Cross Technology Interference Mitigation in Body-to-Body Area Networks

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***Abstract*—In recent years, Body-to-Body Networks (BBNs) have gained momentum as a means to monitor people behavior and simplify their interaction with the surrounding environment; thus representing a key element of the Internet of Things (IoT) networking paradigm. Within BBNs, several transmission technologies sharing the same unlicensed band (namely the ISM band) coexist, increasing dramatically the level of interference, which in turn negatively affects the network performance.**

In this paper, we consider an IoT system composed of several BBNs and we analyze the Cross Technology Interference (CTI) problem caused by the utilization of different transmission technologies that share the same radio spectrum. We formulate an optimization model considering both the Mutual and Cross Technology Interference in order to mitigate the overall level of interference within the IoT system, taking explicitly into account the node mobility. We further develop two heuristic approaches to solve efficiently the interference mitigation problem in large scale network scenarios.

Numerical results show that the proposed heuristics represent two efficient and practical alternatives to the optimal solution for solving the CTI mitigation problem in large scale IoT scenarios.

Keywords*—*Body-to-Body Networks, Internet of Things, Cross Technology Interference, Interference Mitigation, Optimization.

I. Introduction

The ongoing evolution of wireless technologies has fostered the development of innovative network paradigms like the Internet of Things (IoT), where the pervasive deployment of wireless devices endowed with sensing capabilities permits to link the physical to the digital world, thus enabling the development of enhanced services.

Wireless Personal Area Networks and, more specifically, Body-to-Body Networks (BBNs) are emerging solutions for the monitoring of people behavior and their interaction with the surrounding environment, thus representing a key building block of the upcoming Internet of Things networking paradigm [1]. BBNs may correspond to different rescue teams in a disaster scenario or different groups of people, whose Wireless Body Area Networks (WBANs) interact with each other and the surrounding environment.

In their most common configuration, every BBN consists of several WBANs, which in turn are composed of wearable sensor nodes connected through the 802.15.4 protocol (i.e., ZigBee) to their mobile terminals that act as coordinators for their corresponding WBANs. The set of wearable sensors may be used to consistently monitor people's vital signs, like blood pressure, breath rate, skin temperature, or important environmental parameters like temperature and humidity. Furthermore, wireless headsets can be used to enable communication among people of the BBN, while glasses like those recently proposed by Google and Microsoft can be connected wirelessly with a smartphone to provide augmented reality [2].

Mobile terminals are usually equipped with two radio interfaces implementing the 802.15.4 and the 802.11 protocols, which are used, respectively, for coordinating the activity of the wearable sensor nodes and to form the wireless backhaul infrastructure among the WBANs of the BBN.

Due to the broadcast nature of the wireless channel and the limited radio bandwidth, data transmissions between the devices involved in BBNs' communications may interfere, thus reducing the network performance of the entire system. More specifically, successful data transmissions over two or more conflicting wireless links, which use the same PHY technology, cannot be simultaneously performed. Furthermore, as illustrated in [3], the interference caused by frequency overlap across different wireless technologies[1], like ZigBee and WiFi, can highly affect the performance of WBANs both in terms of achievable throughput and reliability. In particular, data transmissions within ZigBee networks can completely starve due to WiFi communications, which use 10 to 100 times higher transmission power.

On the other hand, given the scarce availability of the radio frequency spectrum used by standard wireless solutions, many existing wireless technologies are forced to use the same unlicensed frequency bands. For example, IEEE 802.11 (WiFi), IEEE 802.15.1 (Bluetooth) and IEEE 802.15.4 (ZigBee) all share the same 2.4 GHz ISM band. Hence, interference across these technologies can lead to loss of reliability and an inefficient use of the radio spectrum.

In this paper, we consider a wireless Body-to-Body Network scenario and we focus on the interference mitigation problem, where Mutual (WiFi-WiFi and Zigbee-Zigbee) and Cross-Technology (WiFi-ZigBee) interference arising in a dynamic scenario are taken into account simultaneously.

In summary, our work makes the following contributions:

- We analyze the problem of mutual and cross-technology interference in a dynamic IoT system, where mobile

[1]This type of interference is denoted as Cross Technology Interference in the rest of the paper.

devices use different access technologies on the same spectrum band.

- We formulate the interference mitigation as an optimization problem, proposing an extended interference graph to model cross-technology transmission conflicts. Furthermore, we consider explicitly the network dynamics due to the nodes mobility, by optimizing the worst interference caused by nodes proximity.
- We present two heuristic solutions, namely a customized randomized rounding approach and a tabu-search scheme, to solve efficiently the problem even for large-scale network scenarios.
- We perform a thorough numerical evaluation of the proposed mechanisms, considering both static and mobile network scenarios.

Numerical results show that the proposed model and heuristics reduce significantly the level of interference between different technologies within an IoT, thus improving the overall network performance.

The paper is structured as follows: Section II discusses related work. Section III introduces the communication model as well as the assumptions considered in our work. Section IV formulates the interference mitigation problem as an optimization model, while Section V describes the heuristic approaches we designed to solve efficiently the problem. Section VI illustrates and analyzes numerical results which show the efficiency and validity of our approaches. Finally, concluding remarks are discussed in Section VII.

II. Related Work

In this section, we discuss the most relevant works that deal with the problem of interference mitigation between different technologies (i.e., Zigbee and WiFi) that share the same frequency spectrum.

The problem of minimizing 802.11 interference on Zigbee medical sensors is addressed in [4], where the authors proposed a solution which utilizes a hardware setup that includes both ZigBee and 802.11 transmitters and permits to transmit both 802.11 and ZigBee messages. The goal was to temporarily block out 802.11 messages for a time window large enough such that ZigBee devices can successfully transmit their messages, thereby solving the interference issue. To do so, they developed two types of solutions: (i) periodically jam 802.11 and see if ZigBee would be able to fit its messages into the empty time frames, and (ii) transmit a CTS message directly before a ZigBee message and verify that the ZigBee message has a high delivery rate.

Instead of trying to avoid interference from 802.11 traffic, the work in [3] focused on improving the coexistence of 802.15.4 and 802.11 networks that operate in the overlapping frequency channels. More specifically, this work presented a MAC layer solution (BuzzBuzz) that enables 802.15.4 nodes to coexist with WiFi networks by using multi-headers and forward error correction codes to overcome the packet loss caused by 802.11 interference.

A ZigBee frame control protocol (WISE) is proposed in [5] to deal with the interference between ZigBee and WiFi. WISE first predicts the length of white space in WiFi traffic based on a Pareto model and then adapts the frame size to maximize the throughput efficiency while achieving assured packet delivery ratio. WISE was implemented in TinyOS 2.x and evaluated through experiments using 802.11 netbooks and 802.15.4 TelosB motes, demonstrating some advantages (19.5% and 42.5%) over B-MAC (the default MAC protocol in TinyOS) and OppTx [6], [7], respectively. In [8], [9] the authors proposed two mechanisms that enable the reliable coexistence of ZigBee and WiFi networks. These mechanisms include a frequency flip scheme and a cooperative carrier signaling that prevent the mutual interference between cooperative ZigBee nodes, and a busy tone scheduler that minimizes the interference due to WiFi networks, for both CSMA and TDMA packets.

A tool for understanding 802.11 performance in heterogeneous environments, without the use of dedicated infrastructures, is presented in [10]. This tool, called WiMed, uses 802.11 NICs to produce a time allocation map showing how the medium is used, and is able to detect non-802.11 sources of interference using NIC registers and bit error analysis.

Furthermore, in [11], [12], the authors consider a 802.11-based multiradio mesh network with stationary wireless routers, where each router is equipped with multiple radio interfaces, and multiple channels are available for communication. They address the problem of assigning channels to communication links in the network, while minimizing the overall mutual interference among wireless links that use the same technology. On the contrary, we consider a BBN network system composed of wireless sensors, equipped with a ZigBee interface, and mobile terminals, which are equipped with both ZigBee and WiFi interfaces. Furthermore, the proposed solutions aim at minimizing both the mutual (i.e., WiFi-WiFi and ZigBee-ZigBee) and the cross technology (i.e., WiFi-ZigBee) interference, considering a set of consecutive time epochs to represent the mobility of WBANs in the BBN scenario.

In summary, none of the above reviewed works has investigated an optimization framework to jointly minimize the mutual and cross technology interferences in a mobile IoT system composed of several Body-to-Body networks.

III. Network Model

This section presents the network model and assumptions we adopt in the design of our interference mitigation approach.

We consider an IoT system, composed of a set $\mathcal{N}$ of wearable Mobile Terminals (MTs), that use both the 802.15.4 protocol (i.e., ZigBee) to communicate with the sensor nodes within the WBAN, and the IEEE 802.11 wireless standard (i.e., WiFi) to create a backhaul infrastructure for inter-WBANs communications. The IoT is therefore formed of several Body-to-Body Networks (BBNs) that communicate among each other using the WiFi technology, as illustrated in Figure 1. The radio channels defined by the WiFi and ZigBee technologies are identified using the two sets $\mathcal{K}_w$ and $\mathcal{K}_z$, respectively.

The operating time of the whole system is divided in a set $\mathcal{T}$ of consecutive epochs. We assume that during each epoch the network topology does not change. Specifically, the set $\mathcal{L}_w(t)$ represents all WiFi links established by mobile terminals during the epoch $t \in \mathcal{T}$, which may vary between two consecutive epochs due to WBANs mobility. On the contrary, the set $\mathcal{L}_z$, which contains the ZigBee links used for intra-WBAN communication among the sensor motes, does not change during the entire operating time of the system.

In order to model the different types of interference caused by the utilization of multiple wireless technologies in an IoT environment, we extend the basic *conflict graph* presented in [12] for representing pairs of interfering wireless links. Specifically, we introduce the concept of *cross-conflict edges* to model the Cross Technology Interference (CTI). The cross-conflict edges in the conflict graph connect two vertices that represent communication links using two different technologies (i.e., WiFi and Zigbee). Therefore, the extended conflict graph $G_c(\mathcal{V}_c(t), \mathcal{E}_c(t))$ is defined over the set $\mathcal{V}_c(t) = \mathcal{L}_w(t) \cup \mathcal{L}_z$, which contains all wireless links established by mobile terminals (either WiFi or ZigBee), and a conflict edge $(e_1, e_2) \in \mathcal{E}_c(t)$ exists between two vertices using the same radio technology, (e.g., $e_1, e_2 \in \mathcal{L}_w(t)$ or $e_1, e_2 \in \mathcal{L}_z$) if the corresponding wireless links interfere between each other when they are set on the same channel. Since WiFi channels may be overlapped, the weight of the edge connecting two interfering WiFi links is proportional to intersection area between the spectrum of the two signals [13].

Conversely, when the two vertices represent wireless links using two different radio technologies, $e_1 \in \mathcal{L}_w(t)$ and $e_2 \in \mathcal{L}_z$, a cross-conflict edge is used to indicate that e_1 and e_2 interfere if they use overlapping channels, like, for example, by tuning e_1 on the WiFi channel 1 and e_2 on the ZigBee channel 12.

Figure 2 shows the extended conflict graph of the network scenario depicted in Figure 1, where solid lines are used to represent the classical conflict edges that model the mutual interference between links based on the same technology, whereas dashed lines correspond to cross-conflict edges, which depict the conflicts among links that use different transmission technologies.

Note that we consider only one ZigBee link for any WBAN in the set $\mathcal{L}_z$ (i.e., the link established by the mobile terminal using its ZigBee interface), since all sensor motes within a WBAN use the same wireless channel. Indeed, the Cross Technology Interface affecting all ZigBee links within a WBAN is accurately captured by the cross-conflicting edge that connects the representative ZigBee link with any surrounding WiFi connection.

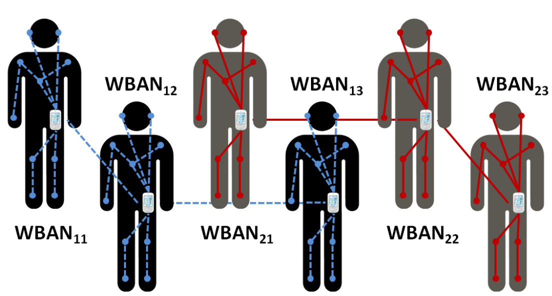


Fig. 1: IoT scenario: Two BBNs corresponding to two different groups of people (i.e., blue and red) are using the same unlicensed spectrum.

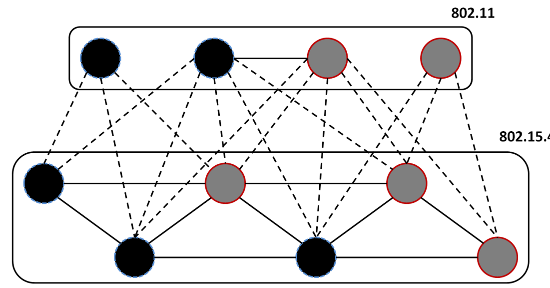


Fig. 2: Extended Conflict Graph representing interfering wireless links (i.e., links that cannot use overlapping channels simultaneously for successful communication) of the scenario illustrated in Figure 1.

Formally, we represent the mutual interference caused by using two overlapping WiFi channels by the $|\mathcal{K}_w| \times |\mathcal{K}_w|$ matrix $\boldsymbol{C}$, whose element $c_{kh} \in [0, 1]$ is proportional to the intersection area between the spectrum of the two signals [13].

Similarly, we model the Cross Technology Interference between two overlapping channels using a $|\mathcal{K}_w| \times |\mathcal{K}_z|$ matrix $\boldsymbol{A}$, whose element $a_{kh} = 1$ states that WiFi channel $k \in \mathcal{K}_w$ interferes with the ZigBee channel $h \in \mathcal{K}_z$.

Finally, the connectivity among the mobile terminals that belong to the same BBN and through which the sensor nodes of different WBANs can communicate, is defined using the $|\mathcal{L}_w| \times |\mathcal{L}_w|$ matrix $\boldsymbol{B}$, whose element $b_{uv} = 1$ indicates that WiFi links u and v belong to the same BBN.

IV. Optimal Cross-Technology Interference Mitigation (CTIM) Problem

This section formalizes the Integer Linear Programming (ILP) model we propose for the joint assignment of 802.11b/g and 802.15.4 wireless channels to the interfaces of the devices that belong to an IoT in order to minimize both the *Mutual* and *Cross-Technology* interference.

We first introduce the decision variables used in our model, then we provide the ILP description of the problem.

Binary variables x^t_{uk} represent the temporal assignment of WiFi channels to wireless links established among the mobile terminals of a BBN using their WiFi interfaces. Specifically, $x^t_{uk} = 1$ indicates that channel $k \in \mathcal{K}_w$ is assigned to wireless link $u \in \mathcal{L}_w$ throughout epoch $t \in \mathcal{T}$. Similarly, the set of binary variables y^t_{vh} represents the ZigBee channels assigned to all communication links used by the wearable sensors of the WBAN v. As discussed in the previous section, we consider only one representative link of the WBAN, since we are assuming that all WBAN's sensors are set on the same channel.

The temporal Cross Technology Interference is defined as follows:

$$I(t) = \alpha \cdot \sum_{(u,v)\in\mathcal{E}^w_c} I^w_{(u,v)}(t) + \beta \cdot \sum_{(u,v)\in\mathcal{E}^z_c} I^z_{(u,v)}(t) + + \gamma \cdot \sum_{(u,v)\in\mathcal{E}^{wz}_c} I^{wz}_{(u,v)}(t). \tag{1}$$

Specifically, $I^{w}_{(u,v)}(t)$ and $I^{z}_{(u,v)}(t)$ account for the mutual interference caused by data transmissions over conflicting links that use WiFi and ZigBee protocols, respectively, in epoch t. Conversely, $I^{wz}_{(u,v)}(t)$ represents the amount of cross technology interference, in epoch t, due to simultaneous transmissions on interfering links established using different protocols. The parameters α, β and γ permit to weight differently the three contributions to the overall interference.

Given the above definitions and notations, the optimal Cross Technology Interference Mitigation (CTIM) problem can be stated as follows:

$$\min\ u \tag{2}$$

s.t.

$$u \geq I(t) \qquad \forall t \in \mathcal{T} \tag{3}$$

$$\sum_{k \in \mathcal{K}_w} x^t_{uk} = 1 \qquad \forall t \in \mathcal{T}, \forall u \in \mathcal{L}_w(t) \tag{4}$$

$$b_{uv}(x^t_{uk} - x^t_{vk}) = 0 \qquad \forall t \in \mathcal{T}, \forall u, v \in \mathcal{L}_w(t), \forall k \in \mathcal{K}_w \tag{5}$$

$$\sum_{h \in \mathcal{K}_z} y^t_{uh} = 1 \qquad \forall t \in \mathcal{T}, \forall u \in \mathcal{L}_z \tag{6}$$

$$x^t_{uk} = x^{t+1}_{uk} \qquad \forall t \in \mathcal{T}', \forall u \in \mathcal{L}_w(t), \forall k \in \mathcal{K}_w \tag{7}$$

$$y^t_{uh} = y^{t+1}_{uh} \qquad \forall t \in \mathcal{T}', \forall u \in \mathcal{L}_z, \forall h \in \mathcal{K}_z \tag{8}$$

$$I^{w}_{u,v}(t) \geq c_{kh} \cdot (x^t_{uk} + x^t_{vh} - 1) \qquad \forall t \in \mathcal{T}, \forall (u,v) \in \mathcal{E}^w_c(t), \forall k, h \in \mathcal{K}_w \tag{9}$$

$$I^{z}_{u,v}(t) \geq y^t_{uk} + y^t_{vk} - 1 \qquad \forall t \in \mathcal{T}, \forall k \in \mathcal{K}_z, \forall (u,v) \in \mathcal{E}^z_c(t) \tag{10}$$

$$I^{wz}_{u,v}(t) \geq a_{kh} \cdot (x^t_{uk} + y^t_{vh} - 1) \qquad \forall t \in \mathcal{T}, \forall (u,v) \in \mathcal{E}^{wz}_c(t), \forall k \in \mathcal{K}_w, \forall h \in \mathcal{K}_z \tag{11}$$

$$x^t_{uk} \in \{0,1\} \qquad \forall t \in \mathcal{T}, \forall u \in \mathcal{L}_w(t), \forall k \in \mathcal{K}_w \tag{12}$$

$$y^t_{vh} \in \{0,1\} \qquad \forall t \in \mathcal{T}, \forall v \in \mathcal{L}_z, \forall h \in \mathcal{K}_z. \tag{13}$$

The objective function (2) along with the set of constraints (3) minimize the maximum cross technology interference generated by data transmissions using different technologies on the same available spectrum throughout all epochs.

Constraints (4) force the assignment of a single WiFi channel to any wireless link established between two mobile terminals. Indeed, this set of constraints prevents the assignment of multiple channels to the single radio interface with which a device is equipped. Similarly, constraints (6) force the utilization of a single ZigBee channel within a WBAN.

Note that removing the edges from the interference graph representing any pair of conflicting links that belong to the same BBN does not guarantee the connectivity of the WiFi mobile terminals. Therefore, we explicitly model the network connectivity among the devices that belong to the same BBN, using the set of constraints (5) that forces the utilization of the same channel for any pair of WiFi links that belong to the same BBN (i.e., $b_{uv} = 1 \Rightarrow x^t_{vk} = x^t_{uk} = 1$). Indeed, since we are assuming that mobile terminals are equipped with only one WiFi interface, we must assign the same wireless channel to all WiFi links established within the same BBN in order to create a multi-hop topology that guarantee the connectivity between any pair of devices.

Constraints (7) and (8) force the utilization of only one channel throughout all time epochs ($\mathcal{T}'$ corresponds to the set $\mathcal{T}$ without the element representing the last epoch). Therefore, the channel assignments x^t_{uk} and y^t_{uk} provided by solving the CTIM problem minimize the worst interference generated by simultaneous transmissions throughout all epochs.

By neglecting these two latter sets of constraints we can easily model the channel switching to account for devices that can select different frequencies between consecutive time epochs.

The two sets of constraints (9) and (10) model the Mutual Interference between WiFi and ZigBee links, respectively; while constraints (11) account for the Cross Technology Interference between conflicting links that use the two different protocols considered in this work. Unlike constraints (9) which model the mutual interference caused by using overlapped WiFi channels, the set of constraints (10) takes into account only the interference generated by setting the same ZigBee channel on conflicting links, since all ZigBee channels are orthogonal.

V. Heuristic Solutions for the CTIM Problem

The Optimal Cross-Technology Interference Mitigation (CTIM) Problem is NP-Hard. Indeed, it can be demonstrated that the *Maximum K-Cut* problem can be reduced in polynomial time to our *CTIM* problem [14]. Finding the exact system optimum can be thus extremely time consuming, especially in large-scale, real IoT scenarios composed of several BBNs, as those analyzed in our numerical evaluation. Motivated by this observation, in the following we present two heuristic approaches to solve efficiently (i.e., in polynomial time) the CTIM problem, while obtaining a low overall interference.

We set out by presenting the algorithm based on a modified version of the Randomized Rounding (RR) technique. Then, we illustrate the Tabu Search (TS)-based solutions.

A. RR-CTIM: Randomized Rounding Algorithm

Algorithm 1 illustrates the main steps of the first heuristic solution, which is based on a modified version of the randomized rounding approach. The algorithm receives as input the parameters that describe the network topology, the extended conflict graph, which contains all wireless links and their conflicts, and the available wireless channels. It produces as output the channel assignment for all BBNs communication links, which are based either on WiFi or ZigBee technologies.

The algorithm proceeds in 3 steps. Step 1 consists in solving the continuous relaxation of the CTIM problem described in the previous section, where integrality constraints (12) - (13) are replaced with the corresponding continuous relaxations, as follows:

$$x^t_{uk} \in [0,1] \qquad \forall t \in \mathcal{T}, \forall u \in \mathcal{L}_w(t), \forall k \in \mathcal{K}_w$$

$$y^t_{vh} \in [0,1] \qquad \forall t \in \mathcal{T}, \forall v \in \mathcal{L}_z, \forall h \in \mathcal{K}_z.$$

Let $\hat{\boldsymbol{x}}$ and $\hat{\boldsymbol{y}}$ be the optimal solutions obtained solving the relaxed version of the CTIM problem. Steps 2 and 3 perform the randomized rounding on assignment variables $\hat{\boldsymbol{x}}$ and $\hat{\boldsymbol{y}}$, respectively. In both steps, for each wireless link we consider the most likely channel assignment throughout all epochs, namely the highest value among the set of variables representing the channel assignment of one link.

Specifically, for WiFi links (step 2), we select from the set containing all variables $\hat{x}^t_{vk}$ corresponding to possible channels assigned to all links of the same BBN (i.e., the set B_u) the variable with the highest value $x^{t_m}_{i_m k_m}$. We then compare such variable with a random value p uniformly distributed in $[0, 1]$: if $x^{t_m}_{i_m k_m} \leq p$, all links using the WiFi technology within the same BBN are tuned on the same channel k_m throughout all time epochs, by forcing all variables $x^t_{vk_m} = 1, \forall v \in B_u, \forall t \in \mathcal{T}$ (the remaining variables are set to zero, $x^t_{vk} = 0, \forall v \in B_u, \forall t \in \mathcal{T}, k \in \mathcal{K}_w, k \neq k_m$). Conversely, the decision about the feasibility of the WiFi channel assignment to all links of the corresponding BBN is postponed to step 4.

Regarding the ZigBee channel assigned to the representative link of a WBAN in step 3, we adopt a similar approach, considering the most likely assignment of a ZigBee channel to a WBAN obtained from the relaxed CTIM problem. However, in this latter case, we can perform the randomized rounding of each variable $\hat{y}^t_{uk}$ by forcing only the utilization of the same channel within a WBAN throughout all epochs, since each element u of the set $\mathcal{L}_z$ corresponds to an independent WBAN.

Finally, in steps 4 and 5, we verify the feasibility of the solution $(\boldsymbol{x}, \boldsymbol{y})$ provided by the previous operations, ensuring that only one channel is assigned to any wireless link (i.e., constraints (4) and (6)) and that all WiFi links of the same BBN use the same channel (i.e., constraints (5)).

Algorithm 1: RR-CTIM

Input : $\mathcal{N}, G_c(\mathcal{V}_c(t), \mathcal{E}_c(t)), \mathcal{K}_w, \mathcal{K}_z, \boldsymbol{B}, \boldsymbol{C}$
Output: $\boldsymbol{x}, \boldsymbol{y}$
1 $(\hat{\boldsymbol{x}}, \hat{\boldsymbol{y}}) \Leftarrow$ Solve the LP relaxation of the model (2)-(13);
$p \Leftarrow rand(0, 1)$;
2 **foreach** $u \in \mathcal{L}_w(t)$ **do**
    $B_u \Leftarrow \{v \in \mathcal{L}_w(t) : b_{uv} = 1\}$;
    $x^{t_m}_{i_m k_m} \Leftarrow \max\{\hat{x}^t_{vk} : v \in B_u, k \in \mathcal{K}_w, t \in \mathcal{T}\}$;
    if $x^{t_m}_{i_m k_m} \leq p$ **then**
        foreach $v \in B_u, t \in \mathcal{T}$ **do**
            $x^t_{vk_m} \Leftarrow 1$;
        end
    end
end
$p \Leftarrow rand(0, 1)$;
3 **foreach** $u \in \mathcal{L}_z$ **do**
    $y^{t_m}_{uk_m} \Leftarrow \max\{\hat{y}^t_{uk} : k \in \mathcal{K}_z, t \in \mathcal{T}\}$;
    if $y^{t_m}_{uk_m} \leq p$ **then**
        foreach $t \in \mathcal{T}$ **do**
            $y^t_{uk_m} \Leftarrow 1$;
        end
    end
end
4 $\boldsymbol{x} \Leftarrow FeasWiFiSol(\hat{\boldsymbol{x}}, \boldsymbol{x}, G_c(\mathcal{V}_c(t), \mathcal{E}_c(t)), \mathcal{K}_w, \boldsymbol{B}, \boldsymbol{C})$;
5 $\boldsymbol{y} \Leftarrow FeasZigBeeSol(\hat{\boldsymbol{y}}, \boldsymbol{y}, G_c(\mathcal{V}_c(t), \mathcal{E}_c(t)), \mathcal{K}_z)$;

B. TS-CTIM: Tabu Search Algorithm

We now describe the tabu search-based approach (TS-CTIM) we propose to solve the CTIM problem in polynomial time. Since TS-CTIM is based on Tabu search meta-heuristic and on the idea of searching in the neighborhood of a given solution, in this section we first define the neighborhoods used by TS-CTIM, then we provide the reader with some background on Tabu search and finally we proceed by illustrating in detail the TS-CTIM heuristic.

Polynomial Size WiFi (WLCAN) and Zigbee (ZLCAN) Link-Channel Assignment Neighborhoods. We define two polynomial size neighborhoods: WLCAN and ZLCAN. The first is considered for the *WiFi link-channel assignment* problem, while the second for *Zigbee link-channel assignment*.

Given a feasible solution f, the neighborhood is generated by applying the procedure $move$ that assigns a new WiFi (or ZigBee) channel k to a wireless link u, such that k is different from the one that has been assigned to u in the current solution f.

Background on Tabu Search. Tabu search is a local search based optimization method [15] that can accept interference-increasing solutions in order to escape from local minima. This feature allows the neighborhood search to explore other parts of the solution space.

For each neighborhood (WLCAN or ZLCAN), the best neighboring solution is used as new current solution and, if it improves upon the best solution found so far, this latter is updated with the best neighboring solution.

To prevent loops which keep exploring the same set of solutions, the algorithm maintains a tabu list containing the solutions explored in the previous iterations. A solution produced by a move belonging to the tabu list, which we refer to as *tabu move*, is discarded. Tabu search stops when it reaches its stopping condition, for instance after a given number of visited neighborhoods without improvement to the best solution.

The tabu search parameters (tabu list size and stopping criterion) play a fundamental role in implementing this metaheuristic. In this work, they have been set according to computational experience:

- Tabu list size: a static tabu list is considered containing up to $L = 100$ moves.
- Stopping criterion: the algorithm stops after $nb\_iter\_max = 20$ consecutive neighborhood searches without improvements to the best solution.

TS-CTIM Algorithm. To solve the CTIM problem, we develop an efficient heuristic (named TS-CTIM) that uses the tabu search approach along with the polynomial size neighborhoods WLCAN and ZLCAN.

To be more precise, we develop two different versions of the TS-CTIM heuristic (TS-CTIM-1 and TS-CTIM-2), which correspond to two different ways in defining, generating and searching the neighborhood of an intermediate solution. The corresponding neighborhoods are denoted respectively by Neighborhood-1 and Neighborhood-2.

At the first glance, the TS-CTIM heuristic, which is illustrated in Algorithm 4, proceeds as follow:

1) Start with a feasible initial solution $f_0 = (x_0, y_0)$.
2) Perform a tabu search using both the polynomial size WiFi and Zigbee link-channel assignment neighborhoods, and considering the following two alternatives for generating the neighboring solutions:
   - **TS-CTIM-1**; **Neighborhood-1** (see Algorithm 2): given a current solution f_i, (1) generate a neighboring solution in WLCAN, then (2) generate r neighboring solutions in the ZLCAN neighborhood and finally (3) go back to (1),
   - **TS-CTIM-2**; **Neighborhood-2** (see Algorithm 3): given f_i, (1) generate a neighboring solution in ZLCAN, then (2) generate r neighboring solutions in the WLCAN neighborhood and finally (3) go back to (1).
3) Return the best solution f_{best} found in step (2).

Note that for the first iteration of TS-CTIM (for $i = 0$), the intermediate solution f_i is initialized to f_0. Furthermore, both Algorithm 2 and 3 generate at each iteration a neighborhood with $r + 1$ new solutions.

More specifically, TS-CTIM takes as input parameters the set of mobile terminals $\mathcal{N}$, the extended conflict graph $G_c(\mathcal{V}_c(t), \mathcal{E}_c(t))$, an initial solution $f_0 = (x_0, y_0)$, the maximum number of iterations nb_iter_max, the size of the tabu list L, the number r of neighboring solutions, and the version of the algorithm used to generate the neighborhood, v. The TS-CTIM algorithm produces as output the best solution f_{best}, which has been found among those analyzed. To this end, the algorithm starts from a random initial solution $f_0 = (x_0, y_0)$, wherein each wireless (WiFi and Zigbee) link is assigned a channel. The two vectors x_0 and y_0 represent, respectively, the initial WiFi link-channel assignment and Zigbee link-channel assignment variables' values. We set the current solution f_i equal to f_0.

The first version of the Tabu Search algorithm, TS-CTIM-1, generates at each iteration the sequence of $r^2 + r$ solutions according to the following procedure. Given the current solution $f_i = (x_i, y_i)$, we first apply one time the $move$ operation on x_i and we obtain a neighboring solution (x'_i, y_i). Then, we apply $move$ on y_i generating r neighboring solutions (x_i, y'_i), and we choose among all these $r + 1$ solutions the one with the lowest interference as new solution (x'_i, y'_i) . This procedure is repeated r times, and among all $r^2 + r$ solutions (x'_i, y'_i) generated using r times Neighborhood-1, the one with the minimum interference is used as starting solution for the successive iteration of the TS-CTIM algorithm, $f_i = (x'_i, y'_i)$, with i updated to $i + 1$. Conversely, the second version of the Tabu Search (i.e., TS-CTIM-2), applies the $move$ operation on the set of variables representing ZigBee links, y_i, producing a novel solution (x_i, y'_i) in which only one channel of a randomly selected ZigBee link is modified. Then the $move$ operation is applied r times on the set of WiFi links, x_i, to generate r nearby solutions (x'_i, y'_i).

In order to modify r ZigBee links, the previous procedure, which is implemented by the Neighborhood-2 algorithm, is executed r times, thus resulting in a set of $r^2 + r$ solutions explored at each iteration.

Algorithm 2: Neighborhood-1

Input : $f_i = (\boldsymbol{x}_i, \boldsymbol{y}_i), r$
Output: F_i
$F_i \Leftarrow \emptyset$;
$\boldsymbol{x}'_i \Leftarrow move(\boldsymbol{x}_i)$;
$F_i \Leftarrow F_i \cup \{(\boldsymbol{x}'_i, \boldsymbol{y}_i)\}$;
while $k < r$ **do**
    $\boldsymbol{y}'_i \Leftarrow move(\boldsymbol{y}_i)$;
    $F_i \Leftarrow F_i \cup \{(\boldsymbol{x}_i, \boldsymbol{y}'_i)\}$;
    $k \Leftarrow k + 1$;
end

Algorithm 3: Neighborhood-2

Input : $f_i = (\boldsymbol{x}_i, \boldsymbol{y}_i), r$
Output: F_i
$F_i \Leftarrow \emptyset$;
$\boldsymbol{y}'_i \Leftarrow move(\boldsymbol{y}_i)$;
$F_i \Leftarrow F_i \cup \{(\boldsymbol{x}_i, \boldsymbol{y}'_i)\}$;
while $k < r$ **do**
    $\boldsymbol{x}'_i \Leftarrow move(\boldsymbol{x}_i)$;
    $F_i \Leftarrow F_i \cup \{(\boldsymbol{x}'_i, \boldsymbol{y}_i)\}$;
    $k \Leftarrow k + 1$;
end

Finally, both alternative versions of the TS-CTIM algorithm terminate after nb_iter_max consecutive iterations without improvements to the cross technology interference. However, every time a solution f_i produces a lower cross-technology interference $CTI(f_i)$, the iterations counter is reset to avoid local minima (step 8).

A formal description of the TS-CTIM algorithm (i.e., TS-CTIM-1 and TS-CTIM-2) is provided in Algorithm 4.

VI. NUMERICAL RESULTS

This section presents the numerical results that illustrate the validity of the proposed algorithms to solve the Cross-Technology Interference mitigation problem. More specifically, we evaluate the impact of the BBN density (i.e., the total number of WBANs in a BBN) on the performance of the overall system using the algorithms developed in the previous sections.

We first describe the experimental methodology of our simulations, then we analyze and discuss the performance achieved by the proposed algorithms.

A. Experimental Methodology

In our simulations, we consider both *static* and *dynamic* BBN topologies, whose nodes (or WBANs) are randomly scattered over an area of $1000 \times 1000m^2$.

In order to evaluate the effect of the node density on the level of interference, we vary the total number of mobile terminals in the range $[20, 50]$. To do so, we fix the number of mobile terminals within each BBN to 5 and vary the number of BBNs

Algorithm 4: TS-CTIM

Input : $\mathcal{N}, G_c(\mathcal{V}_c(t), \mathcal{E}_c(t)), f_0 = (\boldsymbol{x}_0, \boldsymbol{y}_0), nb\_iter\_max, L, r, v$
Output: $\boldsymbol{x_{best}}, \boldsymbol{y_{best}}$
Start with an initial solution $f_0 = (x_0, y_0)$;
$i = 0$, $k = 0$, $f_{best} = f_0$, $I_{best} = CTI(f_0)$;
while $i < nb\_iter\_max$ **do**
  while $k < r$ **do**
    $F_i \Leftarrow$Neighborhood-v(f_i);
    $f_i \Leftarrow argmin_{\boldsymbol{F_i}} I(t)$;
    Add $move(f_i)$ to the tabu list;
    $k \Leftarrow k + 1$;
  end
  if $(CTI(f_i) \leq I_{best})$ **then**
    $f_{best} \Leftarrow f_i$;
    $I_{best} \Leftarrow CTI(f_i)$;
    $i \Leftarrow 0$;
  else
    $i \Leftarrow i + 1$;
  end
end
Return $f_{best} = (\boldsymbol{x_{best}}, \boldsymbol{y_{best}})$;

from 4 to 10. Specifically, BBN centers are scattered according to a uniform distribution inside the simulation area, whereas the mobile terminals are deployed around each BBN center according to a bi-dimensional Gaussian distribution with a standard deviation equal to 100 meters.

In the *dynamic* network scenario, we simulate the BBNs mobility using the random way-point model [16], which is one of the most widely used mobility models in mobile networks. In particular, for each time epoch we compute the random displacements of all BBNs' centers, and we move all mobile terminals within the same BBN towards the same direction according to the displacement vector.

In our simulations, we consider only the three orthogonal channels defined by the WiFi alliance ($\mathcal{K}_w = \{1, 6, 11\}$), whereas for the WBAN links we use all the 16 available ZigBee channels ($\mathcal{K}_z \in [11, 26]$). The transmission powers of WiFi and ZigBee radio interfaces are fixed to 100 mW and 1 mW, respectively. Due to the higher transmission power used by the WiFi than the ZigBee technology, we set $\alpha = 5$, $\beta = 1$ and $\gamma = 10$ in Equation (1).

The extended conflict graph is computed assuming the utilization of an ARQ mechanism as error recovery technique (i.e., we assume DATA-ACK message exchange among the network nodes involved in data communications). The reception and carrier sense thresholds used to decide whether nodes can establish communication links or interfere among each others are defined according to the sensitivity of Atheros (WiFi)[2] and CC2420 (ZigBee)[3] radio chipsets.

The path loss, which is necessary to evaluate the sensitivity of the receiving node, is computed according to the Friis propagation model. We underline that all above assumptions do not affect the proposed algorithms, which are general and can be used to solve any network scenario.

In order to gauge the performance of the proposed heuristic algorithms (Section V) with respect to the optimal solution (Section IV), we consider the Cross-Technology Interference (CTI) defined in Equation (1). Furthermore, in the *dynamic* scenario, we measure the number of times different channels are assigned to ZigBee links across two consecutive epochs, since it provides an indication of the signaling overhead necessary to coordinate the channel switching.

Note that, due to the high computational and space complexities of the ILP model, we could not scale beyond the network sizes and time epochs discussed above (i.e., 40 nodes and 10 time epochs). Indeed, the maximum computational time and memory utilization we measured to solve the optimal CTIM problem using the CPLEX solver on an Intel Core 2 Quad Processor Q8300 with 4 cores, clock speed of 2.5 Ghz and 4 GByte of RAM were approximately equal to 5.5 hours and 70%, respectively. Conversely, the Tabu Search approaches take always less than 3 seconds to find the corresponding solutions (when the parameter $r = 10$).

B. Performance Evaluation

Static Scenario. We first evaluate the effect of the node density and the number of available channels on the performance of our interference mitigation techniques. Specifically, in the network scenario described above, we vary the number of mobile terminals in the $[20, 50]$ range and we progressively increase the number of orthogonal WiFi channels from 1 to 3. Figures 3 show the Cross-Technology Interference obtained using our proposed algorithms. For the sake of clarity, the CTI has been normalized with respect to the maximum value measured by the RR-CTIM algorithm ($I_{RR}(t) \simeq 46000$).

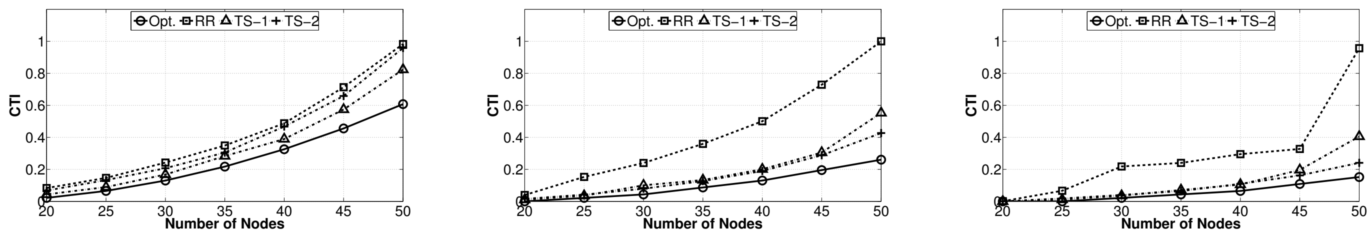
The curves identified by labels "Opt.", "RR" and "TS-v" ($v \in \{1, 2\}$) illustrate, respectively, the performance metrics computed using the Optimal, the Randomized Rounding and the two Tabu Search alternatives that we presented in previous sections.

As illustrated in the figures, the two versions of the Tabu Search algorithm well approach the Optimal solution, whereas the Randomized Rounding technique provides always solutions with higher interference. We observe that in almost all network instances, the decision variables of the LP relaxation have the same values, which are interpreted by the RR-CTIM algorithm as an even channel assignment, thus failing to drive effectively the remaining operations of the algorithm. Indeed, when the optimal solution of the LP relaxation provides the same values to all decision variables, the $FeasWiFiSol()$ and $FeasZigBeeSol()$ functions in Algorithm 1 generate randomly the channels to be assigned to WiFi and ZigBee links.

As expected, increasing the node density within the simulation area leads to higher cross technology interference, since the mobile terminals and the sensor devices of the WBANs get closer, thus increasing the number of edges of the extended conflict graph.

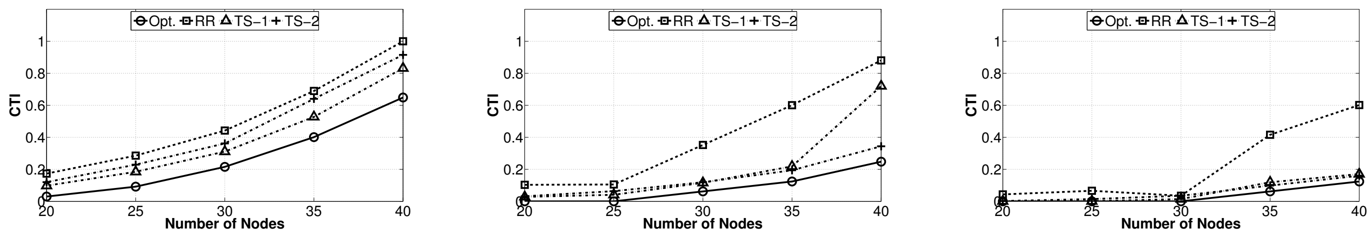
It can be further observed from Figures 3(a), 3(b) and 3(c) that the number of available WiFi channels affects the performance of all approaches. Specifically, the higher is

[2]Available on-line http://www.diswire.com/SpecsCM9.pdf
[3]Available on-line http://www.ti.com/lit/ds/symlink/cc2420.pdf



(a) 1 WiFi Channel (b) 2 WiFi Channels (c) 3 WiFi Channels

Fig. 3: Cross-Technology Interference as a function of the node density and number of orthogonal WiFi channels (i.e., $\{1, 6, 11\}$) measured in the *static* network scenario. All results are normalized to the maximum CTI computed using the RR-CTIM algorithm ($I(t) \simeq 46000$).



(a) 1 WiFi Channel (b) 2 WiFi Channels (c) 3 WiFi Channels

Fig. 4: Cross-Technology Interference as a function of the node density and number of orthogonal WiFi channels (i.e., $\{1, 6, 11\}$) measured in the *dynamic* network scenario. All results are normalized to the maximum CTI computed using the RR-CTIM algorithm ($I(t) \simeq 16000$).

the number of orthogonal channels, the lower is the overall interference of the solution computed by all algorithms. Furthermore, as illustrated in Figure 3(a), when only one channel is available, TS-CTIM-2 provides slightly worse performance than TS-CTIM-1, since the procedure Neighborhood-2 changes only one ZigBee channel, thus generating a neighborhood of r solutions for each iteration instead of r^2 with Neighborhood-1 (r WiFi links are not really affected by the $move$ operation of Neighborhood-2). As long as the number of orthogonal WiFi channels increases, TS-CTIM-2 outperforms TS-CTIM-1, since the algorithm can analyze more alternative solutions.

Dynamic Scenario with Fixed Channels. The second set of simulated scenarios, whose results are depicted in Figure 4, aims at evaluating the effect of the mobility on the performance of our proposed schemes. To this end, within the $1000 \times 1000m^2$ simulation area, we randomly move all nodes throughout 10 time epochs, according to the mobility model described above. The mobile terminal speed is set to 1 m/s, while the duration of a single time epoch is fixed to 10 seconds, which is long enough to capture significant changes in both the network topology and the extended conflict graph during the simulation time.

As in the *static* scenario, the CTI has been normalized with respect to the maximum value measured by the RR-CTIM algorithm ($I_{RR}(t) \simeq 16000$).

The results obtained in the dynamic scenario, and illustrated in Figures 4, confirm the trends observed in the static scenario described above. Specifically, the cross-technology interference improves by increasing the number of orthogonal WiFi channels and decreasing the node density (or equivalently by increasing the spatial reuse). Since the number of orthogonal WiFi channels in the ISM band is limited, BBNs' users should improve the spatial reuse, reducing the transmission power to the minimum level necessary to maintain network connectivity.

Finally, we can observe that node density affects the network performance more than the mobility, since all algorithms minimize the worst cross technology interference throughout all time epochs.

Dynamic Scenario with Channel Switching. In order to provide more insights about the gain achievable by enabling the channel switching, we evaluate the performance in terms of signaling overhead of the algorithms presented in previous sections neglecting constraints (7) and (8) for the optimization based approaches and optimizing the topologies of all time epochs as consecutive instances of the static scenario for the tabu-search approaches. In particular, we illustrate the distribution of ZigBee links that are forced to change channel during the simulation time and the overall number of channels used by the algorithms. Note that the algorithms modified to consider the channel switching functionality achieve the same maximum Cross Technology Interference illustrated in Figures 4.

Figure 5 shows the channel switching distributions of the ZigBee links obtained with the optimal and heuristic algorithms in the network scenario composed of 40 mobile terminals and 3 available WiFi channels. For the sake of brevity, we do not illustrate the results obtained with fewer mobile terminals, since the distributions have similar trends, even if the average number of channel changes decreases. Even though the optimal algorithm achieves the lowest Cross

Technology Interference, it forces all ZigBee links to change their channel at least four times, as illustrated in Figure 5. Conversely, the percentage of links, which changes channel at least four times, decreases to 80%, 30% and 10% using the randomized rounding and the two tabu-search approaches. This is mainly due to the smaller solution space analyzed by the heuristic approaches that indirectly requires a lower channel changes than the optimal algorithm. Indeed, we noticed that the randomized rounding approach selects almost uniformly the channels assigned to each epoch, while the generation of the neighborhood used by the tabu-search techniques limits the channels changes assigned to wireless links.

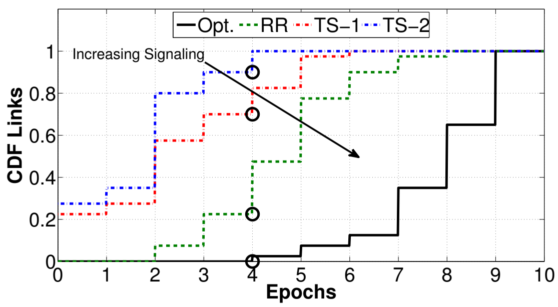


Fig. 5: Channel switching distribution of ZigBee links in the scenario composed of 40 mobile terminals (5 WBANs for each of the 8 BBNs). The black circles represent the percentage of links that switch their channel less than 4 times (i.e., $\mathcal{F}(x < 4)$).

As for the efficiency of the resource utilization, it can be observed from Table I that channel switching increases the total number of channels used by the entire system during the simulation. In particular, the optimal and tabu-search solutions require the utilization of all available ZigBee channels, without improving significantly the maximum Cross Technology Interference experienced by the network nodes.

Therefore, our results suggest that the utilization of the channel switching is not justified, since despite an increased signaling overhead necessary to coordinate the devices and an increased use of the available channels, the algorithms do not reduce significantly the Cross Technology Interference within the network with respect to the solution with fixed channels.

TABLE I: Number of ZigBee channels used in the scenario with 40 mobile terminals during the whole simulation time.

	Fixed channels				Channel switching			
$\lvert\mathcal{K}_w\rvert$	Opt.	RR	TS-1	TS-2	Opt.	RR	TS-1	TS-2
1	12	3	9	8	12	4	16	16
2	12	3	8	6	16	8	16	16
3	11	2	5	4	16	4	16	16

VII. Conclusion

In this paper, we addressed the Mutual and Cross-Technology Interference mitigation (CTIM) problem in an IoT composed of several Body-to-Body networks. We formulated the interference mitigation across different wireless technologies (i.e., ZigBee and WiFi) as an optimization problem, and we introduced a new conflict graph to represent interfering wireless links that use different radio access technologies.

In order to solve efficiently (i.e., in polynomial time) the interference mitigation problem for large-scale IoT instances, we also developed three heuristic approaches based on Randomized Rounding and Tabu-Search techniques.

We evaluated the performance of the proposed algorithms considering both static and dynamic scenarios, illustrating the sensitivity of our algorithms to different parameters, like the BBN density, the total number of available WiFi channels, and the utilization of the channel switching functionality.

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