates. Therefore, on network scope, power control is often coupled with routing and link scheduling optimization, in order to minimize the normalized communication energy cost of the wireless nodes subject to connectivity and data delivery requirements. The seminal works in [90][91] propose algorithmic solutions that jointly optimize routing selection and power allocation in a wireless network, so as to mimimize the normalized energy cost for a given traffic workload that describes the rates, at which traffic is to be delivered between specific source-destination pairs. The optimal route selection takes into account the interference between simultaneous transmissions, thus, schedules neighboring link transmissions in different time slots.

Wireless sensors may, additionally, control the transmission overhead, and, consequently, the communication energy efficiency, by applying *packet length optimization* techniques [92]. Large packet sizes decrease the framing overhead, but lead to higher packet error rates, and, therefeore, frequent retransmissions, since the packets are exposed for a longer period to channel noise and interference from simultaneous tranmsissions. Consequently, large packet sizes may increase the retransmission overhead at the MAC layer. Packet length optimization is, therefore, a crucial design factor for energy efficient communications in wireless networks [93]. Intuitively, packet size and routing may also be jointly optimized for energy efficiency in multi-hop wirless networks [94]. To decrease the normalized end-to-end energy cost of communication, nodes may, for example, select to route their traffic via a larger number of intermediate hops, choosing shorter single-hop links, where large packets can be transmitted with high reliability.

Under coexistence with high-power wireless networks, wireless devices may perform packet length optimization with the help of efficient statistical characterization of the cross-network interference [23]. If the channel activity model of the high-power interferer is known, or can be determined, low-power wireless devices can trade-off larger framing overhead with larger retransmission overhead, to determine the optimal packet size that mimimizes the normalized energy cost [4]. In Paper D we jointly optimize WSN packet size and next-hop transmission distance to maximize energy efficiency under known WLAN interference patterns.

In the context of energy efficient design *topology control* mechanisms are employed in an effort to prolong the lifetime of resource-constrained nodes in the wireless network. A plethora of approaches propose *load-balanced* network topologies, where traffic flows are directed in a way that avoids significant irregularities in the local energy consumption of the nodes [95][96]. In several approaches, topology control is coupled with power control, so that the wireless devices can select the optimal set of neighbor links and then determine the optimal transmission power, based on the experienced interference on each link [97].

Energy efficiency under QoS considerations

While energy efficiency is an important design factor, the vast majority of networking application scenarios introduces equally important QoS considerations, such as the traffic delivery delay and the reliability of the routing paths. In several cases there exists an inherent conflict between these two categories of design goals. Aiming at achieving higher energy savings and increased lifetime, wireless devices might need to compromise the quality of service. Therefore, significant effort is devoted to network optimization oriented towards both energy and performance efficiency.

The trade-off between energy efficiency and network performance may be analyzed under a multi-objective, system-wide optimization perspective. The analysis requires, first, a cost model that quantitatively reflects both classes of design goals. The wireless devices may, then, employ routing selection, power and topology control, to minimize system-wide cost functions, determined by the considered cost model [98]. In other approaches, the desired trade-off between load-balancing and reliability of traffic delivery is reflected in the routing and MAC protocol parameterization [99]. This allows WSNs to dynamically – and in a distributed fashion – adapt to temporal changes in the traffic workload and the link quality in the network.

Several application scenarios lead to dynamic and self-organized sensor networks, where the assumption of system-wide optimization can not be easily justified [100]. In certain cases, wireless devices might be owned by different entities, with an objective of maximizing their own performance. Scenarios with nodes having self-optimizing, or *selfish* goals, are, in principle, studied applying game-theoretic tools. A key question in such cases, is whether the wireless devices can coverge to stable network operation points, namely *Nash equilibria* (NE), where nodes maximize their individual performance that reflects both a high node lifetime, and a low delay overhead [101][102]. Certain contributions demonstrate that Nash equilibria do not always exist under cost models reflecting contradictory objectives [98]. Several other studies employ constructive methodology, to prove that such NE exist, by formulating iterative games that lead to stable energy efficient topologies [103][100][104].

In an attempt to guarantee stable network formations, a few interesting approaches re-formulate the game-theoretic model of the topology control to extend the space of strategies for the wireless devices by introducing bilateral negotiations between wireless nodes that wish to form communication links [105][106]. We follow a similar approach in Paper F, where the wireless nodes negotiate the quality of traffic relaying they offer, in addition to selecting routing paths for their own traffic. We show that such a strategy space expansion leads to stable Nash equilibrium topologies, even when the wireless devices aim for both node lifetime, as well as QoS maximization.

Duty-cycling in wireless sensor networks

Duty-cycling in wireless sensor networks is implemented based on periodic radio *wake-up* [85] and transition to sleep state, unless traffic needs to be exchanged by the sensor device. Such a scheme achieves high sleep ratio, in case of low traffic demand, where nodes sleep most of the time. Key design aspects, which characterize the duty-cycling efficiency are the sleep and wake-up scheduling at the sensors [107]. Schemes with fixed wake-up and doze time lengths, and, eventually, sleep ratios [85] perform well when the traffic demand remains fairly stable over time. In case of temporal variations in traffic workload, agile duty-cycling schemes [107] adapt the durations of wake-up and sleep time for higher energy savings. Further efficiency can be achieved through *dynamic* duty-cycling schemes [108], where *idle listening* is restricted to a short time interval in the begining of the wake-up period, or where appropriate signaling enables nodes to dynamically end the wake-up time upon completion of traffic exchange.

WSNs achieve further energy saving gains when employing interference-aware sleep transition policies [109]. In Paper D, WSN devices sense the channel in the beginning of a wake-up period and transit immediately to sleep mode, if channel activity is detected, so as not to risk a possible frame collision due to overlapping transmissions with interfering radio activity.

Despite the undeniable energy savings, duty-cycling can introduce a significant delay overhead in multi-hop traffic delivery, particularly in case sensors sleep for long periods. *Opportunistic routing* under duty-cycling aims at minimizing the delay overhead, by dynamically relaying sensor traffic via any neighboring nodes that are awake and geographically closer to the destination node [110]. From the system-optimization perspective, the duty-cycling ratio may be jointly optimized along with multi-path routing and duty-cycle scheduling, under target delivery delays, and connectivity requirements, the energy efficiency of the sensor network can be minimized by determining optimal values for the sleep ratio and the wake-up schedule of the sensors [111].

A major challenge in WSN duty-cycling is how to achieve schedule-synchronization between the communicating sensor nodes. Exessive signaling overhead, large node populations, node mobility, or churn do not allow for controlling the duty-cycle schedules of the network nodes in a centralized fashion. Transmitter-receiver *rendezvous* in time is, therefore, achieved, on the basis of transmitter-initiated duty-cycle MAC protocols [112], where potential transmitters use frame *preambles* to wake-up the intended receivers. Approaches like [113] rely on periodic channel sampling checking for preambles that indicate upcoming packet transmissions. In the same context [114] reduces excessive preambling applying short *strobbing*, which additionally embedds target receiver addressing to wake-up only the intended receiver. Instead of using preambling, [115] employs *opportunistic schedule learning*

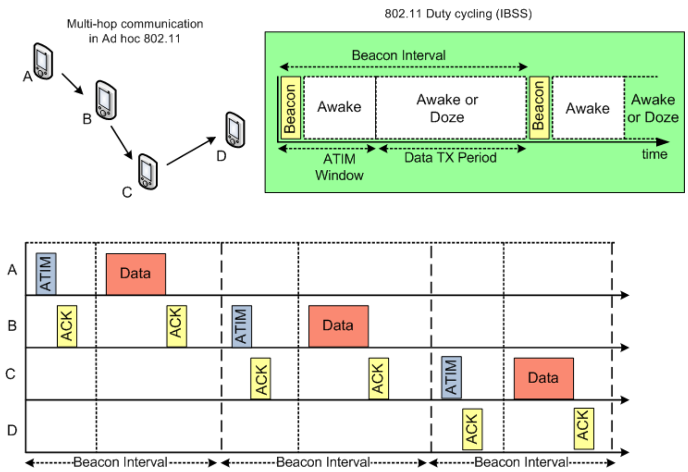

Figure 3.1: Power-saving mode in IEEE 802.11 ad hoc networks.

where WSN devices obtain the scheduling information of nodes within their physical neighborhood by overhearing data transmissions, while in [116] synchronization is achieved through periodically broadcasting scheduling information.

Duty-cycle synchronization is, however, not perfect due to hardware imperfections leading to CPU clock drifts at the WSN devices, and thus, synchronization *gaps* need to be taken into consideration when designing duty cycling-based protocols for WSNs. A common approach to mitigate the effect of synchronization offsets is by slightly increasing the duration of either preamble transmissions or idle listening [116] [113]; a similar approach is implemented in Paper D where sensors wait for a period equal to the maximum synchronization offset before attempting frame transmissions, to guarantee that the intented receiver is awake.

3.3 Duty-cycling in WLAN Ad hoc Networks

The energy consumption of the 802.11-based radio operation is significantly higher compared to 802.15.4-based radio link layers – commonly used in WSN devices – offering, in exchange, higher communication ranges and transmission rates. Such communication characteristics may be beneficial in sensor applications involving generation of a large amount of data traffic. In addition, 802.11 enables sensor devices to interact directly with consumer electronics, such as smartphones, tablets or laptops, that is, market segments where WLAN connectivity dominates over alternative wireless technologies.

However, due to the large transmission energy consumption, 802.11 radio operations can quickly drain the batteries of energy-constrained WLAN-enabled devices.

Therefore, 802.11 duty-cycling, as a means of power-saving, is crucial for enabling WLAN connectivity in WSN and IoT applications [117]. For this reason radio duty-cycling, has been standardized for IEEE 802.11 for both infrastructure (BSS) and ad hoc (IBSS) network mode, and is denoted as *Power Saving Mode* (PSM) [88]. In 802.11 infrastructure networks, stations in power-save mode remain in doze state if they have no traffic to transmit, and wake-up periodically in order to check whether they need to receive data from the access point. Traffic indications for each associated station are embedded in the beacon frame sent periodically by the access point.

In 802.11 ad hoc networks, all stations have synchronized duty-cycle schedules, and compete for a beacon transmission at the beginning of a duty-cycle period (Fig. 3.3), defined as *beacon interval*. Stations in power saving mode must transit to the *awake* state at the beginning of the duty-cycle. The stations announce pending data traffic to other stations by transmitting unicast, short traffic *announcement* (ATIM) frames. ATIM frames are transmitted and acknowledged during the ATIM *window*, during which all stations are awake. After the expiration of the ATIM window, stations transit to doze state for the remaining of the duty-cycle, if they have not been involved in an ATIM/ACK message exchange.

802.11 PSM defines a non-adaptive duty-cycle scheme for decreasing the idle listening at WLAN stations. Interesting research directions in the literature propose protocol enhancements for the 802.11 PSM operation in infrastructure WLANs [118]–[125], involving load driven wake-up scheduling, and joint time division and power control optimization, aiming for further energy preservations through higher achievable sleep ratios. In ad hoc WLANs enhancing the standard PSM involves the introduction of mechanisms for early transition to the doze state [123], [126]–[129], by including additional information in the ATIM frames [126], or by delaying a beacon transmission attempt [123], indicating, implicitely, the lack of pending traffic.

A key approach towards higher sleep ratios is the optimization of the ATIM window length. [127] maximizes the percentage of time the stations remain in doze state by optimizing the duration of the ATIM window subject to throughput constraints for a given traffic workload at the stations. A major challenge in the ad hoc 802.11 PSM is the signalling overhead, imposed by the unicast ATIM frames at each beacon cycle. PSM signaling may be significant in case of multiple concurrent source-destination traffic flows in a WLAN. Exploiting ATIM frame overhearing [130], [131] and deferring from ATIM transmissions is a promising solution towards lower PSM signaling overhead.

Despite the achieved energy savings, PSM results in significant frame delivery delays, as data may need to be buffered at intermediate stations, and delayed until the following beacon interval, when a new ATIM exchange process will notify the next-hop station towards the final destination to remain active and receive the packet (Fig. 3.3). To limit the *multi-hop end-to-end latency* solutions target MAC and routing *cross-layer* approaches, classified as *static* [128] – where the ad hoc networks are organized hierarchically forming a back-bone with PSM-disabled stations – or *on-demand* [132], where stations temporarily disable duty-cycling, if they are notified from on-demand routing protocols that they may need to relay traffic. Inversely, the routing protocol may on-demand select the packet forwarding paths based on knowledge of the current power saving status of the stations [133].

The challenge of decreasing the end-to-end latency in multi-hop 802.11 ad hoc networks can be addressed effectively, if stations that implement duty-cycling can dynamically adapt to instantaneous end-to-end traffic demand and defer from transitions to doze state, so that packets can be forwarded within the same beacon interval. This can be realized through cognitive path prediction mechanisms, where stations infer whether they need to remain awake, based on overheard traffic announcements associated with past end-to-end transmission flows [134]. Such approaches achieve high energy and delay efficiency, paticularly in networks with traffic bursts that are long enough so that stations learn the end-to-end path flows and remain awake until the whole data stream is forwarded to the destination station. In scenarios with sporadic, or very dynamic traffic workload, the performance of path learning mechanisms is limited. In such cases, the objective for joint energy and delay efficiency can be addressed effectively, if stations can immediately infer the final destination of an 802.11 frame and wake-up all involved stations on the routing path, at the event of frame generation or reception. In Paper E we address the above issue by proposing a cross-layer approach, where WLAN stations embed the MAC address of the final destination of a WLAN packet inside the ATIM message. Upon receiving ATIM frames, the stations can determine the destination node of a pending 802.11 packet, and can, therefore, forward the received notification to the next-hop station in the routing path, in the current ATIM window. Under such scheme all stations involved in the end-to-end delivery will be notified to remain awake in the current beacon interval. Therefore, the WLAN packet may arrive at the final destination with minimum delay overhead.

Chapter 4

Analytic Models, Methods & Evaluation Tools

This Chapter presents an overview of the main analytic scientific methods and evaluation tools that are used in the context of this thesis. We begin with the main theoretic background for spectrum sensing techniques and for interference modeling in wireless networks. Spectrum sensing has been studied in Paper A, while interference modeling has been considered for the cognitive MAC design in Paper B. We give a brief introduction on stochastic modeling in wireless networks that has been considered extensively in this work. We continue, by presenting the basic theoretic tools for distribution fitting, parameter estimation, and stochastic model validation, which we later employ in Papers C and D for WLAN spectrum occupancy characterization. We close the Chapter by introducing, briefly, our simulation platforms and implementation tools, based on which we evaluated our protocol design proposals in Papers B and E.

4.1 Modeling of the Physical Interference

As discussed in Section 2.2 the physical interference model aim at describing the success of a frame transmission in the presence of temporary overlapping transmissions in the neighborhood of the receiving device. Therefore, the interference model relies on the underlying signal propagation model.

Under a *path-loss*-based signal attenuation model [135], the received signal power, $P_{Rx}(r)$, degrades with the distance, $r > 0$ between the transmitting and receiving device:

$$P_{Rx}(r) = P_0 \cdot P_{L_0} r^{-\eta} \tag{4.1}$$

where P_{L_0}, η denote the signal attenuation at a reference (one meter) distance, and the path-loss *exponent*, respectively. In order to correctly decode a received packet, a terminal needs to receive it with a *Signal to Noise plus Interference Ratio* (SINR) greater than a given threshold, ζ_{SINR}. Assuming the existence of a single interfering node at distance R_{INT}, the SINR under a path-loss model becomes:

$$\mathrm{SINR} = \frac{P_0 P_{L_0} r^{-\eta}}{P_{\mathrm{INT}} P_{L_0} R_{\mathrm{INT}}^{-\eta} + \sigma_N^2} \tag{4.2}$$

where $P_{\mathrm{INT}}, \sigma_N^2$ denote the power of the interfering signal and AWGN, respectively. The considered SINR threshold combined with the path-loss channel model result in a *disk* interference model, that is a circular interference zone around the receiving terminal, with *interference radius*, $R_{\mathcal{I}}$:

$$R_I(r, \zeta_{\mathrm{SINR}}, P_{\mathrm{INT}}, P_0) \triangleq \sqrt[\eta]{\frac{\zeta_{\mathrm{SINR}} P_{\mathrm{INT}} P_{L_0}}{P_0 P_{L_0} r^{-\eta} - \zeta_{\mathrm{SINR}} \sigma_N^2}}. \tag{4.3}$$

In the event of a temporal overlap between a frame reception and a transmission within the interference zone defined by (4.3), the outcome is a frame collision, resulting in a packet loss event. It is clear that under a fixed SINR threshold the interference radius can be decreased by either increasing the transmission power, P_0, or by decresing the transmission distance, r.

The disk interference model is ideal, as it presents a clear geographic boundary, between the area where frame collision occurs with probability 1, and the area where interference from overlapping transmissions is not harmful. In the presence of shadow fading on the channel, the disk interference model is no longer valid, as the collision events depend on the instantaneous shadowing gains on the transmission and on the interfering link.

Under log-normal shadowing [135] the shadowing *gain* on a transmission link is modelled by a log-normal random variable, thus, (4.1) is extended as:

$$P_{Rx}(d, \zeta) = P_0 \cdot P_{L_0} \cdot r^{-\eta} \cdot 10^{\zeta/10}, \tag{4.4}$$

where ζ is an instance of a zero-mean Gaussian variable, Z with standard deviation, σ_{sh}:

$$f_Z(\zeta) = \frac{1}{\sigma_{\mathrm{sh}}\sqrt{2\pi}} e^{-\frac{\zeta^2}{2\sigma_{\mathrm{sh}}^2}}.$$

Consider that Z_0, Z_{INT} denote the shadowing gains on the transmission and on the interference link. Assuming identical and independent distributions, the instantaneous interference radius $R_{\mathcal{I}}$ is a function of the shadowing realizations:

$$R_{\mathcal{I}}(r, \zeta_{\mathrm{INT}}, \zeta_0, P_0, P_{\mathrm{INT}}) = \sqrt[\eta]{\frac{\zeta_{\mathrm{SINR}} P_{\mathrm{INT}} P_{L_0} 10^{\zeta_{\mathrm{INT}}/10}}{P_0 P_{L_0} r^{-\eta} 10^{\zeta_0/10} - \zeta_{\mathrm{SINR}} \sigma_N^2}}. \tag{4.5}$$

In addition, channel shadowing has an impact on the performance of spectrum sensing. The missed detection probability, p_{MD}, defined in Section 2.2, depends on the received signal power at the sensing device, that is a function of the shadowing

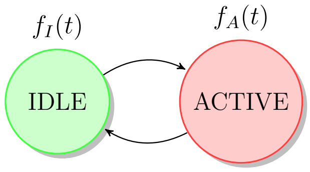

Figure 4.1: A generic two-state stochastic channel occupancy model

gain. Assuming that the gains, ζ_{INT}, is constant within a spectrum sensing period, t_s, the missed detection probability must be averaged over the distribution of the shadowing gain:

$$p_{\text{MD}}(t_s, R_{\text{INT}}) \triangleq \int_0^\infty p_{\text{MD}}(t_s, R_{\text{INT}}, \zeta_{\text{INT}}) f_Z(\zeta) d\zeta, \tag{4.6}$$

while the channel shadowing, clearly, has no effect on the false alarm probability, p_{FA}.

As we show in Paper B channel shadowing introduces uncertainty in the spatial distribution of the interfering sources resulting in lower transmission efficiency in the flat coexistence scenario.

4.2 Stochastic Models for Channel Activity in Wireless Networks

Background

The *channel activity*, or channel usage, in wireless networks is, in general, a stochastic process that reflects the status of the wireless medium, whether it is *active* or *idle*. The channel activity is strongly correlated with the traffic arrival process at the network nodes [136][137]. Its stochastic properties depend, additionally, on the medium access protocol that involves, in general, randomized channel access operations [33][60].

Based on the above consideration, we can use, in the simplest scenario, a *two-state* model to describe the temporal evolution of the channel status in a wireless network. This model is shown in Fig 4.1. The generic functions, $f_{\text{A}}(t), f_{\text{I}}(t)$, denote the probability distributions of the active, and idle channel durations, respectively. As the channel status constantly alters between active and idle state, we can define the stochastic processes, P_{T_A}, P_{T_I}, that describe the sequences of active and idle channel period durations. Thus, $T_I(k)$, denotes the duration of the k-th idle period. $T_I(k)$ is randomly distributed with density function $f_{\text{I}}(t)$.

In general, the random processes, P_{T_A}, P_{T_I}, are not *white*, that is, the process sample values at different sequence indexes are correlated. The correlation is quantitatively evaluated by the *auto-correlation functions*, $R_{T_A}(\tau), R_{T_I}(\tau)$, which are defined as:

$$R_{T_A}(\tau) = \frac{\mathrm{E}[(T_A(k) - \mu_{T_A})(T_A(k+\tau) - \mu_{T_A})]}{\sigma^2_{T_A}}. \tag{4.7}$$

$$R_{T_I}(\tau) = \frac{\mathrm{E}[(T_I(k) - \mu_{T_I})(T_I(k+\tau) - \mu_{T_I})]}{\sigma^2_{T_I}}. \tag{4.8}$$

Under the assumption of the absence of correlation, the channel activity model is classified as *semi-Markovian*[61]. The model becomes a Markovian one, if, additionally, $f_{\mathrm{A}}(t), f_{\mathrm{I}}(t)$ are exponential distributions [23].

To capture more accurately the behavior of the channel status, we can extend the two-state model to a finite state model, where, in each state, the channel is either active or idle, however, the durations of the active or idle periods are not drawn from the same distributions. Multi-state models can better capture the behavior of the channel status, as a function of traffic arrival and protocol dynamics, at the expense of higher complexity.

Under wireless coexistence scenarios, discussed in Chapter 2, a wide range of network protocol mechanisms may be optimized based on the knowledge of the stochastic patterns of the channel activity. The accuracy of the applied models is critical for the performance of protocol optimizations. In the remainder of this Section we present a brief overview of the analytic tools and methodologies for model parameter estimation and verification, that have used in the context of this thesis.

Parameter estimation techniques

Parameter estimation refers to the procedure of determining the parameters of the functions that constitute the model components, based on a finite set of samples collected from the actual random process that is the subject of our modeling. The estimation of parameters is conducted using distribution fitting techniques, i.e. we determine the appropriate parameter values, for which the analytic distribution matches closely with the *empirical* one that is generated using the collected samples.

Maximum likelihood estimation

Consider a random variable T probability density function, $f_T(t|\boldsymbol{\theta}), t \in \mathbb{R}$, where, $\boldsymbol{\theta} = \{\theta_1, \ldots, \theta_K\}$ denotes the vector of the parameters of the density function. The estimation of the parameter set relies on a set of M samples, (or realization) of the random variable, T: $\{t_1, \ldots, t_M\}$.

Based on the collected samples, the *maximum likelihood estimator* (MLE), determines the set of parameters as the solution of the following maximization problem:

$$\boldsymbol{\theta}^* = \{\theta^*_1, \ldots, \theta^*_K\} = \arg \max_{\theta_1, \ldots, \theta_K} f_{T_1,\ldots,T_M}\left(t_1, \ldots, t_M | \theta_1, \ldots, \theta_K\right) \tag{4.9}$$

where $f_{T_1,\ldots,T_M}\left(t_1, \ldots, t_M | \theta_1, \ldots, \theta_K\right)$ denotes the joint distribution density considering all the collected samples. Assuming an uncorrelated sequence of distribution realizations, (4.9) reduces to

$$\boldsymbol{\theta}^* = \{\theta_1^*, \ldots, \theta_M^*\} = \arg\max_{\theta_1,\ldots,\theta_K} \prod_{m=1}^{M} f_{T_m}\left(t_m|\theta_1, \ldots, \theta_K\right). \tag{4.10}$$

or, if considering the *log*-likelihood:

$$\boldsymbol{\theta}^* = \{\theta_1^*, \ldots, \theta_M^*\} = \arg\max_{\theta_1,\ldots,\theta_K} \sum_{m=1}^{M} \log\left[f_{T_m}\left(t_m|\theta_1, \ldots, \theta_K\right)\right]. \tag{4.11}$$

We derive the numerical solution of (4.10) by forcing the partial derivatives to zero:

$$\boldsymbol{\theta}^* = \{\theta_1^*, \ldots, \theta_M^*\} = \arg_{\theta_1,\ldots,\theta_K} \left\{ \frac{\sum_{m=1}^{M} \partial \log\left[f_{T_m}\left(t_m|\theta_1, \ldots, \theta_K\right)\right]}{\partial\theta_K} = 0, \forall k \right\}. \tag{4.12}$$

In Paper B we apply a MLE estimator for deriving the parameters of the generalized Pareto distribution [138] that is employed for modeling the heavy tailed behavior of the 802.11 white spaces, based on a modified estimator developed in accordance with [139], to account for a left-truncated nature of the white space distribution.

Estimation in the Laplace domain

The MLE-based estimation can be applied when the closed-form expression of the probability density function, $f_T(t|\boldsymbol{\theta})$, exists. There are, however, cases of distributions that lack a closed form expression in the probability domain. Such cases include, most commonly, composite variables that are the result of the superposition of individual, random variables.

In some particular scenarios, where this superposition comprises summations of uncorrelated variables, it is possible to derive a closed-form expresion in the *Laplace domain* of a variable,

$$f^*_{T|\boldsymbol{\theta}}(s) = \int_0^\infty f_T(t;\boldsymbol{\theta})e^{-st}dt. \tag{4.13}$$

by expoiting the Laplace transform (LT) property that the sum of independent random variables leads to a joint density function, whose LT is the product of the individual transforms of each variable:

In case of finite discrete random summations, the derivation of the LT expression requires the *generating function* of the discrete distribution that models the random sum. Consider, for instance, that we need to calculate the LT of the following variable:

$$\mathcal{T}_{\mathcal{N}} = \sum_{i=1}^{\mathcal{N}} T^{(i)}, \tag{4.14}$$

where $T^{(i)} \propto T$ and, $\mathcal{N}$ is a discrete variable with probability mass function $p_{\mathcal{N}}$. The generating function of the random variable $\mathcal{N}$ is:

$$\mathcal{G}_{\mathcal{N}}(z) = \sum_{k=0}^{\infty} p_{\mathcal{N}}(k) z^k. \tag{4.15}$$

The, the LT of $\mathcal{T}_{\mathcal{N}}$ is given by:

$$f^*_{\mathcal{T}_{\mathcal{N}}}(s) = \mathcal{G}_{\mathcal{N}}\left(f^*_T(s)\right). \tag{4.16}$$

The above property is applied in [75] and in Paper C, where we derive the Laplace transform of the partially-observed WLAN idle time distribution, as a geometrically distributed sum of WLAN cycles, consisting of consequtive idle an active WLAN periods. Due to this complex combination, the idle time distribution lacks a closed-form expression. Therefore, as MLE can not be applied for deriving the optimal distribution parameters, we develop a heuristic estimation method that relies on the one-to-one correspondence between the Laplace transform and the probability density function [76]. We determine the optimal values for the parameter set as the solution to the following minimization problem:

$$\boldsymbol{\theta}^* \triangleq \{\theta_1, \ldots, \theta_K\} = \arg \min_{\theta_1,\ldots,\theta_K} \frac{1}{S} \sum_{k=0}^{S} \left[f^*_T(s_k|\boldsymbol{\theta}) - f^*_{Te}(s_k;\boldsymbol{\tau})\right]^2 \tag{4.17}$$

where $\mathcal{S} = \{s_0, \ldots, s_S\}$ is a finite discrete subset of the $s-$domain, and $f^*_{Te}(s_k;\boldsymbol{\tau})$ is the *empirical* LT with respect to the parameter set, $\boldsymbol{\theta}$, calculated from the collected distribution sample sequence, $\boldsymbol{\tau} = \{t_1, \ldots, t_M\}$. In Paper C we show that the empirical LT of a random distribution can be calculated on the fly, from the sample sequence as follows:

$$f^*_{Te}(s_k;\boldsymbol{\tau}) = \frac{1}{M} \sum_{m=1}^{M} e^{-s_k t_m} \tag{4.18}$$

Discussion We stress that the outcome of the minimization of (4.17) does not necessarily correspond to the MLE-based estimation of (4.9). The developed heuristic method is, instead, based on the uniqueness of the Laplace transformation, and on the a-priori considered assumption that random distributions with similar Laplace transforms exhibit similar stochastic behaviors. The performance of the proposed heuristic method is assessed in Paper C and in [75], where we evaluate the parameter estimation errors when the heuristic is performed on sample sequences with given parameter sets. In [75] we study the effect of the sample seuqence lengths on the parameter estimation accuracy. We show that the proposed algorithm leads to efficient parameter estimation under sequence lengths in the order of 10^2 to 10^3, while the estimation errors are practicaly eliminated under input sequences with a length of 10^4 to 10^5 samples. The following Section introduces the reader to stochastic optimization-based methodologies for solving the optimization problem in (4.17).

Discrete stochastic optimization

Optimization problems of the form

$$\mathcal{K}_n^* := \arg \min_{\mathcal{K}_n \in \boldsymbol{\mathcal{K}}} \{c(n)\} \tag{4.19}$$

can be solved by applying traditional optimization tools [140], when the objective function, $c(n)$, has a deterministic and closed analytic form. Instead, when the objective function includes stochastic components, optimization is, generally, a harder problem, as the exact relation between the function value with respect to the variables under optimization is obscured. *Stochastic optimization* constitues a general category of methodologies for solving optimization problems, whose objective functions are functions of random variables. Consider the simplest setting of a discrete stochastic optimization problem:

$$\boldsymbol{\mathcal{K}}^* = \arg \min_{\mathcal{K}_n \in \boldsymbol{\mathcal{K}}} \{c(n) = E[X_{\mathcal{K}_n}]\} \tag{4.20}$$

where $c(n) = E[X_{\mathcal{K}_n}]$, is the expectation of a random variable X, whose distribution depends on the variables, $\mathcal{K}_n$, under optimization. *Simulation-based* techniques are employed, when the expectation $E[X_{\mathcal{K}_n}]$ can be determined based on a sequence, $\{X_{\mathcal{K}_n}\}$, of observations obtained via simulations. The optimization problem is *discrete*, when the sample spaces of the variables under optimization are countable sets. Brute force methods, including an exhaustive calculations over all sample space points are, clearly, inefficient for large sample spaces. Approaches such as [78], address the problem by constructing a discrete Markov model over the sample space and study the conditions for convergence to global minima of the objective function. [141] proposes a sample average approximation method for solving discrete stochastic optimization problems with uncostrained objective functions with finite variance. The work assumes a white sampling process over the random objective function and shows that the proposed methods converges to the optimal values under un-constrained sample sizes. In [142] simulation-based stochastic programming is extended to cover constrained optimization problems. A typical consideration in discrete stochastic optimization theory is the covergence rate of the proposed techniques [78], [141], [143], [144]. This consideration is critical in case the stochastic objective function includes time-variant components, and, therefore, time-variant global minimizers. [145] proposes a random-search, Markov-based algorithm that exhibits fast-convergence properties, thus, performing well under stochastic objective functions with high temporal dynamics.

In the context of our work the derivation of the optimal values of (4.17) shall be combined with the process of collecting the sample sequence, $\{t_1, \ldots, t_M\}$, on the basis of an iterative algorithm, where the new samples refine the output of the optimal values. This approach is similar to the ones presented in [78], [141] and has two important advantages. First, the collected samples do not need to be stored in advance before the estimation process begins, limiting the required algorithm memory. Second, by enforcing smart stopping rules, the execution time – with respect to the number of iterations – can be reduced. In the following we detail the desciption of the adopted discrete stochastic optimization methodology.

The iterative stochastic optimization algorithm [78] aiming at solving the problem of Eq. (4.20), has a discrete and finite set of *states*,

$$\boldsymbol{\mathcal{K}} \triangleq \{\mathcal{K}_1, \ldots, \mathcal{K}_K\}$$

that correspond to the set of possible outcomes of the algorithm. Denote by $\boldsymbol{\mathcal{L}} = \{\mathcal{L}_1, \ldots, \mathcal{L}_L\} \subset \boldsymbol{\mathcal{K}}$ the set of global minimizers of the function c, i.e.

$$\forall \mathcal{L}_i \in \boldsymbol{\mathcal{L}}, \mathcal{K}_n \in \boldsymbol{\mathcal{K}} \setminus \boldsymbol{\mathcal{L}},\ c\left(\mathcal{L}_i\right) < c(\mathcal{K}_n) \tag{4.21}$$

$$\forall i, j = 1, 2, ..., L,\ c(\mathcal{L}_i) = c(\mathcal{L}_j). \tag{4.22}$$

Stochastic optimization algorithms take $\{X_{\mathcal{K}_n}\}$ as the input and outputs an element $\mathcal{L}_i \in \boldsymbol{\mathcal{L}}$. The algorithm is *iterative*, that is, it involves a *search* process that repeats itself as more samples of the random sequence are obtained from the sampling process.

Searching initiates from an arbitrary state, $\mathcal{K}_i \in \boldsymbol{\mathcal{K}}$. In each iteration step, m, the process selects a new state, $\mathcal{K}_j \neq \mathcal{K}_i$, uniformly at random, and obtains the observation of a random variable $Z_{l_m}^{\mathcal{K}_i \to \mathcal{K}_j}$, which is a function of the random variables $\{X_{\mathcal{K}_i}\}_{l_m}$, $\{X_{\mathcal{K}_j}\}_{l_m}$. In general, l_m is a function of the iteration step, m. In most of the cases, however, it is convenient to define l_m as the total number of random observations obtained until iteration m. $\{X_{\mathcal{K}_j}\}_{l_m}, \{X_{\mathcal{K}_i}\}_{l_m}$ denote the current estimation of $c(j), c(i)$, respectively, given the collected samples. The stochastic optimization algorithm moves to the new state $\mathcal{K}_j$, if $Z_{l_m}^{\mathcal{K}_i \to \mathcal{K}_j} > 0$.

We denote by $\mathcal{K}_m$ the algorithm state after iteration m and with $Q_m(\mathcal{K}_n)$ the *popularity* of state $\mathcal{K}_n$, that is the total number of times the algorithm has visited (or remained at) state $\mathcal{K}_n \in \boldsymbol{\mathcal{K}}$ until iteration m. The output of the algorithm is chosen as the most popular state.

Discussion Due to the random selection of the next candidate state at each iteration step, the algorithm corresponds to a discrete time, discrete space Markov process, where the state space is the set $\boldsymbol{\mathcal{K}}$. The transition probabilities, however, are time-variant as they depend on the current number of collected samples that refine the empirical distribution of the sampled process.

In [78] it is shown that the algorithm converges almost surely to a minimizer of $c(n)$, that is, a member of $\boldsymbol{\mathcal{L}}$, after sufficiently large number of iterations, if the following conditions hold:

Condition 1. *For each* $\mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}$ *and* $l \in \mathbb{N}$, *there exists a random variable* $Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)}$ *such that the limit* $\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)} > 0\}$ *exists for all* $\mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}$ *and for all* $\mathcal{K}_i \in \mathcal{L}, \mathcal{K}_j \notin \mathcal{L}, \mathcal{K}_n \neq \mathcal{K}_i, \mathcal{K}_j$, *and* $l \in \mathbb{N}$,

$$\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_j \to \mathcal{K}_i)} > 0\} > \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)} > 0\}, \tag{4.23}$$

$$\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_n\to\mathcal{K}_i)} > 0\} \geq \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_n\to\mathcal{K}_j)} > 0\}, \tag{4.24}$$

$$\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i\to\mathcal{K}_n)} \leq 0\} \geq \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_j\to\mathcal{K}_n)} \leq 0\}. \tag{4.25}$$

Condition 2. $\{l_m\}$ *is a sequence of positive integers such that* $l_m \to \infty$ *as* $m \to \infty$.

Condition 3. *The Markov matrix* $\mathcal{P}$ *defined in the following equations is irreducible.*

$$\mathcal{P}(\mathcal{K}_i, \mathcal{K}_j) = \frac{1}{K-1} \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i\to\mathcal{K}_j)} > 0\} \quad \forall \mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}, \mathcal{K}_i \neq \mathcal{K}_j, \tag{4.26}$$

$$\mathcal{P}(\mathcal{K}_i, \mathcal{K}_i) = \frac{1}{K-1} \sum_{\mathcal{K}_j \in \boldsymbol{\mathcal{K}} \setminus \{\mathcal{K}_i\}} \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i\to\mathcal{K}_j)} \leq 0\} \quad \forall \mathcal{K}_i \in \boldsymbol{\mathcal{K}}. \tag{4.27}$$

The above result is asymptotic, i.e. convergence is guaranteed after an infinite number of iterations. In practical cases, however, a stopping rule is required to limit the algorithm execution time. In [75] we define both the maximum number of iteration steps, and a stopping rule based on the number of consequent iteration steps that the algorithm remains in the same state. The maximum number of iterations is determined by the length of the sample sequence and the number of samples integrated into the algorithm at each iteration step.

In Paper C we apply the described stochastic optimization algorithm for the estimation of the distribution parameters of the 802.11 idle period duration, which presents a closed form expression in the Laplace domain, and show that the aforementioned conditions are satisfied ensuring the convergence of the algorithm.

Model validation tools

Stochastic model validation provides us with an analytic framework for verifying whether a physical random process can be accurately described by a stochastic model. In the context of this thesis, model validation is performed by analytic techniques, discussed briefly in this Section.

Goodness-of-fit

First, we aim at evaluating how well a derived analytic stochastic model fits a set of real observations originating from a considered random process; a procedure described as a *goodness-of-fit* evaluation.

D-value: Goodness-of-fit is quantitatively assessed based on the *D-value* of the *Kolmogorof-Smirnoff* test, which is defined as the supremum of the differences between the estimated analytic distribution model and the empirical distribution generated by the set of collected samples:

$$D = \sup_{t_m \in \boldsymbol{\tau}} \left| F_T(t_m; \hat{\boldsymbol{\theta}}) - F_{T_{\text{emp}}}(t_m; \boldsymbol{\tau}) \right|. \tag{4.28}$$

In (4.28) $\boldsymbol{\tau}$ is a sequence of real samples collected from the considered random process, $\hat{\boldsymbol{\theta}}$ is the vector of estimated parameters, while $F_T, F_{T_{\text{emp}}}$ denote the analytic and empirical cumulative distribution functions, respectively, which are evaluated on the values of the collected samples. A low D-value indicates the good fitting performance of the analytic model. We underline, however, that the D-value is a conservative goodness-of-fit metric, as it considers the supremum of the point-wise difference between the two functions, instead of the average.

Kolmogorof-Smirnoff test: The D-value measures the fitting offset between the empirical distribution and its candidate analytic fit. A goodness-of-fit *test* assesses the probability that the collected samples of a given random process do originate from the fitted analytic distribution. In this thesis we employ the *two-sample* Kolmogorof-Smirnoff (K-S) test [74]. In particular, we evaluate the K-S *null hypothesis*, i.e. the probability that a sequence of samples generated from the candidate analytic fit can originate from the same distribution as the sequence of the real collected samples. The evaluation is done considering the two-sample K-S statistic:

$$K_n = \sqrt{\frac{n}{2}} \sup_{t_m \in \boldsymbol{\tau}, \hat{t}_m \in \hat{\boldsymbol{\tau}}} \left| F_{T_{\text{emp}}}(t_m; \boldsymbol{\tau}) - F_T(\hat{t}_m; \hat{\boldsymbol{\tau}}, \hat{\boldsymbol{\theta}}) \right|, \tag{4.29}$$

where $\hat{\boldsymbol{\tau}}$ denotes the sample sequence from the fitted analytic distribution, and n is the length of both sequences. The null hypothesis is assessed by calculating the $p-$value of the test, that is the probability of obtaining a test statistic, K_n, at least as extreme as the observed one. The null hypothesis is rejected at a *significance level* $\alpha \in (0, 1)$, if $K_n > K_\alpha$, where K_α is the *critical* value [74] defined as $K_\alpha = k : \Pr\{K_n > k\} < \alpha$. Typical values of the significance level are $\alpha = 0.1$ or $\alpha = 0.05$.

In Paper B we apply the two-sample K-S test in order to verify or reject the stochastic model that aims at capturing the random process of the 802.11 idle channel durations.

Whiteness property validation

White random processes have the fundamental property that the generated samples are uncorrelated random variables. Such a property is often desired, as it simplifies the stochastic analysis of complex systems. It is, however, not always possible to either justify or verify the assumption of a white random process based on the system functional properties. Therefore, before being introduced as an assumption in the system model, the whiteness property of a random process needs to be experimentally validated.

The whiteness of a stochastic process is, traditionally, verified by inspecting the *autocorrelation* of the sample series generated by the process:

$$R_T(i) = \sum_{m=0}^{n-i-1} t_{m+i} \cdot t_m, \quad t_m \in \mathbb{R}, \ \forall m \tag{4.30}$$

A non-zero *lag-i* autocorrelation, $i > 0$, implies lack of independence among the generated process samples. In most of the cases, howerver, we need to decide on the whiteness of a sample sequence based on a limited number of input samples, which, in general, results in $R_T(i) \neq 0$, for $i > 0$. One solution to this challenge is to compare the statistical behavior of the lag-1 autocorrelation of the input sequence against the lag-i autocorrelation of a *white reference*, that is, a sequence of random samples assumed to be uncorrelated. In case the autocorrelation outputs of the compared processes have significantly different statistical properties, we can safely assume that the input sequence exhibits correlation among the generated samples, and, therefore, the whiteness is not validated. In Paper B we design a test for independence based on this principle, and use it for the characterization of the 802.11 channel usage process in terms of whiteness.

4.3 Simulation Tools

Network simulation tools enable the evaluation of networking scenarios where the complexity limits the applicability of analytically-based performance studies. The particular selection of the appropriate simulation tools is based on the following set of criteria.

An appropriate network simulation tool must provide accurate mathematical models for the real phenomena that are expected to affect the network performance, such as signal propagation and interference models or packet error rate models. A *modular*, or *component-based* structure of a network simulation is desirable, as it facilitates the protocol design and evaluation, allowing for direct testing of a specific network component (e.g. a protocol) by plugging it in the appropriate position in the protocol stack. Simulators should also be *extensible* to enable the design of additional features or components without major modifications in the rest of the simulator platform.

NS-Miracle: The NS-Miracle framework [146], which is based on the popular NS-2 simulation platform, fulfills the aforemention design criteria, and has, therefore, been selected as the platform for the simulation-based evaluation within the context of this thesis. In addition, NS-Miracle offers a broad set of wireless network protocols already implemented and extensively tested, allowing for rapid implementation and evaluation of customized network stacks. Our work in Paper D and in [24], [75], [109] benefits from the feature-rich implementations of the IEEE 802.11 and 802.15.4 protocol variations, while the detailed NS-Miracle physical layer and channel modeling makes it higly attractive for the wireless coexistence scenarios discussed in Chapter 2. The simulation-based study in Paper D is applied to validate the numerical evaluation of the proposed cognitive access mechanism, which is conducted based on a simplifying set of model assumptions and approximations for analytic tractability.

MiXiM framework: The MiXiM framework is an extension of the Omnet++ simulation platform featuring similar libraries for wireless network protocols as NS-Miracle. MiXiM facilitates the debugging of the implementation code, mainly due to its graphical accessories that offer a direct, real-time illustration of network protocol operations. In addition, its statistic toolboxes facilitate the collection of measurement data and its aggregation into network performance statistics. In [59] we have used MiXiM's detailed traffic generation libraries for implementing the various 802.11 traffic workload scenarios for the purpose of WLAN channel occupancy characterization.

Jemula: The *Java Emulator (Jemula)* framework [147] has been used for the simulation development in the context of our work in [148] [149]. Jemula facilitates protocol development and debugging owing to its Java-based implementation, and offers an advanced, real-time graphical interface for protocol operations. Its 802.11 protocol library makes Jemula suitable for the evaluation of the proposed power-save 802.11 MAC enhancements; the lack of detailed physical layer modeling is, however, a major challenge not only for wireless coexistence scenarios, but also for standalone, dense ad-hoc 802.11 network deployments with frequent frame collisions.

Chapter 5

Summary of Original Work

Paper A: Spectrum sharing with low power primary networks
Ioannis Glaropoulos, and Viktoria Fodor
Published in *Proc. of IEEE Dynamic Spectrum Access Networks (DySPAN)*, 2014.

Summary: Access to unused spectrum bands of primary networks requires a careful optimization of the secondary cooperative spectrum sensing, if the transmission powers in the two networks are comparable. In this case the reliability of the sensing depends significantly on the spatial distribution of the cooperating nodes. In this paper we study the efficiency of cooperative sensing over multiple bands, sensed and shared by a large number of secondary users, which form an ad-hoc cognitive network. We show that the per-user cognitive capacity is maximized, if both the number of bands sensed by the secondary network as a whole, and the subsets of these bands sensed by the individual nodes are optimized. We derive the fundamental limits under different sensing duty allocation schemes. We show that with some coordination the per user cognitive capacity can be kept nearly independent from the network density.

The author of this thesis performed the work presented in this paper under the supervision of the second author.

Paper B: Energy efficient COGnitive MAC for sensor networks under WLAN co-existence
Ioannis Glaropoulos, Marcello Laganà, Viktoria Fodor, and Chiara Petrioli
To appear in *IEEE Transactions on Wireless Communications*, 2015.

Summary: Energy efficiency has been the driving force behind the design of communication protocols for battery-constrained wireless sensor networks (WSNs). The energy efficiency and the performance of the proposed protocol stacks, however, degrade dramatically in case the low-powered WSNs are subject to interference from high-power wireless systems such as WLANs. In this paper we propose COG-

MAC, a novel cognitive medium access control scheme (MAC) for IEEE 802.15.4-compliant WSNs that minimizes the energy cost for multihop communications, by deriving energy-optimal packet lengths and single-hop transmission distances based on the experienced interference from IEEE 802.11 WLANs. We evaluate COG-MAC by deriving a detailed analytic model for its performance and by comparing it with previous access control schemes. Numerical and simulation results show that a significant decrease in packet transmission energy cost, up to 66%, can be achieved in a wide range of scenarios, particularly under severe WLAN interference. COG-MAC is, also, lightweight and shows high robustness against WLAN model estimation errors and is, therefore, an effective, implementable solution to reduce the WSN performance impairment when coexisting with WLANs. *The author of this thesis performed the major part of the work presented in this paper, including the analytic modeling and optimization of COG-MAC, the numerical performance evaluation and the design of the simulation experiments. The second author has contributed in the design of the NS simulator, upon which the simulation-based evaluation was conducted. The author of this thesis wrote and revised this paper together with the third author, based on the feedback offered by the fourth author.*

Paper C: Discrete Stochastic Optimization Based Parameter Estimation for Modeling Partially Observed WLAN Spectrum Activity
Ioannis Glaropoulos, and Viktoria Fodor
Published in *Infocommunications Journal*, 2012.

Summary: Modeling and parameter estimation of spectrum usage in the ISM band would allow the competing networking technologies to adjust their medium access control accordingly, leading to the more efficient use of the shared spectrum. In this paper we address the problem of WLAN spectrum activity model parameter estimation. We propose a solution based on discrete stochastic optimization, that allows accurate spectrum activity modeling and can be implemented even in wireless sensor nodes with limited computational and energy resources.

The author of this thesis performed the work presented in this paper under the supervision of the second author.

Paper D: Closing the gap between traffic workload and channel occupancy models for 802.11 networks
Ioannis Glaropoulos, Alexandre Vizcaino Luna, Viktoria Fodor, and Maria Papadopouli
Published in the *Elsevier Journal of Adhoc Networks*, 2014.

Summary: The modeling of wireless network traffic is necessary to evaluate the possible gains of spectrum sharing and to support the design of new cognitive protocols that can use spectrum efficiently in network environments where diverse technologies coexist. In this paper we focus on IEEE 802.11 wireless local area networks and close the gap between two popular levels of modeling, macroscopic traffic workload modeling and microscopic channel occupancy modeling. We consider traffic streams generated by established traffic workload models and characterize the networking scenarios where a simple, semi-Markovian channel occupancy model accurately predicts the wireless channel usage. Our results demonstrate that the proposed channel occupancy model can capture the channel idle time distribution in most of the scenarios, while the Markovian assumption can not be validated in all cases.

The author of this thesis performed the major part of the work presented in this paper, under the supervision of the third author, and based on the suggestions and feedback provided by the fourth author. The second author of the paper performed a significant part of the simulation experiments in Section 5. The paper was written by the author of this thesis in collaboration with the third author.

Paper E: Enhanced power saving mode for low-latency communication in multi-hop 802.11 networks
Vladimir Vukadinovic, Ioannis Glaropoulos, and Stefan Mangold
Published in the *Elsevier Journal of Adhoc Networks*, 2014.

Summary: The Future Internet of Things (IoT) will connect billions of battery-powered radio-enabled devices. Some of them may need to communicate with each other and with Internet gateways (border routers) over multi-hop links. While most IoT scenarios assume that for this purpose devices use energy-efficient IEEE 802.15.4 radios, there are use cases where IEEE 802.11 is preferred despite its potentially higher energy consumption. We extend the IEEE 802.11 power saving mode (PSM), which allows WLAN devices to enter a low-power doze state to save energy, with a traffic announcement scheme that facilitates multi-hop communication. The scheme propagates traffic announcements along multi-hop paths to ensure that all intermediate nodes remain awake to receive and forward the pending data frames with minimum latency. Our simulation results show that the proposed Multi-Hop PSM (MH-PSM) improves both end-to-end delay and doze time compared to the standard PSM; therefore, it may optimize WLAN to meet the networking requirements of IoT devices. MH-PSM is practical and software-implementable since it does not require changes to the parts of the IEEE 802.11 medium access control that are typically implemented on-chip. We implemented MH-PSM as a part of a WLAN driver for Contiki OS, which is an operating system for resource-constrained IoT devices, and we demonstrated its efficiency experimentally.

The protocol design proposed in this paper has been the joint effort of the author of this thesis and the first author of the paper. The author of this thesis carried out the protocol simulation development, the implementation, and the simulation evaluation, while the field experiments were performed in collaboration with the first author. All authors collaborated in writing the paper.

Paper F: The Stability of Multiple Objective RPL Tree Formation
Ioannis Glaropoulos, and Viktoria Fodor
Submitted to *IFIP Med-Hoc-Net*, 2015.

Summary: We address the problem of RPL tree formation in self-organized, multi-hop, wireless sensor networks, where resource-constrained nodes may independently select their routing paths that maximize their performance. We study the result of the tree formation applying a non-cooperative game-theoretic model, and show that multiple objectives may lead to unstable Nash graphs with unwanted traffic cycling. To ensure stability we propose an extension of the node's strategy space, denoted as selective routing, that efficiently eliminates non-acyclic formations from the set of Nash equilibria, while the resulting routing decisions comply standard RPL.

The author of this thesis performed the work presented in this paper under the supervision of the second author.

List of publications not included in this thesis

- Ioannis Glaropoulos, "Energy efficient COGnitive MAC for sensor networks under WLAN co-existence – Revised technical report", KTH, 2015.
- Ioannis Glaropoulos, Vladimir Vukadinovic, and Stefan Mangold, "Contiki80211: an IEEE 802.11 radio link-layer for the Contiki OS", in Proc. of *IEEE International Conference on Embedded Software and Systems (ICESS)*, 2014.
- Hossein Shokri, Ioannis Glaropoulos, Viktoria Fodor, Carlo Fiscione, and Antony Ephremides, "Green Sensing and Access: Energy-Throughput Tradeoffs in Cognitive Networking", submitted to *IEEE Communication Magazine* (major revision), 2014.
- Ioannis Glaropoulos, Stefan Mangold, and Vladimir Vukadinovic "Enhanced IEEE 802.11 power saving for multi-hop toy-to-toy communication", in Proc. of *Green Computing and Communications (GreenCom), IEEE and Internet of Things (iThings/CPSCom), IEEE International Conference on and IEEE Cyber, Physical and Social Computing*, 2014.
- Ioannis Glaropoulos, Alexandre Vizcaino Luna, Viktoria Fodor, and Maria Papadopouli, "WLAN channel occupancy modeling and validation", in Proc. of *Swedish Communication Technologies Workshop* (Swe-CTW), 2013.
- Marcello Lagana, Ioannis Glaropoulos, Viktoria Fodor, and Chiara Petrioli, "Modeling and estimation of partially observed WLAN activity for cognitive WSNs", in Proc. of *IEEE Wireless Communications and Networking Conference (WCNC)*, 2012.
- Ioannis Glaropoulos, and Viktoria Fodor, "Cognitive WSN MAC for WLAN co-existence", in Proc. of *Scandinavian Workshop of Wireless Adhoc Networks*, 2011.
- Ioannis Glaropoulos, Viktoria Fodor, Loreto Pescosolido, and Chiara Petrioli, "Cognitive WSN transmission control for energy efficiency under WLAN coexistence", in Proc. of *ICST Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom)*, 2011.
- Amin Nahvi, Viktoria Fodor, and Ioannis Glaropoulos, "Performance of deterministic local sensing aggregation under interference", in Proc. of *ICST Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom)*, 2010.
- Ioannis Glaropoulos, and Viktoria Fodor, "On the efficiency of distributed spectrum sensing in ad-hoc cognitive radio networks", in Proc. of *ACM Mobicom, Cognitive Radio Networks Workshop*, 2009.

- Viktoria Fodor, Ioannis Glaropoulos, and Loreto Pescosolido, "Detecting low-power primary signals via distributed sensing to support opportunistic spectrum access", in Proc. of *IEEE International Conference of Communications (ICC)*, 2009.

- Ioannis Glaropoulos, and Viktoria Fodor, "Distributed spectrum sensing for opportunistic and cognitive spectrum access", in Proc. of *Swedish National Computer Networking Workshop (SNCNW)*, 2009.

- Viktoria Fodor, and Ioannis Glaropoulos, "On the gains of deterministic placement and coordinated activation in sensor networks", in Proc. of *IEEE Global Telecommunications Conference (Globecom)*, 2008.

Chapter 6

Conclusions and Future Work

This thesis presents cognitive control and cross-layer optimization techniques in wireless systems, aiming at addressing two important challenges in wireless networking: heterogeneous coexistence and energy efficiency. In this chapter we summarize the main contributions of our work, emphasizing on the most significant conclusions that we derived.

We studied the efficiency of cooperative sensing in ad hoc cognitive networks, where the primary and secondary systems bare similar transmission characteristics. We focused on the particular scenario where the secondary users performing spectrum sensing also aim at utilizing the discovered spectrum opportunities, while satisfying, additionally, interference avoidance constraints for primary users. Sensing efficiency was therefore evaluated with respect to the achievable cognitive capacity for the secondary network. We showed that the cognitive capacity approaches zero in dense networks, if cooperative sensing is performed on a limited spectrum bandwidth. We therefore defined and evaluated various sensing allocation schemes, where the cognitive users sense a limited subset of bands. We developed appropriate analytic models for the sensing efficiency under random, coordinated, and optimal allocation schemes, evaluating the performance gaps due to the different levels of coodination among the secondary users. We studied the fundamental limits of the cognitive capacity in highly dense cognitive networks and showed that the achievable capacity converges to a limit that depends on the transmission characteristics of the primary and the secondary users, on the parameters of local sensing, as well as on the primary interference constraints. Using numerical evaluation we concluded that while the performance gap between random and coordinated sensing is significant, optimizing the sensing allocation based on the actual number of secondary nodes leads to little additional gain and does not compensate for the increased coordination overhead in dense secondary networks.

We addressed the challenge of increasing the energy efficiency in low-power, 802.15.4-based wireless sensor networks, operating under the interference of coexisting 802.11 networks, through the introduction of cross-layer control mechanisms, that are cognitive of the radio environment, as imposed by the WLAN activity. We proposed COG-MAC, a new cognitive MAC protocol for wireless sensor networks, that aims at minimizing the energy loss due to unsuccessful WSN communication as a result of WLAN interference on the transmitted channel. COG-MAC builds upon known stochastic models for the WLAN channel activity, uses a smart clear channel assessment mechanism and performs channel access, with optimal packet length and transmission distance, to increase the probability of successful packet transmission. We performed a detailed evaluation of COG-MAC based on an accurate analytic performance model and showed that it significantly outperforms benchmark solutions, particularly under severe WLAN interference. We stressed that all the building blocks of COG-MAC are essential for achieving the objective of energy efficient communication. A detailed simulation study of COG-MAC revealed that the protocol achieves significant gains even in multihop WSN topologies.

We addressed the challenge of developing an easy-to-use, yet, accurate stochastic model for WLAN channel activity, as an essential component of congitive access control. We proposed an iterative, simulation-based, discrete stochastic optimization algorithm, to efficiently estimate the model parameters from a set of observations of the channel activity. We showed that the developed algorithm asymptotically converges to the actual model parameters and evaluated the required number of samples with respect to the target estimation accuracy. In addition, we addressed the question, whether the proposed stochastic WLAN channel activity model is a realistic modeling approach for capturing the channel usage patterns in practical 802.11 networks. In particular, we considered traffic streams, generated by established traffic workload models and, additionally, from real WLAN tracesets, and compared the simulated WLAN activity process with the ones predicted by the stochastic model. Our results showed that in a wide range of scenarios the proposed WLAN model can sufficiently capture the behavioral patterns of real WLAN channel activity. We finally identified the aggregate WLAN channel load, and the particular mixture of application-layer traffic as the dominate factors with significant impact on the accuracy of the proposed channel activity model.

Believing that emerging Internet of Things applications will require low-power communication between IoT radio devices and consumer electronics, typically using Wi-Fi for network connectivity, we addressed the challenge of optimizing the 802.11 duty-cycling mechanism, so as to achieve a high communication performance without compromising its enery efficiency. We proposed a multi-hop extension of the standard IEEE 802.11 power saving mehcanism, that enables low-latency communication in multi-hop ad hoc 802.11 networks. We implemented our solution on an embedded open-source platform, demonstrating its effectiveness via an extensive simulation and experimental evaluation. We showed that the enhanced power saving mechanism increases the sleep ratio of the 802.11 stations, to further extend their lifetime under finite power supply. We stressed two important features of our approach: first, that it is software implementable and, additionally, backward-compatible with the standardized 802.11 power saving mechanism, which guarantees interoperability with legacy WLAN devices.

Finally, we studied the problem of network formation in self-organized, multi-hop, wireless sensor networks, where the wireless devices independently select their routing paths towards a gateway node, in order to maximize their individual performance. In particular, we focused on the case where battery-constrained nodes have multi-objective utility functions, aiming at maximing both the experienced QoS and their lifetime. Considering RPL as the routing protocol in the wireless network, we studied the directed acyclic graph, or tree, formation using tools from non-cooperative game theory, investigating the existence and the quality of mixed-strategy Nash equilibiria in the formulated tree-formation game. Our main results showed that under generic node multi-objective utility functions, multi-parent selection strategies lead to unstable Nash directed graphs, that may contain undesired traffic cycling, strictly prohibited by RPL. We therefore proposed an extension of the strategy profile space of the game, where parent nodes may adopt different forwarding polices for their children. We demonstrated that this policy extension can efficiently eliminate non-acyclic graphs from the set of Nash equilibria of the tree formation game.

Future research directions

Our work on cognitive transmission control demonstrated the importance of both the stochastic characterization of the wireless environment, as well as the cross-layer optimization for the design of efficient solutions that will allow for a smooth coexistence between heterogeneous technologies in the open spectrum bands. Yet, it is clear that including, additionally, power and topology control on a system-wide optimization scheme would lead to further performance gains. The exact way under which all the aforementioned building blocks would be combined in a multi-dimensional optimization scheme remains, however, an open issue.

Cognitive transmission control schemes should be agile, thus, include efficient runtime control mechanisms to adapt to a dynamically changing cross-network interference. Such mechanisms would require a quick, yet, accurate assessment of the impact of the protocol operations and of the current interference on the high-level network performance. Existing runtime protocol adaptation frameworks, such as [150], could be extended, providing a detailed mapping of the stochastic characteristics of the cross-network interference on the system performance.

In-line with a plethora of research contributions, this thesis tackles the problem of energy efficient design in wireless sensor networks of resource constrained devices, as the key factor for realizing green, large-scale infrastructures for monitoring and actuation applications. What remains to be assessed thoroughly is the impact of energy efficient protocol stacks on the performance of upper-level networking, including transport and application layer protocols. The lack of deep experimentation on the inter-operability between energy-efficient design and high-level networking impedes the introduction of such large-scale infrastuctures. Early approaches, such as [110], recognize the challenge of the interplay between energy-efficient medium access control and RPL, and showed, instead, that opportunistic RPL fits well with traditional MAC-layer duty-cycling. Future reseach could focus on analyzing the performance of opportunistic RPL on top of congitive access control schemes, like COG-MAC, under heterogeneous coexistence.

If energy efficient WLAN infrastructures are to be used in large-scale IoT systems, an important question is how the increase in the network scale impacts the interplay between the mechanisms for energy-efficiency and the remaining layers of the wireless protocol stack. The performance of several protocol operations in duty-cycling ad hoc 802.11 networks relies heavily on how accurately the network terminals can synchronize their beacon intervals. Beacon synchronization in large-scale, multi-hop ad hoc WLANs is, however, highly inefficient. The applicability of duty-cycling in multi-hop WLANs is, therefore, an important direction for future investigation. However, network scale raises serious concerns on the performance of cross-layer operations, which constitute essential building blocks of several proposed energy efficiency optimization schemes, but are still under experimentation, or have not yet been fully standardized. A large-scale evaluation of such cross-layer mechanisms is, therefore, crucial for an accurate performance assessment of the various energy efficient design approaches for ad hoc WLANs.

Finally, in the context of the Internet of Things application scenarios, a fundamental research question remains open: Which radio link-layer technology is most suitable for energy-efficient IoT network infrastructures? Several studies, including [151], question whether the combination of IEEE 802.15.4 duty cycle-based link-layers and RPL-based routing over 6LoWPAN results in a network stack with highest preformance with respect to energy efficiency, claiming that under certain application scenarios resource-constrained devices may achieve higher energy savings while operating with an IEEE 802.11-based network stack. Research could, therefore, aim at identifying the key parameters of IoT application scenarios with a decisive impact on the selection of the underlying network stack.

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