UNIVERSIDAD POLITÉCNICA DE MADRID

ESCUELA TÉCNICA SUPERIOR DE INGENIEROS DE TELECOMUNICACIÓN

DOCTORAL THESIS

COGNITIVE STRATEGIES FOR REDUCING ENERGY CONSUMPTION IN WIRELESS SENSOR NETWORKS

Elena Romero Perales

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Resumen

El consumo energético de las Redes de Sensores Inalámbricas (WSNs por sus siglas en inglés) es un problema histórico que ha sido abordado desde diferentes niveles y visiones, ya que no solo afecta a la propia supervivencia de la red sino que el creciente uso de dispositivos inteligentes y el nuevo paradigma del Internet de las Cosas hace que las WSNs tengan cada vez una mayor influencia en la huella energética. Debido a la tendencia al alza en el uso de estas redes se añade un nuevo problema, la saturación espectral. Las WSNs operan habitualmente en bandas sin licencia como son las bandas Industrial, Científica y Médica (ISM por sus siglas en inglés). Estas bandas se comparten con otro tipo de redes como Wi-Fi o Bluetooth cuyo uso ha crecido exponencialmente en los últimos años. Para abordar este problema aparece el paradigma de la Radio Cognitiva (CR), una tecnología que permite el acceso oportunista al espectro. La introducción de capacidades cognitivas en las WSNs no solo permite optimizar su eficiencia espectral sino que también tiene un impacto positivo en parámetros como la calidad de servicio, la seguridad o el consumo energético. Sin embargo, por otra parte, este nuevo paradigma plantea algunos retos relacionados con el consumo energético. Concretamente, el sensado del espectro, la colaboración entre los nodos (que requiere comunicación adicional) y el cambio en los parámetros de transmisión aumentan el consumo respecto a las WSN clásicas. Teniendo en cuenta que la investigación en el campo del consumo energético ha sido ampliamente abordada puesto que se trata de una de sus principales limitaciones, asumimos que las nuevas estrategias deben surgir de las nuevas capacidades añadidas por las redes cognitivas. Por otro lado, a la hora de diseñar estrategias de optimización para CWSN hay que tener muy presentes las limitaciones de recursos de estas redes en cuanto a memoria, computación y consumo energético de los nodos.

En esta tesis doctoral proponemos dos estrategias de reducción de consumo energético en CWSNs basadas en tres pilares fundamentales. El primero son las capacidades cognitivas añadidas a las WSNs que proporcionan la posibilidad de adaptar los parámetros de transmisión en función del espectro disponible. La segunda es la colaboración, como característica intrínseca de las CWSNs. Finalmente, el tercer pilar de este trabajo es teoría de juegos como algoritmo de soporte a la decisión, ampliamente utilizado en WSNs debido a su simplicidad.

Como primer aporte de la tesis se presenta un análisis completo de las posibilidades introducidas por la radio cognitiva en materia de reducción de consumo para WSNs. Gracias a las conclusiones extraídas de este análisis, se han planteado las hipótesis de esta tesis relacionadas con la validez de usar capacidades cognitivas como herramienta para la reducción

de consumo en CWSNs. Una vez presentada las hipótesis, pasamos a desarrollar las principales contribuciones de la tesis: las dos estrategias diseñadas para reducción de consumo basadas en teoría de juegos y CR. La primera de ellas hace uso de un juego no cooperativo que se juega mediante pares de jugadores. En la segunda estrategia, aunque el juego continúa siendo no cooperativo, se añade el concepto de colaboración. Para cada una de las estrategias se presenta el modelo del juego, el análisis formal de equilibrios y óptimos y la descripción de la estrategia completa donde se incluye la interacción entre nodos.

Con el propósito de probar las estrategias mediante simulación e implementación en dispositivos reales hemos desarrollado un marco de pruebas compuesto por un simulador cognitivo y un banco de pruebas formado por nodos cognitivos capaces de comunicarse en tres bandas ISM desarrollados en el B105 Lab. Este marco de pruebas constituye otra de las aportaciones de la tesis que permitirá el avance en la investigación en el área de las CWSNs.

Finalmente, se presentan y discuten los resultados derivados de la prueba de las estrategias desarrolladas. La primera estrategia proporciona ahorros de energía mayores al 65% comparados con una WSN sin capacidades cognitivas y alrededor del 25% si la comparamos con una estrategia cognitiva basada en el sensado periódico del espectro para el cambio de canal de acuerdo a un nivel de ruido fijado. Este algoritmo se comporta de forma similar independientemente del nivel de ruido siempre que éste sea espacialmente uniformemente. Esta estrategia, a pesar de su sencillez, nos asegura el comportamiento óptimo en cuanto a consumo energético debido a la utilización de teoría de juegos en la fase de diseño del comportamiento de los nodos. La estrategia colaborativa presenta mejoras respecto a la anterior en términos de protección frente al ruido en escenarios de ruido más complejos donde aporta una mejora del 50% comparada con la estrategia anterior.

Palabras clave: Redes de sensores inalámbricas, radio cognitiva, optimización energética, redes inalámbricas de sensores cognitivas, teoría de juegos, colaboración, eficiencia espectral.

Abstract

Energy consumption in Wireless Sensor Networks (WSNs) is a known historical problem that has been addressed from different areas and on many levels. But this problem should not only be approached from the point of view of their own efficiency for survival. A major portion of communication traffic has migrated to mobile networks and systems. The increased use of smart devices and the introduction of the Internet of Things (IoT) give WSNs a great influence on the carbon footprint. Thus, optimizing the energy consumption of wireless networks could reduce their environmental impact considerably.

In recent years, another problem has been added to the equation: spectrum saturation. Wireless Sensor Networks usually operate in unlicensed spectrum bands such as Industrial, Scientific, and Medical (ISM) bands shared with other networks (mainly Wi-Fi and Bluetooth). To address the efficient spectrum utilization problem, Cognitive Radio (CR) has emerged as the key technology that enables opportunistic access to the spectrum.

Therefore, the introduction of cognitive capabilities to WSNs allows optimizing their spectral occupation. Cognitive Wireless Sensor Networks (CWSNs) do not only increase the reliability of communications, but they also have a positive impact on parameters such as the Quality of Service (QoS), network security, or energy consumption. These new opportunities introduced by CWSNs unveil a wide field in the energy consumption research area. However, this also implies some challenges. Specifically, the spectrum sensing stage, collaboration among devices (which requires extra communication), and changes in the transmission parameters increase the total energy consumption of the network. When designing CWSN optimization strategies, the fact that WSN nodes are very limited in terms of memory, computational power, or energy consumption has to be considered. Thus, light strategies that require a low computing capacity must be found. Since the field of energy conservation in WSNs has been widely explored, we assume that new strategies could emerge from the new opportunities presented by cognitive networks.

In this PhD Thesis, we present two strategies for energy consumption reduction in CWSNs supported by three main pillars. The first pillar is that cognitive capabilities added to the WSN provide the ability to change the transmission parameters according to the spectrum. The second pillar is that the ability to collaborate is a basic characteristic of CWSNs. Finally, the third pillar for this work is the game theory as a decision-making algorithm, which has been widely used in WSNs due to its lightness and simplicity that make it valid to operate in CWSNs.

For the development of these strategies, a complete analysis of the possibilities is first carried out by incorporating the cognitive abilities into the network. Once this analysis has been performed, we expose the hypotheses of this thesis related to the use of cognitive capabilities as a useful tool to reduce energy consumption in CWSNs.

Once the analyses are exposed, we present the main contribution of this thesis: the two designed strategies for energy consumption reduction based on game theory and cognitive capabilities. The first one is based on a non-cooperative game played between two players in a simple and selfish way. In the second strategy, the concept of collaboration is introduced. Despite the fact that the game used is also a non-cooperative game, the decisions are taken through collaboration. For each strategy, we present the modeled game, the formal analysis of equilibrium and optimum, and the complete strategy describing the interaction between nodes.

In order to test the strategies through simulation and implementation in real devices, we have developed a CWSN framework composed by a CWSN simulator based on Castalia and a testbed based on CWSN nodes able to communicate in three different ISM bands.

We present and discuss the results derived by the energy optimization strategies. The first strategy brings energy improvement rates of over 65% compared to WSN without cognitive techniques. It also brings energy improvement rates of over 25% compared with sensing strategies for changing channels based on a decision threshold. We have also seen that the algorithm behaves similarly even with significant variations in the level of noise while working in a uniform noise scenario. The collaborative strategy presents improvements respecting the previous strategy in terms of noise protection when the noise scheme is more complex where this strategy shows improvement rates of over 50%.

Keywords: Wireless Sensor Networks, Cognitive Radio, energy optimization, Cognitive Wireless Sensor Networks, game theory, collaboration, spectrum efficiency.

Agradecimientos/Acknowledgments

Aquí estamos… el trabajo acabado y una lista inmensa de gente que en estos años ha estado conmigo para lo que hiciera falta. Para ellos un cachito de esto…

A Alvaro, mi director, porque al final esta tesis está aquí porque te has empeñado tú. Por las broncas en el momento necesario y los ánimos cuando hacían falta. Por dejarme miniperlas en forma de artículos encima de la mesa que me ayudaban a dar pequeños saltos y avanzar. Por la idea loca de la radio cognitiva que vino contigo de Berkeley y por tener el carisma que hizo que nos ilusionara. Por el apoyo constante incluso cuando los atascos eran más que evidentes. Porque al final has creído en esta tesis más que nadie. Porque no se me ocurre un mejor director.

Al B105 por todo lo que he aprendido. Este grupo es maravilloso. A Octavio por el soporte y por confiar en mí. Por permitirme el tiempo necesario para dar el salto y madurar, como dices. Por formar este grupo y luchar por él más allá de lo imaginable. A Alvaro, por dejarte la piel, el sueño y la vida por el 105. Por elegir a los mejores, por hacer especial al labo, por convertirlo en rock and roll. Disfrútalo. A Javi por ser mi compañero en estos 5 años de camino. Por acompañarme y hacer la tesis un poco un trabajo de grupo. Por las planificaciones de cognitive, las listas de special issues, las submissions in extremis, los resoplidos, las crisis y avances de Castalia y las siete pruebas de Asterix. Aquí estamos compañero. A Paco que aun siendo un externo era todo un 105. Y como las cosas ponen a todo el mundo en su sitio, aquí te tenemos. Por ponerle pasión a todo lo que haces. A Alba, tonadi. Por ser mi compañera en este men's world. Por las risas y el humor leonés. Por la routing layer. Por instaurar el hobbit con su idiosincrasia que hace un poquito más grupo al grupo. A Guille con sus despistes de postureo, sus ahora bajo, su no104 y la perfección hasta el agobio. A Rober por su yetismo de litrona, por ser el genio debajo de las camisetas desgastadas. Por tomar el relevo con los juegos. A Rami por el yetismo bohemio, la calma y el consenso en chanclas. Por querer ser un 105. Por la guitarra y el ukelele, por la diferencia. A Mariano, fuente original del saber y el comodín de la llamada más que nunca en esta tesis. De mayor quiero ser como tú. A Curro por el festival del humor Romeril, triunfará. A mis niños del cogito, porque somos un equipo: Agus, Javi, Fer, Guille, Juan, Cobo, Jose, North, Rasines y Malarcon. Por los esfuerzos en un proyecto común. A todos los que fueron, son y serán el 105, porque de todos queda algo que da color al labo.

I would like to thank also the TKN in Berlin, I had a really profitable and enjoyable time with you, learning about different things, specially to Daniel Willkomm and Adam Wolisz.

A mis niñas de teleco por la primera parte de esta andadura, a mis niñas del conser, por estar ahí desde bien pequeñas, a lo locos de teatro porque me dan otro espacio cuando hace falta, a mis "vecinas" de la casa por cuidarme tanto y a mis amigos de verdad porque si os sigo llamando así no hace falta que explique más.

A los maestros y profesores que me han acompañado en todas las etapas de mi vida. Todos forman parte un poquito de lo que soy. Desde la guardería y el cole, pasando por el instituto, profes-músicos del conservatorio y la universidad. A los profesores que me han enseñado un poco a ser profe, los que me han ayudado en las colaboraciones docentes, mi madre y sus compañeras. Gracias.

Y por supuesto, a mi familia, porque si he sido capaz de terminar esto es por vosotros. A mis padres, mi hermano, mis abuelos, mis tíos, mis primos, mis mellis... sois lo más importante que tengo. Espero que sepáis todo lo que os quiero. En especial a mis abuelos Enriqueta, Juan, Amelia y Juanito, por ser ejemplo de creatividad, trabajo, bondad y constancia. A Hen por los ánimos SIEMPRE. A papá por convencerse de que esta locura es un trabajo de verdad y que es el que quiero. A mamá por implicarte, apoyarme y poner todo tu empeño en este proyecto de doctora. A los dos por el apoyo y el respeto a mis decisiones, por la enseñanza de vida, por el tiempo dedicado. Por ser los maestros más importantes. Mil gracias por todo lo que me habéis enseñado.

Mamá, papá: aquí está. Por fin.

Y a Alvaro, por marcar el minuto, por los desayunos con jamón en la terraza, por el vértigo, por dejar que me coma todos tus frutos secos, por los resúmenes de viajes, por desafiar el oleaje sin timón ni timonel, por un kalimotxo fresquito, por cantarme en todas las ciudades... que no se acabe esta noche y que no me enamore yo. Por los transceptores con mensaje. Ya ves, todo arde si le aplicas la chispa adecuada.

Y a todos los que por las prisas me dejo en el camino. Si lees esto, a ti.

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The beginning is always today

Mary Wollstonecraft

1 INTRODUCTION

Global mobile data traffic in telecommunications grows annually at a rate of 70%, and it reached 2.5 exabytes per month at the end of 2014 [1]. Global mobile data traffic is expected to increase nearly tenfold between 2014 and 2019, growing at a compound annual growth rate (CAGR) of 57% from 2014 to 2019. The estimated traffic level per month is projected to reach 24.3 exabytes by 2019. Taking this prediction into account, the current rate of power consumption per unit of data cannot be sustained.

While the growth in traffic is stunning, the rapid adoption of wireless technology across the globe and its penetration through all layers of society is even more amazing. The increasing number of wireless devices that are accessing mobile networks worldwide is one of the primary contributors to traffic growth. The number of mobile-connected devices exceeded the world's population in 2014 and reached 7.4 billion according to the CISCO report. Almost half a billion mobile devices and connections were added in 2014.

One of the main causes of this spectacular growth of mobile traffic is the increase of mobile-connected laptops and tablets and the emergence of smartphones.

Smartphone use has resulted in 439 million net additions in 2014. The trend in mobile device growth can be seen in Figure 1-1. The average smartphone will produce 4.0 GB of traffic per month by 2019 according to CISCO predictions. By 2019, aggregate smartphone traffic will be 10.5 times greater than it is today, with a CAGR of 60%.

This data traffic is even larger for mobile-connected tablets since each tablet generates 2.5 times more traffic than the average smartphone. By 2019, mobile-connected tablets will generate nearly double the traffic generated by the entire global mobile network in 2014. In addition, a large percentage of mobile-connected laptop users consider mobile broadband their primary means of accessing the internet. Nowadays, there are more than 190 million laptops on the mobile network, and the traffic generated by each laptop is around 3.2 times greater than the average smartphone. Smartphones, tablets, and laptops are usually connected via Wi-Fi or Bluetooth, which work on a 2.4 GHz unlicensed band.

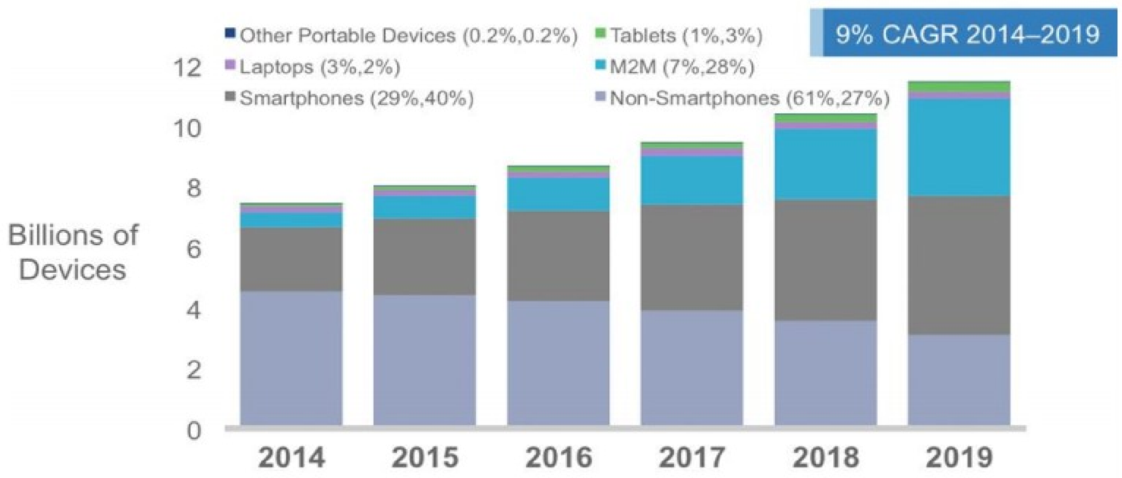


Figure 1-1. Global mobile devices and connections growth [1].

Looking at Figure 1-1, we can notice that Machine-to-Machine (M2M) communication is shown as one of the most important trends linked to the growth of the Internet of Things (IoT) paradigm. Machine-to-Machine technology enables wireless communication between multiple devices, which turns data obtained through daily objects into useful information. The phenomenal growth in smart, wearable, and end-user devices is a clear indicator of the growth of the IoT. This new paradigm brings together people, things, data, and processes to make internet access a non-intrusive, natural process.

Worldwide, there are nearly 109 million wearable devices (a sub-segment of the M2M category) generating 15 petabytes of monthly traffic (see Figure 1-2 and Figure 1-3. Globally, traffic from wearable devices will grow 18-fold from 15 petabytes per month in 2014 to 277 petabytes per month by 2019 (CAGR 78%).

Figure 1-2. Global connected wearable devices.

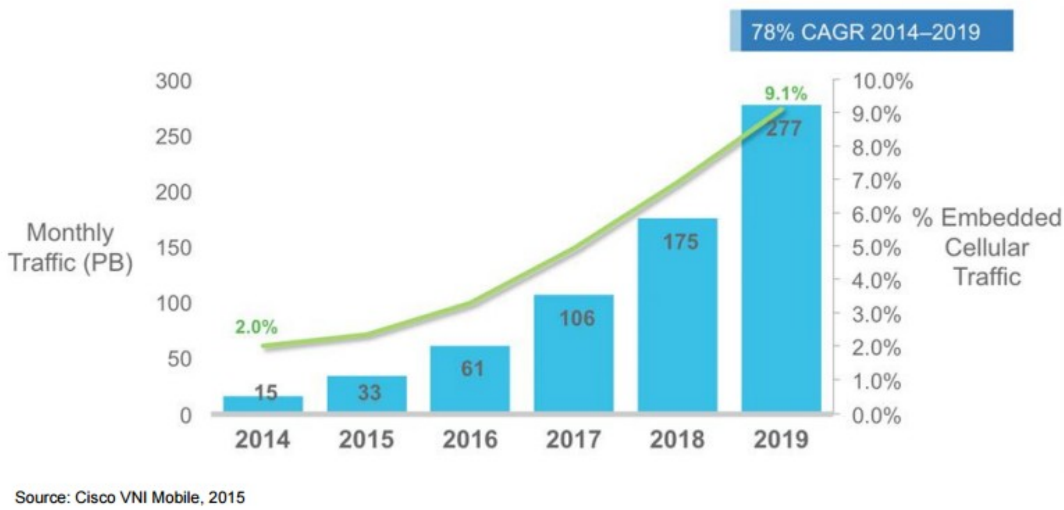


Figure 1-3. Global wearable devices traffic impact.

Wireless sensor networks (WSNs) provide a technological solution to this challenge, so their growth is closely linked to these data. A WSN consists of a large number of sensor nodes distributed over an area of interest for local environment monitoring. This acquired data is locally processed, stored, and shared with other nodes so that information can be used by the whole network. Wireless Sensor Networks are built by several nodes (from dozens to several hundred depending on the application). Each node typically has four modules: (a) a microcontroller, (b) a radio transceiver with an internal or an external antenna, (c) one or more sensors, and (d) an energy source (usually batteries or an energy-harvesting system). A WSN node has several constraints in terms of size, cost, energy consumption, memory, and computational capabilities. The potential fields of application for WSNs arise from home control to military scenarios, vehicular networks, or critical information infrastructure protection. For that reason, WSNs are increasingly introduced into our daily lives. The number of devices connected is expected to grow from 2 billion in 2014 to 8 billion in 2020.

One of the most important challenges to overcome in WSNs linked to this growth is certainly the spectral coexistence, as most WSN solutions operate in unlicensed frequency bands. In general, they use Industrial, Scientific and Medical (ISM) bands, which are radio spectrum bands reserved worldwide for the use of radio frequency energy for industrial, scientific, and medical purposes. Typical examples of these uses include microwave ovens and medical electromagnetic emissions. As the power emitted by these devices can create interferences in radio communication, they are assigned to certain spectrum bands. Despite the objective of the original allocations, the fact that they are unlicensed has encouraged the implementation of short-range, low power communications systems in this spectrum such as Bluetooth, Zigbee^{TM}, or Wi-Fi.

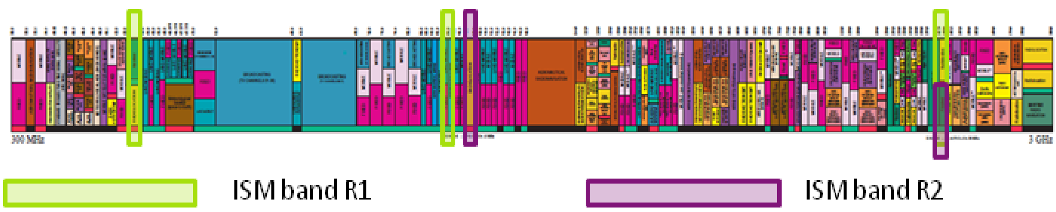


Figure 1-4. ISM bands for Region 1 and Region 2 between 300 MHz to 3 GHz.

Among the ISM available bands that are shown in Figure 1-4, WSNs in Europe (belonging to Region 1) used to emit in three of them: (a) 433 MHz, (b) 868 MHz, and

(c) the worldwide available 2.4 GHz band. This 2.4 GHz band is used by a large number of popular wireless applications (for example, those that work over Wi-Fi, Bluetooth, or new wireless technologies such as Zigbee™/IEEE 802.15.4). One of the main causes of the growing intensive usage of these bands is the increase of wireless-connected laptops, tablets, and smartphones, which was mentioned before. By 2016, more than half of all traffic from mobile-connected devices will be offloaded to the fixed network by means of Wi-Fi devices and femtocells [1].

For this reason, the unlicensed spectrum bands are becoming overcrowded with the increasing use of Wireless Local Area Network (WLAN) based systems and Wireless Personal Area Network (WPAN) based systems. As a result, coexistence issues in unlicensed bands have been subject of extensive research [2]. In particular, it has been shown that IEEE 802.11 (Wi-Fi) networks can significantly degrade the performance of Zigbee™ /802.15.4 networks (WSNs) when operating in overlapping frequency bands [3].

Considering the stunning growth of wireless communications, one of the main challenges to overcome is the spectral coexistence. To address this challenge, Cognitive Radio (CR) [4] has emerged as the key technology enabling opportunistic access to the spectrum. This new paradigm has appeared in order to solve the general spectrum saturation problem, and it is not specifically related to ISM bands.

Spectrum usage in the U.S.A. is illustrated in the chart in Figure 1-5 from the Office of Spectrum Management of the U.S. Commerce National Telecommunications and Information Administration. With the increasing demand of wireless communications and the democratization in the access to connected devices, the congestion across the used frequencies increases, reducing their network performance. With this depicted scenario, the demand for new communications models arises. In this way, the conscious spectrum usage and the cooperation between devices introduced by CR allows better spectrum use and better data reliability.

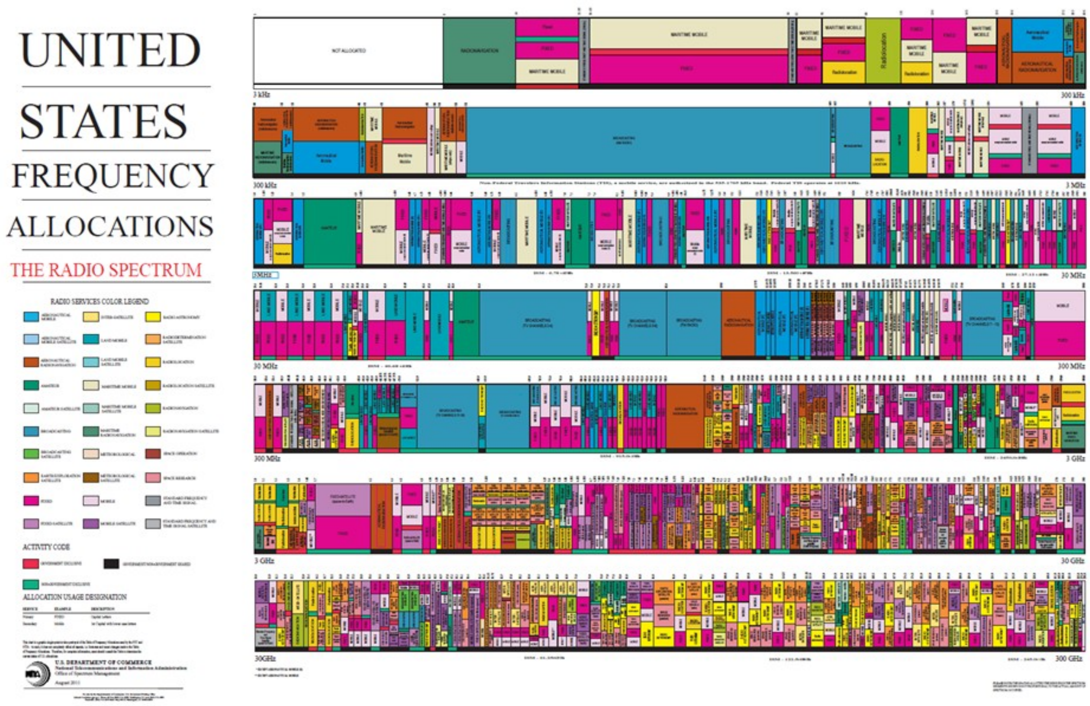


Figure 1-5. Radio spectrum frequency allocations in the United States in 2011.

The concept of a Cognitive Network (CN) was proposed as a wireless network in which each node can adapt its transmission and reception parameters according to its operating radio environment via spectrum sensing [5]. The spectrum holes can be used through dynamic spectrum access by these CR devices in order to achieve efficient communications as seen in Figure 1-6.

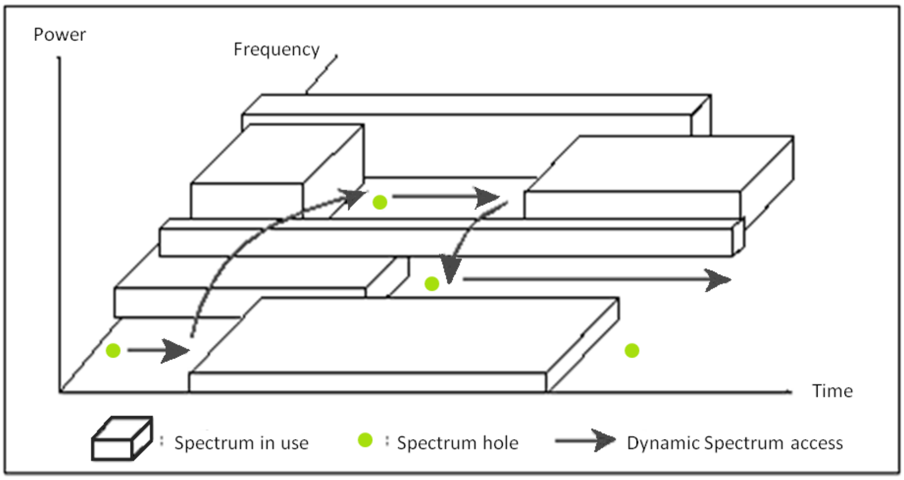


Figure 1-6. Use of the spectrum holes through dynamic spectrum access.

In the first definition of a CN provided by Mitola in 2000 [4], a CN was defined as an intelligent wireless communication system that is aware of its surrounding environment and adapts its internal parameters to achieve reliable and efficient communication (in terms of power consumption, too). Since its first appearance, there has been rapidly increasing interest in CNs due to their optimization regarding using spectrum resources, their capacity to allow more reliable communication, and their new offered services. Cognitive Networks are based on three main technical components: (a) the cognitive capabilities of devices, (b) collaboration among terminals, and (c) network knowledge.

Therefore, the introduction of cognitive capabilities into WSNs allowing us to optimize their spectral occupation seems to be a good option. Cognitive Wireless Sensor Networks (CWSNs) could not only increase the reliability of communications, they could also have a positive impact on parameters such as Quality of Service (QoS), network security, or energy consumption [6].

The WSN has historically been a technology with numerous problems related to energy consumption [7]. Due to the number of nodes, its wireless nature, and its deployment in difficult access areas, WSN nodes should not require any maintenance. In terms of consumption, this means that the sensor nodes must be energetically autonomous, the networks should not require human intervention, and therefore the batteries cannot be changed or recharged. In these kinds of scenarios, node lifetimes should last for years, making low energy consumption a dramatic requirement [8]. If energy consumption has not been taken into account, nodes will eventually shut down.

Therefore, the subject of energy consumption in WSNs is a known historical problem that has been addressed from different areas and on many levels. It has been approached from the specific physical implementation of the nodes themselves to the application level, including routing protocols or media access control (MAC) ad-hoc implementations. Nevertheless, the problem of energy consumption in WSNs should not be approached only from the point of view of efficiency for survival. A major portion of the communication traffic has been migrating to mobile networks and systems. This fact, coupled with the increasing use of smart devices, and the introduction of the IoT give WSNs a great influence on the carbon footprint. Thus, optimizing the energy consumption of wireless networks could reduce their environmental impact considerably.

With the new paradigm derived from the increasing demand for wireless communication (especially in the unlicensed bands) and the proposal of CWSNs as a potential solution, we cannot overlook the reality that the introduction of CR into WSNs implies some important changes. Intrinsic challenges related to CR capabilities include hardware complexity, algorithmic constraints, and network design problems. Indeed, the added complexity of the nodes to enable cognitive capabilities makes them consume more energy. On the other hand, the introduction of CR features into WSNs could not only solve spectral saturation problems, but also give the WSNs several advantages such as [9]:

- A higher transmission range.
- Fewer sensor nodes required to cover a specific area.
- Better use of the spectrum.
- Lower energy consumption.
- Better communication quality.
- Lower delays.
- Better data reliability.

The introduction of CR capabilities in WSNs provides a new paradigm for energy consumption reduction. It offers new opportunities to improve it, but also creates some challenges. Specifically, the sensing of the radio spectrum, collaboration among devices -which requires extra communication-, and changes in the transmission parameters all increase the total energy consumption of the network. In this way, all steps must be taken into account for a holistic optimization.

Considering all these points, it is extremely important to optimize every step of wireless communications (ranging from the manufacture of equipment to communication algorithms). Since the field of energy conservation in WSNs is widely explored, we assume that new strategies should emerge from the new opportunities presented by cognitive networks. Thus, information sharing, the history and network operation, and the ability to change the transmission parameters should serve as tools to design cognitive strategies to reduce energy consumption in CWSNs.

Taking advantage of the new cognitive capabilities of a CWSN can have a great impact on energy consumption. These new opportunities unveil a wide field in the energy consumption research area. However, the introduction of CR capabilities also creates some challenges. When designing CWSN optimization strategies, the fact that WSN nodes are very limited in terms of memory, computational power, and energy consumption is not insignificant. Thus, light strategies that require a low computing capacity must be found. The implementation of complex algorithms that would help us optimize energy consumption is not a valid approach due to the low processing capabilities of the nodes.

1.1 OBJECTIVES

Considering the importance of reducing energy consumption in WSNs due to its increase and future trends and the new CWSN paradigm introduced to solve the spectrum coexistence problem, the future scenario needs an effort in terms of solving intrinsic energy consumption WSN problems. Thus, the main objective of this doctoral thesis is to reduce energy consumption in CWSNs by exploiting the new capabilities introduced by the cognitive radio concept. Due to the number of nodes, their wireless nature, the new capabilities introduced, and the intensive use of these networks, energy consumption in CWSNs is a cornerstone for the viability of this new paradigm.

The specific objective of this work is to propose strategies to optimize energy consumption in cognitive WSNs by taking advantage of the new possibilities introduced by CR almost to overload the extra energy consumption introduced for executing cognitive tasks. The work is supported by three main pillars. The first is that the cognitive capabilities added to the WSN provide the ability to know the state of the spectrum and change the transmission parameters. The second pillar is that the ability to collaborate is a basic characteristic of CWSNs. Finally, the third pillar or important aspect to consider is that CWSN nodes have constrained resources. The proposed strategies should have characteristics of lightness and simplicity that make them valid to operate in these networks.

The main objective can be divided into three sub-objectives:

1. The analysis and identification of main opportunities for energy consumption reduction arising from the introduction of CR into WSN.
2. The design of energy consumption reduction strategies based on these new capabilities that are light enough to be implemented in a resource-constrained CWSN node.
3. The implementation and testing of the designed strategies in order to assure validness and performance under different scenarios.

1.2 METHODOLOGY

For the development of this work and the achievement of the previous objectives we have followed a continuous feedback based methodology. A sequential approach is used enriched with feedback in two fundamental steps: simulation and implementation in real devices. Along with the use of feedback, the main characteristic of the methodology followed in the development of this thesis is that it is based on a progression from the simplest to the most complex.

The phases of this methodology can be grouped into three fundamental sections: design, testing, and feedback. In the design phase, optimization strategies are analyzed and designed. In the next phase, these strategies are tested in the CWSN framework designed and implemented in the B105 Lab for the purpose of this work. Once the strategies are tested and proven, and not before, we analyze the results and obtain feedback. With this feedback, we optimize the methods and strategies and we add complexity if necessary in order to enrich the performance. This schema has been followed from the simplest to the most complex approaches.

In a more detailed inspection, the followed methodology phases are: Strategy proposal, analysis, and design, (belonging to the group we have called design), simulation and testing in real devices (belonging to the group identified as testing) and evaluation and feedback (which we have named together as feedback).

It is also necessary to notice that to carry out the stages of simulation and testing in real devices, the design and implementation of the tools (simulator and testbed) that would enable their achievements has been necessary. The development of this test framework is also based on a progression from the simplest to the most complex.

In the following sections we explain more thoroughly the contents of each of these phases that can be seen in the **Figure 1-7**.

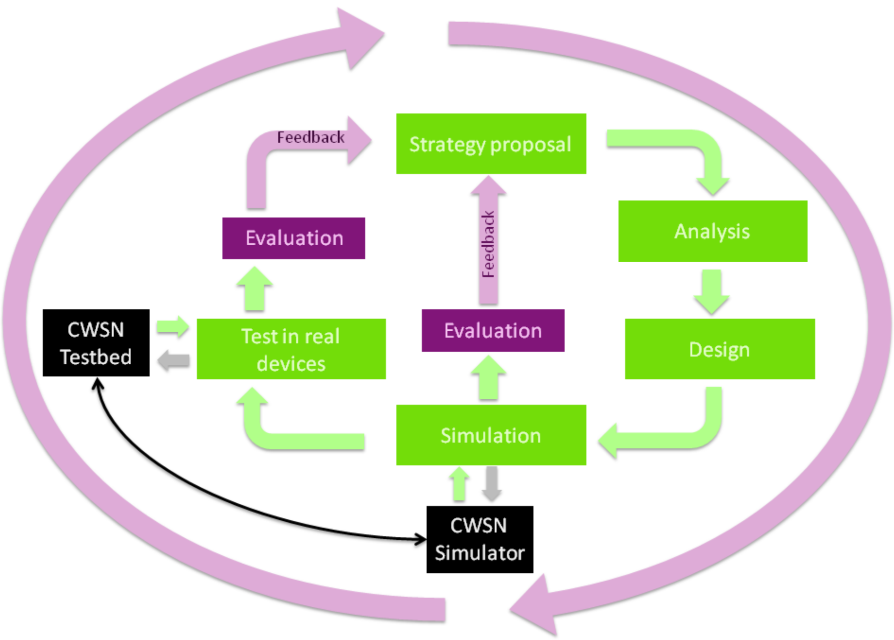


Figure 1-7. Continuous feedback methodology used.

1.2.1 STRATEGY PROPOSAL

After the initial study of the problem and alternatives phase, strategies to provide solutions to the problem of energy efficiency have to be proposed.

Considering the conclusions arisen of both the opportunities analysis and the selection of optimization model for CWSNs two strategies have been developed. These two strategies are designed to improve energy consumption in CWSNs taking advantage of introduced cognitive capabilities. These strategies are based on game theory and have used the selection of the communication channel as the resource to be modeled. Again, these two strategies have been designed following the iteration loop described before.

1.2.2 FORMAL ANALYSIS

Once the energy efficiency strategies are raised, we perform the formal analysis of them. This stage aims at the theoretical formulation and verification of the expected results. At this stage we have performed the necessary mathematical analysis and we have confirmed the existence and convergence of equilibriums and optimums to ensure that theoretically expected results are met.

1.2.3 STRATEGY DESIGN

Once formulated and analyzed the strategies, we design the strategy operation needed to be implemented into the CWSN.

The design decisions regarding which nodes and at what time will be carried out each of the required tasks belong to this stage. Also, the decisions regarding which modules of the architecture are involved in each task. They are also taken at this stage decisions about interactions between nodes; what information has to be exchanged, which messages will be shared or what data will be available at each node in each phase.

To sum up, this stage corresponds to the design of the strategy implementation for each of the network nodes.

1.2.4 SIMULATION

The designed strategies are tested then in the simulation stage. Simulators provide the ability to simulate an immense variety of networks and topologies. The implementation of such diverse configurations in real devices and the deployment of a network composed by a large number of physical nodes would be very costly. These simulations serve to validate the strategies and verify that with the available model in the simulator, the optimizations yield satisfactory results.

This stage requires the implementation in the simulator of the designed CWSN strategies.

1.2.5 DEVELOPING CWSN SIMULATOR

One of the difficulties we have encountered when testing experimentally the developed algorithms have been the lack of available tools.

As we are going to present in the Chapter 4 there are not many simulators adapted to CWSN, which makes mandatory at this stage of the work to progress on the development of our own cognitive layer for the well known WSN Simulator Castalia.

Among the tasks that we have made for this adaptation, we can list the implementation of the necessary cognitive module for the strategies development, the implementation of extra functionality that allows the change of the transmission parameters, the implementation of a Virtual Control Channel (VCC) and the adaptation of the architecture of the nodes to support more than one communication interface.

These tasks have been carried out progressively as we would need extra features. The result of this work is presented in Section 4.3.

1.2.6 TEST IN REAL DEVICES

Once the simulated results are obtained, if successful, the strategies have been implemented in real nodes where the behavior under typical environmental conditions has been measured.

This implementation in real nodes serves to validate the strategies designed with real constraints for WSNs nodes. Although validated first in the simulator, the physical deployment on nodes provide us the ability to find problems that are not possible to be discovered at the simulator since the models of simulated nodes always have some limitations to reflect as closely as possible the real conditions. This way, we can detect problems of timing, memory access times, collision of control packets, and also validate that the strategies can be implemented in constrained devices.

1.2.7 DEVELOPING CWSN TESTBED

To carry out the real nodes implementation phase it is necessary to design and implement a testbed based on CWSN nodes that allows us to have more access to radio parameters and greater possibilities of changing parameters that the current existing WSN nodes.

This development, like the improvement of the simulator has been progressively achieved and functionalities have been added to complete the testbed at the final step of this thesis. The nodes developed in the B105 Lab permit access to three different frequency spectrum bands and the modification of transmission parameters such as frequency channel, power emitted or packet size.

For the nodes development, we have designed and implemented both the physical hardware and the integrated software that enables the management of the three different protocol stacks and also a cognitive module. The result of this testbed implementation could be seen in Section 4.4.

Also, for a complete feedback, once the results are validated in real nodes, the measurements taken in these nodes are reintroduced in the simulator in order to keep improving the accuracy of the results. This way we are able to get the network performance for large deployments based on real consumption measures of devices. Adding data taken from functional prototypes to the simulator could demonstrate the suitability of simulations to reality. Thus, the combination of both elements results in a complete and useful framework for validation of policies and optimization mechanisms for energy consumption in cognitive networks.

1.2.8 FEEDBACK

During the development of this thesis, this process has been repeated several times, sometimes only until the first one simulation feedback and sometimes completely to the implementation feedback.

Feedback is an essential feature in the development of this thesis. With each of the tests performed on the designed strategies we were analyzed the results and the need to modify the design of the strategy itself arose whether the results were not satisfactory. Also, the possibility to add complexity to further optimize the energy consumption has been assessed.

An example of this repetition performance for each of the strategies can be seen in the Figure 1-8. The first row shows a development process when the feedback is produced into the first simulation test and after, with the subsequent implementation in real devices. The second row shows a development process with two times feedback arisen from the simulation phase.

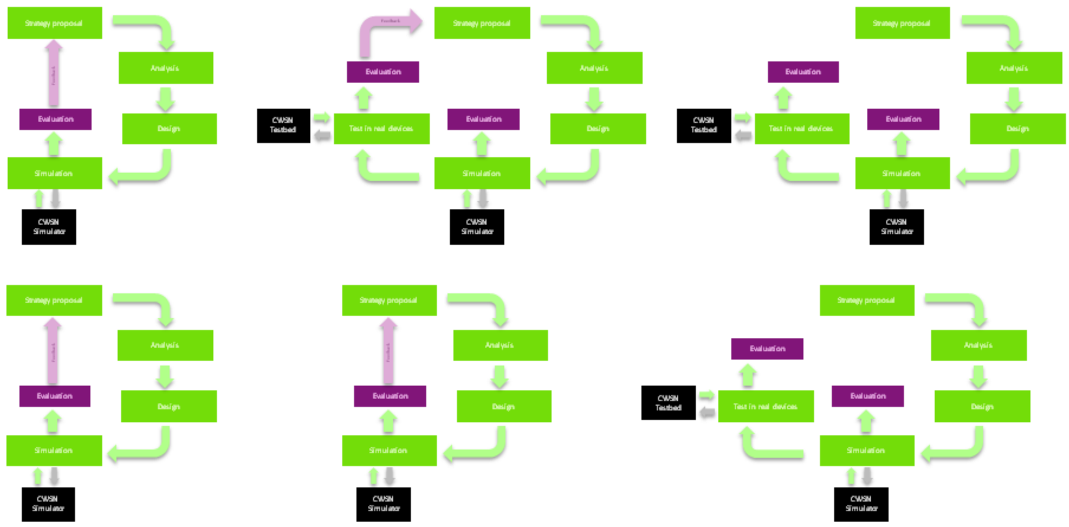


Figure 1-8. Example of cycle of methodology usage.

1.3 DOCUMENT ORGANIZATION

The organization of the PhD Thesis document is as follows:

First, we have conducted a thorough analysis both in terms of reducing energy consumption opportunities and algorithm design in Chapter 2. Thanks to this analysis, delimiting the contribution of this work is possible. We have divided the opportunities into three main characteristics of CR, the ability of sense the spectrum, the capability of change transmission parameters and the collaboration among devices. With the analysis performed and the complete information regarding opportunities (in Section 2.1) and modeling methods (in Section 2.3) we are able to delimit the specific area of this thesis.

After the review of the energy optimization opportunities introduced by cognitive radio in WSN, we present a state of the art focused in different cognitive techniques for energy efficiency in CWSNs also in Chapter 2, Section 2.2. This review is performed in order to delimit and enclose the research area, allowing us to focus our work. Since CWSNs shares some features with CR, we also present and analyze some works not specifically designed for WSNs but that might be useful as ideas to be applied. Also, a review of some energy efficiency techniques historically developed for WSN that could be improved with the introduction of CR capabilities is presented. Finally, some conclusions about the state of the art and the most interesting research opportunities are provided.

After the opportunities analysis, the algorithm methods and the state of the art reviewed, we expose the hypotheses of this thesis. These hypotheses combine the conclusions drawn from the three points above. These hypotheses are drawn in Section 2.4.

After the hypothesis statement, Chapter 3 presents the main contribution of this PhD Thesis. We begin with the working scenario definition in Section 3.1, delimiting the available nodes' resources and constraints. After, in Section 3.2 we present the cognitive architecture used in the design and implementation of the strategies. We continue with a brief review of the most important mathematical concepts used in the strategies in order to lay the foundation of the formal definition, classifications and terminology in Section 3.3.

In Section 3.4 and Section 3.5 we present a detailed description of the two energy optimization strategies, constituting the fundamental contributions of this work. For each strategy, we present the model game, the formal analysis and the complete strategy describing the interaction between nodes.

Chapter 4 presents the tools developed for the strategy validation. The CWSN framework that we have developed to test the proposals is presented and described. This CWSN framework is composed of two fundamental elements: a network cognitive simulator and the implementation of a CWSN testbed composed by a new low-power platform with three different wireless interfaces, the cNGD. They are presented in Section 4.3 and Section 4.4 respectively.

Results and discussion are presented in Chapter 5. For each strategy, we present the baseline scenario and the different scenario configurations used in the simulations in order to validate different aspects of each strategy. Afterwards, the results obtained through the implemented CWSN framework are presented and discussed.

Finally, conclusion and future lines are depicted in Chapter 6.

1.4 PUBLICATIONS

We list in this section the set of publications obtained as a result of this work. First, we show the international journal publications and after the contributions presented into international conferences.

1.4.1 INTERNATIONAL JOURNAL PUBLICATION

- E. Romero, J. Blesa, A. Araujo, and O. Nieto-Taladriz, “A game theory based strategy for reducing energy consumption in cognitive WSN”, International Journal of Distributed Sensor Networks, vol. 2014, 9 pages, 2014,
  IF: JCR (2013) 0.923
- A. Tena, G. Jara, J. Domingo, E. Romero, and A. Araujo, “Cognitive Wireless Sensor Network Platform for Cooperative Communications”, International Journal of Distributed Sensor Networks, vol. 2014, 8 pages, 2014,
  IF: JCR (2013) 0.923
- E. Romero, A. Mouradian, J. Blesa, J.M. Moya, A. Araujo, “Simulation Framework for Security Threats in Cognitive Radio Networks”, IET Communications. Special Issue on Cognitive Communications. vol.6, no.8, pp.984. 7 pages, 2012
  IF: JCR (2013) 0.72
- A. Araujo, J. Blesa, E. Romero, and D. Villanueva, “Security in cognitive wireless sensor networks. Challenges and open problems”, EURASIP Journal

on Wireless Communications and Networking, vol. 2012, no. 1, p. 48. 8 pages. 2012
IF: JCR (2013) 0.805

- A. Araujo, E. Romero, J. Blesa, O. Nieto-Taladriz, “A framework for the design, development and evaluation of Cognitive Wireless Sensor Networks”, The International Journal on Advances in Telecommunications. pp 141-152. 2012
- F. López, E. Romero, J. Blesa, D. Villanueva, A. Araujo, “Cognitive Wireless Sensor Network Device for AAL Scenarios”, Lecture Notes in Computer Science. Ambient Assisted Living. vol. 6693 pp. 116-121. 2011.

1.4.2 CONFERENCE PAPERS

- E. Romero, J. Blesa; A. Tena, G. Jara, J. Domingo, A. Araujo, “Cognitive test-bed for wireless sensor networks”, 2014 IEEE International Symposium on Dynamic Spectrum Access Networks, DYSPAN 2014, pp. 346–349, 2014. 1-4 April 2014, McLean, VA, USA.
- J. Domingo, E. Romero, A. Araujo and O. Nieto-Taladriz, “Protocol stack adaptation for providing access to three ISM bands in a CWSN node”, Proceedings of 57th ETRAN Conference, 2013, pp. EL3.5.1-4. 3-6 June, 2013, Zlatibor, Serbia.
- A. Araujo, E. Romero, J. Blesa, O. Nieto-Taladriz, “Cognitive Wireless Sensor Networks Framework for Green Communications Design”, II International Conference on Advances in Cognitive Radio. COCORA 2012. 29 April - 4 May 2012. Chamonix, France.
  BEST PAPER AWARD
- E. Romero, A. Araujo, J. Blesa, O. Nieto-Taladriz, “Developing Cognitive Strategies for Reducing Energy Consumption in Wireless Sensor Networks”, II International Conference on Advances in Cognitive Radio. COCORA 2012. 29 April - 4 May 2012. Chamonix, France.
- J. Blesa, E. Romero, J.C. Vallejo, D. Villanueva, A. Araujo, “A Cognitive Simulator for Wireless Sensor Networks”, V International Symposium of

Ubiquitous Computing & Ambient Intelligence, UCAmI2011 5-9 December 2011. Ribera Maya, Mexico.

- A. Araujo, E. Romero, A. Fernandez-Villamil, J. Blesa, J. M. Moya, “Cognitive Networks for AAL scenarios”, II International Workshop of Ambient Assisted Living, IWAAL2010. 8-10 September 2010. Valencia, Spain.

Cuanto más se dividen los obstáculos, más fáciles son de vencer

Concepción Arenal

2 ANALYSIS AND HYPOTHESIS PROPOSALS

The first step toward proposing energy optimization methods for CWSNs is to conduct a thorough analysis both in terms of reducing energy consumption opportunities and algorithm design. Thanks to this analysis, delimiting the contribution of this thesis is possible.

For this purpose, a complete analysis of the possibilities introduced by incorporating the cognitive abilities into the network is carried out. We expose and discuss these possibilities and divide them into three main groups depending on the CR feature to which they belong. Secondly, we review the state of the art strategies in energy consumption reduction for CWSNs. The strategies are divided into the same three groups as the possibilities in the opportunities analysis. After the state of the art in energy optimization for CWSN research, we study and analyze some of the main techniques used in the field of optimization and decision making for communications networks. We present and analyze the utilization of some of the most used methods in CWSNs.

With those analyses performed and the complete information regarding opportunities and modeling methods examined, we propose the hypotheses of this thesis and verify them in the following chapters. These hypotheses combine the conclusions drawn from the three points listed above.

2.1 OPPORTUNITIES TO REDUCE ENERGY CONSUMPTION IN CWSNS

Current energy efficient wireless communications research directions have to consider CR capabilities to enable energy reduction in WSNs as we stated in Chapter 1. Also, we can declare that the reduction of energy consumption in a CWSN is a task that could involve the overall design across all layers of the communication protocol. Focusing on layer by layer of the protocol stack, several strategies for optimizing energy consumption can be listed for each layer. Nevertheless, our proposal according to the analysis performed is that, due to CR characteristics, addressing the problem of energy consumption in a CR approach has more advantages. Taking into account that, along with CR, new energy-consuming tasks that belong to different layers are introduced and the idea of a cross-layer approach is supported by the research community, studying the opportunities from a wider perspective has more benefits.

Along this line, we propose to address the problem of energy consumption more clearly and decide where to focus our efforts by dividing the opportunities to optimize energy consumption into three: (a) those that are derived through the spectrum sensing stage, (b) those related to the capability to change transmission parameters, and (c) those that depend on the ability to share knowledge of the network. The first two aspects are directly related to the introduction of cognitive capabilities in the WSNs nodes and they did not exist in common WSNs. However, although essential for CR, the third aspect related to the communication between devices is one of the basic characteristics of common WSNs. In CWSNs, it is enriched with cognitive information.

Henceforth, we propose a series of available optimizations for each aspect that could be used to reduce energy consumption in CWSNs thanks to the introduction of cognitive capabilities into traditional WSNs.

2.1.1 SPECTRUM SENSING

Related to the sensing stage, we can consider several strategies to lower energy consumption. The influence of the sensing strategy is crucial to the viability of the network since its associated energy consumption is one of the highest within the new features of the CWSN. In terms of energy consumption, we need to answer one of the main questions: “What is the most efficient sensing method in terms of energy?” The answer must combine results about period, duration, and the number of nodes involved.

Number of nodes: A larger number of nodes involved in spectrum sensing would provide better information. However, the number also affects the overall consumption of the network because a larger number of nodes would be involved and thus diminish its available energy. But also, if we limit the number of nodes that perform spectrum sensing and this information should be shared, the necessary communications to exchange the results increase in respect to the situation where spectrum sensing is done individually.

Sensing frequency: As an expensive task in terms of energy consumption, performing spectrum sensing more frequently produces better sensing network status information. However, it is more expensive in terms of energy consumed.

Sensing duration: This decision affects the quality of the results obtained or the number of scanned channels. A complete channel sensing set provides a wider range of decision possibilities. There are also strategies consisting of limiting the sensing time and the number of scanned channels in order to reduce energy consumption [10].

Sensing method: The sensing method used when discovering the state of the spectrum affects the energy consumed. As stated in [11], different sensing methods exist for CR (energy detection, match filtering, waveform based, or cyclostationary) and they have different implications regarding energy consumption.

Individual or cooperative: Although this feature does not specifically belong to spectrum sensing but to decisions derived from sensing, it is closely related. Decision-making can be node-oriented or network-oriented. In the first case, each node makes their own decisions. In contrast, the sensed data should be exchanged in order to make a coordinated decision in the second case. This exchange of data involves extra communication and therefore increases energy consumption.

Centralized or distributed sensing: Similar to the number of nodes that perform sensing, the number of nodes involved in decision-making also influences the final energy consumption of this stage. Regardless of the quality of the result and focusing only in terms of energy consumption, if the sensing stage is done cooperatively, centralized configuration can reduce the amount of messages exchanged that are required for the decision compared to a distributed decision.

2.1.2 CAPABILITY TO CHANGE TRANSMISSION PARAMETERS

A network can reduce energy consumption through the variation of several transmission parameters linked with sensed information. Examples of these parameters are transmission power, channel allocation, packet size, or modulation.

Channel allocation: Often in WSN scenarios, due to congestion of the network and low power transmission, some packets are lost. This loss forces retransmissions. Cognitive Radio provides the ability to sense the spectrum and change transmission parameters according to it. Thus, if a less noisy channel is found in the sensing stage, it may be optimal to change the transmission channel in order to avoid duplicate transmissions, thus reducing the global consumption of the network.

Transmission power: In the same way as in the previous case, cognitive features provide the ability to transmit in less noisy channels. If we control the power emitted, we can interfere with less nodes in the network. This way, the spectrum is less congested and we can reduce the number of retransmissions associated with the collisions. We can reduce the transmission power by ensuring that the messages reach their destination without masking other nodes in the networks (or belonging to different networks). Considering that communication is one of the most energy expensive tasks for a CWSN node and transmitted power is one of the most important involved parameters, reducing power transmission also saves the energy of the emitter node, and therefore, that of the network.

Modulation: Using less noisy channels provides the possibility of using more energy efficient modulations. Energy consumption could be reduced by using less robust modulations with lower energy consumption if we use a channel with low interferences. More energy can be conserved by dynamically adopting the modulation according to instantaneous traffic load and the congestion of channels.

Radio interfaces: Based on data rate requirements, and if more than one radio interface is available, network devices can modify their communication radio interface to assure a specific data rate with the lowest energy consumption. Networks can use the most efficient wireless interface for a required data rate.

Packet size: A decision about packet size influences energy consumption. The transmission of small packets performs better under varying channel conditions, but it is more expensive in terms of overhead. On the contrary, increasing the packet size increases the packet loss probability. This practice results in retransmissions, and hence, increased energy consumption, but it reduces the overhead of each packet.

It should also be considered that, in addition to each of these optimizations separately, the different parameters can be combined into multi-factor optimizations.

2.1.3 ABILITY TO SHARE KNOWLEDGE OF THE NETWORK

The CWSN paradigm allows us to modify several parameters with an influence in energy consumption beyond the transmission ones listed above. These parameters could belong to every stack level from the application layer to the physical radio interface, but we focus at this moment on enhancing existing energy efficient methods with spectrum knowledge.

Devices with higher energy consumption could be switched off: Nodes temporally or locally placed in high interference level areas can be turned off and thereby save the energy consumed by excessive retransmissions. In highly dynamic environments where channel conditions vary over time, they would turn on when a spectral gap appears. In this way, the nodes would avoid wasting energy.

Load balance: Despite the previous point, sometimes load balance could be beneficial to reduce the overall consumption of the network even when using a priori nodes with higher energy consumption levels. If nodes with the lowest consumption or in an interference-free location become stressed, their batteries could be depleted, which would force the network to pass all future messages by nodes with higher consumption.

Transmitting with power enough to reach only some nodes: Taking into account that the network is aware of the topology, the packets could be sent directly to the destination if they are within the transmission range. Otherwise, instead of increasing transmission power, messages could be sent to intermediate nodes, which then would forward the packets to other nodes until the destination is reached. This multi-hop transmission coupled with spectrum information takes advantage of the exponential decrease in radiated power to save energy.

Developing more energy efficient protocols and routing algorithms: Related to the three approaches above, there is a vast field of research related to routing schemes. These new schemes could combine data from individual node consumption, load balancing, the distance between nodes, the number of hops to reach the destination, and spectrum information to design more efficient routing protocols.

Design more energy efficient MAC protocols: As in the previous case, changing the sensing/transmission/idle modes based on spectrum information could decrease the energy consumption of the network. Information can be stored in a node for the needed time, limited by the latency limit, until the node finds a spectral hole through which to transmit it. During that time, the receiver can be also be switched off to save energy.

Adaptive communication based on application QoS requirements: Because of the spectrum knowledge, a network could send more important packets using better modulation, a frequency channel, or a shorter path (even with an energy penalty if needed). Also, the network could use crowd channels to transmit packets with low QoS requirements if it could save energy in this way.

2.1.4 CROSS-NETWORK DECISSIONS

After reviewing the three blocks derived from the introduction of CR in WSNs, a general issue that we cannot forget remains: the influence of information distribution and decision-making. The sharing of information across the network and the decision level is important not only for the sensing stage, but also for parameter changes. As in sensing, this can be done at the node level, the cluster level, or the network level. On this basis, the required communication and the chosen optimization could be very different.

Energy consumption optimizations are highly dependent on the optimization level and communications required to do it. Is it better to optimize at a node level or at a network level? Which kind of data is important for these optimizations? Should they be individual decisions or a globally taken decision? These questions need to be explored in order to find an answer related to energy.

A summary of the main opportunities for energy consumption reduction in CWSNs could is stated in Figure 2-1.

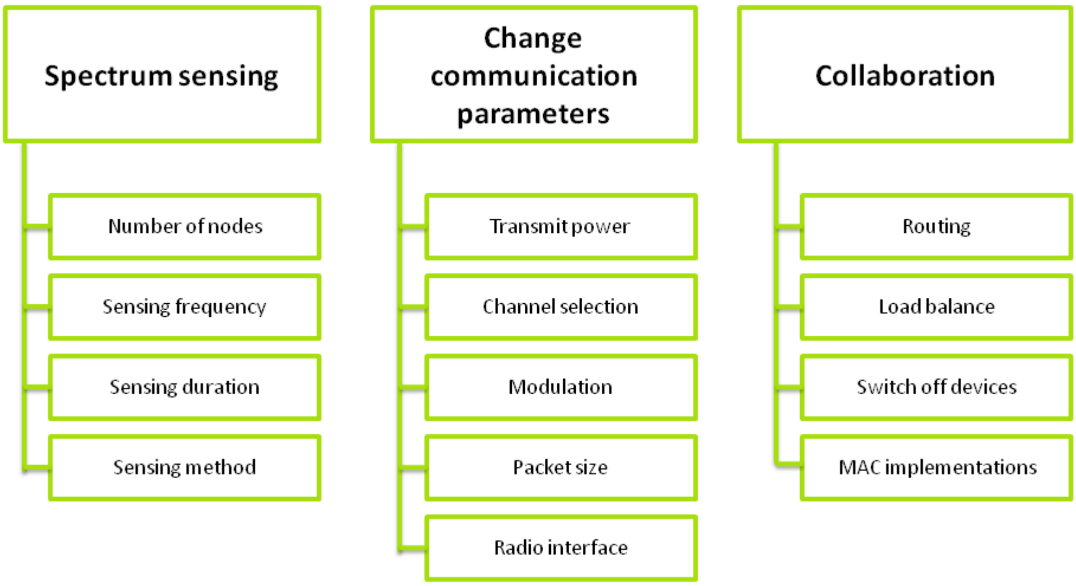


Figure 2-1. Summary of energy consumption optimization opportunities.

2.2 STATE OF THE ART

In this section, once the opportunities are analyzed, a literature review in energy consumption optimization for CWSN is presented in order to delimit and enclose the research area. To survey the main contributions in the area allows us to find the unanswered question for focusing our research. First, we are going to present a state of the art in different cognitive techniques for energy efficiency in WSNs. Since the state of the art in CWSNs is relatively recent, we have to take advantage of other more developed areas that can provide us interesting ideas to consider. In this line, we present and analyze some works not specifically designed for low-resources networks but that might be applied. Also, a review of some energy efficiency techniques historically developed for WSNs that could be improved with the introduction of CR capabilities is presented. Finally, some conclusions about the state of the art and the most interesting research opportunities are provided.

Focusing on CWSN the first works have appeared around 2008, when most of them just introduce the idea of apply cognitive techniques into WSN and promote the research on this topic. Along this line, authors present in [12] an overview of CWSNs, discussing the emerging topics and the potential challenges in the field. The main advantages and functioning are discussed and possible, but vague, solutions to the problems are suggested. In the same line, a comprehensive survey of CWSNs is presented in [13], where the main design principles, topologies, algorithms, sensing and decision techniques, advantages, application areas and architectures of CWSN are exposed. It remarks the interest of the research in this area and lists suitable tasks divided by layers. In [14] the vision and advantage of a holistic approach to cognition in sensor networks is provided. In [15] a methodology, a theoretical framework, and some novel ideas on performance modeling are presented. It is also remarked that energy-aware routing studies do not use to address application layer constraints even though literature is rich in cross-layer suggestions. Cavalcanti introduces in [9] the new features incorporated into the PHY and MAC layers in WSN to support cognitive operation. For this implementation 802.15.4 standard is considered and analyzed.

Once we have seen that introducing CR in WSN to improve spectral efficiency and WSN performance is interesting according to different studies because of the intrinsic WSN functioning environment, we face the challenge of energy consumption. However, we must ask whether the improvement in energy efficiency is possible with the introduction of cognitive capabilities.

Namboodiri in 2009 address this topic in [16], where he stated that benefits of adding CR is well studied in terms of performance of communication but the benefits in terms of reduced energy consumption have not been quantified yet. This work mentions too one of the most crucial problems in energy consumption reduction: the spectrum sensing state. Scanning the spectrum to provide cognition is expensive in terms of energy expenses and need to be taking into account. This is the first work that explores whether a CR can save energy over a conventional radio. Several circumstances and parameters (sensing time, sensing techniques or channel sensed) are analyzed and their impact on energy consumption studied. One of his main conclusions is that increasing the number of sensed channels deteriorates energy efficiency without contributing with an increase of performance.

Considering the fact that research in energy efficiency for CR is more advanced than its analogue in CWSN, we can find different works in this area. Focusing on achieving power-efficient spectrum use, authors present in [17] a transmission power management to minimize interference with PUs and to guarantee an acceptable QoS level for the cognitive transmission. A method of spectrum sharing with multi-user cognitive network based on interference temperature limits model is proposed in [18]. Taking into account the channel occupancy probability is possible to develop a variable power-bandwidth efficiency strategy. Reducing the bandwidth efficiency by 50% can increase the battery life by 400% [19]. In [20] the power constraint is integrated into the objective function named power efficiency which is a combination of the main system parameters of the cognitive network.

If we move to the specific area of consumption reduction in CWSN, there is still much work to do due to the novelty of the field. Focusing on low-resources networks exploiting CR features to achieve energy efficiency, first works as [21] notice in 2011 the importance of using CR features to improve energy consumption. Similarly, but lightly vague, authors notice in [13] that CR could be able to adapt to varying channel conditions, which would increase transmission efficiency, and hence help reduce power used for transmission and reception. Also, within the same line, some advices are given too in [9] related to reduce the number of sensing nodes to achieve more efficient energy sensing.

Over the time, the interest in reducing energy consumption in CWSNs has been increasing. We have studied the most remarkable works to see a general map of the state of the art in this area. These works are divided into different categories depending on the CR feature they exploit as in Section 2.1. Thus, spectrum sensing techniques will be presented first; we will pass through changes made in communication parameters (as power control, channel allocation or packet size and mixed strategies which mix at least two parameters into the optimization). Third group is related to the knowledge spreading in the network (MAC layer optimizations and routing strategies enhanced with spectrum information). Also, cross layer strategies are presented.

2.2.1 SPECTRUM SENSING

Spectrum sensing techniques are one of the cornerstones both for standard CR and for CWSNs. Actually, the first works in CR area deal with design efficient techniques for spectrum sensing. Once you add the cognition to WSN the first research and improvements also have been focused on this topic. Knowledge about the status of the spectrum is essential for applying cognitive strategies; therefore, adapting sensing techniques to scarce resources networks is one of the first steps to do. Some of these techniques are designed also for minimizing energy consumption.

Optimal cooperative spectrum sensing was addressing in 2009 by [22]. This work assumed that network sensors are powered constrained and tries to minimize energy consumption in the sensing step. Given a threshold for accuracy, the optimal number of sensing nodes and the optimal period of sensing are searched. The lower and upper bounds for sensing nodes are proposed and then, they address the sensing period problem. Numerical calculations are presented too in order to validate the optimal sensing interval and the optimal number of collaborating nodes that minimize the energy consumption of the cooperative sensing.

Among the same authors there is another approach for minimizing energy consumption at sensing stage [23]. In this work the IEEE P802.22 standard is used. This standard forces to maintain accuracy and false alarm probability, hence, the problem is addressed under these constraints and the accepted presence of PUs. As in [22], the number of sensing sensors is found first, and then, authors formulate the optimization problem. Even the approach sustains the importance of energy efficiency in CWSNs, the used standard does not match our specifications.

Reducing power consumption in the sensing stage is the main objective in [24]. Authors prove the developed algorithm in an energy constrained system comprising two sensor nodes (one transmitter and one receiver) trying to avoid interference by exploiting spectrum holes in the time domain. The importance of carrying out this task adopting a cross-layer approach for spectrum sensing and optimizing the sensing procedure on energy consumption is remarked. The algorithm design tries to minimize the average energy required for the successful delivery of a packet. The cross-layer approach accounts for channel occupancy, power allocated and packet size. The results show that using short length of packets can significantly improve energy efficiency leading to gains of up to 50% compared with traditional spectrum sensing methods. One of the most remarkable results outlined in this work is that avoiding interference in the time domain might be effective for energy efficiency only if noise is sporadic in time. For heavily interfered channels, another avoidance schemes have to be adopted. Authors point on implementing channel surfing as one of the best solutions.

Another approach for distributed spectrum sensing is discussed in [25]. This scheme combines sleeping and sensing periods for minimizing energy consumed in sensing. This method must achieve constraints on minimum target probability of detection and a maximum permissible probability of false alarm. Sensors are based on IEEE 802.15.4 and ZigBee™ radios. Simulation results are presented with different scenarios regarding sensing and transmission costs in terms of energy consumed. If transmission energy is much higher than sensing energy, the optimal sleeping rate is higher than when the sensing and transmission energy are similar.

Deng et al. propose in [26] an optimal scheduling of sensors activation time for extends network lifetime. This proposal divides the sensors into a number of subsets, based on their individual channel condition, which would be activated one by one. No activated subsets are put in a sleep mode to extend the network lifetime. The sensors from the activated subset are responsible for performing spectrum sensing and guarantee that the network satisfies the necessary detection and false alarm thresholds. This problem is modeled as a scheduling problem solved with Greedy Degradation. Three approaches to solve the problem have been proposed and simulated in order to verify the performance and to study the effect of adjustable parameters.

Another work in the same line of energy minimization in cooperative spectrum sensing is [27]. As in the previous work, the proposed scenario is not a CWSN, but a CR using a WSN dedicated to spectrum sensing. Even if the scenario is not CWSN, the constrained resources make it similar in terms of critical algorithm design. These kinds of networks are named sensor-aided cognitive radio networks. The proposed scheme is based on reducing switching frequency and optimizing the schedule order. As in [26], Greedy Heuristic is proposed to find the minimum node switch with low computational complexity.

As in [22] and [23], the minimum number of cooperating nodes in cooperative spectrum sensing is searched in [28]. This work presents a user selection scheme in order to minimize the energy consumed by cooperative spectrum sensing in CWSN. This scheme is formulated as a knapsack-based energy-efficient problem for selecting active cooperating nodes that participate in the spectrum sensing process among the potential nodes subject to the energy constraint of the network. The proposed technique is evaluated using several simulations.

Carrying out a more specific design for CWSNs, [29] presents a cooperative spectrum sensing scheme, specifically designed for these networks. Energy efficiency is obtained by using the correlations of sensing data to diminish the number of nodes that perform spectrum sensing. As in [25], the rest of the nodes can switch to a low-energy sleep mode. This way, significant amount of energy consumption reduction is obtained. Latency is also affected for the using of a reduced number of nodes because minimizing the nodes sharing information also reduced it. Simulations are presented in order to validate the solution.

A similar proposal is presented in [30], where the problem of sensor selection for energy efficient spectrum sensing in CWSN is addressed. The aim of the solution is minimize energy consumption while improving spectrum sensing performance. Given thresholds for cooperative detection and false alarm probabilities, authors find the optimal sensing interval and sensor number to minimize energy consumption. To achieve more energy efficiency, they formulate the problem of joint sensing nodes and decision node selection. In this approach a decision node exists and their best location must be found. The problem is solved using convex optimization methods and verified with simulations.

Similarly to previous works as [22] and [23], Yang claims for energy efficiency in cooperative sensing process [31]. This paper offers the solution on two practical optimization problems: sensors selection and a scheduling problem leading to increase network lifetime. Heuristic algorithms are proposed and validated with experiments by simulations.

In the same way, the problem of sensor selection for energy efficient spectrum sensing in CWSNs is presented in [32]. As in previous works, due to the difficulty in solving the original modeled problem, it is divided into suboptimal problems and solutions are extracted based on convex optimization framework.

Another sensor selection problem is presented in [33]. This work is not specifically designed for CWSN but for a conventional CR with PUs and SUs using sensor-aided networks limited in terms of resources. A formal model is proposed to analyze the process of energy consumption for sensors and the modeled system is based on different sensors consuming various amounts of energy and different time-dependent rates of participation for cooperative spectrum sensing. The proposed algorithm achieves approximate fairness among sensors in terms of lifetime increasing also network duration.

Moving again to CWSN, [34] address the problem of nodes selection. As in previous works, an optimization problem is solved to obtain the minimum required number of cognitive users, and then, the most eligible cognitive users are identified through a probability-based approach. The novelty of these works fall to combine the energy consumption as well as the cooperative spectrum sensing accuracy proposing a novel method that is both energy-aware and accurate. Two benchmarks are defined to observe the effects of accentuate accuracy and the remaining energy level. Simulation results show network's lifetime at several sensing accuracy thresholds.

A novel cooperative coarse sensing scheme named CC4C based on sequential sensing is proposed in [35] to address the problem of designing energy efficient spectrum sensing methods. The proposed CC4C is a coarse spectrum sensing scheme used in a two stage spectrum sensing method for CWSN improving their work in [29]. Simulations show that this method accomplishes energy efficiency and is simple and fast.

Another feasible opportunity to design sensing methods is the use of the use of historical data. The problem of propose intelligent spectrum sensing for achieving long term energy consumed in spectrum stage for CWSNs is presented in [36]. This work models the sensing period for a specific location of the spectrum based on the history. Constraints regarding low computational cost and low memory usage are taken into account in this work. In this respect, a lightweight model for collecting spectrum occupancy information and utilizing them for predicting the future spectrum occupancy is the key contribution of this work.

Finally, a definition of sensing as a cross activity which mix application and spectrum data is presented in [37]. The novelty of this work resides in the consideration of sensing as a complex task which involves both the application data and the spectrum situation. The method is called Joint Source and Channel Sensing (JSCS) and is specifically devised for CWSNs. By exploiting the relation between the two "sensing" tasks and jointly analyze them they try to minimize energy consumption. For that reason authors present a sensing and transmitting scheme validated through simulation results.

2.2.2 CHANGE COMMUNICATION PARAMETERS

After reviewing sensing techniques to minimize energy consumption, we proceed now to explore one of the main pillars in CR, the possibility of adapting transmission parameters for achieving a better spectrum utilization. At this point we present energy consumption optimizations obtained by modifying the most significant parameters such as emitted power, packet size, modulation schemes, or communication channel.

2.2.2.1 POWER ALLOCATION

Most of the previous works related to power control pay their attention to improve QoS of cognitive PUs without taking into consideration energy efficiency. As mentioned before, when we design protocols or algorithms for WSNs, we need to take energy efficiency into account and power emitted is directly related to energy consumed in a WSN. Along this line, we can find few works with this purpose applied to CWSNs.

Chai et al. studied maximization of energy efficiency through power allocation in CWSNs where WSN nodes opportunistically use the spectrum originally owned by PUs in [38]. The work is based on Game Theory where the utility function is defined oriented to achieve energy efficiency. As we are going to present in Section 2.3 game theory is vastly used for modeling resource competition in cognitive networks. The game is designed as a non-cooperative game and a numerical analysis is performed in order to prove the existence of Nash equilibrium, identified through best response algorithm. Simulations are presented in order to demonstrate the achievement of energy consumption reduction. Features as fast convergence and fairness have been studied too. In this work, energy efficiency is defined as maximization of data rate per power unit. Even if the game and the utility function are designed to achieve energy efficiency, one of the fundamental premises of the scenario envisaged in this work is to respect and no saturate channels used by PUs. Then, although this work seems to be interesting since its objective is reduce energy consumption, it does not apply to our scenario, given that it should not be forgotten that in CWSNs there are no spectrum owners.

2.2.2.2 PACKET SIZE

The same premise of maintaining PUs channel quality is followed in the work presented in [39]. The objective of this work is determining the packet size that optimizes energy efficiency while maintaining PUs channels under acceptable interference level. To decide the optimal packet size is one of the main problems in this kind of CWSN with PUs and SUs because choosing short packets performs better under varying channel conditions and decreases the interference encountered by PUs but it is more expensive in terms of overheads and hence in terms of energy consumption. In contrast, increasing packet size improves throughput for SUs but enlarges packet loss probability resulting in retransmissions and hence, increasing energy consumption.

Optimal packet size for energy efficiency is analytically formulated and found, and its dependence in relation to diverse network parameters is verified by simulations. Results expose that PUs behavior and bit error rate are the most affecting parameters, causing variation between 100 bits to 600 bits.

2.2.2.3 MODULATION

Another parameter that could be changed in order to adapt communication to the spectrum situation is signal modulation. The use of an adaptive modulation is proposed in [40] in order to increase lifetime of the CWSN. After sensing the entire spectrum and select the preferred channel, an adaptive modulation strategy which select the optimal constellation size is used. The strategy is verified through simulation. Even the solution is interesting; the implementation of different modulations schemes in real WSNs devices is not as easy as other parameter modifications.

It should be also pointed out that this work predates first proposals of CWSN concept, which gives an idea of the interest of introducing cognitive techniques not only to increase spectral efficiency but also for the sole purpose of increasing energy efficiency of WSNs.

2.2.2.4 CHANNEL ALLOCATION

Choosing the appropriate transmission channel is one of the first optimizations that come to mind when talking about optimizing spectral holes in CR. That is the reason why over the years several schemes have been proposed first to increase spectral efficiency, but also to help in reducing energy consumed.

One of the first works in this line is presented by Byun in [41] where the network allocates the transmission channels in a centralized way in order to improve energy efficiency and fairness in channel usage. Also, several objectives as the maximization of spectrum usage, the priority among nodes and the reduction of the spectrum handoff are taken into account. The problem is formulated as a multi-objective problem solved by game theory, specifically as a cooperative game. The algorithm allocates spectrum "fairly" based on sensor priority while it tries to minimize channel switching.

Despite being part of the objectives of the work, no results concerning energy efficiency are presented. The only mention made is presented as a consequence of reducing the number of channel hops, which is expensive in terms of energy consumption, but beyond that no results are provided to validate it.

Although the proposed algorithm operates in a centralized manner, allocating spectrum in a distributive manner by a non-cooperative game is presented as a future work with a warning of implementing it as less computationally complex as possible because of constrained resources available.

The priority of PUs is also a key aspect of the channel management scheme proposed in [42]. In this work, an operation mode selection scheme for improving energy efficiency in CWSNs is presented. According to the sensed information and the energy consumption associated with each stage, the network is able to adaptively select its operation mode among channel sensing, channel switching, or data transmission/reception. Taking into account that the sensed information could be incorrect, the proposed scheme is based on partially observable Markov decision framework. Simulation results validate the proposed scheme showing energy savings while maintaining a PUs protection. Again, guaranteeing PUs protection is the first requirement of the scheme, which differs to our scenario.

Along the same line of protecting PUs priority is presented in [43], with a channel assignment problem formulated for a cluster-based CWSN. For the formulation, channel conditions (primary user behavior) and energy available in each node is taken into account (current residual energy and expected energy consumption).They examine three channel assignment approaches: random pairing, Greedy channel search and optimization-based channel assignment. The last one outperforms the other two approaches according to simulation results. This time, even PUs protection is not a goal itself, it is very present since it restricts free access to the spectrum.

Also a scenario with PUs and SUs is presented in [44] where a dynamic spectrum allocation scheme is proposed to reduce collisions and increase efficiency. The presented scheme employs firstly a Greedy algorithm to select a set of SUs according to the amount of data on a node, its residual energy, privacy and preference. Then, a reverse auction bidding strategy based on non cooperative game is used to select the optimal SUs from the set. Mixing these two strategies, authors ensure the optimal number of involved SUs, reducing spectrum switching to save energy consumption and prolong network lifetime.

Another big problem in terms of energy consumption when channel selection algorithms arise is sensing stage. Although we have seen that many energy efficient spectrum sensing CWSN techniques are developed, sensing remains the task more expensive in terms of energy along with channel hopping. Trying to alleviate this problem, Stabellini proposes in [10] an algorithm that limits energy expenses on sensing allowing the nodes to decide whether is better to stop the sensing and transmit on the selected channel or continue sensing additional channels. This algorithm is formulated as a stochastic control problem whose solution is validated through simulations and experimental results. The experimental results are conducted with a very simple scenario with only two nodes which is insufficient to guarantee the validation of the algorithm. The results obtained for reducing consumption are better compared to sense all the available channels strategy even if channels are sensed in a random order.

2.2.2.5 MULTI-FACTOR OPTIMIZATION

After seeing how playing with a single transmission parameter helps to achieve energy consumption reduction, there are still another group of strategies which are designed to combine two or more different parameters into the optimization. There are no cross-layer strategies because parameters belong to the same layer of the protocol stack, but they combine different parameters as multi-factor optimizations.

Authors present in [45] an optimization defined with a different objective function that takes energy efficiency into account. The proposed optimization is a distributed channel selection and power allocation algorithm that minimizes energy consumption per bit for a given required data rate and without introducing harmful interference to PUs. In each slot, the users with new traffic demand sense the entire spectrum and locate the available subcarrier set. Given the requirements the proposed algorithm selects the channel and the power to transmit. Simulations are performed in order to demonstrate that the proposed approach performs close to the centralized optimal solution while it provides prolonged network lifetime.

A similar channel assignment coupled with power control is presented in [46] for ad-hoc networks. Authors present four dynamic channel assignment techniques under the same set of assumptions, comparing the efficiency of their power and channel allocations. The techniques compared are Interference-based, distance-based, conflict graph-based and minimum power re-adjustment based. Results show that with the increase of the number of channels, the differences in the performance of the four techniques become more pronounced. Among the techniques studied, the conflict graph-based technique achieves the highest number of feasible links and the lowest average power consumption.

In the same line, another jointly channel and power allocation method is presented in [47]. This time, the optimization is designed for a Wireless Body Area Sensor Network (WBASN). The protocol, called Cognitive-Receiver Initiated CyclEd Receiver (C-RICER), adapts both transmission power and channel frequency to reduce the interferences and therefore, the energy consumption. Results obtained through OMNET++ simulator show that C-RICER is able to outperform traditional RICER3b protocol under high interference environment in energy consumed, network throughput and packet delay.

A completely different approach is presented in [48]. Authors propose a cognitive access scheme for WSNs coexisting with WLANs. The access scheme is based on the knowledge of the WLAN idle time distribution functions in advance. Using this information along with the sensed data, packet size and next hop distance are decided in order to optimize energy consumption. Results are given in terms of normalized energy cost (energy required to successfully transmit one unit of information over one unit of distance) without constraints on data delivery delay or throughput. WLAN interference is not taken into account. The proposed scheme is compared with simple carrier sensing and random access solutions showing energy gains.

As a conclusion of the review of these works we can notice that every of them are helpful as tools for saving energy consumption in CWSNs. Whether those that optimize power allocation, modulation, packet size or transmission channel can be used to achieve greater energy efficiency once CR is introduced in WSNs.

However, in almost every reviewed work, depicted scenarios are WSNs that have the capability to access licensed spectrum bands which leads to design decisions invalid for us. Our scenario does not match with the premise of accessing licensed frequency bands for two fundamental reasons: the first one is renting cost and the second one is the use of typical WSNs nodes without extra radio interfaces or hardware prepared for licensed band.

2.2.3 COLLABORATION ENHANCED WITH SPECTRUM INFORMATION

As we have stated before, one of the fundamental characteristics of CR is collaboration being also a characteristic of WSN. We are going to proceed now with the works based on collaboration by exploiting the feature of spectrum knowledge provided by CR. That is, we are not using new capabilities that allow us to save energy, but how can be energy efficiency methods improved with spectrum information. In this respect, found techniques are divided into those referring to MAC and routing optimizations.

2.2.3.1 MAC LAYER OPTIMIZATIONS

Compared with the number of the traditional MAC protocols, there are fewer MAC protocols for CWSN because of the young age of the technology. Existing WSNs schemes cannot simply be used in CWSNs nodes since they should deal with additional aspects such as spectrum sensing periods or the use of a common control channel as a mechanism for the distribution of spectrum and decision information. On the other hand, resources constraints inhibit the utilization of existing CR based schemes in CWSNs.

First approach to a MAC layer exploitable in CWSN which takes into account spectrum is presented in 2007 [49], even before the concept of CWSN was launched. It was presented as a MAC protocol design for dynamic channel access for spectrum agile WLANs. Nevertheless, constrained resources are even harder in CWSN.

A specific design for multi-hop CWSN is presented in [50] combining cognitive radio features for typical resources constraints WSNs. It proposes a cluster based protocol for multi-hop networks which allows sensor nodes to dynamically select an interference free channel for data communication. The presented scheme is a schedule-based protocol, which perform different phases in the cluster head: channel sense and selection phase, channel schedule phase, data transmission phase and sleep phase. Curiously, this work uses a sensing method similar to the presented in [10] where only a few channels are sensed in order to save energy. The performance evaluation is made by Network Simulator 2 (NS2) simulator showing better energy performance as well as higher throughput, less delay and lower packet loss radio.

An energy efficient spectrum aware approach which caters to the requirements of CR and WSNs are presented in [51] and [52] by the same authors. The MAC protocol presented is designed as a spectrum aware asynchronous duty cycle approach. It defines a node sleep/awake cycle performing standard tasks as sensing, negotiation and data transmission in the active part. The scenario used is composed by PUs and SUs. The asynchronous protocol designed is used by SUs in order to access PUs channels. The performance of the proposed MAC is evaluated via simulations and analytical methods. The results are compared with a multichannel MAC protocol designed for WSNs [53]. The comparative results show that the proposed approach outperforms the previous scheme.

2.2.3.2 ROUTING

Routing strategies for CWSN arise as an analogous case as the MAC optimizations. There are a large number of routing strategies for energy savings through the history, but the introduction of spectral information can enhance them.

Spachos proposes in [54] an Energy Efficient Cognitive Unicast Routing (EECUR) protocol that tries to keep a balance between the energy consumption and the packet delay. The presented protocol selects the next hop dynamically following the network conditions and the channel availability considering also energy consumption per node. The protocol tries to maintain energy consumed of each node at a similar level. Network performance in terms of throughput and latency are as well taken into account. This protocol, in contrast with simple location based dynamic routing protocols, includes energy information to select the next hop. The energy model that is used in this work takes into consideration energy expenses in term of transmitting/receiving messages, spectrum sensing and idle mode. Simulation results presented exhibit a 30% increase in network lifetime compared with location opportunistic routing, maintaining the packet delay.

Same authors propose in [55] an opportunistic routing protocol for CWSNs which objective is to improve the network performance after increasing network scalability. The introduced protocol is simulated into complex indoor environments and shows better results in this scenario in terms of throughput, packet delay and energy consumption.

In the scenario depicted in [56], sensor nodes act as SUs, opportunistically accessing vacant channels within a band originally licensed to a PU. Authors discuss how to cluster CWSN nodes in a dynamic frequency environment introducing Cognitive LEACH (CogLEACH) which is a fast, decentralized, spectrum-aware, and energy efficient clustering protocol for CWSNs. This protocol is an extension of the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol that is able to take into account the spectrum holes. CogLEACH clusters the nodes and decide which node become the cluster head using the number of vacant channels as a weight in a distributed manner without the need for intensive collaboration. According to the simulation, CogLEACH improves the throughput and lifetime of the network compared to the regular LEACH protocol.

The optimization presented in [57] chooses the best relay for each node while minimizing the total energy consumption in the network under interference and satisfying a specific Bit Error Rate (BER) for the CR system. Each node should decide either sends directly to the base station or forwards to another node. Even if the results throw better performance than non-relaying method in energy efficiency and network throughput, it is also showed that their first approach is not good enough in terms of network lifetime as the formulation does not consider residual energy of sensor nodes as a parameter. Then, authors add another selection criterion, where residual energy is included in the formulation, enhancing network lifetime results.

The residual energy is also a parameter used in [58]. The proposed method tries to reduce the frequency for randomly channel switching in order to avoid packet collision thus reducing energy consumption. They propose a Comprehensive Optimal Cooperative Routing Algorithm (COCRA) based on virtual Multiple Input Multiple Output (MIMO) and virtual sinks which combines the channel conditions of PUs, the residual energy of SUs and the distance among nodes. Simulation results show that COCRA not only has a good performance on the energy consumption of the CWSNs, but it can also offer considerable enhance of spectrum use.

The idea of using less crowded spectrum bands in order to reduce energy consumption when designed a routing protocol is used also in [59]. The routing method proposed claims for the use of licensed bands in order to increase reliability and decreasing packet delay. Authors state that this routing protocol balances the energy consumption, diminishes routing overheads, and decreases channel interference allocating the traffic over different channels and time slots. This protocol is conceived for highly delay sensitive data and both the scenario and the requirements do not match with ours.

As in classical WSNs routing problem seems to be well studied, and the introduction of spectrum information has been used in order to enhance performance of typical routing algorithms.

2.2.4 CROSS-LAYER STRATEGIES

The possibility to act or use information from multiple layers of the protocol stack is interesting to consider and promising according to the previous works presented as [9] and [24]. The protocol stack when talking about WSNs or CWSNs is more flexible and level-disaggregate and not as rigid as in other technologies or protocols.

We present here strategies to reduce energy consumption which combines different strategies belonging to different layers. Usually, these strategies combine the design of a routing protocol which also modifies the transmission parameters according to the spectrum information.

This is the case of the work presented in [60] where spectrum information, power allocation and routing are jointly considered to maximize lifetime, information capacity and resource utilization. The problem considers as its main goal information capacity maximization but energy is also considered. The framework proposed uses a multi-hop protocol where energy adaptation mechanisms are introduced according to spectrum sensing.

A different approach is followed in [61] where a central planner is used in order to share the spectrum resources between different heterogeneous networks. The main goal is to improve the use of available resources and infrastructure and the overall performance of the wireless networks. The designed planner is based on shared incentives and is able to propose changes in transmission parameters as power allocated and also modifications in the routing paths. This work is validated through testing in real devices for the specific goal of energy consumption reduction. Authors stated than a global reduction around 75% is obtained. The main difference here is the use a central planner that allocates resources for heterogeneous networks. Therefore, it is mandatory to have control over several networks which is not the case in our scenario.

Different parameters are used in [62] where authors propose Cog-MAC, a cognitive MAC scheme for WSNs that minimizes the energy consumption for multi-hop communications. The scheme proposes a lightweight MAC design able to change packet sizes and hop transmission distances (and therefore routing paths) based on the interference from WLANs. The evaluation is made analytically and compared with previous MAC schemes. Numerical and simulation results show a decrease in energy consumption up to 66% particularly under severe WLAN interference.

2.2.5 RELATED OPTIMIZATIONS

After the presented review of the most important works of energy efficiency for CWSNs, we cannot forget that these networks are relatively young, and therefore, the research in this field practically begun 7 years ago.

Thus, we present previous works for energy consumption reduction in non cognitive WSNs, useful in terms of offering interesting techniques adapted to low resources typical in such networks. On the other hand, we present CR energy efficiency optimization which although not take into account low resources of WSNs, they exploit cognitive abilities.

One of the works that states the importance of share and use knowledge in optimization algorithms is [63]. Authors state that the effectiveness of the different optimizations depends on the amount of knowledge available to the nodes about the network state. Particularly they examine the price of ignorance in topology control for CR with power and spectral efficiency objectives. They propose a distributed algorithm that minimizes the transmitted power and the spectral footprint, but the most interesting outcome for us is the discussion between local or global knowledge. Depending on the optimized parameter, the strategy and the model employed, sometimes having global knowledge imply better results, whereas other times it may just add complexity and overhead to the network.

Authors show for their spectral and power optimizations that due to the high cost of maintaining network knowledge for highly dynamic networks, the cost/performance tradeoff makes it advantageous for nodes to operate under some degree of local knowledge, rather than global knowledge. They also determine that the cost of maintaining global knowledge is justified only when the network is fairly static.

A good work reviewing the state of the art in decision making for CR is [64]. This work depicts a general canvas of the first 10 years of CR, specifically in decision making and learning from an equipment perspective. Authors group optimization problems into three sets depending on which one impose the constraint: the environmental (frequency bands, interferences, propagation), the equipment (modulation implemented, transmit power) and user expectation (quality of service, bit error rate allowed).

Another interesting conclusion for this work is the discussion about how during the first 10 years of CR, researchers often use the same design space, however, the main difference resides in the knowledge they assume available. Accordingly, they use the available knowledge as classification criteria to present the proposed techniques to solve adaptation in CR.

Some of the most interesting surveys are presented in [65], [66], and [67]. The first one is related to swarm intelligence for designing routing algorithms; while the last two are both related to game theory used as a tool for modeled decision making in CR in the first work and in WSN in the second one. These surveys prove the viability of use both game theory and particle swarm optimization in our target network. It is interesting to notice how game theory fit well with the characteristics of cognitive networks in one hand and deal perfectly with low resources in WSNs.

Along the line of using game theory for modeling decision making, [68], [69] y [70] present different game models for different optimizations. An algorithm for fairly allocate spectrum in CR is presented in [68]. The proposed game is a bargaining game modeled for two users. In [69], an energy fairness problem is designed for heterogeneous WSNs. Each node models the transmission of information as a game and while each node tries to optimize its payoff, the global objective is achieved. They introduce the use of punish mechanisms for selfish nodes in order to assure delivery rate and delay constraints too. The proposed game for WSNs in [70] is an incomplete information cooperative game. Each node estimates the game state as a first step and secondly, it adjusts its equilibrium strategy changing its local parameters.

Cluster based optimizations are another trend in energy savings protocols, frequently used for routing optimizations. Clustering methods for energy efficiency in WSNs are presented in [71] and [72]. The first one proposes a distributed algorithm where cluster heads are elected based on its residual energy. Second work tries to minimize energy consumed by the nodes reducing transmission distance. Cluster heads are also chosen by their energy remains. A taxonomy and review of clustering algorithms for WSNs are presented in [73]. The taxonomy classifies the algorithms by objectives, features and complexity and compares them.

Another global claim is to design cross-layer strategies as we have seen in Section 2.2.4. Along this line, [74] proposes a cross-layer design for energy efficiency in Transmission Control Protocol (TCP) traffic in CR. Even if TCP traffic is not our goal, the proposed strategies claims about low energy consumption and takes parameters as modulation or packet size into consideration. Moving to WSNs, we can find a survey on cross-layer solution for WSNs in [75]. This work proposes to discuss the main problems addressed by cross-layer design for WSNs, pointing out the main one, energy consumption, and its relation to the other presented problems. Taking account cross-layer design is important because the behavior derived by one optimization could affect the performance of others.

A complete review of techniques for energy conservation in WSNs is presented in [7]. Firstly, authors separate the energy consumption into the different components of a sensor node, and then present the main directions to energy conservation in WSNs. Finally, they present taxonomy of energy conservation schemes. Existing WSN schemes cannot simply be used in CWSNs as the cognitive nodes must now handle additional aspects such as spectrum sensing periods, the use a control channel or dealing with delays resulting from the change of transmission parameters.

Center our attention into specific cognitive optimizations to take into account for reducing energy consumption in CWSN, we can find [76], [77] and [78]. The first one presents an energy efficient distributed game for resource allocation modeled as a multi-objective problem. Again, low resources are not taking into consideration, but the idea is inspirational. Authors propose in [77] a scheme where each node adjusts its power depending on the dynamic spectrum. The algorithm is designed as a competition between selfish users. Finally, in [78] an algorithm to dynamically select channel and power emitted is presented. The goal is to maximize the total number of feasible links while minimizing the aggregate transmitted power. This work includes too a comparison between different power and channel allocation methods concluding that when few channels are available, the effectiveness is comparable and thus the best option should be selecting the simplest one..

2.2.6 CONCLUSION

As a result of the process of reviewing previous works, we can draw some conclusions. On the one hand, the state of the art is still in the early stages. While several authors emphasize the advantages of incorporating cognitive capabilities to WSNs, research activities are nowadays given a boost. For the specific field of energy saving in CWSN, most of the works for energy optimizations in CWSNs arise after 2012.

Among those, we can divide them into 3 groups as we have done in Section 2.1. The first group is the one responsible to optimize one of the main novelties introduced by the CR and certainly the most expensive in terms of energy consumption: spectrum sensing. Raise spectrum sensing techniques that can be implemented in CWSNs is a major cornerstone. Whether by the reason of the use of low computational resources or to make it energy feasible, it has attracted the efforts of several research groups.

Moreover, with the introduction of the spectral information, the other major change that arises is the ability to change the transmission parameters to make a more efficient use of spectrum. By this side, we have presented some works optimizing different parameters, such as modulation, transmission power, packet size, and communication channel. Although they are not very numerous for CWSNs, they establish the first foundations in the field. Again, we want to notice that the optimizations reviewed are envisaged to CWSNs capable of accessing licensed spectrum bands and therefore PUs will always have the priority. This is a fundamental difference with the scenario presented in this thesis since PUs restriction is not presented in unlicensed bands as we are going to state in Section 3.1.

The third main block is composed by energy consumption optimization methods which use the spectrum sensing information to enhance energy strategies. This group is primarily composed by routing protocols that use spectral information to reduce energy consumption, and secondly MAC proposals which thanks to the sensed information are able to enrich their energy performance.

According with these three groups, the reviewed works could be divided as seen in Figure 2-2.

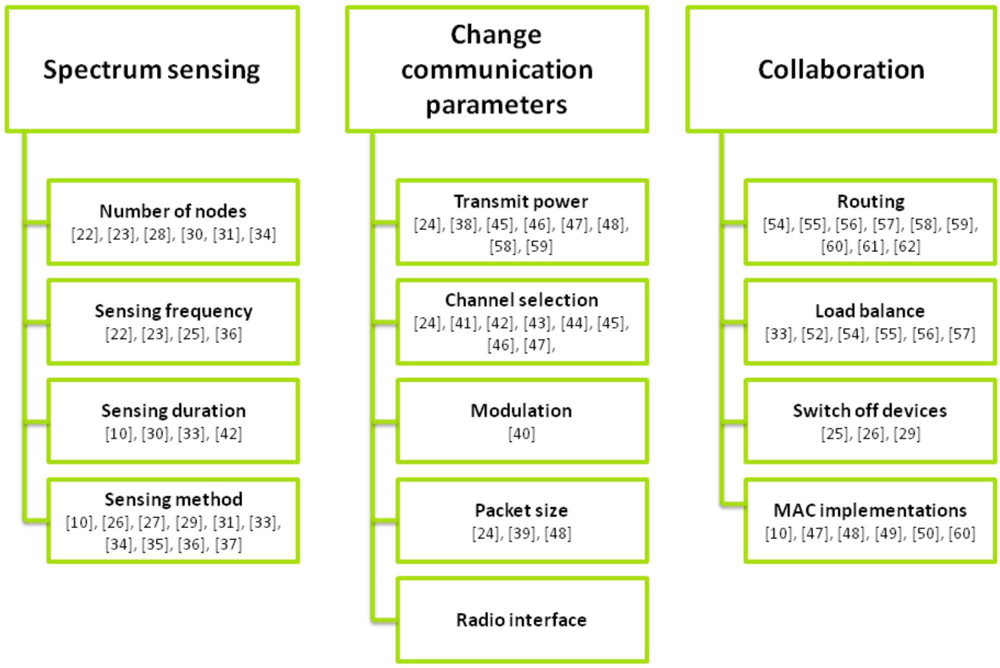


Figure 2-2. Summary of the review of the state of the art.

On the other hand and moving out of CWSNs optimizations, we have reviewed some works designed for CR or WSNs that despite not fitting perfectly with our requirements, they can provide us tools and useful ideas when designing strategies for energy efficiency in CWSNs. In this line, we have seen that the most commonly used optimization algorithms in low resources networks are particle swarm optimizations and clustering techniques (especially for routing) and for decision making, also game theory. On the other hand, we have seen that game theory and swarm optimization are also largely used in CR since they fit well to the network characteristics and capabilities.

Finally, as a side conclusion, we notice that most of the works, models or strategies are tested in wireless networks simulators. Only a few results are founded in real devices. Moreover used simulators are not specifically designed for CWSNs.

Therefore, we can conclude that address the research in the area of reducing energy consumption in CWSNs is interesting. Also, one of the main characteristics of our scenario is the exclusive use of unlicensed bands. This feature makes most of the studies analyzed do not fit our scenario. It is important to work on this research line for making sensor networks energy efficient once introduced cognitive capabilities for increasing their performance. Achieving viable-energy CWSNs is the next step to advance in the use of these networks.

2.3 ALGORITHM ANALYSIS

Once the opportunities generated by the introduction of cognitive abilities have been presented, we have to move to decide the mathematical algorithm that help us in our optimization model or with the decision making process used in our strategy.

In the search for different possibilities of problem modeling, we have analyzed three of the main options which are widely used in communications networks as we have seen in the previous section to find optimal solutions: Genetic Algorithms (GAs), Particle Swarm Optimizations (PSO) and Game Theory (GTh). These methods have proven to be suitable for network modeling in CWSNs according to the literature in the area.

2.3.1 GENETIC ALGORITHM

Genetic Algorithms are used to generate solutions to optimization and search problems inspired in the processes observed in natural evolution and genetics such as inheritance, mutation, selection, and crossover. Their application fields ranges from computational science to signal processing, machine learning, economics, robotics, or biotechnology.

GAs are based on consecutive generation where the fittest individuals survive and propagate their genes. This foundation is used to solve optimization problems. Each generation (a set of individuals) compete for resources and the best prepared to "survive" propagate their genes through the next generation resulting in a process of evolution where the best characteristics are transmitted from parents to children. The idea behind the GA method is maintaining a population of chromosomes (solutions) each of them associated with a fitness value. Each generation will be replaced with the next generation of solutions generated through the best genes of the individuals of the previous one. This way, successive generations will contain better individuals than previous ones, and over successive iterations it is possible to find better solutions for the modeled problem.

The first step when modeling a GA for problem solving is defining the fitness function. The fitness is usually the value of the objective function in the optimization problem being solved.

Once the fitness function is defined, the GA proceed begins and performs as shown in Figure 2-3 through repetitive application of the method.

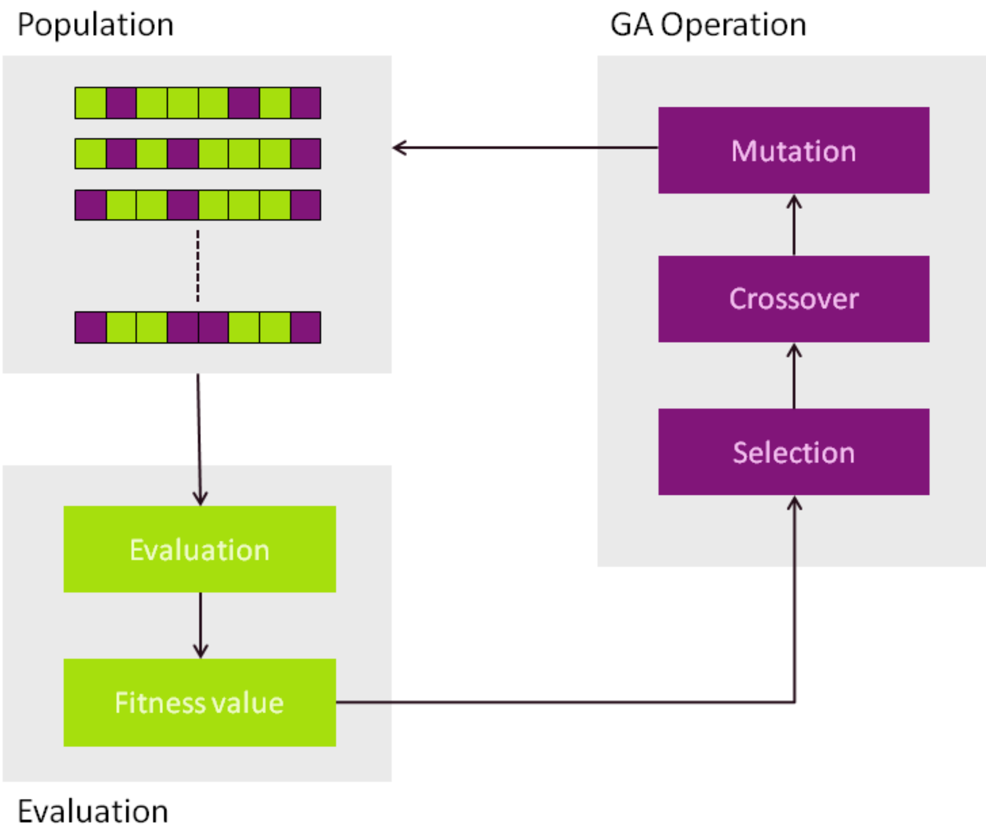


Figure 2-3. Genetic Algorithm process. [79]

- In the first phase, the init population is chosen (sometimes randomly and sometimes within an optimal expected area). The population size could vary between several hundreds and thousands of possible solutions.
- After the initialization, each of the individual solution are evaluated through the fitness function and best solutions are selected.
- The next step is to produce the next generation of solutions from the previous one through two genetic operators as it is shown in Figure 2-4, crossover and mutation.
- After these processes the obtained generation will be different from the previous one, and commonly, the average fitness will have increased since only the best solutions from the first generation have been selected for breeding.
- This process is repeated until a termination condition has been reached. This situation could be accomplished by different circumstances such as found a solution which satisfies the condition, arrive to a convergence value where a

plateau is reached and the solutions are not improving, or reach the maximum number of iterations.

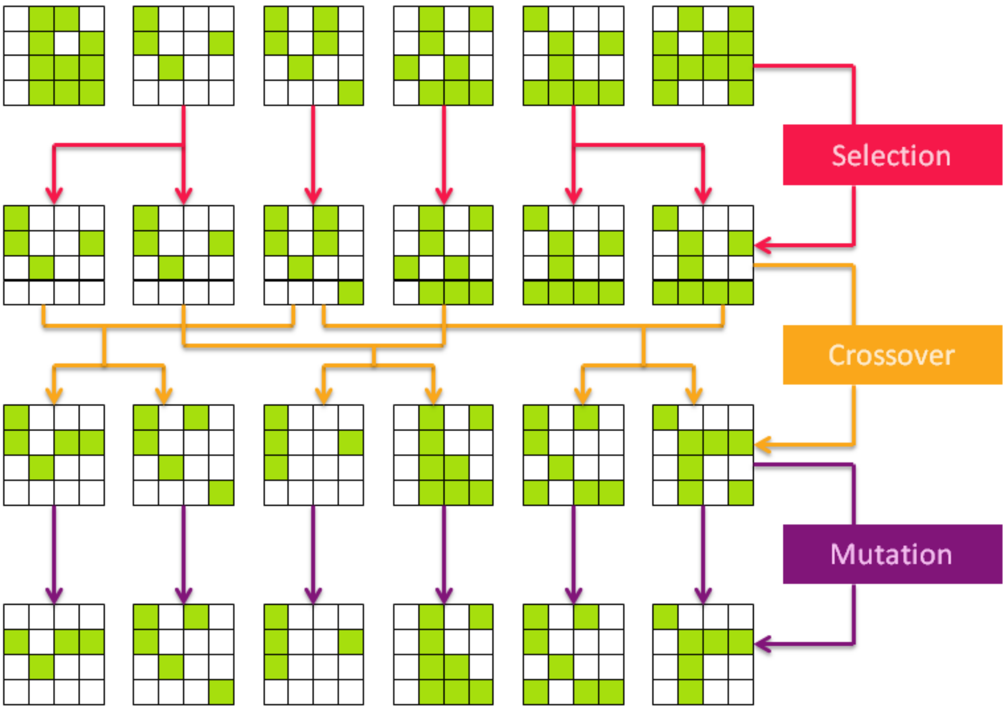


Figure 2-4. Genetics operators used by GAs optimizations. [80]

Even the GA method is powerful in problem solving it has some limitation compared with other optimization algorithms. One of the most important and closely related to WSNs resources is the expensive cost of repeated fitness function evaluation. Typical problem models could require several hours or days to be evaluated, which makes this method unsuitable for low resources networks. Nevertheless, some GAs have been implemented for WSNs when the accuracy of the optimization is the key factor [81], [82] and [83], most of them for routing, clustering and data aggregation modeling.

For specific optimization problems, other optimization methods may be more efficient than GA in terms of resources consumption and speed of convergence. A very used alternative in WSNs is swarm intelligence.

2.3.2 PARTICLE SWARM OPTIMIZATION

Particle swarm intelligence belongs to the field of evolutionary computing. Particle Swarm Optimization is a computational method based also in a population-based approach. PSO is simpler than GA and is also effective and computationally efficient which makes it a good option to implement in WSNs. PSO has been very used for finding an optimal deployment and node locations, developing routing protocols and designing clustering methods [84], [85], and [65].

Even most of the PSO used in WSNs are related to clusters and routing, looking for works related to dynamic change of communication parameters modeled through PSO, we can find [86] and [87]. Di Lorenzo proposes a method based in birds looking for food for modeled spectrum allocation (time and frequency slots) for CR in a cooperative manner without any centralized control. The goal of this work is minimize transmission collisions. Kunyuan proposes a method based on PSO for Primary Users (PUs) and Secondary Users (SUs) spectrum sharing looking for maximization of bandwidth and SUs access fairness.

PSO is based in a population of possible solutions (particles) which are moving in the search space. This movement of the particles (position and velocity) is determined by their own knowledge and by the global knowledge. As GA, PSO optimizes a problem by iteratively trying to improve a candidate solution. However, PSO has no evolution operators (crossover and mutation), but the particles adapt themselves tending to move together following the current optimum particles. Compared with GA, all the particles tend to converge to the best solution quickly.

In PSO also exists a fitness solution that particles are looking to optimize. Each particle keeps its position and speed which are related to a fitness value. Each iteration, the particles change its own velocity trying to get closer to two best possible values: pbest (the best solution it has achieved) and gbest (the best value any particle have achieved).

As in GA, PSO is initialized with a random group of particles and then, they begin the search for the optimum following the path depicted in Figure 2-5.

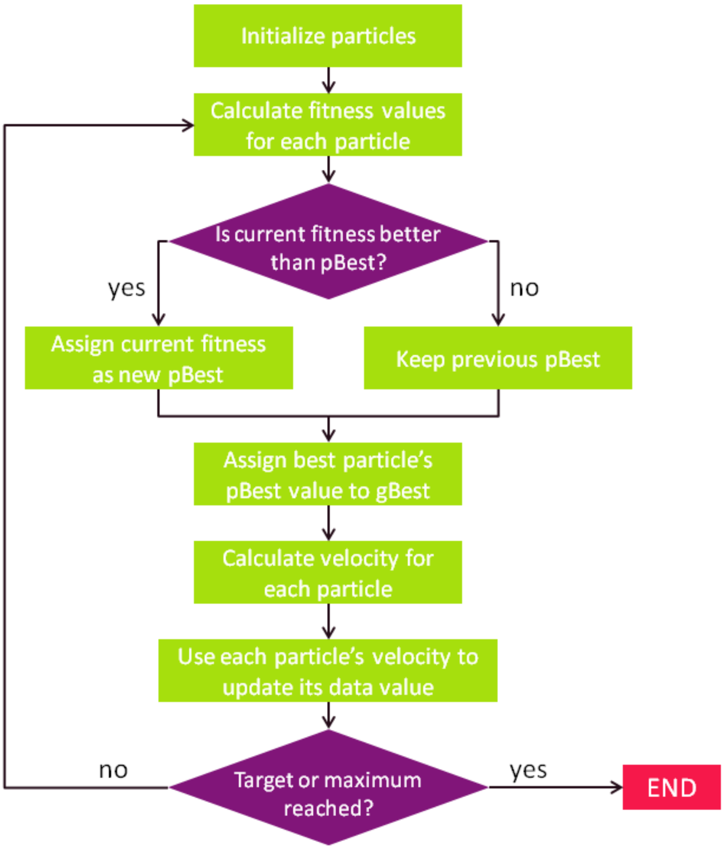


Figure 2-5. Flowchart for PSO.

As in GA, PSO methods depend on information sharing among population members. Although PSO are accuracy-lower than GAs, it is able to produce good results modeling groups problems. Also, PSO is habitually more computationally efficient than the GAs, especially in unconstrained problems in dynamic environments [88]. PSO is easy to model and implement, give accurate solutions and its computational efficiency and speed of convergence makes this method a good option to use in WSNs. Also, PSO is a decentralized method, which makes it fit well with WSNs architecture.

2.3.3 GAME THEORY

Game theory belongs to mathematical area of the decision making. GTh models decision about a resource as a mathematical problem between intelligent and rational agents which can fight or cooperate to obtain it. Game theory is largely used in social sciences such as politics, economics or psychology, but also in computer science or robotics.

A game is defined by several characteristics. The *resource* being modeled, the *players* involved in the game, the *information* available at each moment, their *strategies*, and the *actions* they can take. Thereon, *costs* associated with each action, and, the *payoff* of each outcome. The *utility function* is defined with these payoffs.

According to the study presented in [89], more than 330 research works related to game theory and WSNs were published from 2003 to 2011. They present a huge variety of games modeling MAC implementations, routing protocols or task scheduling.

Related to the recent advances in technology and the growing need for pervasive and cognitive communications GTh has recently gain attention as a useful tool for modeling interactions between CR nodes [66]. These nodes have the ability of adapting their behavior to the context they communicate, and transmission parameters such as power emitted [90], rate or channel, [76] [44], could be modeled as a game. This is mainly due to the need of incorporate decisions making methods into the future networks generations to allow them to operate efficiently.

Games could be designed as cooperative or non-cooperative games. While in the first case, players are looking for the common interest of the system, in the second case, nodes are treated as selfish players which only try to maximize their own benefit. The second case fits very well with a distributed method for sensor networks.

One of the most important elements of GTh is the concept of Nash equilibrium. Nash equilibrium is a strategy profile where each player's action is the Best possible Response taking into accounts the other players' actions at that moment. The Best Response (BR) can be defined as the action of a player that maximizes its utility taking into account the actions of the others.

By its intrinsic nature, GTh can be easily used for modeling problems in WSNs. In addition, games can be simplified enough without losing functionality to make them supported by a WSN node, even if its processing capability is limited.

One of the most challenging issues related to GTh applied to communication networks is the fact that GTh was essentially envisaged as an instrument to be used in social sciences, and sometimes only to analyze situation not to model it. Therefore, the modeling stage has to be taken carefully into consideration in order to model dynamic scenarios and to suit communication standards. As Han stated in [91] design effective models from GTh that can be applied to the design of future networks would be the quest for communication engineers.

2.3.4 CONCLUSION

The first conclusion we can draw from the study carried out is that even that GA provides accurate results; it is very expensive in terms of resources consumption (memory and computation resources) and especially in terms of energy wasted. According to the results extracted in [88], we can declare that for dynamic scenarios, the advantage of using GAs does not compensate the convergence time or the extra energy consumed.

That is the reason why we can state that PSO algorithms fit better our scenario (dynamic context variations and constrained resources of nodes) and it is postulated as a good option to implement optimization methods. Indeed, as we have seen in the works reviewed in this section, several works have modeled WSNs and CR networks such as PSO systems.

Related to the third method, game theory, we have seen a wide collection of implemented models in WSNs based on game theory. Complexity of this method is more than acceptable to be implemented in a low resources network which is, in fact, one of its main advantages.

Although both PSO and GTh fit well with our scenario, we have also seen that most of the models corresponding to PSO are related to nodes deployments, clusters organization, and especially designing and optimizing routing algorithms while GTh is used more for resource competition.

2.4 HYPOTHESIS

Once the analysis of the possibilities offered by the introduction of cognitive abilities to WSNs is completed, and considering the review of the work done in Section 2.2, we can draw the following conclusion.

The spectrum sensing area has been the main topic of interest since CR was introduced. A large number of previous works explored and designed different solutions to this problem. Even from the standpoint of energy efficiency, we can find multiple solutions. Taking a step towards CWSNs and according to the state of the art analysis, we can see that there are different solutions dealing with the different parameters that we have listed. We cannot say that research in the area is a solved issue in which there is no possibility of improvement, but we think that the first major effort has already been undertaken.

Turning to the third aspect, which is to enrich typical WSN strategies with spectral information, we found a similar scenario. Historically, the problem of energy consumption has been a priority for the viability of WSNs, so this is a vastly studied topic. Once cognitive capabilities were introduced, the scientific community took the step forward to incorporate this information into the strategies designs. As before, the research in this area is not complete and many works continue to enrich and enhance these designs, but the state of the art analysis already has several works in this topic.

We found a different picture related to the second group of strategies (those related to the capability of change communication parameters). Although these strategies have attracted the attention of the researchers along with the appearance of CR together with the sensing stage, the differences arising from the CWSN scenario render the approach completely different.

The CR optimizations reviewed are envisaged for networks capable of accessing licensed spectrum bands. Therefore, in these networks, PUs will always have the priority. As this thesis is conceived for a CWSN without the PUs restriction as unlicensed band users, this constraint does not apply. Secondly, the characteristics of computational capabilities and available memory, and the constraints arising from energy consumption, cost, and size, make it very difficult to have Software Defined Radio (SDR) systems in CWSNs.

For this reason, within this group, energy optimizations designed for CR do not apply to our scenario. The energy efficiency strategies approach needs to consider the resources offered by a CWSN and try to adapt transmission parameters according to the hardware associated with these nodes. Therefore, we conclude that the potential of this field is much broader and more promising than first envisioned.

2.4.1 PRELIMINARY TESTS

Among the parameters available within this group change the transmission channel, the emitted power, and communication interface have been valued. As a preliminary test for these ideas, some scenarios have been implemented with very simple low power optimization algorithms.

Results show as a simple cognitive radio strategy can reduce the amount of consumed energy. The first scenario refers to the capability to change radio interface. It is composed by five nodes provided with Wi-Fi and 802.15.4 radio interfaces. Four nodes are sending data to the coordinator. In this scenario nodes simulate two different applications. The first one is a multimedia application where both bit rate and packet size are high. The transmission rate needs a Wi-Fi interface while WPAN has not the capacity for multimedia applications. However, the nodes run a WSN environmental monitoring service too, where sensing data (temperature, light, humidity) requires low data rates. In this scenario, the energy optimization strategy consists on using the interface with less energy consumption for a specific data rate. When the data rate is high only 802.11 is possible, but for low demands on data rate 802.15.4 performs better because of its less energy consumption. This algorithm could be dynamically changed according to other constraints as battery life, distance between nodes or quality of service. Real data is used in the power model from a MRF24J40MA-based device for 802.15.4 protocol and MRF24WB based device for Wi-Fi transmissions. As shown in Figure 2-6, when the data rate is high 802.11 is used for transmission, but when data rate decreases 802.15.4, is better because of its less energy consumption.

The second part of this figure (zoomed in Figure 2-7) shows the consumption with Wi-Fi and WPAN common sensing application with the same packet size and the same interval between messages.

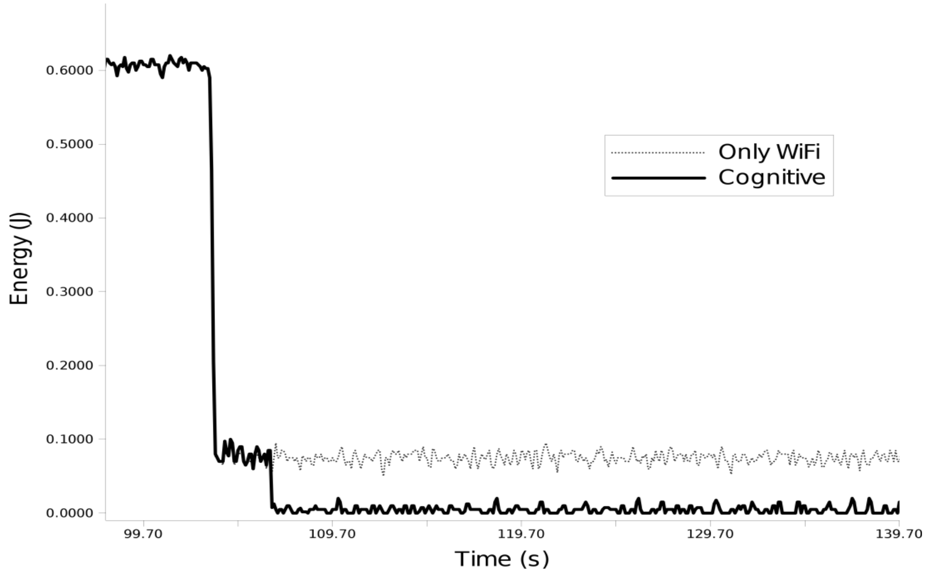


Figure 2-6. Energy consumption for interface optimization (scenario 1).

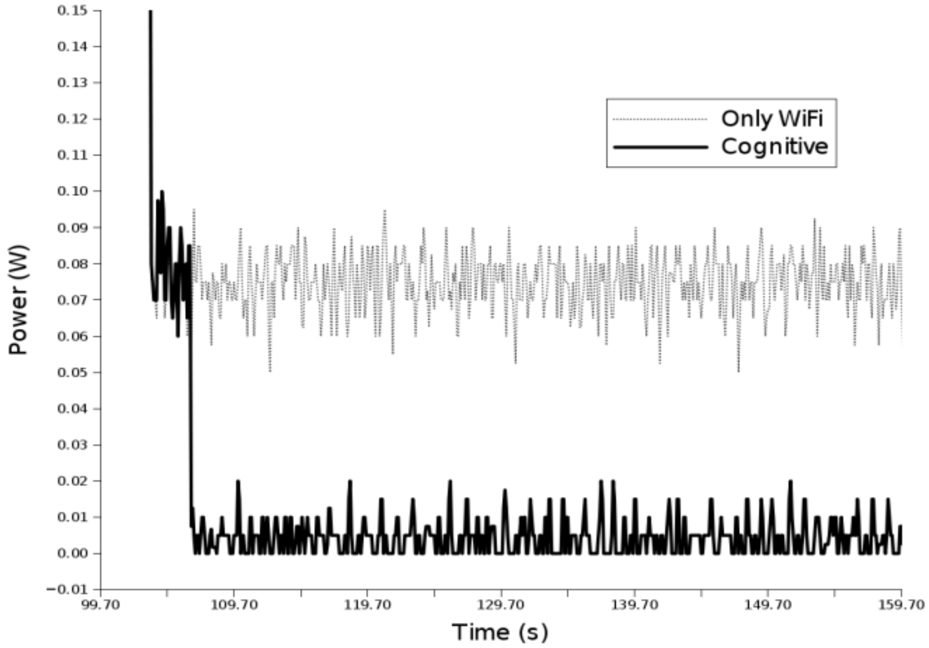


Figure 2-7. Detail of energy consumption for the cognitive algorithm and Wi-Fi.

Using a low power protocol the system can saves the 94% of energy (Figure 2-7). Only in the commutation period, where the nodes need to communicate the interface change, the consumption is similar to Wi-Fi. After that, the energy saving is considerable.

The second scenario simulates an application whose nodes send packets with the maximum payload allowed by the simulator (1000 bytes with 802.11 and 100 bytes with our implementation of the WPAN protocol). The application starts sending a packet every 10ms and the time is increased until the bit rate reached by 802.11 is supported by the WPAN protocol (reached at time 600). Figure 2-8 shows how the consumption of WPAN in the first period of the simulation time is greater than Wi-Fi because WPAN needs more transmissions for the same amount of data. We can conclude that 802.15.4 does not always reduce the energy consumption of every application with a low bit rate but a cognitive module choosing the right protocol in every time can achieve that goal.

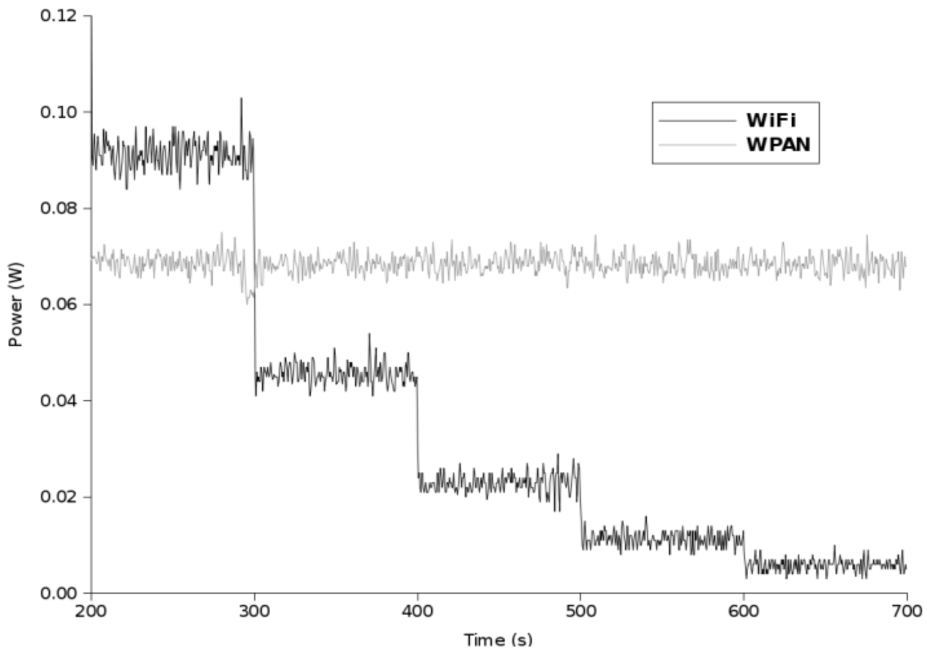


Figure 2-8. Energy consumption for interface optimization (scenario 2).

The third scenario shows optimization through changing power emitted depending on the spectrum sensing. The scenario consists of two nodes with 802.15.4 radio interfaces. One of them (the receiver node) moves (in 70 sec) through space and the other (transmitter node) is fixed as depicted in Figure 2-9. Within the path of movement experienced by the mobile node, sometimes node B will be closer to the node A than others. In a common network design, the node A will transmit information with a fixed power. That makes the loss of certain packets (by radio coverage) and the excessive power emitted to transmit others. Adding cognitive capabilities to this scenario, the network could be aware of the minimum power necessary to ensure the reception of packets while minimizing energy consumption.

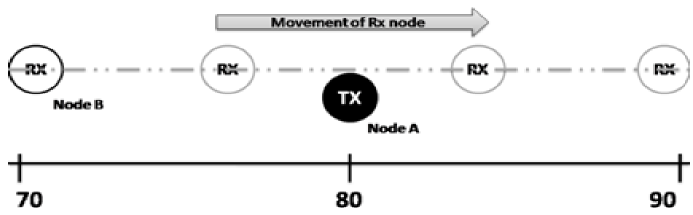


Figure 2-9. Mobile node representation (Scenario 3).

In Figure 2-10, instantaneous energy consumption of transmission (for the named node A in Figure 2-9) is shown. Dotted line represents the consumption of node A in a network without cognitive capabilities and the solid line shows the consumption of the same node when the low power consumption algorithm is added. Hanging power transmission in relation to distance between nodes can reduce energy consumption. Using this simple algorithm implies a reduction of up to 60% in some sections.

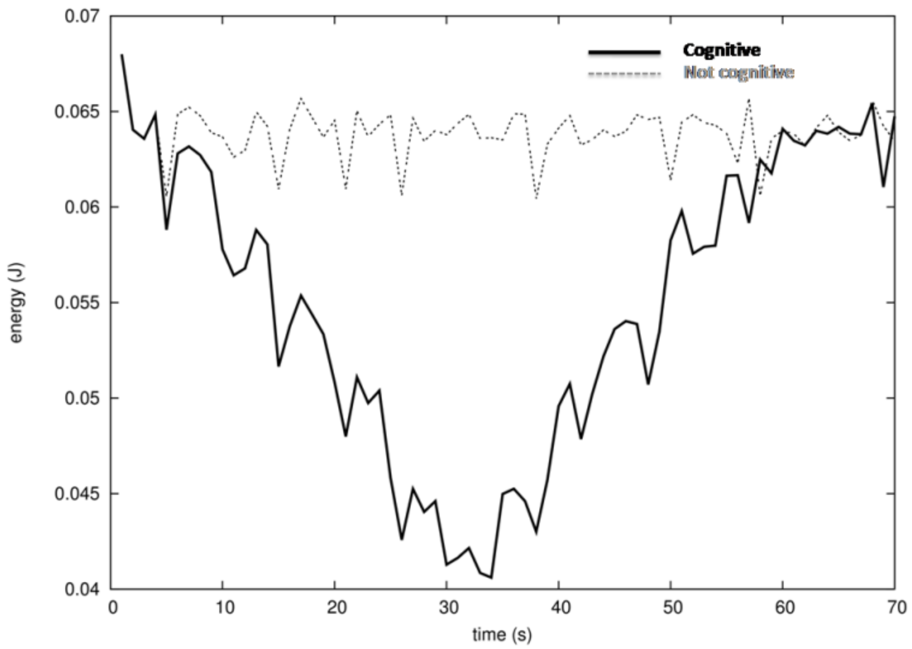


Figure 2-10. Energy consumption for power optimization (scenario 3).

The fourth scenario consists of two nodes exchanging information in a noisy environment. Communication between nodes takes place in a channel occupied by another network that emits information simultaneously. This situation results in numerous retransmissions that cause unnecessary expenses in energy consumption. Simply by sensing the spectrum and changing the communication channel to a less noisy channel, we can reduce energy consumption by avoiding retransmission.

Figure 2-11 shows the energy consumption of the two nodes that constitute the scenario (transmitter [dotted line] and receiver [gray line]). Also, the addition of consumption (black line) gives an idea of the saving energy in this scenario. Taking into account that this kind of networks usually are formed by hundreds nodes, not only two, the optimization could be potentially increased. As shown in Figure 2-11 the reduction in consumption is up 40% on average.

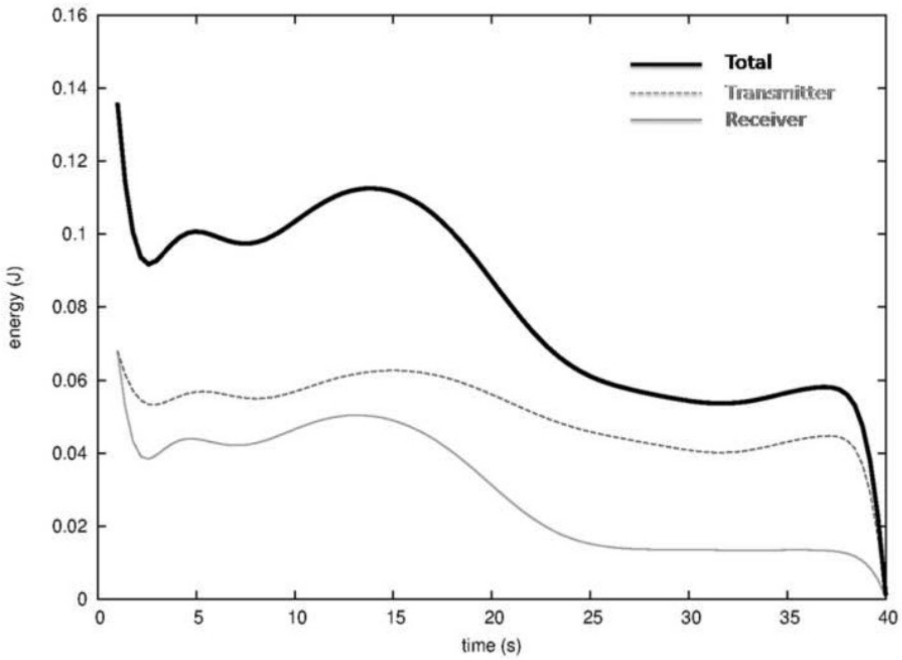


Figure 2-11. Energy consumption for channel optimization (scenario 4).

We have decided to approach the problem first by using channel allocation, one of the pillars of CR, as a method to reduce interferences and hence retransmissions. Therefore, the contribution of this thesis will be focused on optimizing the communication channel to meet the main objective of reducing energy consumption.

Related to the algorithm choice, and reviewing the conclusion stated in Section 2.3.4, we have concluded that beginning with the use of the game theory for modeling the energy problem is a good idea because it fits better in resource competition. However, we can also state that PSO is also a valid option.

2.4.2 HYPOTHESES DEFINITION

After choosing the optimization parameter and the mathematical algorithm, we are ready to present the three hypotheses of this thesis.

1. The energy consumed by a cognitive wireless sensor network can be reduced using the cognitive capabilities available in the network.

This first hypothesis refers to the use of cognitive abilities and states that they could reduce the total energy consumption of a CWSN. As we said in Chapter 1, we start from the premise that cognitive features are introduced to solve the existing problems related to spectrum saturation in the ISM bands due to the spectral coexistence of CWSNs with other CWSNs and WLANs that overlap their performance. Therefore, we assume that we start from these CWSNs, and from this point, we hypothesize that, thanks to these new capabilities introduced, we will be able to reduce energy consumption at least to the level prior to the introduction of CR in WSNs. In this way, the introduction of CR capabilities does not become harmful in terms of energy consumption.

2. The energy consumption in a CWSN can be decreased by designing a strategy based on a non-cooperative game for the choice of the communication channel.

We formulate this hypothesis on the possibility of reducing the energy consumption of a CWSN by modeling the decision on the transmission channel as a non-cooperative game played between two players (which correspond to two network nodes). Pursuing the goal of reducing consumption at each node of the network in a selfish way, we should be able to reduce the overall energy consumed by a CWSN.

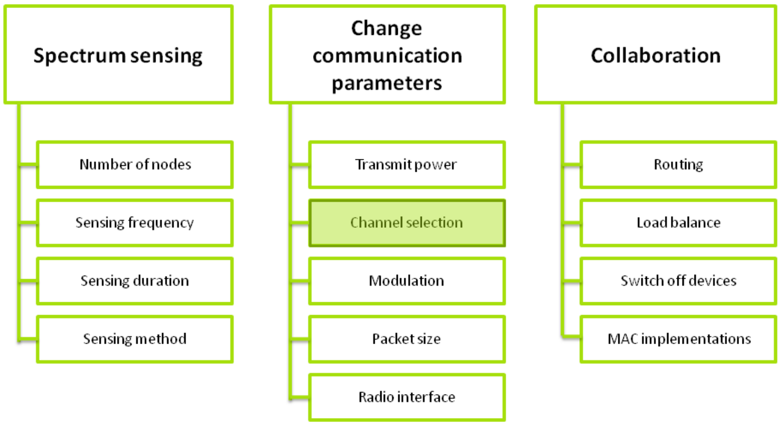


Figure 2-12. Summary of energy consumption optimization opportunities and selection.

3. The energy consumption of a CWSN could be diminished by designing a strategy based on a collaborative game for the choice of communication channel. This game will be more resistant to dynamic interference environments (spatially and temporally distributed).

In this case, the hypothesis states that it is possible to reduce the energy consumption of a CWSN further if the modeled game is collaborative. Thanks to the collaboration introduced, this strategy is even more resistant to dynamically changing scenarios in which the interference varies both temporally and spatially.

There is no gate, no lock, no bolt that you can set upon the freedom of my mind

Virginia Woolf

3 STRATEGIES DESIGN

This chapter presents the main contributions of this PhD Thesis. We begin with the working scenario definition, delimiting the available resources in the nodes, pointing out their constraints, characterizing their traditional parameters of communication exchanges, and finally presenting the current context where they communicate. As well, the coexistence issues related to other CWSNs and even with different radio technologies are addressed.

After the complete scenario definition, we present the cognitive architecture used. This architecture named Connectivity Brokerage (CB) has been defined in collaboration with some of the most active research groups in CWSNs and has been validated through its application in research projects.

We continue with a brief review of the most important concepts in game theory in order to lay the foundation of the fundamental definition, classifications and terminology. This way, we are able to explain the essential ideas where the proposed strategies are based and their theoretical implications.

Finally, we present the detailed description of the two energy optimization strategies designed for this PhD Thesis. These two strategies constitute the fundamental contribution of this work. Both use game theory as a decision tool into the optimization strategy. The first one is based in a non-cooperative game played between two players. In the second strategy the concept of collaboration is introduced. Despite the game used is also a non-cooperative game, the decisions are taken through collaboration. This time, the number of players is not limited.

For each strategy, we present the modeled game, the formal analysis of equilibrium and optimum and the complete strategy describing the interaction between nodes.

3.1 SCENARIO

In this section, we describe the main characteristics of the application scenario. We divide the scenario in three fundamental parts. First, we depict the cognitive wireless sensor network. As we have said in Chapter 1, a CWSN is a common WSN with the additional cognitive capabilities, and therefore, sharing most of their main characteristics with traditional WSNs. The characterization of the network and the typical communications parameters is important because of the strategies should operate with this constraints. We cannot design a strategy which requires a higher data rate o assume a longer transmission distance than the usual CWSN ones.

Next, we describe typical CWSN nodes. These nodes, with their limitations and constraints are the main actors in the networks, so we have to assure that the designed strategies can be implemented with their resources without overload their performance. Also, we count on the capabilities offered by the nodes to implement the optimization strategies.

Finally, we describe the radio environment that usually surrounds the CWSN operation. This description includes the coexistence issues with others WSNs or different radio technologies.

3.1.1 CWSN

As stated in Chapter 1, CWSNs are based on typical WSNs, improved with several features provided by cognitive networks. Thus, typical CWSNs are similar to WSNs in components, distribution and behavior.

A typical CWSN consists of a number of autonomous nodes, typically varying from tens to thousands, distributed in an environment in order to perform measurements. The obtained values could be processed locally and shared or transmitted directly to be processed together with aggregated data. In any case, data transmission is one of the main tasks in CWSNs. These communications are performed wireless. CWSNs allow multi-hop communication and networks topologies such as star, tree or mesh as depicted in Figure 3-1.

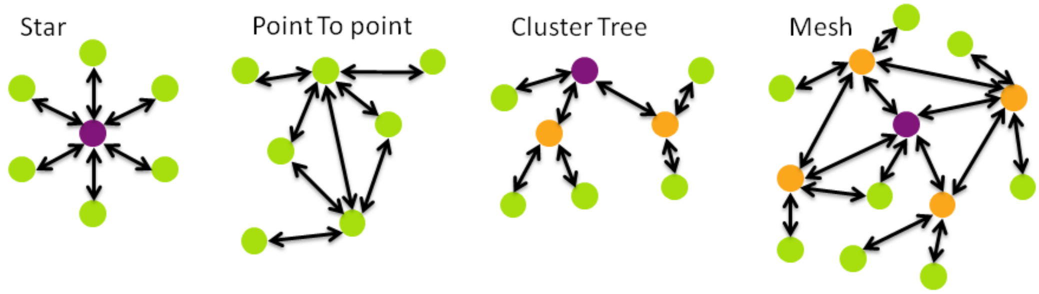


Figure 3-1. Topologies supported by CWSNs.

CWSNs use to communicate using the unlicensed bands as we have noted in the Chapter 1. Therefore, in our scenario we use the assumption of communicate in ISM bands. Typical standards for WSNs are IEEE 802.15.x defined for Wireless Personal Area Networks. In particular, IEEE 802.15.4 is widely used together with IEEE 802.15.1 or IEEE 802.15.6 although lesser extended. In the Figure 3-2 we can see the available channels and their frequency distribution in three different ISM bands corresponding to the first release of the IEEE 802.15.4 standard. In addition, we use also the 433 MHz ISM band available in Region 1 (including Europe) added to the IEEE 802.15.4f release. These three ISM bands for region 1 (433 MHz, 868 MHz and 2.4 GHz) are the most used for WSNs deployment because raising the frequency increase also the energy consumption, and lowering the frequency implies smaller data rates and bigger implementation of antennas.

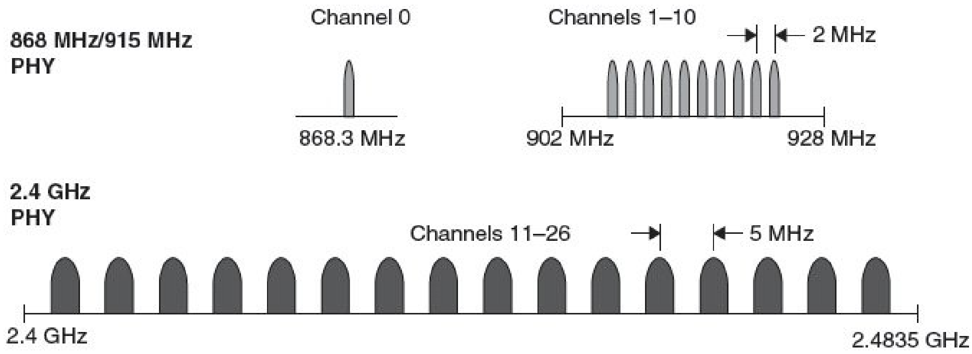


Figure 3-2. Channel distribution for 802.15.4 bands.

Theoretical data rates varies from 20 to 250 Kbit/s depending on the specification, but in general, typical applications use to have lower data rates ranges from 10 to 1000 bit/s. As an example, a home-monitoring application sending typical environmental data such as temperature, humidity, light or gases values does not need to employ bigger data rates. The transmission power is limited also by specification to 100 mW (20 dBm) but in typical application due to requirements of coverage and energy consumption constraints use to be lower than 1 mW (0 dBm). Usual values of communication range could vary between few meters to 100 m.

Even if one of the main characteristics of CR is the existence of PUs and SUs this distinction does not apply in our scenario. The main reason is because of the use of unlicensed channels. According to their formal definition, PUs are the "owners" of the spectrum band and have the right to communicate without restrictions, while SUs can use the spectrum if they do not disturb PUs. In this scenario no distinction has to be made between them given that CWSNs operate on unlicensed bands. Moreover, the strategy can be applied for every network node improving their energy consumption in any case.

3.1.2 CWSN NODES

A CWSN is composed by nodes constrained in resources as memory and computational capabilities. These nodes are small in size ranging from millimeters to few centimeters. In fact, WSNs nodes are also known as motes, according to their size. A CWSN has also a limitation in cost; the implantation in everyday tasks requires a target prize around few dollars. It is true that depending of the integrated sensors, the complexity and the application requirements, sometimes we can find nodes whose prize could rise to hundreds of dollars. Nevertheless, for our scenario we can assume low-profile sensor nodes.

CWSNs nodes are usually composed by different parts: a low-power microcontroller, a radio transceiver implementing low-power modes coupled with the antenna, the required sensors and an energy source (typically batteries). Size and cost limitations results also in energy, memory and computational restrictions.

CWSN nodes could be modeled for our scenario as a CC2420 [92] or CC2520 [93] Texas Instrument transceiver commonly used in WSNs. Typical values of current consumption extracted from the datasheet give results around 20 mA for transmission (at 0 dB) and reception and below 1 µA in low-power modes. Moreover, the sensing mode is performed by energy detection and could be modeled as a long-lasting reception mode. Time required in reception mode for sensing stage is related to the frequency range that we need to sense. For a typical node working in 2.4 GHz band assuming 16 channels, this time is 200 ms verified through experimental measurement.

These nodes are battery powered as we have said before. We can assume usual values of batteries ranging from coin cell batteries of 300 mAh at 3.3 V to two typical AA batteries of 1700 mAh at 1.5 V. That results in a range of energy available between 3600 J to 18000 J.

3.1.3 ENVIRONMENTAL SCENARIO

The typical scenario assumed in this work corresponds to a CWSN communicating in a noisy environment. Because CWSN nodes transmit on ISM bands coexisting with other CWSN or even different radio technologies as Wi-Fi or Bluetooth (in the 2.4 GHz band), we consider a scenario where multiple wireless technologies communicate simultaneously. This scenario is very common due to the growth of consumer electronics (such as laptops, tablets and smartphones) communicate over these technologies that we have depicted in Chapter 1.

Due to the Wi-Fi channels bandwidth and their transmission power, each Wi-Fi channel can mask up to four CWSNs channels when both technologies coexist in the 2.4 GHz band as we can see in Figure 3-3. This fact has to be taken into account due to degradation issues depicted in [3].

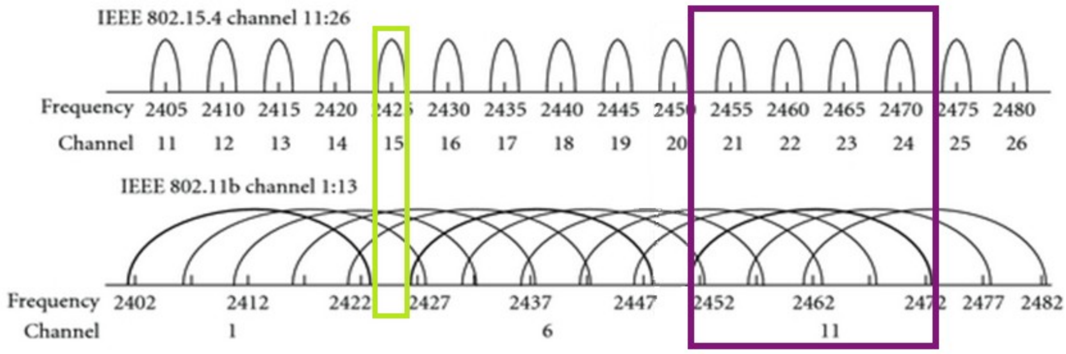


Figure 3-3. Overlapped channel under 802.15.4 and 802.11 coexistence.

3.2 ARCHITECTURE

For the development of this PhD Thesis we have been working with the Connectivity Brokerage (CB) framework [94]. This framework was developed by B105 Lab members from the Universidad Politécnica de Madrid (UPM) in collaboration with a team of the most important research groups focused in CWSN research from different universities as the Berkeley Wireless Research Center (BWRC) from the University of California, and the Telecommunication Network Group (TKN) form the Technical University of Berlin (TUB). This framework has been also used in other research projects and the work over the architecture still continues for implementing and strengthening the approach.

The CB allows coordination and cooperation between different components and devices, even if they belong to different networks. This framework represents a step forward regarding previous approaches. The main difference falls on the fact that different networks can collaborate rather than compete with each other for common resources as they did before.

3.2.1 CONNECTIVITY BROKERAGE FRAMEWORK

The CB framework enables to exchange information and collaboration between devices and networks building a structure where is possible to jointly optimize the spectrum resources. This framework provides a level of abstraction enough to be used as multiplatform and it is modular, adaptable, resilient, and scalable.

The CB framework takes advantage of three important opportunities closely related to our CWSN scenario such as cooperation, collaboration and adaptation.

As defined in the architecture, "CB provides a universal architecture that enables diverse wireless networks competing for resources to actively exchange information and perform joint optimization in light of changing environmental and workload conditions, resulting in an improvement in the performance metrics of choice".

CB framework provides the architecture to collaborate, but works only in the management plane being able to coexist with several data communication stacks as it is depicted in Figure 3-4.

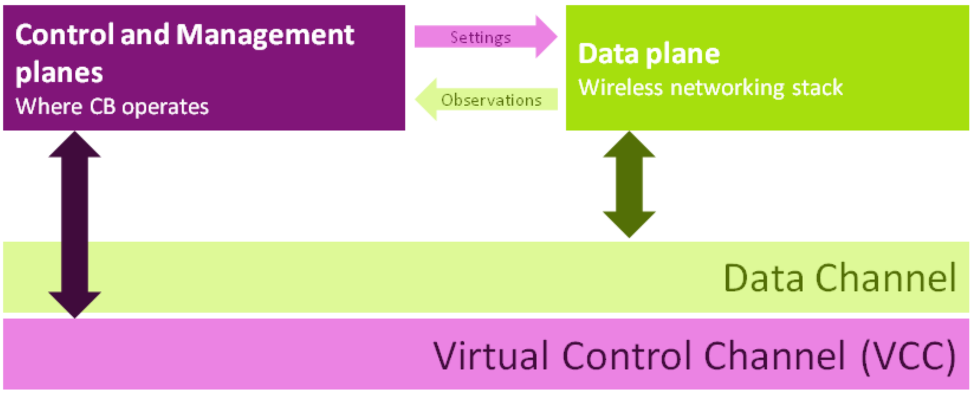


Figure 3-4. Coexistence and interaction between CB framework and protocol stacks.

The basic components of the CB framework are the Connectivity Agents (marked as CAgents). A CAgent is a generic object that represents a particular interest in the scenario. CAgent could be a single device, a node cluster, a wireless network, or a combination of collaborating networks.

The CB framework provides the means to collaborate. The CAgent model provides for a clear and well defined separation of functionality. Each CWSN entity could decide on the most appropriate strategy and acts accordingly.

3.2.2 CAGENTS MODULES

Each CAgent contains 6 modules as can be shown in Figure 3-5 to perform cognitive communications.

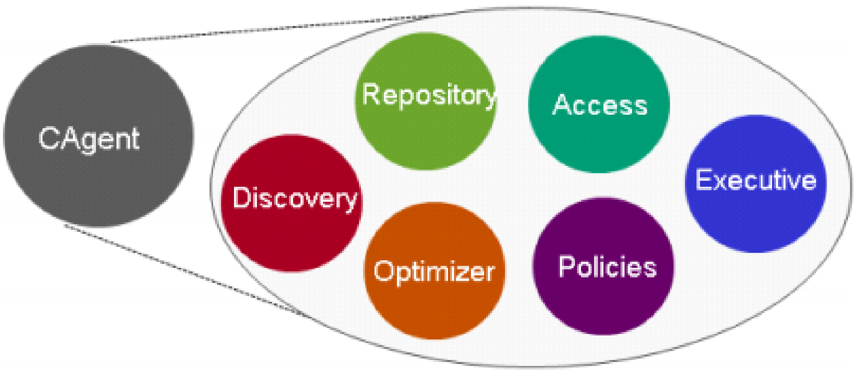


Figure 3-5. CAgent modules.

The modules functionality are described below:

Repository – For being able to provide effective cooperation and collaboration, an indispensable requirement is that information learned, decisions made, and current state of each CAgent could be available (at least partially) for the rest of the modules of the CAgent or even for any other CAgent that interacts with it. In the CB framework, this is enabled through a distributed repository where each CAgent could publish part of its own information to the global CB repository, making it accessible. The repository is one of the fundamental components that enable cooperation through dynamic information exchange.

Discovery – One of the bases of the CB concept is the capability to acquire the state and properties of the environment. The discovery function is able to acquire, extract and filter information about radio levels and spectrum usage which could be collected from different levels and layers of the wireless systems. The resulting information is stored in the repository for their future usage.

Optimization – The obtained information have to be used to optimize the performance of the network. The system has to be configured in order to meet the performance goals or other criteria within the boundaries of the guiding rules and policies. The optimizations required to meet the goals could be fully implemented in just one optimization module or in a distributed or manner. Optimization algorithms belong to this module.

Execution – The outcomes of the optimization process need to be transmitted and executed in a reliable way. The execution module is responsible to send the orders related to the change of communication parameters to the physical layer in the protocol stack, for example. The execution of distributed decisions might require relatively complex coordinated communication process to synchronize the actions in the entire network.

Access control – The control about how the information is disseminated through the system and which modules or agents are allowed to take part in the collaborative management process is subject to rules. The access control is included to avoid the influence of malicious attackers and to improve the security and access control in cooperative systems. One of its tasks is the authentication of the different CAgents for accessing the repository data.

Policy Support – Policies set the prioritization of the optimization processes. The policies could vary dynamically if the boundaries conditions change, and the networks should be able to adapt. The policies module could be described as a set of weighting parameters which helps to set priorities over different parameters. The policies can be defined by regulators or set by network. Even more, they could vary locally and temporally as they provide the ability to be redefined if the scenario changes. It is an innovative essential element of the CB model.

As we have said before, the CB framework is based on CAgent interacting with each other through messages. This statement implies that the CAgents are able to communicate with each other. This is a crucial issue which is solved through the creation of a explicit control channel, dedicated to the exchange of control information. This is the Virtual Control Channel (VCC). Every CAgent communicates with each other over the VCC using a standardized protocol. When setting up the VCC, the most challenging problem is to decide and start the required communication links.

Once the scenario and the architecture are defined and described, we are going to present the designed strategies for energy consumption reduction. As these strategies are based in game theory, the main formal fundamentals are described in the subsequent section.

3.3 GAME THEORY FUNDAMENTALS

Game theory is a branch of applied mathematics, this one of decision-making, employed frequently in social sciences as economics, politics and psychology. Despite its relative novelty (70 years) it has entered into a multiplicity of other areas such as biology, computer science or wireless communication.

Modern game theory has started with the publication of *Theory of Games and Economic Behavior*, a book written by John von Neumann and Oskar Morgenstern [95]. The mathematical framework described by John Nash in his PhD Thesis [96] lays the foundation about non-cooperative games which led him to win a Nobel Prize in Economics in 1944 with John Harsanyi and Reinhard Selten.

Game theory models a decision about a resource as a mathematical problem between intelligent and rational players which always want to maximize their benefits.

3.3.1 GAME CLASSIFICATION

According to different characteristics, a game can be classified into different categories. In the following sections, we describe the most important classifications.

3.3.1.1 ZERO-SUM OR NON-ZERO-SUM

In a Zero-sum game the available resources cannot be modified by players' actions. The total benefit or cost associated with player actions remains constant for every combination of strategies. That is, the amount of the resource one player earn is the same as the amount that the rest of the players lose. Poker or chess are simple examples of a zero-sum game.

On the contrary, in non-zero-sum games the resources to distribute are different depending on player actions. In these games, the total amount of profit to divide has not relation between the profits and loose of the players and, for example, every player could earn simultaneously. One of the most famous examples of a non-zero-sum game is the well known prisoner's dilemma.

As the prisoner's dilemma is going to serve for explaining some important concepts in this approach, we are going to describe the game.

The prisoner's dilemma is one of the best-known examples in game theory. This game represents a situation where two prisoners (players) are suspect in a serious crime (a murder during an armed robbery). Both players participate in the robbery but no clues are given about whom discharges the gun. The police have the evidences for the robbery but do not know the identity of the murder; therefore, they need the testimony from at least one of the prisoners. The police decide to separate the prisoners and questioning each one in a different room without communication among them. Each suspect is offered a deal that reduces the sentence if he confesses or denounces his partner. His alternative is remains silent. If both prisoners remain silent, then both get 2 years sentence for robbery. If one player denounces his partner, he gets only 1 year for cooperation and the partner 5 years for murder. If both of them denounce the other one, both gets a 4 years sentence (murder reduced by cooperation).

3.3.1.2 SYMETRIC OR ASYMECTRIC

In a symmetric game, the profit or cost associate with an action taken by a player depends only on the action itself and the other actions played by the rest of the players but not on who is playing them. This way, does not matter which player is taken which action if the set of actions are the same. The players could exchange their personalities and the benefits or costs associate with the actions would remain the same. The prisoner's dilemma is a symmetric game.

Oppositely, an asymmetric game depends on which player takes which action to calculate the profits. Even more, the actions that could be taken depend on the player. Typical asymmetric games are those related to player differences or privileges as in the ultimatum game where the first player has to propose how to share a sum of money between himself and another player. The second player chooses to accept or reject this proposal. If the second player accepts, the money is split according to the proposal. If the second player rejects, the money is lost.

3.3.1.3 SIMULTANEOUS OR SEQUENTIAL

Games where players take their actions at the same time are simultaneous games. Also, a game is simultaneous if the actions are not taken simultaneously but the subsequent players do not know the action taken by the first-move player. On the other side, sequential games are those where the second and subsequent player takes their actions with some knowledge about the previous players' moves even if this information is not complete. For example, talking about poker, the second player could know that the first player has take three cards even if he does not know which cards are.

3.3.1.4 PERFECT INFORMATION AND IMPERFECT INFORMATION

A game is defined as a perfect information game if every player knows the actions taken previously by all the other players. Taken into account the previous classification, only sequential games can be perfect information games because in simultaneous games players takes their actions at the same time or without knowledge of previous moves.

An imperfect information game is that with some knowledge about the previous moves from other players but not the exactly action or not for every player. As we have said in the previous classification, poker is a imperfect information game while chess is a perfect information game.

3.3.1.5 COOPERATIVE OR NON-COOPERATIVE

A non-cooperative game involves a number of players having conflicting interests in the resource to share. In a non-cooperative game, players act in a selfish way trying to maximize its own profit. Taken into account that this is part of the game definition, we can say that non-cooperative games are the most traditional games.

Nevertheless, cooperative games exists. In these games players cooperate forming groups or coalition with a common objective. This way, they fight for the profit of the coalition, taken actions that leads to maximize them, even sometimes could be different to their actions if they act in an individual non-cooperative way.

Collaboration (as we understand in a CWSN) is not a characteristic only for cooperative games. Non-cooperative players could communicate and collaborate but always looking for their own individual interest.

The games modeled for the strategies proposed in this PhD thesis are non-cooperative as we decide to model distributed games where nodes are autonomous in their decision, even with a selfish behavior. We focus on these games to further explain their components.

3.3.2 NON-COOPERATIVE GAMES

In general, a game is defined by a set of participants (*players)*, a set of decision (*actions*) they can take, and the benefit or costs (*payoffs)* associated with each action (and the other players' actions). Derived by the concept of action, in GTh we use the concept of *strategy*, corresponding to a complete plan of action that a player takes under some circumstances in the game. Strategies could be seen as a mapping from the information available to a player to the action set of this player. Taking into account that the difference depends on information available, actions and strategies are similar for simultaneous games while differs in sequential games.

The concept of information available at each decision point is crucial too for the game definition, even more if the game is sequential.

For a better understanding of the following section, we have convened a common notation:

A non-cooperative simultaneous game can be defined as a triplet of elements:

$$G = \left(N, S_{i(\forall i \in N),} u_{i(\forall i \in N)}\right) \quad (1)$$

Where:

- N is the finite set of players.
- S_i is the set of available strategies for player i.
- u_i $S \rightarrow \mathbb{R}$ is the utility function for player i.

3.3.3 GAME REPRESENTATION

Depending on which kind of game we model, we use two fundamental methods of representation. The difference is based on the classification between simultaneous or sequential game. Often, normal form is used for representing simultaneous games while extensive form is used to represent sequential games. Despite this distinction, extensive representation could be transformed into normal form if needed but not in reverse.

3.3.3.1 EXTENSIVE FORM

Extensive form is used to represent games with sequential actions. The typical extensive representation is similar to a tree as it can be shown in Figure 3-6.

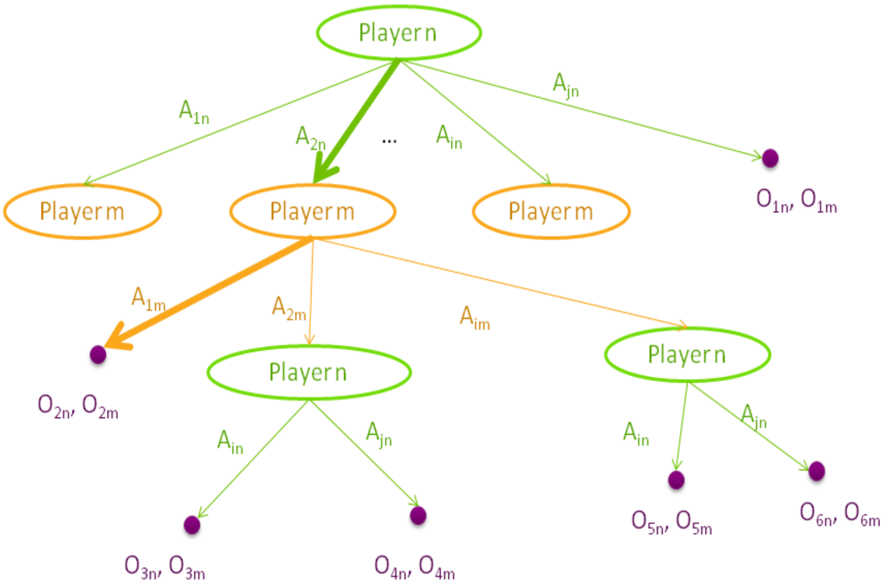


Figure 3-6. Example of a extensive form representation for a two player game.

In the figure, each oval represent a decision point (or decision round) for one player. The player involved in the decision is written inside the oval. As we can see, the actions are taken sequentially and after a player move, a move from the other player follows. The arrows coming out from the oval represent the possible actions for that player, marked by A_{pi}. The outcomes are specified at final rounds represented by a point which correspond to the end of the game, marked as O_{ip}.

The game pictured in the Figure 3-6 is played by two players. The way this game is played is as follows: Player n "moves" first by choosing among A_{1n} to A_{jn}. Next in the sequence, Player m, who knows that Player n has moved and has chosen A_{2n} decide his movement among A_{1m} and A_{jm} in this case. Once Player m has made his choice, the game is considered finished. Each player gets their respective outcomes which in this game are O_{2n}, O_{2m}.

3.3.3.2 NORMAL FORM

Normal form is used to represent simultaneous games. For representing a non-cooperative game in normal form, we have to define the players, their strategies and their potential payoffs. The normal form game is usually represented by a matrix as it is depicted in Table 3-1. It can be represented also by a function association every payoff for each player with every possible combination of actions.

	A_{1m}	A_{2m}
A_{1n}	O_{1n}, O_{1m}	O_{2n}, O_{2m}
A_{2n}	**O_{3n}, O_{3m}**	O_{4n}, O_{4m}

Table 3-1. Example of a normal form representation for a two player game.

In the figure, actions from player n (A_{1n} and A_{2n}) are depicted in green rows and actions from player m (A_{1m} and A_{2m}) are presented in columns into purple cells. Each white cell represents the end of the game resulting from the choice of players' actions related to the row and column associated with it. The outcomes are written in the interior of the white cell separated by a comma. The first number is the payoff received by the row player (player n in our example) and the second one is the payoff for the column player (player m in our example) in notation (player n outcome, player m outcome).

When a game is presented in normal form, it is presumed that each player acts simultaneously or, at least, without knowing the actions of the other. If players have some information about the choices of other players, the game is usually presented in extensive form. Nevertheless, there are ways to convert extensive form into normal form. The games designed in this work are presented in normal form for a compact representation. Also, an extensive form is provided for the collaborative strategy game in order to clarify the performance of the strategy.

3.3.4 GAME THEORY EQUILIBRIA AND OPTIMUS

Once the game is defined and represented, next stage is its formal analysis searching for the best performance related to outcomes.

3.3.4.1 DOMINATING STRATEGIES

A useful concept in non-cooperative games is that of dominating strategies. The use of dominating strategies simplifies the game solving since it permits to eliminate some player strategies.

The concept of dominating strategies can be defined as:

A strategy $s_i \in S_i$ *is said to be dominant for player* i *if*:

$$u_i(s_i, s_{-i}) \geq u_i(s_i^{'}, s_{-i}), \forall s_i^{'} \in S_i \text{ and } \forall s_{-i} \in S_{-i} \quad (2)$$

Where $S_{-i} = \prod_{j \neq i} S_j$ is the set of all strategy profiles for all players except i.

The dominant strategy for the player i, is the players i's best strategy. That is the strategy that maximize the utility of player i regardless the other players strategies. If a dominant strategy exists for player i in a game, he has not any incentive to change his choice.

If a dominant strategy exists for every player in the game, none player wants to choose any strategy different to this one.

We can define then:

A strategy profile $s^* \in S$ *is the dominant-strategy equilibrium if every element* s_i^* of s^* *is a dominant strategy of player i.*

Beyond the concept of a dominant strategy, we can define the opposite, a strictly dominated strategy.

A strategy $s_i' \in S_i$ *of a player* i *is said to be* strictly dominated *by a strategy* $s_i \in S_i$ if:

$$u_i(s_i, s_{-i}) > u_i(s_i^{'}, s_{-i}), \qquad \forall s_{-i} \in S_{-i} \quad (3)$$

A strategy strictly dominated always has a strategy which performs better in any case and under any other players' decisions. This way, choose a strictly dominated strategy would be irrational and, as said before, one of the game theory premises is that every player must be rational. This leads to one of the first ways to solve game theory problem: the iterative elimination of strictly dominated strategies. That reduces the number of possible actions to take and simplifies the game.

Related to the concept of strict domination of a strategy, we can define the concept of weak dominance:

A strategy $s_i' \in S_i$ *of a player* i *is said to be* weakly dominated *by a strategy* $s_i \in S_i$ if:

$$u_i(s_i, s_{-i}) \geq u_i(s_i', s_{-i}), \qquad \forall\, s_{-i} \in S_{-i} \tag{4}$$

Performing a iterative elimination of weak dominated strategies results in different games depending on the elimination order and therefore different outcomes results.

Strict and weak dominance are useful tools to reduce the scope of the game but there is not always a solution since the majority of the games are not solvable through iterative dominance elimination.

3.3.4.2 NASH EQUILIBRIUM

The most accepted solution concept for a non-cooperative game is Nash equilibrium presented by Nash in his PhD Thesis [96]. Nash equilibrium for non-cooperative games is a state where any player cannot improve their outcome by changing his action taking into account the actions taken by the other players.

In a formal definition:

A pure-strategy Nash equilibrium of a non-cooperative game $G = \left(N, S_{i(\forall i \in N),} u_{i(\forall i \in N)}\right)$ *is a strategy profile* $s^* \in S$ *such that* $\forall\, i \in N$ *we have the following*:

$$u_i\,(s_i^*, s_{-i}^*) \geq u_i\,(s_i, s_{-i}^*), \qquad \forall\, s_i \in S_i \tag{5}$$

A strategy profile is a Nash equilibrium if no player has an incentive to unilaterally change its strategy while the rest of the players' strategies remain unchanged.

As an example, prisoners’ dilemma is analyzed in order to find the Nash equilibrium. Given the normal form representation of the game, the Nash equilibrium is marked in orange in Table 3-2.

	Silent	Denounce
Silent	2, 2	5, 1
Denounce	1, 5	4, 4

Table 3-2. Prisoners' Dilemma Nash equilibrium analysis.

We can assure that in a game played by rational players, Nash equilibrium (if it exists) is the stationary end of the game.

We can affirm two fundamental statements about Nash equilibrium:

- Nash equilibrium does not have to be unique. A non-cooperative game could have, none, one or multiple Nash equilibria.
- Nash equilibria do not necessarily match the situation with the best solution in terms of payoffs.

That is why the study of the existence, the multiplicity and the efficiency of Nash equilibrium is one of the main cornerstones in Game Theory.

3.3.4.3 PARETO OPTIMAL

Talking about games with multiple Nash equilibria, selecting the optimum one is important because it is the best one in terms of payoffs. One of the most important ratios of efficiency is the concept of Pareto optimality:

A strategy profile $s \in S$ is Pareto-superior *to another strategy profile* $s' \in S$ if*, for every player* $\forall\, i \in N$ *we have*:

$$u_i(s_i, s_{-i}) \geq u_i\left(s_i^{'}, s_{-i}^{'}\right) \tag{6}$$

and it is strictly greater for at least one player.

A strategy profile $s^o \in S$ *is Pareto-optimal if there exists no other strategy profile Pareto-superior to* s^o.

Thus, the outcome of a game is Pareto-optimal if there is no other outcome that makes every player at least as well off and at least one player strictly better off. If we have many Nash-equilibria we prefer to select that which correspond with the Pareto-optimal if it is possible (sometimes Nash-equilibrium and Pareto-optimal do not match).

As an example, prisoners' dilemma is analyzed in order to find the Pareto-optimal strategy profiles. Given the normal form representation of the game, the Pareto-optimums are marked in orange.

	Silent	Denounce
Silent	2, 2	5, 1
Denounce	1, 5	4, 4

Table 3-3. Prisoners' Dilemma Pareto optimal analysis.

The dilemma in this game is the not-matching situation among Nash equilibrium and Pareto optimal.

Once useful concepts about game theory, game representation and definition and formal analysis are presented, we proceed with the presentation of the strategies. Both of them focused on the ability to change transmission parameters based on sensed information and also taking advantage of the network cooperation to share the information.

3.4 NON-COOPERATIVE P2P STRATEGY

We are going to present in this section the first cognitive strategy for energy consumption reduction in CWSNs. This strategy is denoted as non-cooperative P2P strategy.

As mentioned in Chapter 1, constrained resources are an intrinsic challenge when talking about CWSNs. The additional complexity added to the nodes to enable cognitive capabilities makes nodes have higher energy consumption. Moreover, processing capability of WSN nodes is limited, so the strategies implemented should have low complexity.

3.4.1 INTRODUCTION

The proposed non-cooperative Peer to Peer (P2P) strategy is based on a channel shift strategy to prevent unnecessary retransmissions. The use of less noisy channels avoids extra retransmissions and makes possible the global energy consumption reduction of the network. An improper selection of the transmission channel produces an extra consumption due to the retransmission of packets and the loss of QoS due to delays, packet losses, etc. Thus, based on the ability to sense the spectrum and change the transmission parameters, a strategy for reducing energy consumption is presented.

As we have shown in Chapter 2, game theory is widely accepted for resource optimization in cooperative WSN, and now, with cognitive capabilities, could fit even more. By its intrinsic nature, a sensor-network resource problem can be easily modeled like a game. In addition, games can be simplified enough without losing functionality to make them supported by a WSN node, even if its processing capability is limited.

This P2P strategy is composed by different parameters, being a non-cooperative game the master piece for decision making. The strategy and the game are presented in the next sections.

3.4.2 STRATEGY

The presented strategy improves energy consumption by taking advantage of the new change-communication-channel capability. Based on game theory, the strategy decides when to change the transmission channel depending on the behavior of the rest of the network nodes and the sensed information. The modeled game is used in the design phase of the strategy.

For the implementation of this strategy, always running the maximization of the payoff of the formulated game in background is possible. Nevertheless, in terms of energy conservation and computing capabilities optimizing only when the transmission channel is noisy enough is more efficient. In this way, the strategy considers that the optimization will be triggered only when necessary, taken into account other parameters like the Received Signal Strength Indicator (RSSI) received in the communication channel (as a energy detection spectrum sensing) which is related to noise presence.

The optimization strategy is described below and presented in Figure 3-7 and in pseudocode in the Figure 3-8.

Optimization strategy performs as follows:

1. Every node in the CWSN receives application messages by the assigned channel and saves RSSI samples from each message received as energy detection.
2. If the RSSI value saved in node i is above a certain threshold (calculated for a certain number of samples), node i activates the optimization algorithm modeled as a game. That evaluates the payoff function to decide if changing the channel is interesting at this moment or not.
3. If the result of this evaluation is a change, node i senses the spectrum, chooses the least noisy channel, and change its communication channel to the selected new channel.
4. Node i communicates its decision to the rest of the network nodes and the new chosen channel according to its sensing values.
5. The rest of nodes evaluate this change and decide whether to change the channel depending on their payoff function. If this evaluation results in a change, node –i change its own communication channel. The decision is communicated back to other nodes in the network.
6. The value of the stored accepted change channel request is updated to save a history of accepted changes and then being able to learn and evolve.

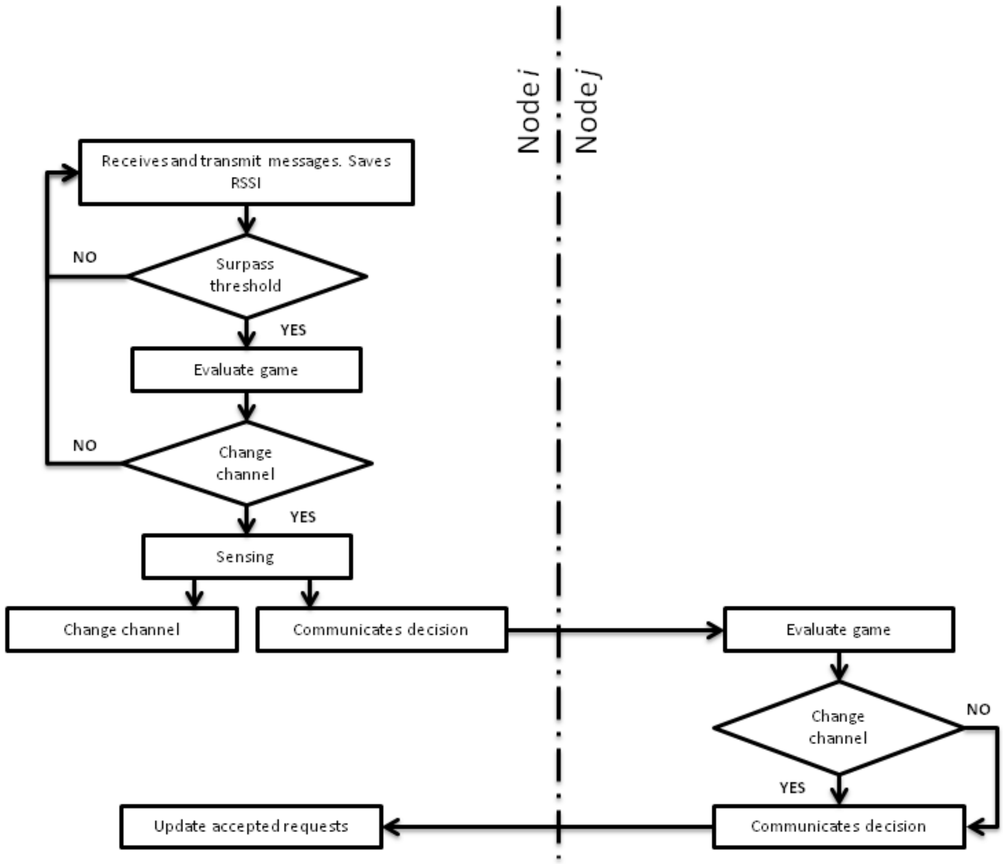


Figure 3-7. P2P Strategy flowchart.

```
For node i (when receiving an App msg):
        RSSIvalue = readRSSI (channel)
        saveRSSIvalue (channel, RSSIvalue)                     (1)
        if (averageRSSIvalue >= RSSIthreshold)
                changeChannel = maximizePayoff(node)           (2)
        if (changeChannel){
                chosenChannel = senseSpectrum()                (3)
                changeCommChannel(chosenChannel)
                sendChangeChannelMsg(node,chosenChannel)       (4)
        }

For the node -i (when receiving a request msg):                (5)
        changeChannel=evaluatePayoff(node,channel)
        if (changeChannel){
                changeCommChannel(chosenChannel)
        }
        sendEvaluation(node,changeChannel)

For node N:
        actualizeAceptedRq(node);                              (6)
```

Figure 3-8. Strategy performance in pseudocode.

Applying the criterion of maximization of this simple algorithm in every device, it is possible to optimize the consumption of each node without impacting the breakdown of other nodes in the network. Thus, maximizing the lifetime of each network node, the lifetime of the network as a whole is prolonged. Although this statement is not always true, the energy saving in each node has a positive effect on the overall operation of the network.

The lightness of the strategy could be appreciated in Figure 3-8. Each node only has to save RSSI values when receiving an application message and after a simple verification of a threshold perform the payoff maximization process if needed. As we are going to see in the next section, this calculation only involves two simple mathematical operations. When this calculation results in a change, send a message to communicate the decision.

Although in this work the sensing state only involves one node, this approach could be adapted to any type of sensing depending on the network features. In this approach, only the triggered node is responsible for sensing. However, new collaborative techniques or channel negotiation in clusters could be included according to the location of the nodes.

According to the CB architecture, as shown in Figure 3-9, the strategy performance involves the following modules:

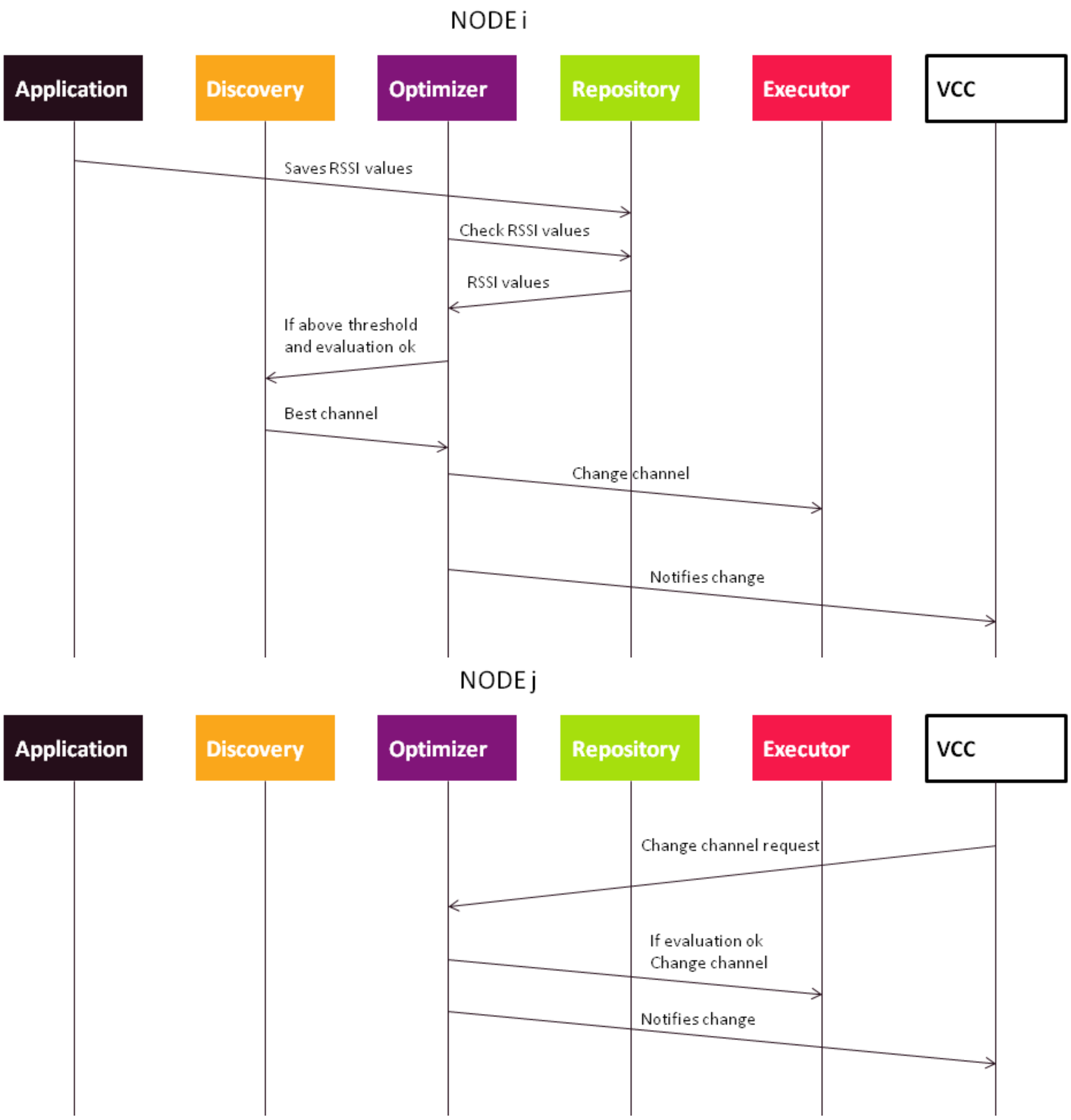


Figure 3-9. P2P strategy in CB architecture for node i and node j.

Messages related to the strategy are sent by the VCC. Just node i senses the spectrum. The evaluation of payoffs is performed in the optimizer module and measurements about RSSI and accepted requests are stored in the repository.

3.4.3 GAME FORMULATION

As we have said in Section 3.3, a game is defined by several characteristics. The *resource* being modeled, the *players*, their *strategies* and the *actions* they can take. Thereon, the *benefits or costs* associated with each *action*, and the *payoff matrix and function*.

In this P2P strategy, the game is modeled as a finite resource game due to the use of powered-batteries nodes, which provides them with a finite energy. The *resource* is the energy available in each node. *Players* are CWSN's nodes, and the *actions* are those relating to the selection of the communication channel. The feasible *actions* that each one of the *players* can carry out in this first strategy are to change or not change the transmission channel. This *action* can arise from themselves or after a *move* -request- from another *player*. Energy consumption is modeled as the *resource* for which players compete. Thus, the *payoffs* and *costs* are those energy expenses associated with the *actions* taken.

A summary of the notations used in the game modeling of the game can be seen in Table 3-4:

Symbol	Description
C	Cost associated to a player taking an action.
C_o	Cost of transmitting in noisy channels.
C_n	Cost of communications in a channel not shared with the receiver.
C_{ch}	Cost associated with a change of the communication channel.
$C_{sensing}$	Cost associated with sensing tasks.
C_{tx}	Cost of transmitting one packet.
C_{rx}	Cost of receiving one packet.
n_rtx	Number of retransmissions in the history for this channel.
max_rt	Maximum number of retransmissions allowed by a node.
n_{msg}	Number of needed messages to communicate a channel change.
N	Nodes (players). Each CWSN node.
A	Actions. Set of actions CWSN nodes can take.

U	Utility function.

Table 3-4. Notations used in the P2P game model.

With this notation, the P2P-game could be defined by

$$P2P\ Game = (N, A, \mathrm{u}) \tag{7}$$

Where:

- $N = \{n_1, n_2, n_3 \ldots n_i\}$
- $A = \{a_1, a_2, a_3 \ldots a_i\}$
- $u = \{u_{Z1}, u_{Z2}, u_{Z3} \ldots u_{Zi}\} \quad Z \rightarrow \mathbb{R}$

This game can be described as a non-cooperative game (even communication between nodes can lead to the common good). It is a non-zero-sum game, in which there is no correlation between one player's payoffs and another player's losses. In fact, there may be values that maximize the payoffs of every player. The game is sequential because actions are performed sequentially. This game is asymmetrical since payoffs are different depending on the players. In this case this dependence refers to the position of the players and the traffic between them.

For the calculation of the *payoff* matrix of this game, it is taken into account the resulted *payoffs* arisen from the combination of the following *actions* taken by the *players*, to change or not to change the transmission channel.

Even if the game is sequential, due to its simplicity and for a more compact depiction we use a normal form representation.

The *payoff* matrix for *player* i that communicate with *player j* is shown below:

$P_{i,j}$	j changes channel	j does not change channel
i changes channel	C_{ch}, C_{ch}	C_{ch}+ C_n, C_n
i does not change channel	C_n, C_{ch}+ C_n	C_o, C_o

Table 3-5. Payoff matrix for player P2P game.

And the *payoff* matrix for the node i could be expressed as:

$$Pi = \begin{pmatrix} Cch & Cch + Cn \\ Cn & Co \end{pmatrix} \quad (8)$$

Where:

Cch is defined as the energy cost associated with a change of the communication channel. It is calculated as the addition of the extra energy cost associated to the sensing mode (*Csensing*) and the cost of the transmission (*Ctx*) and reception (*Crx*) caused by the agreement messages needed to negotiate the channel change (n_{msg}). Thus, the energy cost of the action of change the communication channel is:

$$Cch = Csensing + (Ctx + Crx) \cdot n_{msg} \quad (9)$$

Co is the energy cost associated with communication in noisy channels. It is calculated as the cost of a packet transmission taking into account that it requires a number of retransmissions named *n_rtx*. This *n_rtx* depends on the observed and stored number of retransmissions needed by previous packets and is calculated as the average of the needed message retransmissions for the previous *k* (parametrizable) messages.

$$Co = Ctx \cdot n\_rtx \quad (10)$$

Cn is the energy cost associated to communicate in a channel not shared with the receiver. Even that this situation is not very common could happen if several CWSN perform the strategy without agreement. *Cn* is calculated as the cost of transmission when the number of retransmission is run out and consequently the maximum allowed is reached (*max_rtx*).

$$Cn = Ctx \cdot \max\_rtx \quad (11)$$

3.4.4 ANALYSIS

As we use GTh into the design phase of this strategy, we need to analyze the stationary and optimal behavior of the game in order to implement the results into the nodes.

To determine the optimal value of payoff that the node can achieve, we evaluate *Cch, Cn* and *Co.*

As we can see through the formal definition of costs, Cn will be always greater or at least equal as Co derived by the fact that n_rtx could not be greater than $\max\_rtx$. For that reason, we can assure that:

$$Cn \geq Co \qquad (12)$$

Even more, $Cch \geq 0 \rightarrow Cch + Cn \geq Cn$ and because of (12), $Cch + Cn \geq Co$.

With this data, and the definition in (5) and (6) the only Nash equilibrium could be the cells marked in orange which are also the Pareto-optimums.

$P_{i,j}$	j changes channel	j does not change channel
i changes channel	C_{ch}, C_{ch}	C_{ch}+ C_n, C_n
i does not change channel	C_n, C_{ch}+ C_n	C_o, C_o

Table 3-6. Nash and Pareto analysis for P2P game.

We cannot assure a relation among *Co* and *Cch* because they depend on the dynamic parameters related to the network as *n_rtx*. With this information we have to calculate only the cost associated with *Cch* and *Co* each time the strategies requires to. The lowest among them would be the optimum equilibrium of the game.

There exists the possibility of having a optimum equilibrium which changes depending on the context of the network or the presence of noise. But the strategy will be able to adapt. This strategy is defined by lightness requirements, and its simplicity is its best value. The application of this strategy helps to reduce energy consumption in noisy scenarios without increasing the node's computational effort.

Along this line, it is important to remark that we use game theory for the design phase of the algorithm allowing us to assure the optimal energy consumption for each individual network node. Even if the strategy is very simple, their simplicity is one of their strong points making its implementation affordable for very constrained networks while ensuring energy savings. As explained before, the nodes only have to saves RSSI values and when the threshold is surpassed, calculated the payoffs and decide. As the payoffs function is very simple, this stage involves only a very simple mathematical operation.

3.5 GTH COLLABORATIVE STRATEGY

Advancing one step forward and trying to improve the strategy when facing dynamic noise environment, we evaluate and decide to introduce collaboration among nodes. This time, the choice of the channel would not be a single and selfish selection; nevertheless it has to be negotiated. Even if this strategy is more complex than the previous one, we cannot forget the nodes constraints. The scenario and the nodes are the same as in the previous case, those described in Section 3.1.

3.5.1 INTRODUCTION

The proposed collaborative strategy is also based on channel shifting to prevent unnecessary retransmissions. Thus, based on the ability to sense the spectrum and change the transmission parameters, a strategy for reducing energy consumption is presented. The choice of this parameter for reducing interferences as proposed as well in the previous strategy is simple and promising.

This collaborative strategy is composed by different parameters being, as before, a non-cooperative game used to model the decision making of this strategy. The strategy and the game are presented in the next sections. The main difference resides in the use of collaboration among nodes for information sharing and decision about the chosen communication channel without forgotten that it continues to be a non-cooperative game.

3.5.2 STRATEGY

As in P2P strategy, when designing an energy optimization strategy, the first step is to decide when to trigger the optimization algorithm. It is possible to always run the maximization of the payoff in the background, but in terms of energy conservation and computing capabilities it is more efficient to optimize only when the transmission channel presents a certain amount of noise. The optimization is triggered when the RSSI level detected in the communication channel exceeds a configurable threshold.

This measure is related to the presence of noise in the channel. Although we have chosen this threshold since it is associated to the channel saturation and easy to measure, the number of retransmissions experienced by a CWSN node could be also used without any change in the strategy. Both parameters are related to the spectrum saturation providing us a useful threshold to use.

The main difference related to the previous P2P strategy is the introduction of collaboration. Once the game evaluation results in a decision of change, the node senses the spectrum and shares this information with the rest of the network nodes to which it communicates along with the request of change. Once this information is received by the other nodes, they evaluate the game and if this evaluation and chosen channel are the same, they proceed to the change and notify their decision. However, if the channel is not the same, they respond to the request with their preferred channel together with the sensed information. This way, every node involved in the change step has the whole information to take the best decision.

Even if the decision of change is taken in an individual way, the information is shared across the network in order to collaborate and improve the performance in energy consumption.

A flow chart is presented below in Figure 3-10.

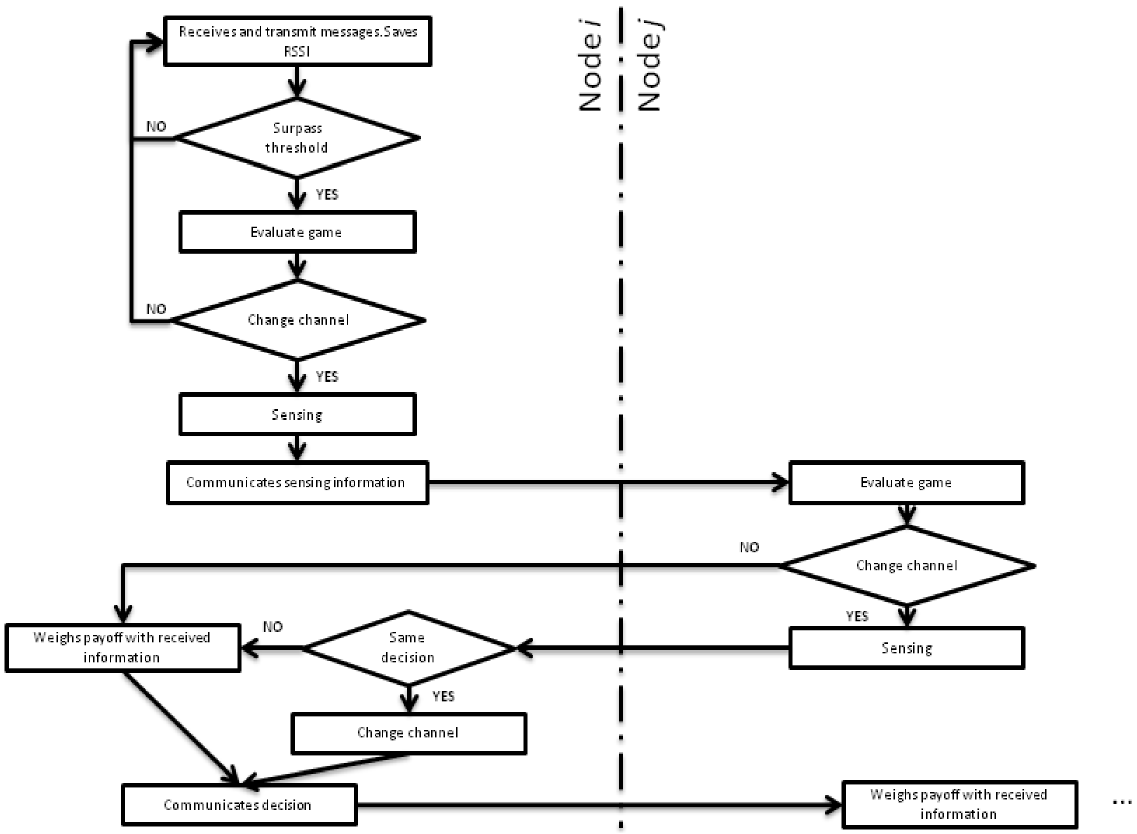


Figure 3-10. Flow chart of the collaborative strategy.

The collaborative strategy is executed as follows:

- Each CWSN node $\{n_1, n_2, n_3 \dots n_i\}$ receives and transmits application messages through the assigned channel normally. When a message arrives, the receiving node saves its associated RSSI sample.
- When the RSSI values stored in n_i surpass a certain threshold (we take some extra samples in order to avoid false measurements), the node n_i activates the optimization algorithm.
- The node n_i enters into sensing state, saves the RSSI values of every available channel (as a sensing method based on energy detection) and determines the less noisy channel.
- The node n_i communicates the sensed information and the chosen channel to the rest of the CWSN nodes for collaboration.
- The rest of the nodes n_{-i} receive the request for changing the channel and the preference for which channel to change to. Each n_{-i} node evaluates the

costs associated to each action and decides whether or not to change the channel depending on its payoff function. This decision will be communicated to the other nodes in the network.

- If the evaluation results in a change of the communication channel, this n_{-i} enters into sensing state and checks if the preferred channel is its best option. If it is not, n_{-i} responds with its own sensed spectrum information in order to improve collaboration choosing the destination channel.
- After receiving the n_{-i} responses, n_i evaluates the sensed information received. If the preferred channels do not match, n_i weighs its payoff function according to the new information received.
- Every node informs the rest of the CWSN nodes about the final decision taken for improving the overall network performance.

Although in this work every node can sense the spectrum, this approach can be adapted to any type of sensing strategy depending on the network features. New collaborative techniques or distributed sensed information can be included taking into account the location of the nodes.

According to the CB architecture, this strategy could be represented as in Figure 3-11

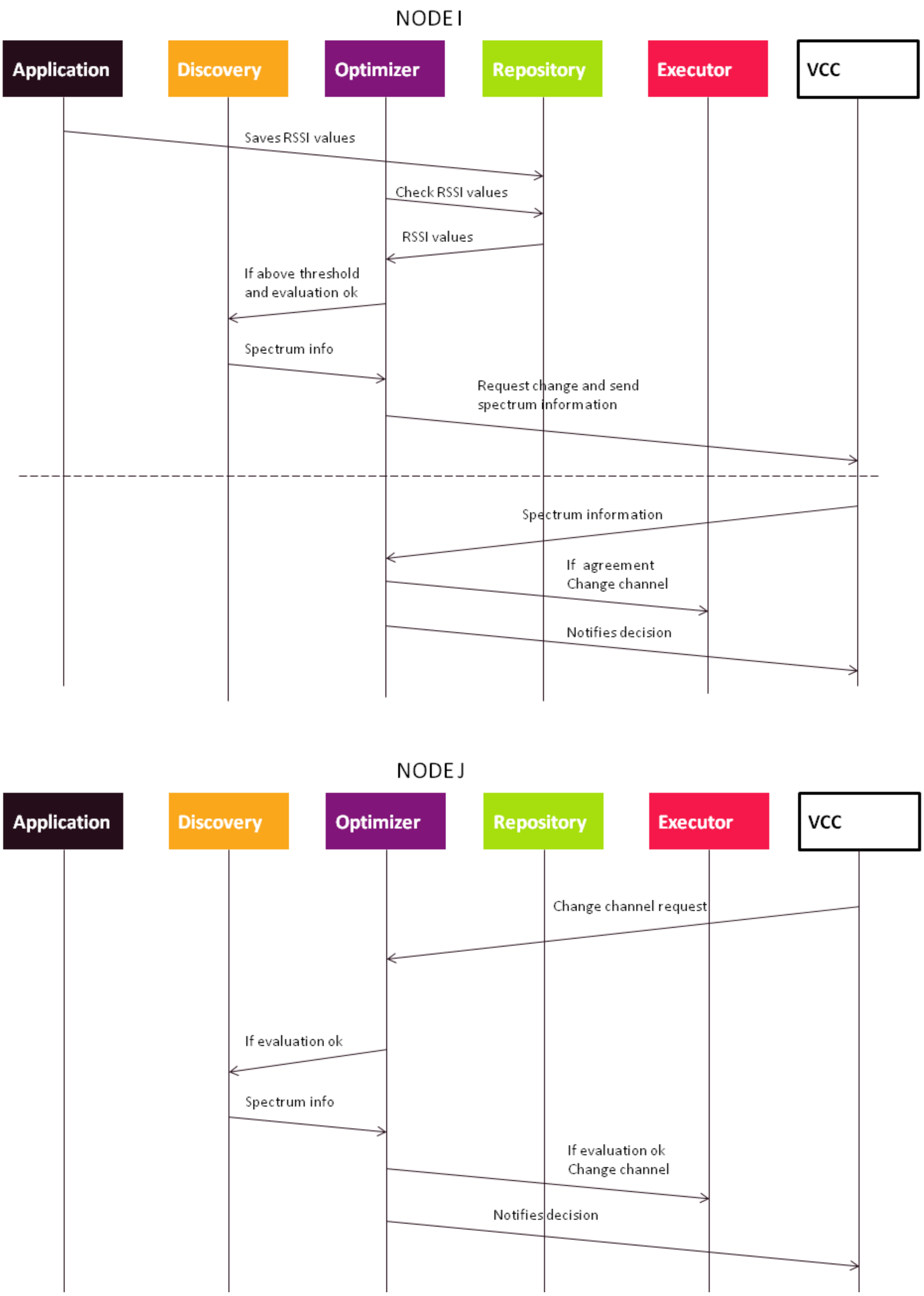


Figure 3-11. Collaborative strategy according to CB architecture.

Discovery is in charge of sensing stage (in every node) and optimizer is the core module for the strategy where the payoffs are calculated, data are stored in the repository and CR messages are transmitted by the VCC.

3.5.3 GAME FORMULATION

In this approach, the modeled game is a finite resource game taking the energy available in the nodes as the *resource* to be modeled. The *players* are all of the individual CWSN nodes, and the *strategies* are related to the selection of the transmission channel. Specifically, the actions each player can take are either changing to a specific channel (among the available to him) or remaining in the same transmission channel. This *action* can arise from themselves or after a *move* -request- from another *player*. This decision will be taken depending on the *player* that makes the request, the state of the spectrum and the history. *Payoffs*, in this model *costs,* are the energy expenses incurred by each *player* based on their *actions* and those of the other *players*.

A summary of the notations used in the modeling of the game can be seen in Table 3-7.

Sym	Description
C	Cost associated to a player taking an action.
C_o	Cost of transmitting in noisy channels.
C_n	Cost of communications in a channel not shared with the receiver.
C_{ch}	Cost associated with a change of the communication channel.
C_{sensi}	Cost associated with sensing tasks.
C_{tx}	Cost of transmitting one packet.
C_{rx}	Cost of receiving one packet.
n_rt	Number of retransmissions in the history for this channel.
max	Maximum number of retransmissions allowed by a node.
n_{msg}	Number of needed messages to communicate a channel change.
N	Nodes (players). Each CWSN node.
A	Actions. Set of actions CWSN nodes can take.
H	Decisions rounds. At this point actions must be performed by some
Z	Final round. End of the iteration.
P	Players function. Assigns which players take actions in each round.
X	Action function. Assigns which actions can be taken in each round.
Σ	Next step function. This function assigns each pair (h,a) to a new h or z.
U	Utility function.

Table 3-7. Notations used in the collaborative model.

Although this game is collaborative, this collaboration is carried out during the game, but the decisions about the actions are taken by the nodes selfishly. That is, the nodes collaborate by sharing spectrum sensing information to try to improve their overall performance, but the decision of each node about the channel change depends only on its own costs. This is not a cooperative game.

Following game theory terminology, this game can be described as a non-zero-sum game, since there is no correlation between a player's payoffs and the losses of the rest of the players. In fact, there may be actions that minimize the losses of every player. It is a sequential game in which actions are taken one after the other. When actions are taken, players know in which game round they are playing and some information about the decisions of other players. The game is asymmetrical because the costs are not the same for every player. Specifically, they depend on the location of the player (different influence of noise in different areas) and the data rate.

For the calculation of the payoff matrix of this game, the resulting payoffs come from the combination of the actions taken by the players (to change or not to change the transmission channel). As we can see in Table 3-8, the feasible actions are not limited to change or not the communication channel. This strategy allows to take decision for every available channel. The number of possible actions depends then of the available CWSN channels.

The payoff matrix for player n_i that communicates with player n_j is shown in Table 3-8:

$P_{i,j}$	Not change	Channel 1	Channel 2	...	Channel n
Not change	C_o, C_o	C_n, C_{ch}+ C_n	C_n, C_{ch}+ C_n	C_n, C_{ch}+ C_n	C_n, C_{ch}+ C_n
Channel 1	C_{ch}+ C_n, C_n	C_{ch}, C_{ch}	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n
Channel 2	C_{ch}+ C_n, C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}, C_{ch}	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n
...	C_{ch}+ C_n, C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}, C_{ch}	C_{ch}+ C_n, C_{ch}+ C_n
Channel n	C_{ch}+ C_n, C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}, C_{ch}

Table 3-8. Matrix representation of the collaborative game.

Where: C_{ch} , C_o and C_n are described as in the previous strategy.

Cch is defined as the energy cost associated with a change of the communication channel. It is calculated as the addition of the extra energy cost associated to the sensing mode (*Csensing*) and the cost of the transmission (*Ctx*) and reception (*Crx*) caused by the agreement messages needed to negotiate the channel change (n_{msg}). Thus, the energy cost of the action of change in this case is:

$$Cch = Csensing + (Ctx + Crx) \cdot n_{msg} \tag{13}$$

Co is the energy cost of transmission in noisy channels. It is calculated as the cost of a packet transmission taking into account that it requires a number of retransmissions named *n_rtx*. This *n_rtx* depends on the observed and stored number of retransmissions needed by previous packets and is calculated as the average of the needed message retransmissions for the previous *k* (parametrizable) messages.

$$Co = Ctx \cdot n\_rtx \tag{14}$$

Cn is the energy cost associated to communicate in a channel not shared with the receiver. Even that this situation is not very common could happen if several CWSN perform the strategy without agreement. *Cn* is calculated as the cost of transmission when the number of retransmission is run out and consequently the maximum allowed is reached (*max_rtx*).

$$Cn = Ctx \cdot \mathrm{max}\_rtx \tag{15}$$

The values of these associated costs are variable over time due to the network context, so they must be calculated dynamically. The variation of these values makes the game evolve.

Once the costs associated with the communication between two nodes are calculated, it is necessary to weigh the costs associated with the number of messages exchanged between the different network nodes. This information can be collected from the application directly or through history values. This way, a node should be more influenced by the nodes with which it communicates the most.

Due to its sequential nature, and since this game is lightly more complex, a representation of the game in extensive form can be better suited. An extensive game is defined by:

$$Game = (N, A, H, Z, \chi, \rho, \sigma, \mathrm{u}) \tag{16}$$

Where:

$N = \{n_1, n_2, n_3 \dots n_i\}$

$A = \{a_1, a_2, a_3 \dots a_i\}$

$H = \{h_1, h_2, h_3 \dots h_i\}$

$Z = \{z_1, z_2, z_3 \dots z_i\} \quad Z \neq H$

$\rho = \{\rho_{H1}, \rho_{H2}, \rho_{H3} \dots \rho_{Hi}\} \qquad \forall\, h \in H \qquad \rho_{Hi} = \{n_i, n_j \dots n_k\}$

$\chi = \{\chi_{H1}, \chi_{H2}, \chi_{H3} \cdots \chi_{Hi}\} \qquad \forall\, h \in H \qquad \chi_{Hi} = \{a_i, a_j \dots a_k\}$

$\sigma(h_i, a_j) = h_k \; or \; z_k$

$\forall\, h_1, h_2 \in H; \;\; \forall\, a_1, a_2 \in A; \quad if \quad \sigma(h_1, a_1) = \sigma(h_2, a_2) \implies h_1 = h_2 \; and \; a_1 = a_2$

There is only one possible path to get to $\mathrm{h_k}$ or $\mathrm{z_k}$. Decision and final rounds form a tree.

$u = \{u_{Z1}, u_{Z2}, u_{Z3} \dots u_{Zi}\} \qquad Z \to \mathbb{R}$

The extensive form representation of this collaborative game can be seen in Figure 3-12.

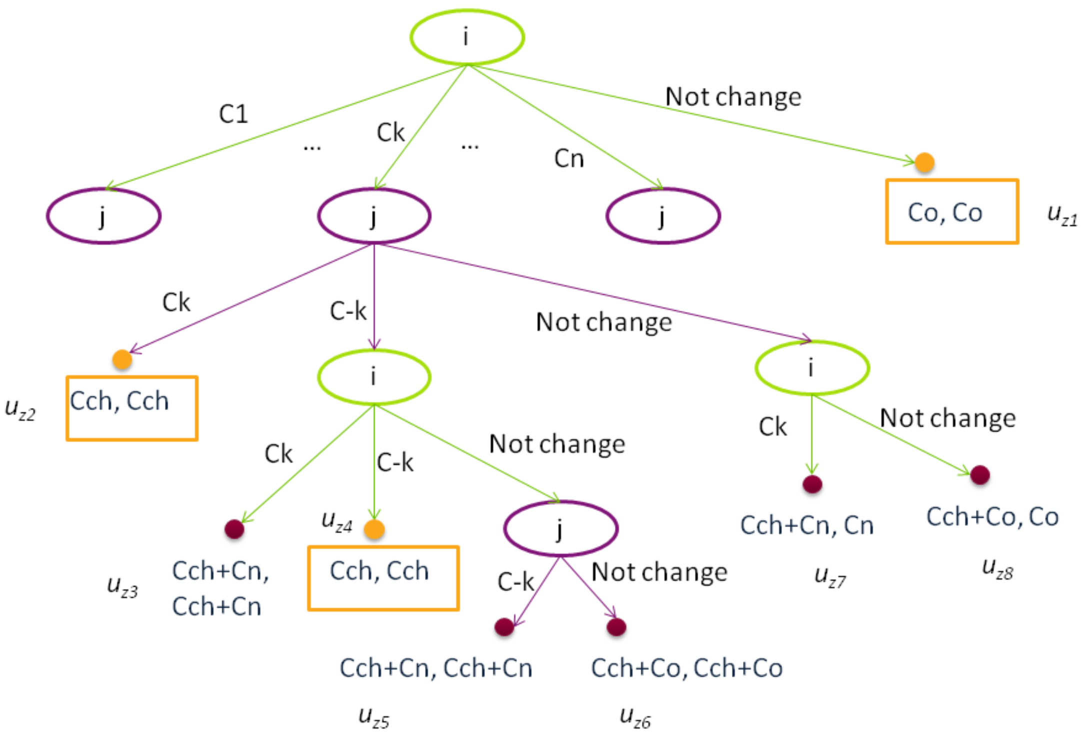


Figure 3-12. Extensive form representation.

3.5.4 ANALYSIS

To carry out a formal analysis of Nash equilibrium in the proposed game, as we have performed for the previous one in order to implement the results into the nodes :

Cn is always greater or at least equal as Co according to their formal definition and derived by the fact that n_rtx could not be greater than $\max\_rtx$. For that reason, we can assure the same inequality as in (12) and eliminates those cells marked in light purple in Table 3-9.

Taking into account that $Cn \geq 0 \rightarrow Cch + Cn \geq Cch$ and because of (12) $Cch + Cn \geq Co$.

With this data, it is possible to eliminate the cells marked in light green in Table 3-9 confirming along with (5) that the pairs of actions belonging to the Nash equilibrium correspond to those found on the diagonal of the Table 3-8; that is, the cases when both nodes takes the same action. These cells are marked in orange in the Table 3-9

Looking at the proposed game, Pareto optimal match the Nash equilibrium pairs (those found on the table diagonal) for the same reason and the definition in (6). Depending on the values of C_o and C_{ch} calculated dynamically the optimality would be one pair or other (C_o, C_o or C_{ch}, C_{ch}).

As in the previous strategy, the cells in the diagonal are the only possibilities of optimal equilibrium solutions

$P_{i,j}$	Not change	Channel 1	Channel 2	...	Channel n
Not change	C_o, C_o	C_n, C_{ch}+ C_n	C_n, C_{ch}+ C_n	C_n, C_{ch}+ C_n	C_n, C_{ch}+ C_n
Channel 1	C_{ch}+ C_n, C_n	C_{ch}, C_{ch}	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n
Channel 2	C_{ch}+ C_n, C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}, C_{ch}	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n
...	C_{ch}+ C_n, C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}, C_{ch}	C_{ch}+ C_n, C_{ch}+ C_n
Channel n	C_{ch}+ C_n, C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}+ C_n, C_{ch}+ C_n	C_{ch}, C_{ch}

Table 3-9. Formal game representation of the collaborative game with the optimal equilibrium marked.

Analyzing the Nash equilibrium and the Pareto optimality in this extensive form and taking into account that every cost is a negative value, it is possible to confirm that they are the same pairs as mentioned previously. In the notation of the Figure 3-12, the Nash equilibrium corresponds to values u_{z1}, u_{z8}, u_{z2} and u_{z4}. Strategies profiles corresponding to Pareto optimality are those for u_{z1} and u_{z2}.

As we use game theory in the design phase of the algorithms we can ensure the optimal behavior in terms of energy consumption.

As stated before, with this information we have just to calculate the cost associated with *Cch* and *Co* each time the strategies requires to. The lowest among them would be the optimum equilibrium of the game. Considering the Nash equilibrium and Pareto optimality formally obtained in this analysis, it could be expect that players take actions that lead to stabilize the game in one of the pairs obtained depending on the network context.

There exists the possibility of having an optimum equilibrium which changes depending on the context of the network or the presence of noise. But the strategy will be able to adapt. Even more, the strategy could adapt to the presence of dynamic noise also locally different distributed. Some of the nodes can choose a communication channel different than the others forming clusters based on their profile communication. That is, the relation among nodes and the amount of data exchanged by them.

Also, when multiple CWSN coexists even if they do not collaborate among them, the use of this strategy could bring energy savings. As every CWSN implement this strategy, even without collaboration among different networks (only among the same network), they are able to adapt their communication channel for optimizing their performance. If every network performs in the same way, it results in an optimized channel selection for every network improving the energy consumption one step forward. Envisioning a wireless future as we have depicted in Chapter 1, this strategy brings lots of benefits without increasing network complexity or implementing intricate protocols for heterogeneous networks.

After the presentation of these strategies and being performed the formal analysis, next step according to the methodology proposed in Section 1.2 is to test the strategies through simulation and implementation in real devices. For that purpose we have developed a CWSN framework in the B105 Lab that is described in the next chapter.

The most effective way to do it, is to do it

Amelia Mary Earhart

4 DEVELOPED TOOLS

In this section we present the B105 Lab tools used in this thesis in order to extract the results of the proposed strategy. We have developed this framework in order to validate the proposed strategies, and this work constitutes also a part of the progress of this thesis as we stated in Section 1.2.

First, we present a review regarding current CWSN tools in order to depict the general state of the field and the necessity for developing our own framework. After, the two main components are described: the simulator and the testbed.

Similarly as the rest of the thesis methodology, the process of the development of this framework has been gradual, from the simplest to the most complex, adding capabilities when needed. Also, the feedback is used in order to enrich and improve the results.

4.1 CURRENT TOOLS

Because of the novel research field there are not a lot of specific frameworks for design over CWSNs. As we note in Section 2.2, most of the works are based on simulators, in particular WSNs simulators. There are several WSNs simulators used by researchers when developing their work. For example, NS2 [97] is one of the most well-known simulators together with OMNETT++ [98]. A large part of the WSNs research society used NS2 simulator for testing their algorithms by 2010 when tools were needed for testing the first stages of this thesis. Nevertheless, the latest release was launched in 2008 and the maintenance and support seemed to be finished. NS-3 was launched as a substitute but at that time it was still in the early stages. Also, a cognitive patch for NS2 exists, Cognitive Radio Cognitive Network (CRCN), but with a high number of limitations. In fact, our first simulations to prove the validity of the simple algorithms presented in Section 2.4.1 have been carried out under CRCN in NS2, but the overall performance was not satisfactory because of the difficulty of using CRCN, coupled with their design for classical CN with PUs and SUs and where localization were one of the most important parameters for dynamic spectrum allocation. Therefore, CWSNs where nodes are mobiles and the power emitted between PUs and SUs is not a important parameter in order to distinguish users, do not fit well with this CRCN patch.

OMNET++ [98] is the other framework very well known among researchers. It proposes a modular library which could be used to develop network simulators. Only by composing different modules, the developer could create its own simulator or scenario. Examples of WSNs simulators developed over OMNET++ are MiXiM [99] and Castalia [100].

Several other simulators have been developed and used for WSNs. TOSSIM [101] based on the TinyOS operative system, COOJA [102], OPNET [103], GloMoSim [104], JSim [105] or NetSIm [106] are other WSN simulators without cognitive features. Authors show in [107] different approaches on CWSN, like architectures or techniques. Inside the techniques section an implementation of cognitive solutions over OPNET simulator is mentioned [9].

In SEnsor Network for Dynamic and cOgnitive Radio Access (SENDORA) FP7 project, a simulator platform has been developed based on the network simulator NS2, enhanced with the Miracle extension [108], which provide the support of multi-layer, multi-stack architecture, and a more realistic propagation model to simulate different network protocols over the same physical channel within the same simulator. Even if the developed extension is named in some works, there are not more details about the simulator.

After studying the available solutions in simulations, we have conclude at the beginning of this PhD Thesis that a lot of work on simulation tools should be done in order to get the next step in the development cycle, the implementation. And after the simulation stage, researchers usually use testbeds before the real networks implementation. There are multiple testbeds for specific developments, but usually they are limited as a WSNs testbeds or a CR testbeds. Sometimes, those described as a CWSNs testbed are common WSNs testbeds with some distributed USRPs for spectrum sensing tasks.

Because of their general propose features and their quality, we want to put the attention into the following: TWIST [109] and VT-CORNET [110].

- **The TKN Wireless Indoor Sensor Network Test-bed (TWIST)** is a multiplatform, hierarchical test-bed architecture developed at the Technische Universität Berlin. The self-configuration capability, the use of hardware with standardized interfaces and open source software makes the TWIST architecture scalable, affordable, and easily replicable. The TWIST instance at the TKN office building is one of the largest remotely accessible test-beds with 204 SUT (System Under Test) sockets, currently populated with 102 eyesIFX [111] and 102 Tmote Sky [112] nodes. The nodes are deployed in a 3D grid spanning 3 floors of an office building at the TUB campus, resulting in more than 1500 m2 of instrumented office space.
- **The Virginia Tech COgnitive Radio NEtwork Testbed (VT-CORNET)** is a collection of Cognitive Radio nodes deployed throughout a building on the Virginia Tech main campus. The test-bed consists of a total of 48 Software-Defined Radio nodes, located in the ceiling throughout a newly built building. There are 12 nodes per floor, each one with a varying distance between the neighboring nodes. In addition to the static 48 nodes deployed in the ceiling,

low-power mobile nodes will also be available in order provide a research environment that accommodates a wide variety of research topics. Testbed is implemented with a combination of a highly flexible RF front end, and an openly available Cognitive Radio Open Source System framework.

Nevertheless, none of them offer the access to different spectrum bands. This feature is very interesting when talking about CWSNs to research and test the utilization of frequency agility.

The lack of tools for CWSNs experimentation and research leads us to get involved in an ambitious project at 2010. The design, develop and implementation of a useful tool composed by a simulator and a testbed which allows us for testing our strategies. Also, when finished, the idea is to release it in order to encourage the research in CWSNs area. This project is a collective group project performed into the B105 Lab which has involved many people along the last five years.

4.2 CWSN FRAMEWORK

As seen in Chapter 1 cognitive characteristics are applicable to efficient energy management. However, despite the potential of CWSNs, due to their early research stage they are not yet deeply explored. Real or simulated scenarios scarcely exist and this contributes to the shortage of results in this area. Thus, providing a CWSN framework to test the new strategies, to assess collaboration schemes and to validate different optimization mechanisms is important.

Our B105 Lab CWSN framework is composed of two fundamental elements: a cognitive network simulator and the implementation of a CWSN testbed composed by a new low-power platform with three wireless interfaces. Both of them implements the CB architecture defined in Section 3.2.

The components that are going to be described in detail in the following sections consist on a set of versatile and modular platforms which provides access to three different RF spectrum bands, and a simulator based in Castalia, modified to allow cognitive capabilities in WSN. The design, implementation and test of the platform are accomplished with promising results as well as the implementation of the main functions in the simulator. The main objective is to deploy a real testbed that allows the test of different strategies, algorithms and configurations in order to advance the state of the art of CWSNs. As in the whole course of this thesis, feedback has been into account in the process of the framework development.

Most common network simulators provide their own energy models, but these are theoretical models covering general cases. Being able to introduce real measured data from a real device into the simulator is very interesting in order to make the simulations more realistic. This concept is applied to sensing time, energy consumption or transmission parameters switching that can be introduced in order to improve in accuracy the simulation results.

Despite of having CWSN devices, deployment of real networks is very difficult and expensive, especially if the network has a large number of devices. This is the great advantage of the introduction of simulators. By adding data taken from functional prototypes to simulators, we have improved the accuracy of the simulations. As said, feedback is a cornerstone in this work.

The simulator allows the extraction of results in large network scenarios when real devices are impossible to deploy. Hardware and software models are developed and combined to create a powerful instrument useful for research in CWSNs. Thus, the combination of both elements results in a complete and useful framework to validate optimization mechanisms for energy consumption.

We present in the subsequent sections a deep description of the two fundamental components that we have developed: the simulator in Section 4.3 and the testbed in Section 4.4.

4.3 CWSN SIMULATOR

Accordingly with Chapter 1, a cognitive network has two main characteristics: to maintain awareness of the environment (including the spectrum) and to optimize its radio parameters according to the requirements. These two main features could be divided in several derived characteristics for which a CWSN simulator should be implemented.

The CWSN simulator implemented in the B105 Lab is based on Castalia simulator. As observed in the previous section, the amount of WSN simulators is very large. That, along with the common features between CWSN and WSN, has led us to create our simulator based on a WSN simulator. The decision about which simulator fits better was made based on these reasons:

- Castalia simulator is focused on WSN. This feature is very important because of the scope of the simulator. Despite CR has multiple applications and scenarios, constraints and features of CWSNs fits better with WSNs.
- Castalia simulator is based on OMNET++, which has a modular and simple implementation. As the intention is to develop a cognitive architecture inside the simulator, new modules and interfaces are easy to include. OMNET++ brings us a lot of facilities to make it possible.
- Castalia and OMNET++ development was very active with releases every year when the decision has taken. The work is based on Castalia and OMNET++ in order to create a usable tool for any cognitive project.
- Castalia physical layer and radio models are one of the most realistic models found in the WSN simulator area. Emphasizing in the physical and radio layer, Castalia offers multiple characteristics as path loss, mobility support in the nodes, simple interferences, multiple modulations and sleep states. The cognitive simulator can use all this features in order to create more realistic scenarios.
- Castalia simulator supports most common modulation and routing protocols and it is also prepared to include new ones.
- Moreover, some typical radio transceivers for WSN are included, such as CC1010 or CC2430.

With the base simulator chosen, next step is to define the requirements that the cognitive simulator needs to achieve and Castalia does not fulfill.

- Spectrum sensing. Cognitive nodes have to be aware about the spectrum context, so they need to extract that information from the spectrum.
- Multiple frequencies, channels and modulations implementations. An essential characteristic is to bring the possibility of changing communication parameters such as frequencies bands, communication channels or modulations.
- Virtual Control Channel (VCC). According to the CB architecture, an implementation of the VCC allows the nodes to share information.
- Interferences are one of the crucial aspects. Noise detected in the spectrum is crucial for the behavior of the network. For that reason, the interference model should be very precise.
- Easy results extraction and data representation. They are essential for the analysis of the results.

Once the requirements have been explained, the CWSN simulator is going to be described in detail. For that purpose, we present the original Castalia implementation first, and after, in Section 4.3.2, our improvements and modifications in order to provide cognitive capabilities to the CWSN simulator.

4.3.1 ORIGINAL CASTALIA IMPLEMENTATION

Once Castalia is decided as a starting point, we are going to present its structure and main characteristics that we have to improve afterward. The original network structure of Castalia is depicted in Figure 4-1.

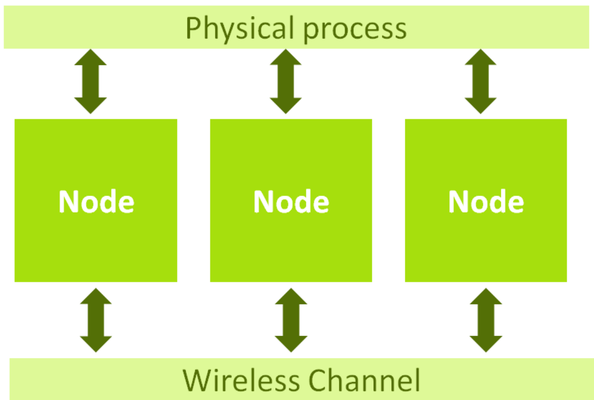


Figure 4-1. Original Castalia network architecture.

According to the OMNET++ philosophy, Castalia uses modules and messages to implement a WSN. Castalia nodes connect to each other through the wireless channel module which is responsible for delivering the messages. Also, the wireless module models the path losses. In addition, a physical process module implements the physical events which provide the simulator the ability of modeling environmental sensor acquisition data.

Each node in the network is built as a composite module with its inner structure is represented in Figure 4-2.

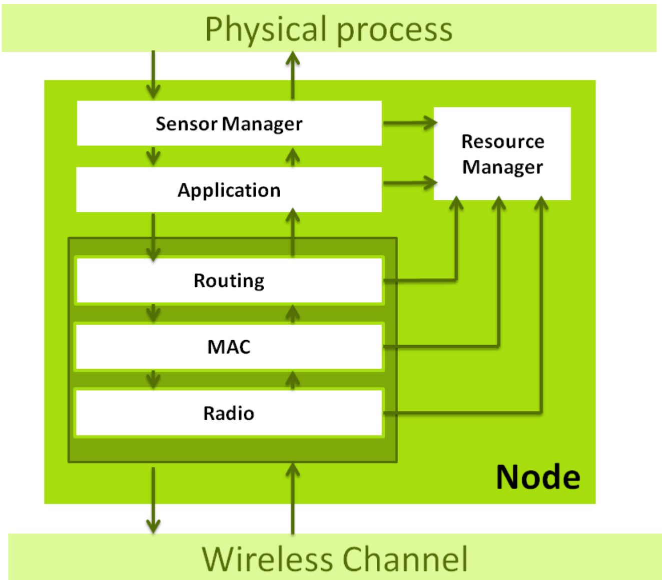


Figure 4-2. Interior structure of the original Castalia nodes.

Every node contains one communication module composed of radio, MAC and routing layers. The communication module connects directly with the wireless module. This structure limits the architecture to support only one radio interface per node, which is one of the most important limitations of Castalia for our scenario.

Radio module processes the incoming messages from the wireless channel and detects interferences among them. Also, this module manages radio parameters such as carrier frequency, bandwidth, bit rate or modulation. However, although it can control the carrier frequency, the original Castalia implementation does not provide a real support for channels and interferences between adjacent frequencies.

MAC, routing and application modules are implemented as general masks without any functionality. They are prepared to accept any MAC, routing or application implemented by researchers in order to validate their specific implementations. Nevertheless, Castalia includes some implementations of typical MAC, routing and application layers in order to been used if needed.

The resource manager module gathers information about the memory, energy and CPU consumption from every module in the node.

4.3.2 COGNITIVE RADIO EXTENSION FOR CASTALIA

In order to provide cognitive capabilities to Castalia, we have modified its internal structure. Figure 4-3 and Figure 4-4 show the new simulator structure. The original code has been modified as slightly as possible in order to introduce the minimum changes to third-party applications and module implementations.

Cognitive networks can be distinguished from others due to the adaptation of their parameters according to information gathered about the environment. Although Castalia simulator bring the opportunity of a limited spectrum sensing it is not enough for a cognitive network. Multiple changes has been necessary to be performed in Castalia, starting for a complete spectrum sensing module, following with the storage of this information and concluding with the spread of the information which is an important feature of cognitive networks. A Virtual Control Channel is needed for that purpose. Also, some changes in resource manager have performed in order to add several parameters interesting to monitor.

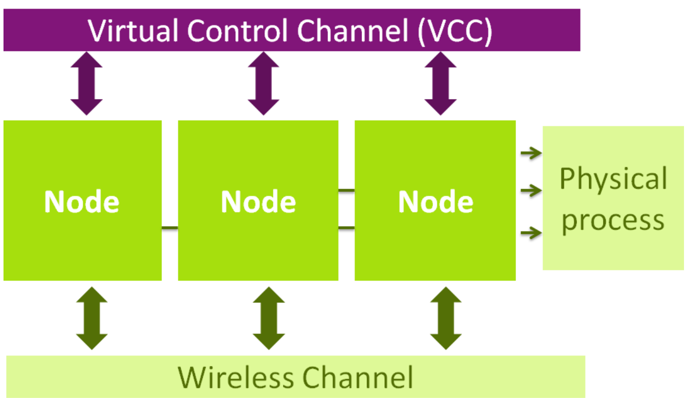


Figure 4-3. Castalia network architecture adapted to Cognitive Radio.

In the new model, the nodes have multiple communication modules which can be configured with different parameters. That allows simulating multiple interfaces in a wireless node. Every interface is connected with the application module and also with the wireless channel. This model coincides with our test platform implementation as we are going to see in Section 4.4. The new simulator structure provides functions for changing the default interface with a complete backwards compatibility so previous non-cognitive samples and modules are not needed to be modified.

A node with multiple interfaces brings flexibility to the network while provides the opportunity of compare technologies performance, or using cognitive strategies that implies two or more radios and freedom in order to change the parameters of each interface independently.

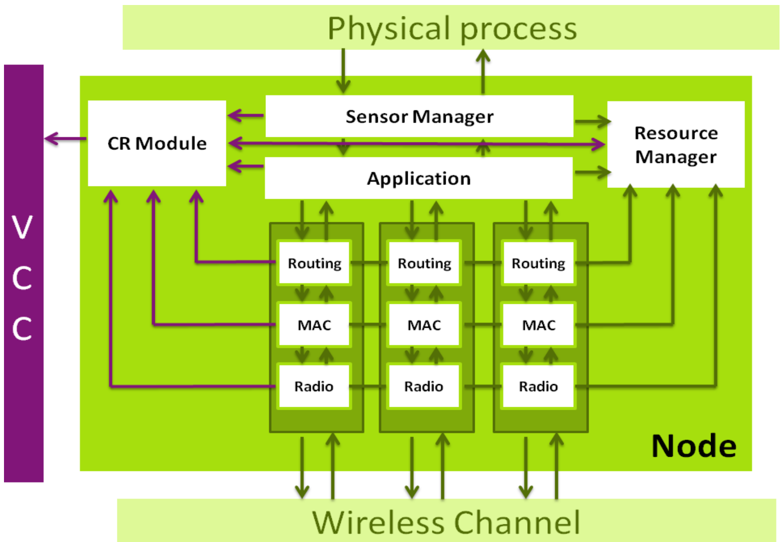


Figure 4-4. Castalia node internals adapted to Cognitive Radio.

We provided also new API methods for changing the active channel in the radio module of each communication module. This change allows performing spectrum scans and hops among channels easily. This added possibility of channel changing increases the flexibility of the network but also completes the wireless protocols such as Wi-Fi or ZigBee™, where nodes utilize multiple channels.

Also, even if nodes could use some of the different MAC layers that Castalia includes none of these MACs implement different channels. Depending on the interface, it would have a different channel bandwidth, first and last frequencies available and a different number of available channels. By combining multiple channels and multiple interfaces, scenarios are very realistic.

Spectrum sensing is a key factor in cognitive radio. Nodes should analyze the spectrum to detect the presence of users or interferences. The decision about which channel or interface are the best each time should be based on realistic and plentiful data. For that reason we have also improved the interference model on Castalia simulator. Before the changes, if the frequencies of transmitter and receiver were different, the packet was dropped and it did not create any interference. Now, the model is more realistic and the packets create interferences if they are within the signal bandwidth. This interference is proportional to the distance between carriers and is related to the modulation.

We have also performed some changes to the resource manager block in order to add the possibility to control the energy consumption of the added modules (several radio interfaces or new modules).

These changes transform Castalia into a simulator capable of running CWSN experiments, although it still lacks any cognitive capabilities. In order to turn Castalia into a real cognitive simulator it has been equipped with a new module that includes all the cognitive features of the nodes.

The key part aside from the inclusion of multiple radio interfaces is the implementation of a CRModule structure according to the CB architecture presented in Section 3.2. Most of the work is focused on developing the cognitive radio module that adds cognitive behaviors into the simulator.

The structure of the implemented CRModule is shown in Figure 4-5. It is composed of six elements, as the CB architecture, adapted to the existing Castalia structure and allowing us to simulate different scenarios. Therefore, multiple interactions between these modules are created.

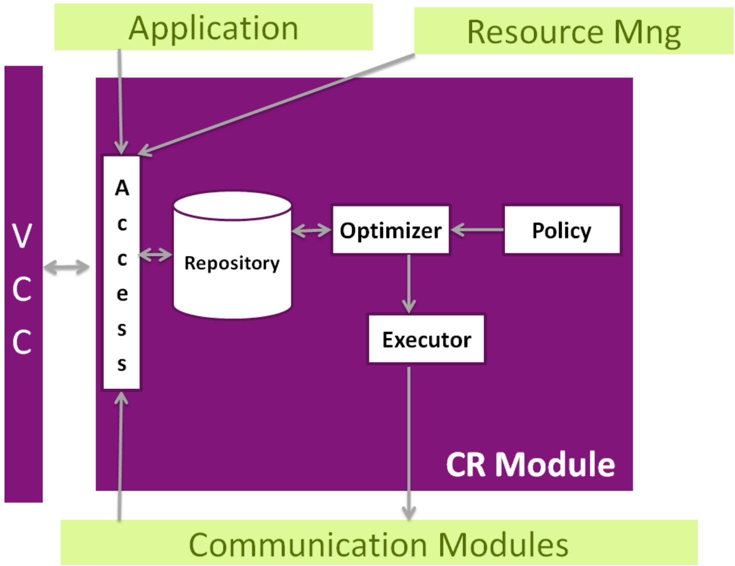


Figure 4-5. Cognitive Radio Module structure.

The Repository stores the information captured by the nodes about the local and/or remote nodes: information learned, decisions made or current state. The kind of information stored depends on the context, the optimiztion and the requirements of the system. Each node publishes a part of its own repository to the network, making it public through the VCC. The Access submodule controls which part of the repository is public and which nodes are allowed to access it. The Policy submodule is a set of weighting parameters that control the priority of the different network goals. The Optimizer is the submodule which implements the optimizations to test. It processes the Repository information bearing in mind the requirements imposed by the Policy submodule. The Executor carries out the actions derived from the Optimizer decisions.

Finally, the VCC is a new “channel” for sharing cognitive information among the CR modules. It allows CR modules to be aware of their surroundings and even of the whole network. The VCC gives the nodes a common interface to communicate among each other, ignoring the details of how the information is delivered and the precise nature and location of the communication partners.

Since all the elements are developed as Castalia modules, they communicate and access each other via the OMNET++ message system.

Energy model can be fed from real device measures. This framework uses the real cNGD devices implementations exposed in the next section to measure different energy characteristics that are included into the energy model.

For facilitating us the simulation process and in order to extend the use of this cognitive simulator, we have developed also a Graphical User Interface (GUI) for it. The original Castalia launches the simulation defined by the "*omnetpp.ini*" through command line. The file *omnetpp* serves as a scenario definition where every parameter in the simulation has to be initialized. Typical parameters are the number of nodes, the simulation time, the initial energy, the number of interfaces, which MAC or Routing layer implements each node and the communication parameters. Even more, when designing a simulation to validate a strategy, several configurations have to be simulated in order to compare the behavior under different situations. The definition of a scenario is very time-consuming, and when the strategy demands for multiple configurations, this task consumes too much time.

For that reason we have developed a GUI in GTK+ [113], a well known toolkit for creating GUIs. The GUI implementation helps the researcher to create the configurations needed and define the different scenarios through an easy to use interface. One of the most important contributions is the pre-filled *omnetpp* file which helps to not forget any parameter. Also, the GUI allows not only creating news files, but also to read previous *omnetpp* files and import the parameters and values defined. A screenshot of the GUI could be seen in Figure 4-6.

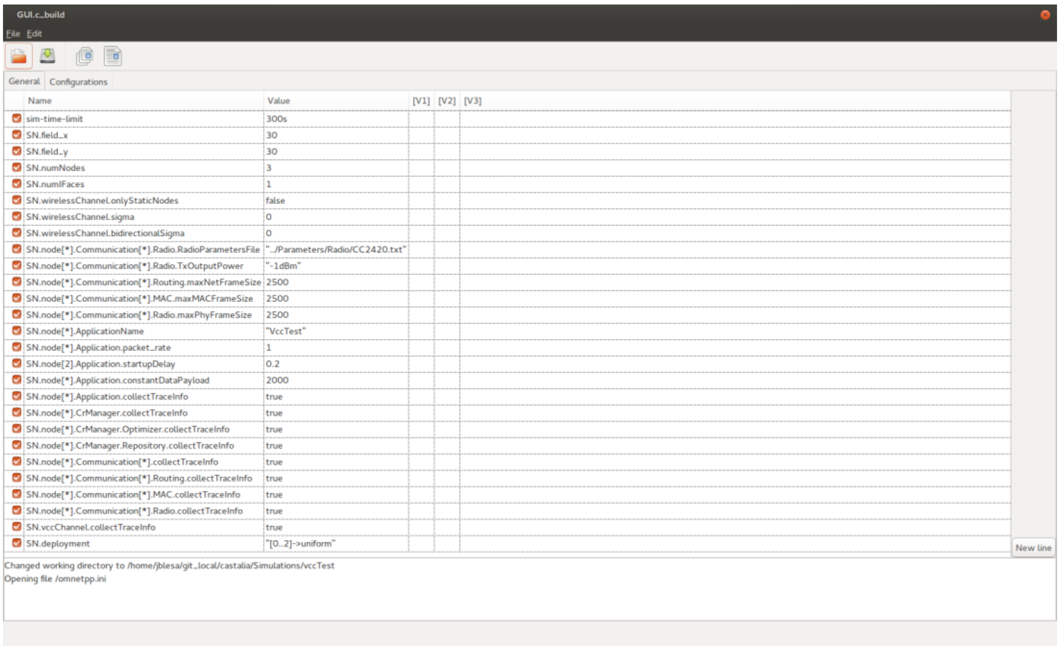


Figure 4-6. GUI developed for the cognitive Castalia simulator.

After the scenario definition, the GUI allows the simulation launching. Next planned step includes a more advance graphical tool which allows placing the nodes in a map and configuring each one by clicking on it. Also, the representation of the simulation results is going to be added.

4.4 CNGD TESTBED

As said in Section 4.2 the developed framework consists of two elements. After the simulator, we present the B105 Lab Testbed based on a platform also designed and implemented in the B105 Lab, the cognitive New Generation Device (cNGD). The cNGD is a new platform that responds to WSN criteria introducing cognitive capabilities. It has access to three different ISM unlicensed spectrum bands, thus making it a very powerful tool for CWSN research and development.

As the simulator and according to the followed methodology, the process of the testbed implementation has been gradual, from the basic to the most complex, adding capabilities when needed.

The first CWSN platform built in the B105 Lab [114] contains a microcontroller and three different radio interfaces (IEEE 802.11, IEEE 802.15.4 at 2.4 GHz, and a CC1010-

based at 868 MHz) in order to provide flexibility. The first version platform developed is shown in Figure 4-7.

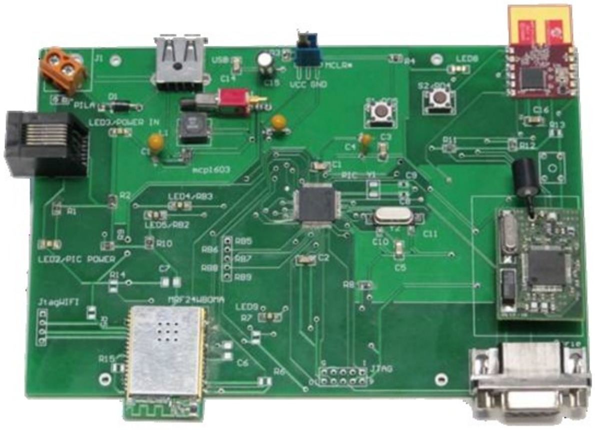


Figure 4-7. First CWSN B105 platform.

This first approach is designed in a generic way and able to connect to different standards or commercial devices.

The core of the platform is a Microchip PIC32MX795F512H [115], which is a 32-bit flash microcontroller. This is a high performance processor with low consumption and low cost. Even if the processor is more powerful than the usual WSNs microcontroller, we are trying to develop a versatile test platform and that is the reason for choosing a bigger core.

As said, the first CWSN platform has three radio interfaces:

- A Wi-Fi Microchip device which can handle data rates of 2 Mbps and uses a band operation between 2.412 GHz - 2.484 GHz. Wi-Fi is based on the IEEE 802.11 standards.
- A MiWi interface, a Microchip protocol which can handle data rates about 250 kbps and uses a band operation between 2.405 GHz - 2.48 GHz. This is a proprietary wireless protocol designed by Microchip Technology that uses small, low-power digital radios based on the IEEE 802.15.4 standard for WPAN.
- Last interface is based on the Texas Instruments CC1010 [116]. It can handle data rate of 76.8 kbps and uses a band operation around 868 Mhz.

This interface provides a new communications band also in an ISM frequency.

Even though this platform is a good starting point, does not satisfy some of the requirements in terms of low power consumption, cost, size, and communication capabilities. Therefore, we have implemented a new platform. The aim is a flexible scheme based on three different RF bands. As a CWSN platform, it must have a downward trend regarding power consumption, cost, size and resources. The desired device must be modular and feature-expandable, scalable and fully configurable.

4.4.1 HARDWARE

This new platform designed also in the B105 Lab, named Cognitive Next Generation Device (cNGD) [117] is shown at Figure 4-8.

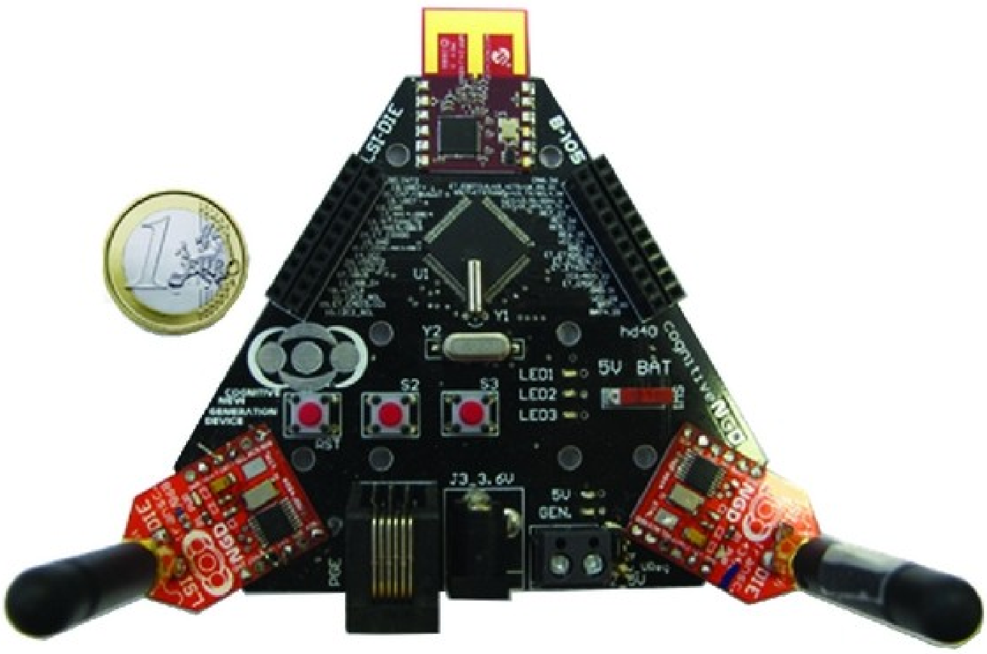


Figure 4-8. Picture of the B105 Lab cNGD.

Together with the design of the node itself, we have developed too some other ad-hoc devices such as proper size transceivers and expansion pluggable boards. These boards, called shields, aim to expand the possibilities of the main device through its generic and modular nature while meeting, at the same time, the low cost and size constraints.

The cNGD is based on a single core unit. The control core is a PIC32MX675F256L [118], and is replaceable by its larger flash memory version if needed. This is a low power and low cost RTCC-including 32-bit microcontroller able to perform a throughput high enough for test-benching purposes.

cNGD executes its RF communications over MiWi™ protocol, an IEEE 802.15.4 proprietary standard for WPAN. It presents great advantages for low transmission rates, short distances and cost constrained networks. The physical layer of this communication stack can operate over three different ISM bands: 434 MHz, 868 MHz and 2.4 GHz. This is one of the most important features of the device and makes it the only CWSN node with these features.

In order to transmit in 434 MHz and 868 MHz bands, we have included two transceivers based on the MRF49XA [119] chip and implemented following the design guidelines provided by Microchip. We have designed the transceiver modules used for the 433 MHz and 868 MHz bands as ad-hoc developments based on the MRF49XA Microchip device. They had to be developed from scratch because of the non-existence of modules operating in these bands that fit the size requirements for our platform.

On the other hand, an MRF24J40MA RF module [120] is responsible for the 2.4 GHz band. All of the embedded interfaces allow enabling sleep modes and they offer quite low power consumption at transmission. Additionally, they let the applications carry out spectrum sensing through energy detection.

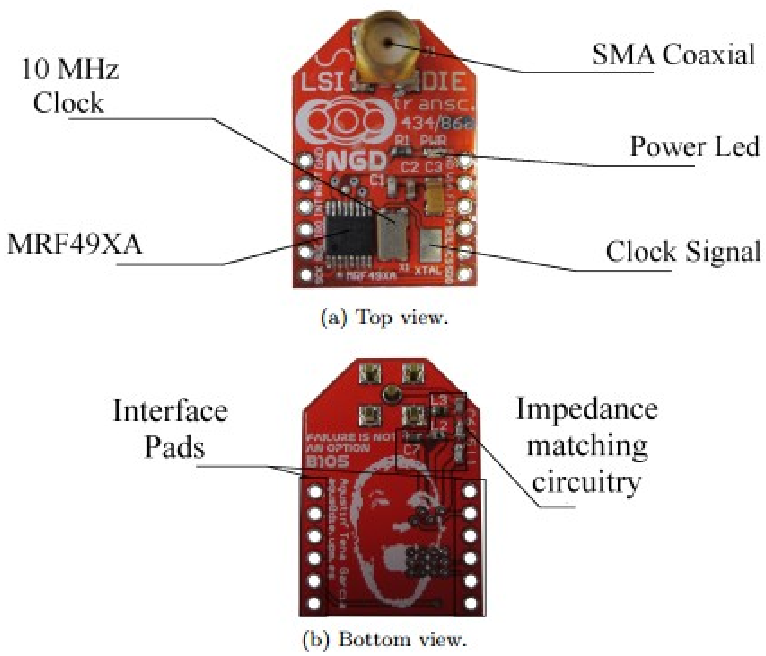
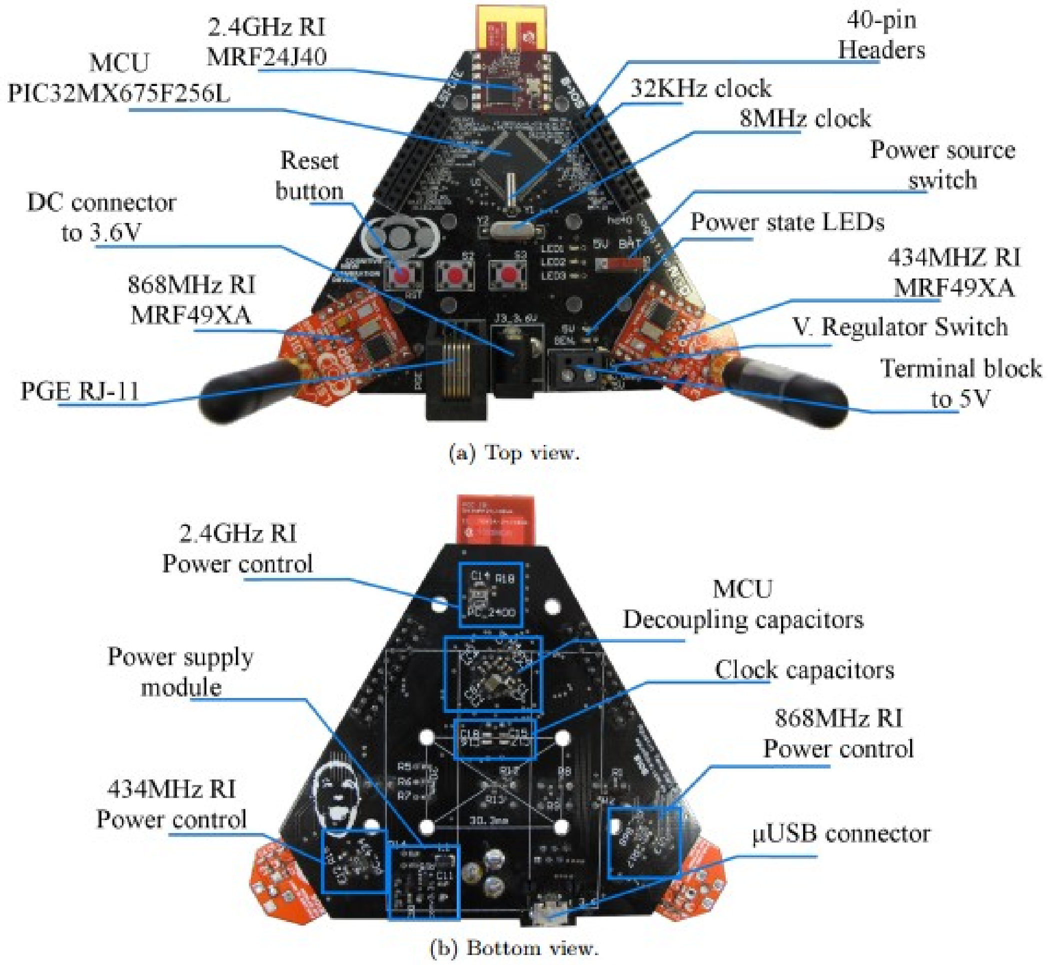


Figure 4-9. Detailed view of the implemented MRF49xA RF module.

The hardware includes access to different peripherals since it is not designed for a specific kind of application and must be useful as a development platform, providing the researcher with some extra functionalities if necessity. To accomplish this requirement, a set of headers are accessible through a pair of 20-pin connectors. These headers make the cNGD suitable for expansion with pluggable and stackable shields or even with other entire nodes. This option supposes a highly valuable feature of the device, reducing its cost but expanding its possibilities through modularity. The accessible peripherals include battery connection (for charging purposes), General-purpose input/output (GPIOs), external interruptions, analogue inputs, Universal Serial Bus (USB), Ethernet module, Inter-Integrated Circuit (I2C) bus, Universal Asynchronous Receiver/Transmitter (UARTs) and Serial Peripheral Interface (SPIs).

The main parts of the cNGD are depicted in the Figure 4-10:



(a) Top view.

(b) Bottom view.

Figure 4-10. Detailed view of the cNGD implementation.

As said before, we have also implemented several expansion shields for the cNGD. A RS-232 shield for debugging purposes and a battery charger shield could be seen in the Figure 4-11 and Figure 4-12 respectively.

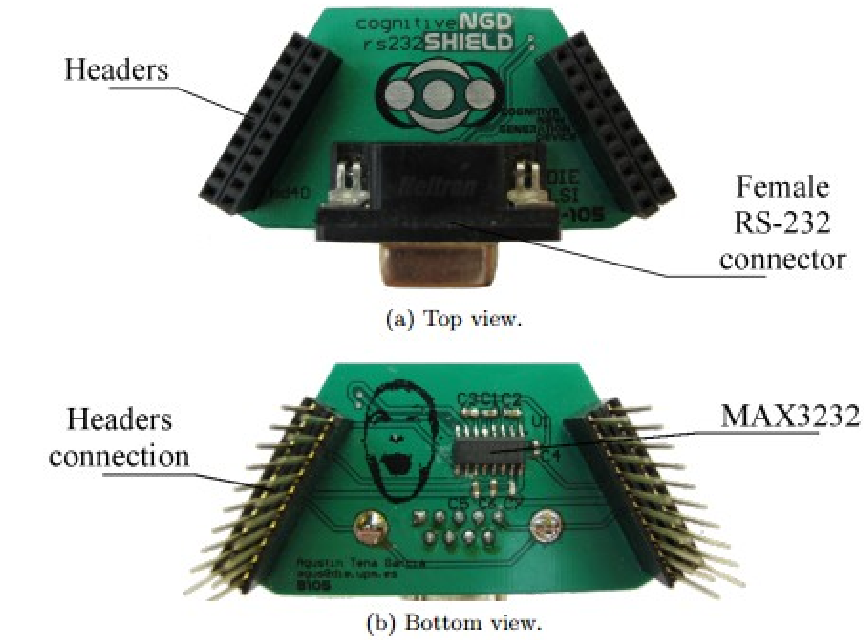


Figure 4-11. Detailed view of the RS232 shield.

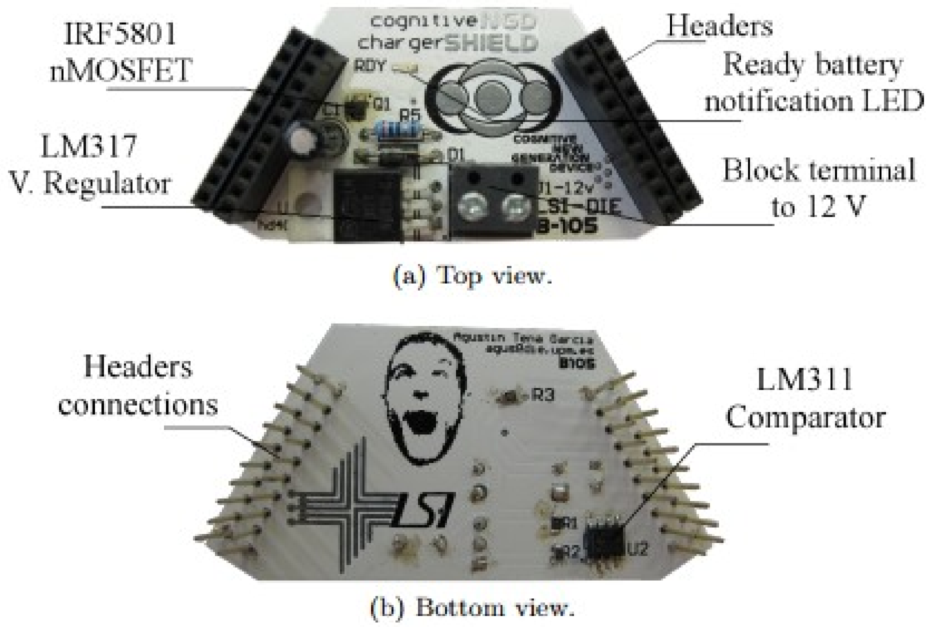


Figure 4-12. Detailed view of the charger shield module.

As CWSNs we have implemented a sensor shield which serves to provide their application functionality. For testing purpose, serves as a real hardware consuming hardware resources and helps the implementation of real applications in the testbed. This sensor shield has the typical environmental monitoring sensors: temperature, humidity, light and presence. As actuators, some LEDs, a buzzer and a InfraRed (IR) header are added. A picture of this shield is shown in Figure 4-13.

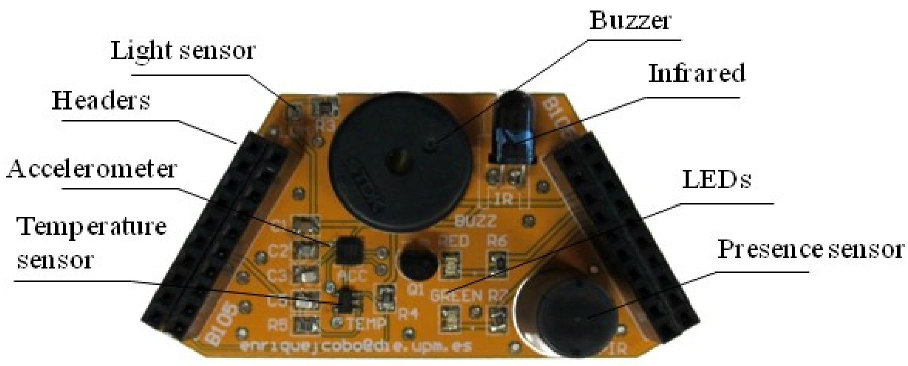


Figure 4-13. Detailed view of the sensor shield for the cNGD.

One of the most interesting features implemented in the testbed is the ability to program and collect results remotely. Considering that the nodes are wireless such action should be Over The Air (OTA) programming.

The Wi-Fi shield allows any node having Wi-Fi connectivity. While this communication interface has a high consumption for our scenario requirements, it not has to be used by every node. We send the new code to be implemented in the testbed to a coordinator node by this Wi-Fi shield. Likewise this shield serves to send back the traces generated in the experimentation after being collected by the coordinator to any computer for further processing. A picture of this shield based on the MRF24WB0MA [121] device is shown in Figure 4-14.

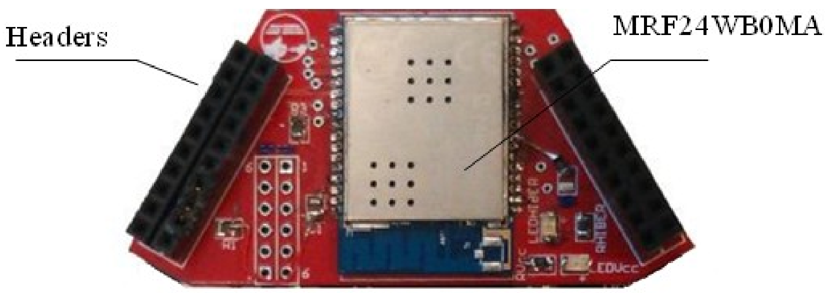


Figure 4-14- Detailed view of the Wi-Fi shield for the cNGD.

An additional difficulty resides in the fact that the nodes are battery-powered and therefore most of the time these nodes are working in a sleep-mode to save energy. To address this challenge, we have designed and implemented another expansion shields and the associated software: the Wake on Radio (WoR)-shield.

Once communication with the computer is resolved, we have the problem of waking the network nodes to send the new program to load. For performing this task we need a bootloader and a way to awake the nodes when they are in the lowest energy consumption mode. We have implemented a Wake on Radio (WoR) shield that keeps the nodes listening for a radio signal with a very low consumption. This WoR shield is presented in Figure 4-15:

Figure 4-15. WoR shield developed for the cNGD.

The received signal is demodulated through an envelope detector, and after verification that the order of awakening is for that node by its address, the shield sends a pulse interrupt to the cNGD, also entering into the programming mode. Once the CWSNs' nodes are listening for a new code program, the coordinator node sends the new code by either three interfaces.

The cNGD can work using either an external 5 V power supply, as a USB standard, or a 3.3 V battery. The hardware also provides wired serial communication using USB 2.0, which provides interoperability and facilitates data transfer from the running application to any device, normally a computer. An RJ-11 connector embedded in the main board is used to the program the controller, by taking advantage of the development framework provided by Microchip.

Now, after the hardware description of the cNGD, we are going to describe the software implementation.

4.4.2 FIRMWARE

Regarding software, as a development platform, the software architecture must provide advantages when implementing cognitive strategies in order to be a valuable tool. Due to the fact that the microcontroller and the RF transceivers belong to the same manufacturer, their integration has been manageable. Unfortunately, nowadays there is no protocol stack developed for managing several radio interfaces simultaneously.

Thus, our objective has been to design and adapt the node's firmware able to manage up to three radio interfaces in different frequency bands with the same protocol stack. In order to deal with its inherent complexity, it is interesting to design a Hardware Abstraction Layer (HAL) to be used by future developers as an Application Programming Interface (API). Figure 4-16 shows a scheme of system's architecture. We can see that the proposed architecture is similar to the CB architecture with separate planes for CR management and application.

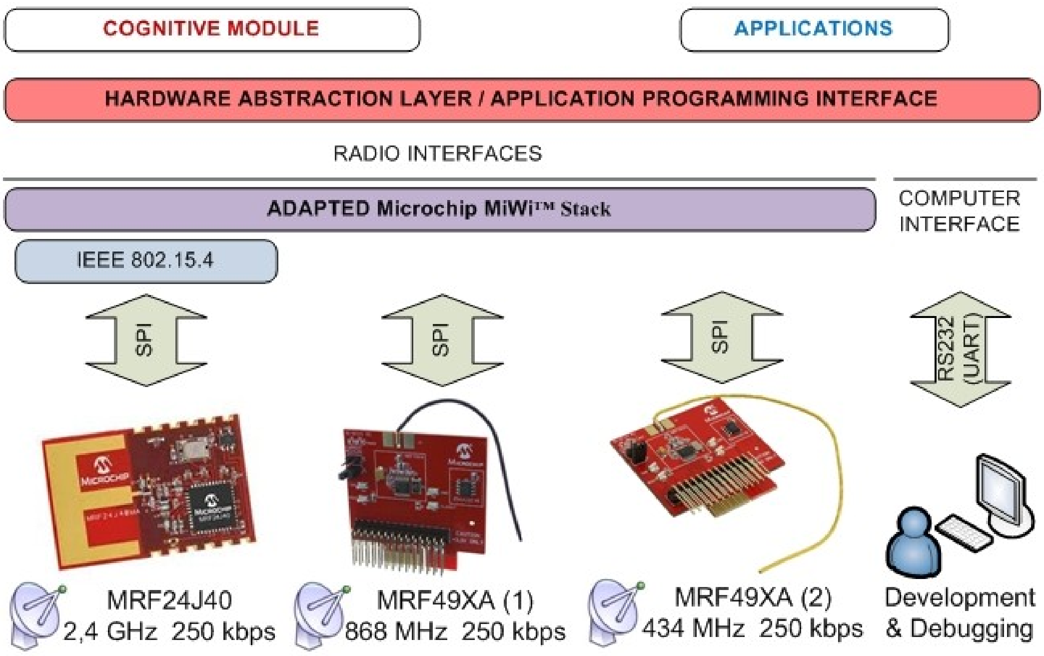


Figure 4-16. Proposed CWSN node architecture scheme.

The chosen transceivers can work as in either with Microchip's proprietary MiWi^{TM} protocol stack (free of charge) or with ZigBee^{TM} stack (under license). It was decided to use MiWi^{TM} since this one supposes and easier and lighter solution. Its features cover CWSN requirements such as reconfiguration of radio parameters, spectrum sensing capabilities and enough data rate for potential applications.

The MiWi^{TM} protocol stack is structured in layers according to the OSI model and the IEEE 802.15.4 standard. Its implementation covers the physical layer for several radio transceivers and a Microchip's MAC interface (MiMAC) for transceiver control. It also gives us the possibility of using different protocols at the network layer, depending on network's topology and requirements. Finally, Microchip's top layer interface (MiApp) offers an API for developing user applications. Figure 4-17 shows the basic Microchip architecture with the MiWi^{TM} protocol stack.

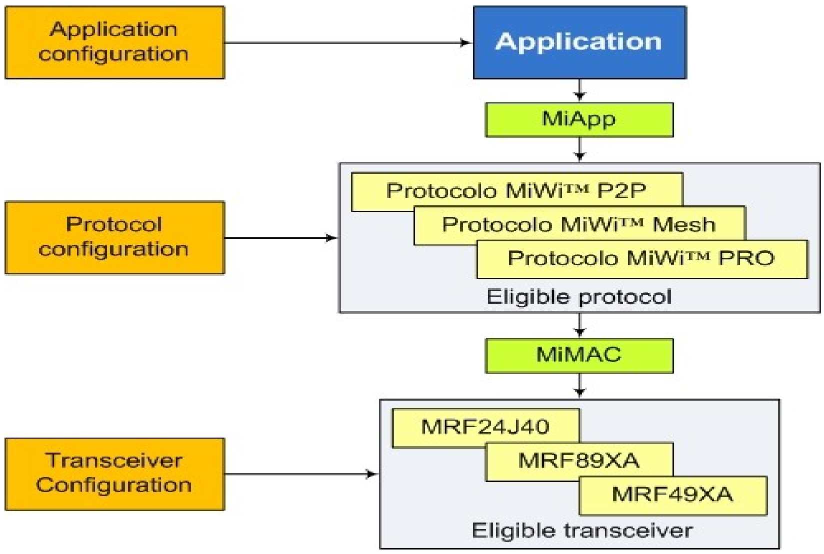


Figure 4-17. Microchip protocol stack. Microchip documentation.

As was the case of the transceivers in the physical layer, the network layer offers some versatility. Three network protocols in the MiWi™ stack are given: MiWi™ P2P, MiWi™ Mesh and MiWi™ PRO.

The first one is used for small or basic networks with star or peer-to-peer topology. No routing capabilities are present. Thus, communication is restricted to any in-range device. MiWi™ Mesh is a more complex protocol, enabling some routing features and larger networks. Finally, MiWi™ PRO is addressed to those networks that overpass 1024 nodes and require more routing nodes and capabilities. As our network is intended to serve as a test-bed platform for research and development with not so many nodes, we have not adapted the last protocol. Figure 4-18 shows the adapted topologies.

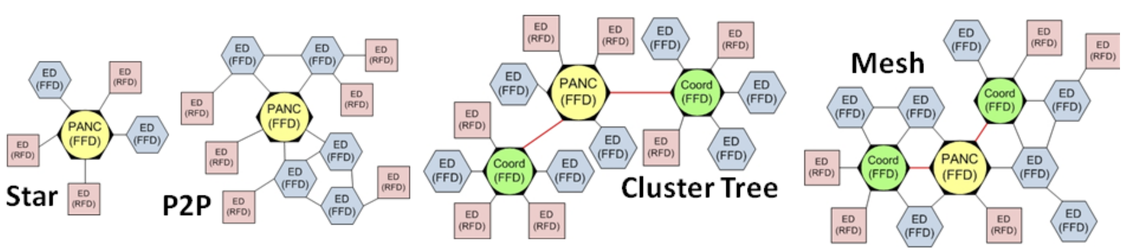


Figure 4-18. Topologies adapted in the cNGD firmware implementation.

Originally, MiWi™ stack was designed to work only with one of its compatible transceivers at a time. In order to admit the three desired devices, an exhaustive

MiWi™ protocol stack adaptation is carried out. Thanks to the adaptation, the node firmware can handle and manage all the transceivers' routines and protocols' tasks together as a whole. Otherwise, the replication of the stack threefold would have been very inefficient in terms of processing capacity and memory usage.

In order to avoid redundancies and to make the protocol stack be flexible and reconfigurable we try to share with all transceivers as much stack items as possible. In cases when modules or functionalities cannot be shared, we try to adapt them. Replication has been limited to those cases where it was unavoidable, i.e., for items attached to a single radio interface. The firmware adaptation is presented in Figure 4-19.

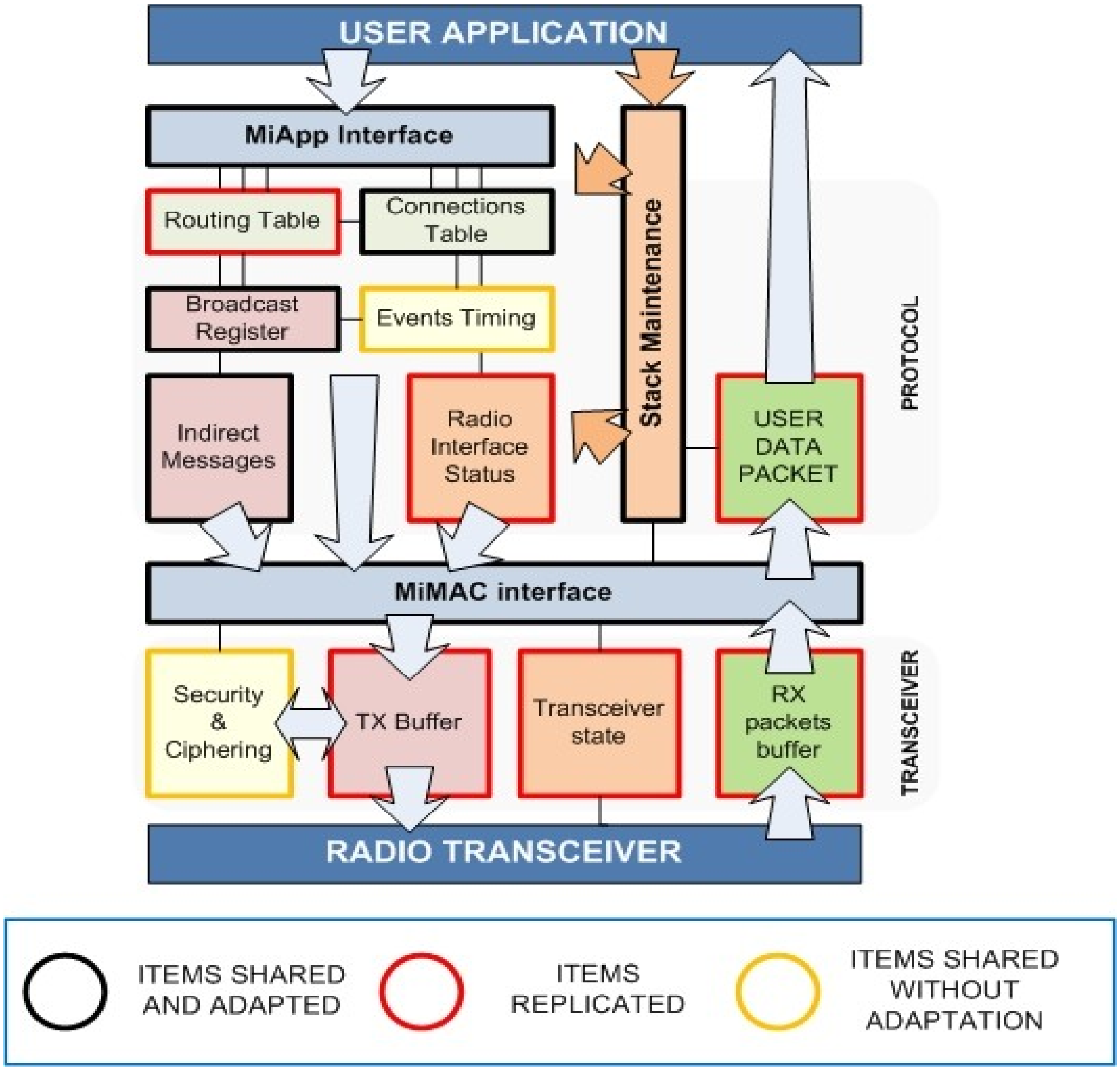


Figure 4-19. Adaptation of the items forming the MiWi™ stack.

The integrated firmware should be a modular and flexible design. The firmware must be coherent with the hardware design, but also must be highly reconfigurable and admit upgrades. The design decisions pursue optimal resource utilization and independence from the hardware design. For instance, if a simplified node implementation with just two RF modules were desired, the firmware will still work after minimal configuration changes.

In order to isolate the developer from the complexity of the adapted protocol stack, we have implemented a HAL. It offers to the upper layers a set of functions as an API, enabling the development of application or modules without the need of understanding lots of the stack details.

The HAL deals with network initialization and maintenance, power management and debugging, among others. However, as the design is intended to be a node for CWSN, the emphasis was placed on radio communication and reconfiguration.

HAL functions are designed for returning an error code in case of the requested action has not been properly finished. Thus, the application layer or the cognitive module becomes aware of it and can undertake countermeasures once identified the error cause. This constitutes another way of reducing development time making the debugging process easier.

Despite the fact that HAL implementation implies more Random Access Memory (RAM) and flash memory usage, the obtained advantages make up for this drawback.

4.4.3 CB ARCHITECTURE

As previously exposed the cNGD is based on the CB architecture scheme. Besides the separation between the application layer and the cognitive module which can be seen in Figure 4-16 corresponding to the CB design, the other key issue is the implementation of the CAgent. As said in Section 3.2 the CAgent is composed by six different modules and the VCC in the implemented CB architecture for the cNGD.

- Repository stores information regarding the node, the network and the environment.

- Discovery module collects information considered interesting such as Received Signal Strength Indicator (RSSI), Link Quality Indicator (LQI), and different information regarding the discovered nodes.
- Optimization module executes the desired cognitive strategy.
- Execution module takes actions to perform communication changes.
- Access Control module is the responsible to permit the access to modules or node information.
- Policy module keeps some variables representing different policies such as energy consumption, security and others. Different weights of these variables will force Optimization module to take different actions.
- VCC implements a channel to communicate control messages required to perform the cognitive strategy.

Apart from these modules, one more is added to the structure, Messenger. This module serves as a communication tool to exchange messages between modules. Regarding the implementation of the messenger, there are basically two types of messages depending on whether their destination and source modules belong to the same node or not.

When the messages are intra-node the Messenger module acts as a bridge providing communication through the rest of the modules. When implementing cognitive strategies in a node, one of the problems to be faced is the flow of a relatively high amount of messages between modules. A Messenger module is helpful since it relieves and makes easier the communication tasks.

On the other hand, we have the control message. These messages are sent when a module from one node sends a message to a module in a different node. A simple VCC module has been included in the CRModule due to the need of sending messages among modules in different nodes. Once at the destination node, the VCC module requests will arrive to the destination module through Messenger and also upon Access Control approval. When Messenger is prompted to process a message that comes from the VCC module, it automatically knows that it is a control message coming from a different node. Therefore, prior to sending the request to the destination module, it will check the permissions for the origin node, destination module and specific function that are requested in the Access Control module. Figure 4-20 illustrates this sequence.

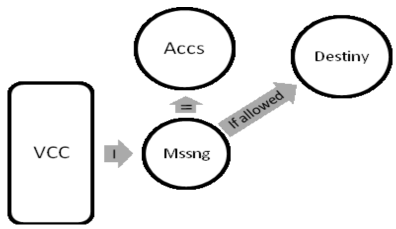


Figure 4-20. Protocol launched when receiving a control message.

The CRModule provides a platform for carrying out cognitive and cooperative strategies not only in one node but in a network, and makes their implementation less complex and more efficient in terms of memory.

4.4.4 TESTS AND RESULTS

The cNGD has been tested in order to prove and characterize valuable features such as radio interface agility, energy consumption and data rate achieved. Results are shown throughout this section.

In Table 4-1, information about the energy consumption of the platform is shown.

Design element and operation modes	Supply current
434/868 MHz Radio Interfaz (RI) (RX mode)	11.8 mA
2.4 GHz RI (RX mode)	16.5 mA
Trasnsceivers 434/868 MHz (sleep mode)	2.2 mA
Trasnsceivers 2.4 GHz (sleep mode)	1.1 mA
MCU (run mode at 80 MHz)	50.9 mA
MCU (sleep mode)	0.83 mA

Table 4-1. Information about cNGD current consumption.

Flash memory needed by the firmware is 88.2 KBytes, whereas required RAM memory is 2.1 KBytes at its widest configuration. On the other hand, Flash memory required by the cognitive architecture is 32.6 KBytes.

Table 4-2 shows the time costs of the communication protocol stack management. The results gather separately the measured times for different radio interfaces and protocol versions.

Management part	P2P (µs)	Mesh (µs)
Common management	134.1	150.6
434 MHz RI	1.3	1.3
868 MHz RI	1.2	1.2
2.4 GHz RI	1.2	1.2
Total	137.8	154.3

Table 4-2. Time costs on the communication protocol management tasks.

Results presented in Table 4-3 provide the time cost for different operations at the three RIs. Results are similar for 434 MHz and 868 MHz RIs since they both use the same transceiver model. Spectrum scan stage takes longer than others due to the introduction of software delays needed at the respective MiWi™ routines.

Operation	434 MHz RI	868 MHz RI	2.4 GHz RI
Transmission channel switch	30.45 ms	30.4 ms	0.151 ms
Transmission power change	55.8 µs	55.8 µs	70.1 µs
Sleep and wake up	15.4 ms	15.4 ms	0.364 ms
Spectrum energy scan	194.48 ms	908 ms	410.13 ms

Table 4-3. Time costs on the radio interfaces control tasks.

Finally, the effective rate provided at the application level was measured for broadcast and unicast TX modes. 434 and 868 MHz RIs have been tested for two different bit-rate configurations. P2P protocol is employed with a 90-byte packet payload size. Table 4-4 gives the results. It can be observed how the theoretical RI maximum bit-rates shrink at the application level to around 30 Kbps. This is due to protocol overheads and data encryption, but also because of a data processing bottleneck located at the reception.

TX mode	434/868 MHz RI (38.4 kbps)	434/868 MHz RI (115.2 kbps)	2.4 GHz RI (250 kbps)
Broadcast	28.94 kbps	31.25 kbps	28.8 kbps
Unicast	20.67 kbps	24.51 kbps	28.47 kbps

Table 4-4. Effective rate at the application level for different tx modes.

This testbed supposes a versatile platform to work over CWSNs development and deployment. Combining hardware and software modules, it offers a flexible modular design widely adaptable over the range of CWSNs applications.

The hardware fits the conditions and requirements to be a CWSNs platform for testing. Low power consumption, size and cost limitations are taken into account in order to achieve real test-benching purposes. To keep the downtrend on complexity, consumption, size and cost, an expansion system for the platform is implemented, allowing developers to create ad-hoc attachable functionalities or improvements for the nodes.

The cNGD's firmware is developed with a focus on abstracting researchers from the direct hardware management. Furthermore, a single MiWi™ stack was adapted to deal with the three RF transceivers instead of using three different stacks. The average program memory saved with this firmware is of 31%. The firmware also exhibits scalability and modularity, being adjustable to diverse applications. To carry out the cognitive algorithms, the software architecture implements the CB scheme, including some extra modules to achieve a greater flexibility and reduce complexity of the cognitive model structure.

The advantages of this solution over previous test-beds are the possibility to have three different interfaces in three different ISM bands, optimized and integrated software that abstracts the developers from the hardware and a wireless programming system. It allows the test-bed to be completely wireless system and not interfered by physical wires.

The work in progress includes the planning for the physical deployment of the nodes at the university building. The deployment has to take into account the nodes' range and the power sources. The platform is autonomous in terms of battery, but some nodes will be powered from USB or the electrical grid depending on their roles.

First works related to the fabrication and testing of the cNGDs nodes have begin and the proposal of the first deployment is done. As a sample, the B105 Lab distribution of nodes is shown in Figure 4-21.

Figure 4-21. Planned deployment of the B105 Lab Testbed.

This is only one of the five rooms where the deployment is previewed to be deployed. The first deployment comprises the installation of 50 cNGDs.

Hope & curiosity about the future seemed better than guarantees.

The unknown was always so attractive to me...and still is

Hedy Lamarr

5 RESULTS AND DISCUSSION

In this section we present and discuss the results derived by the energy optimization strategies designed. For this purpose, the tools developed described in the previous chapter are used. For each designed strategy, we present the baseline scenario and the different scenario configurations used in the simulations. Finally, the extracted results are presented and discussed.

5.1 NON-COOPERATIVE P2P STRATEGY

In this section, we are going to present and discuss the results related to the first proposed strategy based on game theory for reducing energy consumption in CWSNs. This is a light optimization strategy that enables its implementation in CWSNs even though the nodes computing resources are very limited. This strategy is based in a non-cooperative game where nodes play the game in pairs and the decision in taken in a selfish way.

5.1.1 SCENARIO DESCRIPTION

As CWSNs are based in typical WSNs, common CWSN are similar in components, distribution and behavior as WSNs.

The baseline scenario where carried out the simulation tests is deployed in a 100 m x 10 m area, such as an example of a WSNs scenario. Specifically this scenario simulates the university corridor where the B105 Lab is placed in order to test in real devices and compare with the simulation results when the testbed is installed. It contains two coexisting networks, a CWSNs and a Wi-Fi network as a typical situation where WPANs and WLANs coexist.

The CWSN network is set up with 10 nodes, to verify the behavior of a CWSN without overload the simulator. In the baseline scenario, 100 Wi-Fi nodes randomly distributed are assumed, and even it could seem a high number, data extracted from [94] support this choice. Nowadays the number of smart phones and laptops with Wi-Fi connectivity doubles the population number. If we imagine the area selected as an apartment building or a company building it would not be difficult to find this number of Wi-Fi devices without counting on any extra devices. Nevertheless, simulation varying number of Wi-Fi nodes are performed (from 50 to 200 devices) in order to assure the validity of the strategy under different context situations. This Wi-Fi network is taken into account as a noise for our purpose. Wi-Fi network does not implement any optimization strategy.

A representation of the baseline scenario for this strategy is presented in the Figure 5-1.

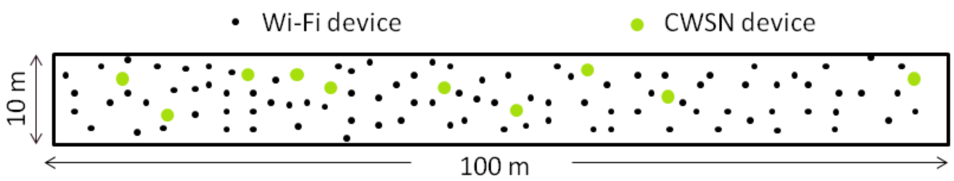


Figure 5-1. Representation of the baseline scenario for the non-cooperative P2P strategy.

CWSNs are modeled with a Texas Instrument CC2420 transceiver. Values of energy consumption are extracted from datasheet (for transmission, reception and idle modes and energy costs of transitions between modes) and verified through experimental measurement using the cNGD platform. Typical current consumptions are 20 mA in transmission or reception mode and below 1 mA in stand-by mode as stated before. Sensing stage is modeled as a reception mode lasting for 200 ms according to real tests in the cNGD. We assume the CWSNs nodes communicate their sensor measurements just to the network coordinator (as a WSN star topology).

CWSN nodes transmit common WSN packets of 50 Bytes at -5 dBm while Wi-Fi network transmits the usual Wi-Fi packets of 2000 Bytes at -3 dBm. Both networks use the worldwide available ISM band at 2.4 GHz. The CWSNs channel bandwidth is assumed as 3 MHz and Wi-Fi bandwidth 22 MHz as seen in Figure 5-2. Due to their bandwidth and their transmission power, each Wi-Fi channel can mask up to four CWSN-channels when both technologies coexists.

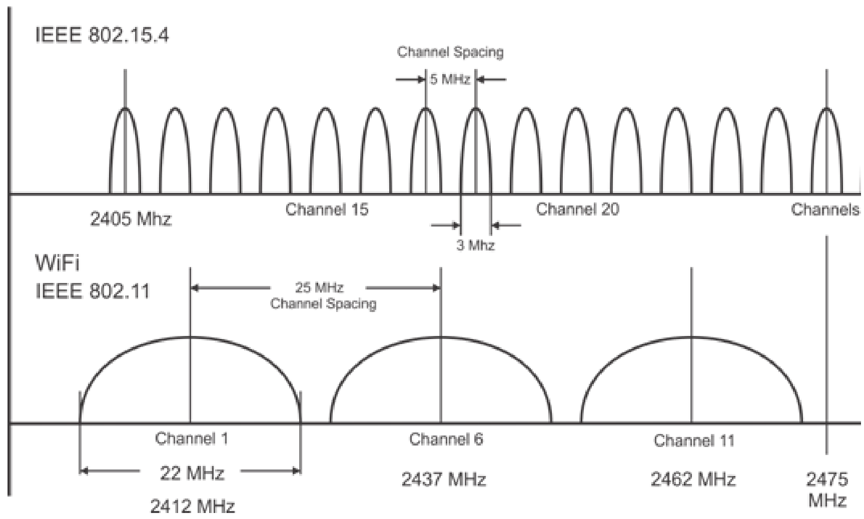


Figure 5-2. Frequency allocation and channel bandwidth for the non-cooperative scenario.

Data rate for CWSN packets is assumed as 1 packet (50 Bytes) each 10 seconds as a typical environmental application. For the WLAN network we choose a data rate of 5 packets (2000 Bytes) each second. That corresponds to a data rate of 80 Kbps which correspond to a typical usage of a laptop connected to internet. A maximum number of 20 retransmissions are set for CWSN and Wi-Fi nodes in the baseline scenario. However, it is interesting to validate the behavior of the strategy varying the maximum number of retransmissions allowed. Therefore, a simulation for this purpose is included.

For the baseline scenario, the RSSI received serves as a trigger for the non-cooperative P2P strategy. The RSSI threshold is set in -150 dBm for the baseline scenario taking into account 5 samples. Nevertheless, simulations with different number of samples and variable RSSI threshold are also performed in order to check the dependencies.

In order to facilitate simulations of different configurations, due to the time consumed by a single configuration scenario, a reduction in simulation time 10 times lower in every magnitude is assumed. For this assumption, a long term simulation is also performed showing similar results to those presented in this section. Thus, simulation time is 300 s, and network rates of 1 packet per second on CWSN and 50 packets per second on Wi-Fi are chosen.

For simulating new Wi-Fi configurations or the appearance of new Wi-Fi networks or nodes in the area, these simulated nodes change their communication channel every 30 s.

In all the results shown, figures show the energy consumption in accumulated Joules over time. For a real reference, typical 2 AA batteries for CWSN have a total energy of 18000 J as we have said in Section 3.1.2.

Again, in this scenario no distinction shall be made between PUs and SUs. According to their formal definition, PUs are the "owner" of the spectrum band with right to communicate without restrictions, while SUs can use the spectrum if they do not jam PUs. Because of the use of the 2.4 GHz unlicensed band, not distinction is made between them.

Summarizing, the scenario configuration values are shown in Table 5-1.

Parameter	Value
Area (m)	10 x 100
CWSN nodes	10
CWSN topology	Star
CWSN tx/rx current consumption (mA)	20

CWSN stand-by current consumption (mA)	Below 1
CWSN available energy (J)	18000
CWSN packet size (Bytes)	50
CWSN transmission power (dBm)	-5
CWSN frequency band (MHz)	2400
CWSN bandwidth (MHz)	3
CWSN data rate (bps)	40
Wi-Fi nodes	100 -> 50-200
Wi-Fi packet size (Bytes)	2000
Wi-Fi transmission power (dBm)	-3
Wi-Fi frequency band (MHz)	2400
Wi-Fi bandwidth (MHz)	22
Wi-Fi data rate (bps)	80000

Table 5-1. Baseline scenario configuration for the Non-Cooperative strategy.

After the scenario description, we present the results extracted through simulation.

5.1.2 RESULTS

In this section results of different simulations are presented and discussed. Even if the simulations do not last as long as the battery life, energy consumption reduction can be appreciated for enhancing the network lifetime. Presented results always show the energy consumption for a CWSN node.

For the first simulation, the baseline scenario is simulated with three different CWSN optimization strategies. The first one, (marked in red), is a typical WSN network without cognitive capabilities, named by -noCR-. Nodes performing this strategy must remain on their initial channel even if this channel becomes very noisy, because they do not have cognitive capabilities. The second one marked with a green line and named -simpleCR-, shows a first approach to CWSN, where cognitive nodes are able to sense the spectrum and change their transmission parameters accordingly. This first approach to CWSN senses the spectrum each 2 s and changes the transmission and reception channel for the whole network. In this way, the least noisy channel is assured each 2 s. The third CWSN strategy, depicted in purple and named -gtCR-, correspond with the proposed non-cooperative optimization strategy based on GTh explained in Section 3.4. Results obtained for the baseline scenario described above are presented in Figure 5-3.

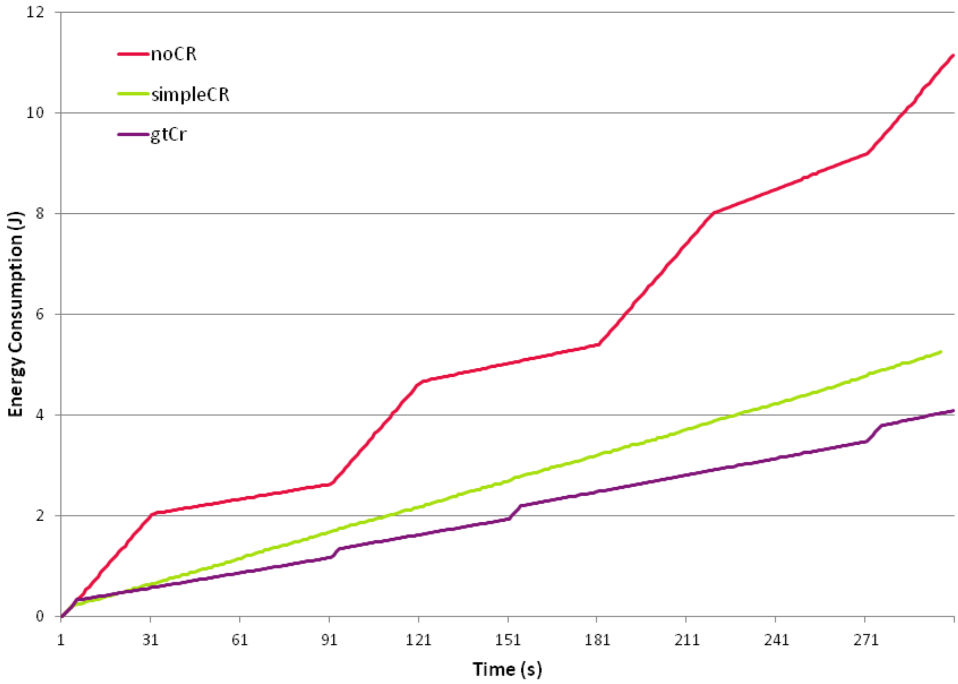


Figure 5-3. Baseline Scenario performing 3 different CWSN strategies.

Figure 5-3 shows, that in the first 300 s, gtCR strategy provides energy consumption savings of around 65% compared with noCR scenario. Furthermore, these savings will increase over time as both noCR and simpleCR have steeper slopes in energy consumption. In relation to simpleCR, gtCR saves energy consumed by approximately 25% in the first 300 s. As in the previous case, these energy savings are increasing over time.

In order to clarify the energy consumed by the CWSN a representation of instantaneous energy expenses is provided.

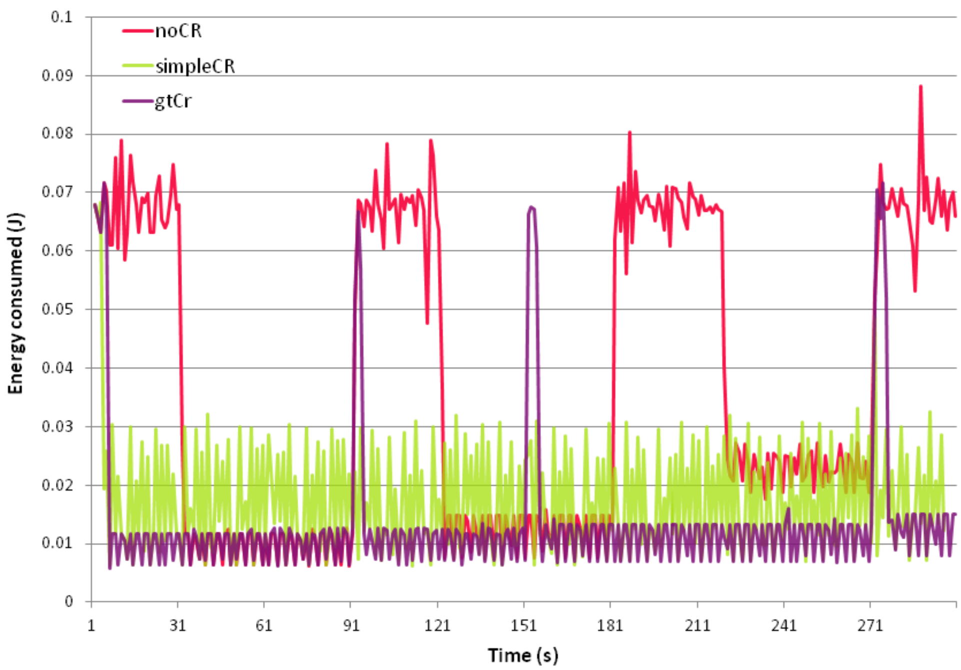


Figure 5-4. Instantaneous energy consumption for the baseline scenario.

Figure 5-4 shows the energy consumed each second instead of the accumulated consumption over time for the baseline scenario. This figure allows contrasting the detailed energy consumption of the algorithm each time it is triggered. Looking at the noCR line, we can notice that energy consumption is lower than simpleCR when Wi-Fi channel does not overlap with the CWSN one. However, in those times that CWSN channel is overlapped by Wi-Fi channel (0-30 or 90-120 seconds) energy consumption in the figure is shot up.

Focusing on simpleCR, energy consumption is almost regular throughout the simulation. This is due to that this strategy assures the less noisy channel during the whole operation, and therefore there is not energy peaks due to collisions and retransmissions. Nevertheless, in this ideal situation (without Wi-Fi coexistence) energy consumption imposed by the sensing state is much higher than the energy consumption in transmission and reception modes, so the biggest amount of energy consumed comes from the sensing state.

Turning to the gtCR strategy, some energy peaks are found due to node processing consumption for the strategy calculation or the retransmission needed until the decision is made. We can notice that these peaks always correspond to a multiple of

30 s, when Wi-Fi nodes change their communication channel. If the new Wi-Fi channels overlap the CWSN communication channel, the gtCR strategy is triggered and energy consumption is increased until the new communication channel is settled. However, this energy consumption peaks are balanced out thanks to the energy consumption savings avoiding noisy channels.

With this baseline scenario, the energy savings could be clearly seen in Figure 5-5. The energy wasted due to unnecessary retransmissions leads the nodes of the noCR scenario to be depleted in just in 56 days. With the gtCR strategy, the batteries last for 152 days, increasing three times the lifetime of the network. Compared with the simpleCR strategy (accomplished 125 days of duration), the increase reach 25%. Even if the batteries duration seems scarce, we cannot forget that we are assuming a very aggressive scenario.

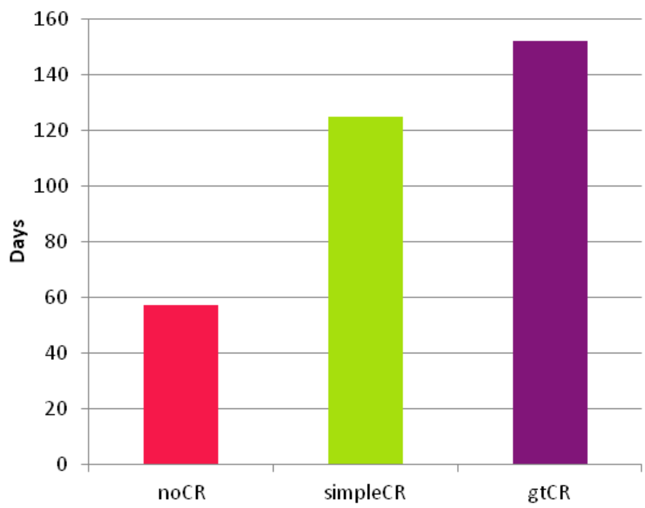


Figure 5-5. Duration days for 2 AA batteries in the baseline scenario.

Next simulations show the results for these three strategies varying the number of Wi-Fi nodes on the baseline scenario to change the amount of noise in the area. These results are depicted in Figure 5-6, which 50 Wi-Fi nodes are deployed instead of 100 which correspond to the baseline scenario, and Figure 5-7, with 200 Wi-Fi nodes for simulating a very noisy ambience.

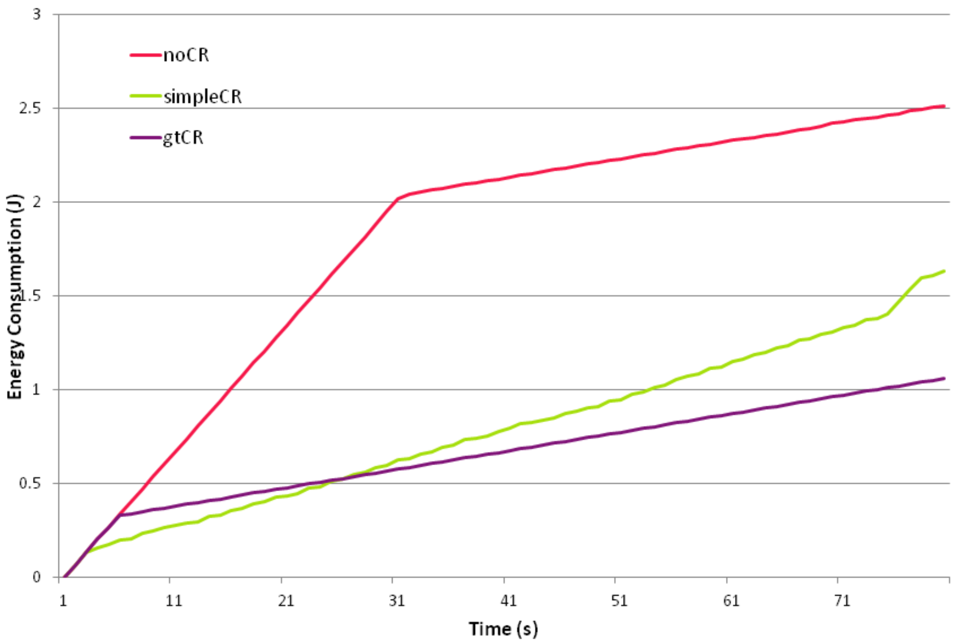


Figure 5-6. Baseline Scenario with 50 Wi-Fi nodes.

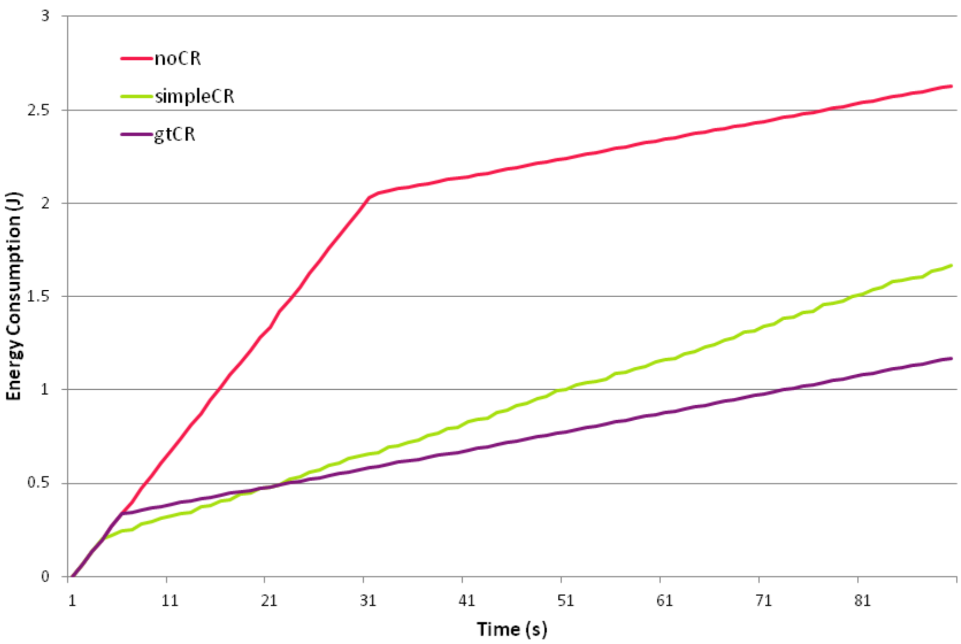


Figure 5-7. Baseline Scenario with 200 Wi-Fi nodes.

As can be seen in the zoomed figure, both simulations are similar in shape and values as baseline scenario, so it can be concluded that the proposed algorithm is not influenced by the amount of noise present in the scenario.

Next simulated scenario modifies the RSSI threshold value used by the gtCR strategy as a first decision mechanism. This simulation is performed in order to test if this threshold value influences the behavior of the strategy. In Figure 5-8 the behavior of the algorithm for different decision thresholds (in dBm) is shown.

As said before, the use of RSSI as a threshold is a first approach related to the energy detection spectrum sensing strategy that could be implemented in real CWSN nodes. Nevertheless, any other parameter reflecting the channel saturation could be used.

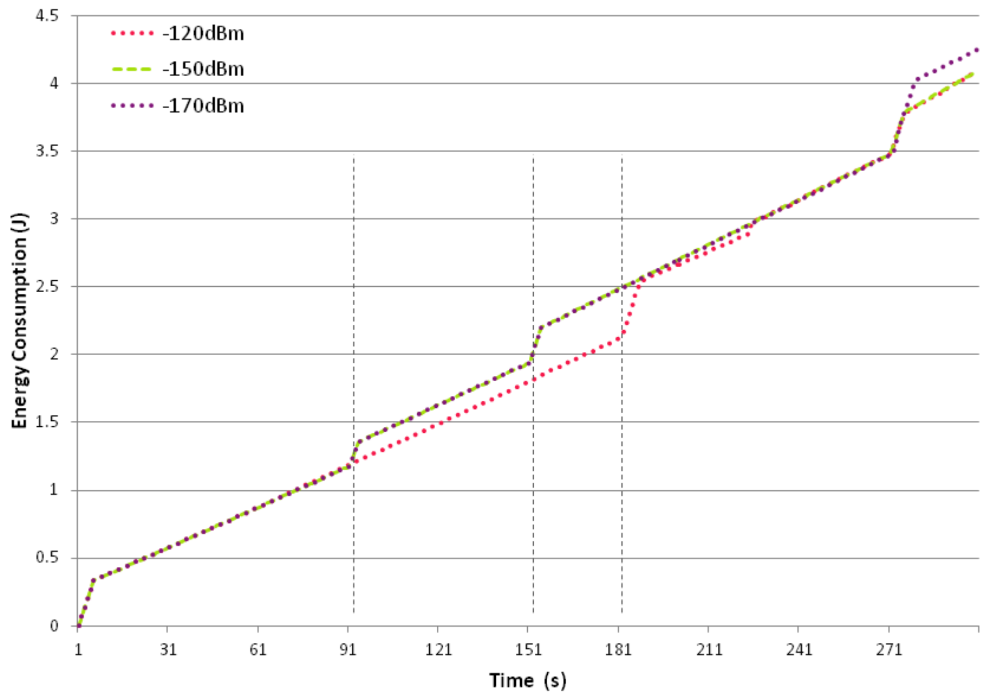


Figure 5-8. Scenario varying RSSI threshold.

As shown in Figure 5-8, algorithm performance is not greatly influenced by the chosen threshold. This is because of the game-theory-based strategy design which takes into account subsequent corrections such as the number of retransmissions used to calculate the best moment to decide the channel change.

Small difference appreciated in the center values of the figure are due to the random character of the channel chosen by the Wi-Fi nodes. That reason makes variable the overlapping situation and the triggered of the algorithm. Therefore, CWSN nodes take the decision of change at 90s or at 180s depending on the existing noise in the channel, but energy consumption at the end of 300s is similar for every chosen threshold.

Next scenario is designed in order to test also the influence of the threshold value. This time, the number of RSSI samples taken into account to calculate the RSSI value is the parameter to change. The intention of these different values is to probe the strength of the strategy against anomalous measures of RSSI. For this simulation, depicted in Figure 5-9, different numbers of samples are chosen.

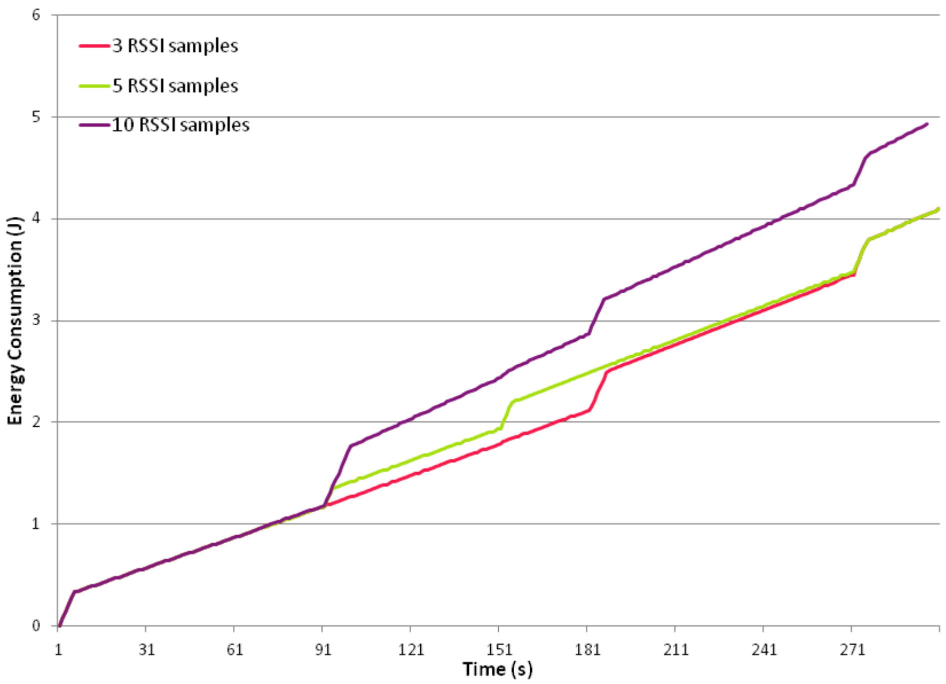


Figure 5-9. Scenario varying number of RSSI samples.

The increased value of energy consumption for the use of 10 RSSI samples is due to the time waste produced by sampling RSSI with every received packet. As the packet rate in the simulation for CWSN is 1 packet per second, it must wait longer to obtain more samples, thereby making the algorithm takes longer to react to changes and trigger the game-theory-based strategy. Although increasing the number of samples protects the algorithm from possible erroneous samples, it is shown that the reaction time causes the CWSN node remain on a noisy channel longer, thus the number of retransmissions increases, raising its consumption. The number of samples must be chosen depending of the WSN application scenario and the randomness of the noise.

For the next scenario, we have decided to vary the maximum number of retransmissions allowed by the CWSN nodes, as this parameter has a direct influence on the decision to change the channel or not in the game-theory based strategy design as it is a parameter of costs calculation.

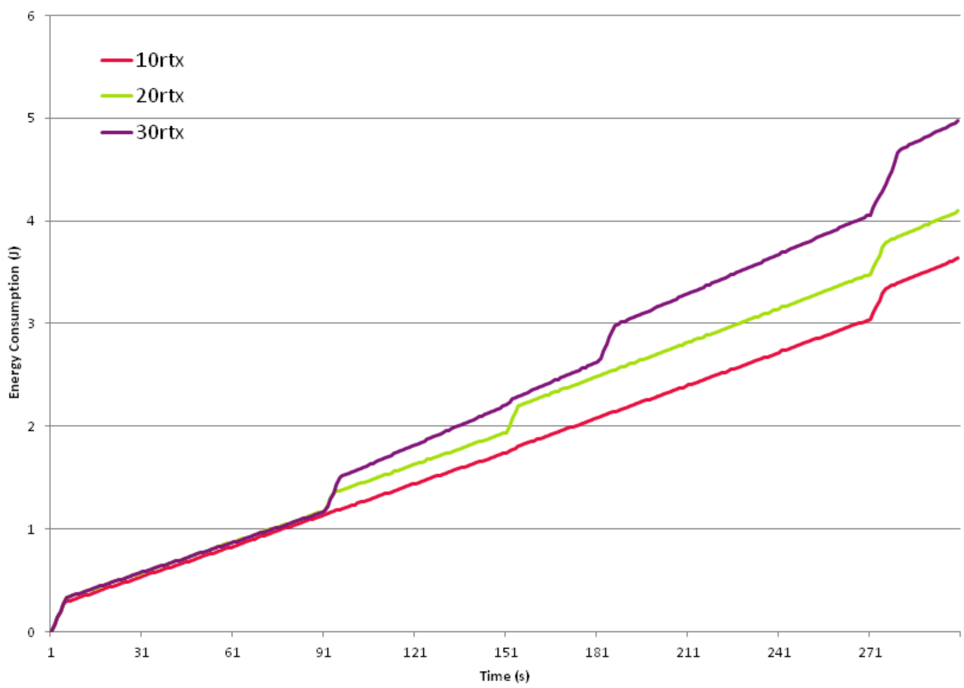


Figure 5-10. Scenario varying number of Rtx.

As shown in Figure 5-10, the greater the maximum number of retransmissions is set, the higher the energy consumption produced. In this case, not related to the strategy but with the final application, a compromise between energy consumption and network reliability depending on the final application of the CWSN or the importance of the data transmitted by the nodes should be reached.

For the next scenario, we want to verify if the initialization reputation of the nodes has an influence on the system. As we have explained in Section 3.4 the strategy is able to learn and evolve with the history. The strategy stores values related to the accepted requests of channel changes. One of the questions we want to answer is how the strategy behaves depending on these initialization values. Next simulation scenario looks for verify if the strategy could adapt to real behavior or instead, relies heavily on initialization values. In this case several experiments that include initialization values from 0 to 100% of change requests accepted are performed showing the following results.

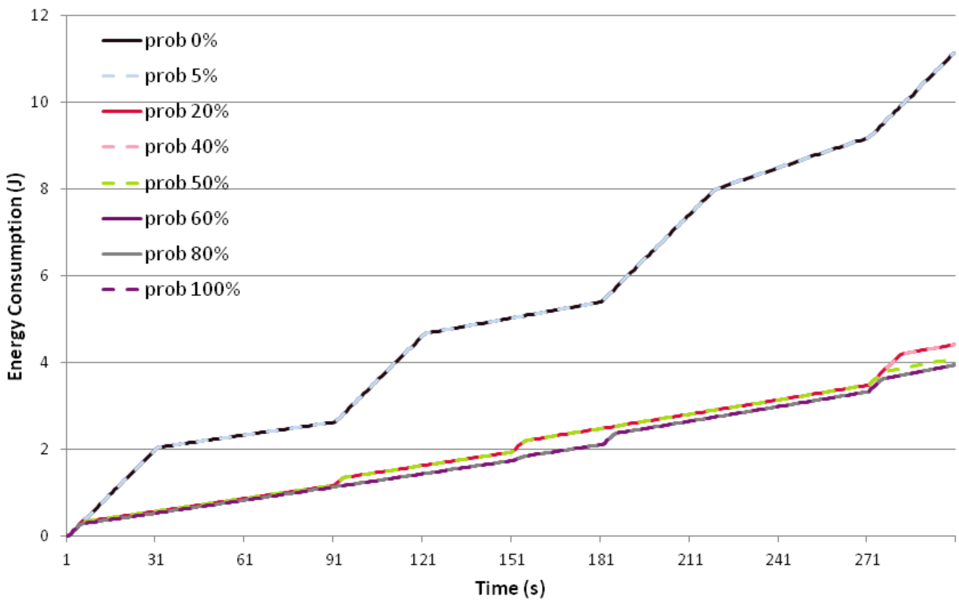


Figure 5-11. Scenario varying the initialization value of probability of change acceptance.

Figure 5-11 shows that probability values from 0 to 5% demonstrate similar values to noCR strategy in energy consumption (depicted in Figure 5-3). Moreover, 80% to 100% values are exactly the same, as are 50% to 60% and 20% to 40%.

In any case, initialization values between 20% and 100% are quite similar in terms of long term energy consumption, indicating that the algorithm, regardless of its initialization, moves rapidly toward a stationary situation based on the sensed spectrum around the node and the behavior of the rest of the devices.

5.1.3 DISCUSSION

The results obtained in testing the non-cooperative game theory based strategy for reducing energy consumption in CWSNs shows promising results. The use of GTh for the decision design phase renders this a very light optimization algorithm that can be implemented in CWSNs although the node computing resources are very limited.

The developed strategy has been tested on a framework based on Castalia Simulator and real devices. As stated in the previous section, the strategy brings energy improvement rates of over 65% compared to a WSN without cognitive techniques and energy improvement rates of over 25% compared to sensing strategies for changing channels based on a decision threshold.

We have also seen that the algorithm behaves similarly even with significant variations in the level of noise. Likewise, the RSSI decision threshold and the number of samples taken into account for their calculation do not influence the operation of the algorithm, which implies certain independence between the strategy and the trigger value. With regard to the number of samples, the only relationship arises from taking a large number of samples, which increases the consumption as the node stays in the noisy channel for too long.

Concerning the maximum number of retransmissions allowed for CWSN nodes, energy consumption increases along with them, but it is caused by the retransmissions themselves and is completely unrelated to the algorithm. In this case, a compromise should be reached between energy consumption and network reliability. The initialization value of the probability of accepting a change request from other nodes does not significantly affect the performance of the algorithm for values above 20%, since this probability evolves based on the noise and the node's behavior and not on its initialization. The obtained results for the dependence of the values used in the payoff matrix are shown in Table 5-2.

Parameter	**Dependence**	**Factors**
Number of nodes	No	
RSSI threshold	No	
RSSI samples	Yes	Application Data rate Sensing period
Number of Rtx	Yes	Network reliability
Init acceptance prob.	No (above 20%)	

Table 5-2. Results summary for non-cooperative strategy.

Another important claim related to this strategy is that it could be applicable in conjunction with other energy consumption optimizations. This way, the results can be improved further by incorporating proved efficient routing protocols or MAC implementations for low consumption.

The simplicity and lightness of the strategy makes it suitable for CWSN scenarios where nodes are very constrained in terms of energy or computational resources. On the one hand, as we use game theory in the design phase of the algorithms, we can ensure optimal behavior in terms of energy consumption. This makes the strategy effective. On the other hand, the strategy only has to store a certain number of retransmissions and RSSI samples, and when the threshold is exceeded, calculate two cost functions (only simple mathematical operations such as addition and multiplication). With the information related to these costs, the node senses the spectrum and takes its selfish decision regardless of the rest of the nodes. If the decision conducts to a channel shift, the node communicates its decision with a message. This efficient strategy performance is simple enough to be achievable by almost every CWSN node.

The simplicity and lightness of this strategy is one of its strong points, but it could be its main weakness, too, when the network performs in difficult noisy scenarios. The fact that the nodes take their own decisions without collaboration works in a suitable way when the noise scenario is simple and uniform as every node finds a similar level of noise in the same channels. However, if the noise distribution is locally variable, node positioning has a great impact on sensed spectrum information. That situation brings different channel assignments, which make CWSN communication unfeasible. In this situation, collaboration among nodes could resolve this situation.

5.2 GTH COLLABORATIVE STRATEGY

After the first strategy, we are going to present and discuss the results related to the second proposed strategy based on game theory and collaboration for reducing energy consumption in CWSNs. This time, as described in Section 3.5, the game is a little more complicated than the previous one and collaboration plays a crucial role in the strategy. Nevertheless, the strategy is still light enough to implement it in a CWSN.

5.2.1 SCENARIO DESCRIPTION

As in the previous scenario, CWSN is considered similar to typical WSNs in components, distribution and behavior.

This time, the simulated scenario is composed by 100 CWSN nodes deployed in a 60 m x 60 m area simulating a monitoring application installed in a hose building in an urban area. This scenario is designed compacter than the previous one in order to increase the noisy perceived by the nodes. These nodes communicate following the IEEE 802.15.4 standard.

The 100 CWSN nodes include one network coordinator, 4 routers and 95 end devices (environment monitoring sensors). The total simulation area is divided into four equal regions of 30 m x 30 m. The coordinator and the routers positions are fixed, the coordinator in the center of the square, and each router in the center of each region. The end devices are uniformly deployed in each region. A representation of the baseline scenario for this strategy is presented in the Figure 5-12.

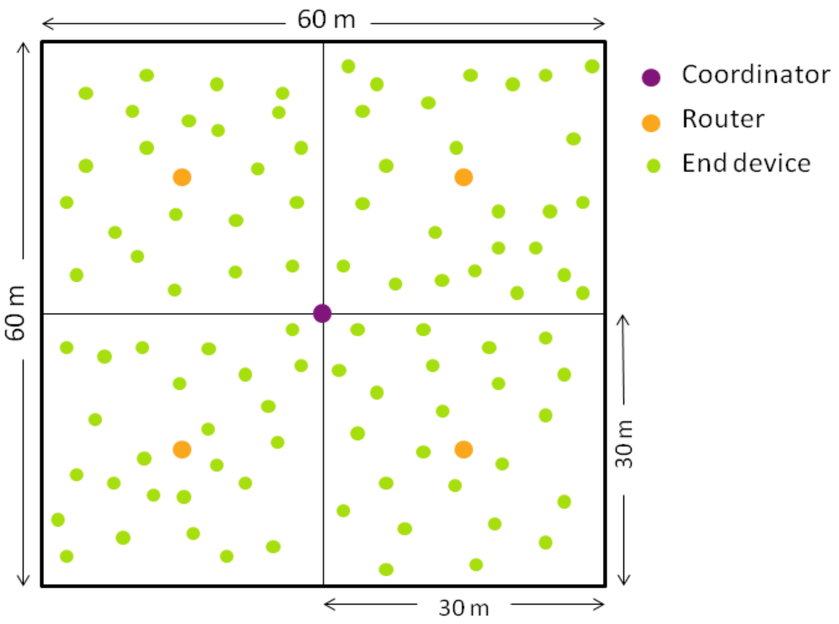


Figure 5-12. Representation of the baseline scenario for the collaborative strategy.

In the depicted scenario, two coexisting networks are communicating, a CWSN and a Wi-Fi network. The baseline scenario has 4 Wi-Fi access points and 100 Wi-Fi devices (such as handheld devices). Access points are located in the center of each region, like the CWSN routers, and Wi-Fi devices are randomly deployed following a uniform distribution. Also, we only consider Wi-Fi communication as noise. We do not have any influence over the Wi-Fi network and it does not implement any optimization strategy.

For the baseline scenario typical WSN and Wi-Fi packets are chosen. As in the previous scenario, end devices transmit WSN packets of 50 bytes at -5 dBm to their region router. Routers send ACK messages after a sensor data reception and also notify the network coordinator when they collect 10 measurements from each sensor node.

The Wi-Fi network transmits Wi-Fi packets of 200 to 2000 bytes at -3 dBm. We introduce in this scenario the variability of noise quantity by changing data rate instead of number of Wi-Fi devices. As in the previous scenario, both networks operate on the 2.4 GHz ISM band. A maximum number of 20 retransmissions are set for the CWSN and the Wi-Fi nodes in the baseline scenario.

CWSN nodes are modeled by a Texas Instrument CC2420 transceiver common used for WSN. The values of energy consumption are extracted from its datasheet (for transmission, reception, idle modes and energy costs of transitions between modes) and verified through experimentation in the real testbed. Typical current consumptions of CWSNs nodes are 20 mA in transmission or reception mode and below 1 mA in stand-by mode. Moreover, the sensing mode refers to a long-lasting reception mode. The sensing stage is modeled as a reception mode lasting for 200 ms (time required to sense the 16 channels in 2.4 GHz band tested trough experimental measurements in the testbed).

For the baseline scenario, a RSSI threshold of -150 dBm averaging 5 samples is assumed. According to the results derived by the previous strategy, this threshold does not have a great dependence with the performance of the strategy. Even as said before, the use of RSSI as a threshold is a first approach related to the energy detection spectrum sensing strategy. Nevertheless, any other parameter reflecting the channel saturation could be used.

Data rate for CWSN packets is assumed as 1 packet (50 Bytes) each 10 seconds as a typical environmental application. For the Wi-Fi network we choose a data rate of 5 packets (200-2000 Bytes) each second. That corresponds to a data rate of 8-80 Kbps which corresponds to a typical usage of a smart phone or a laptop connected to internet.

Analogously to the previous scenario definition, in order to facilitate simulations of different configurations, simulation time is decreased 10 times, and fixed to a maximum of 100 s. Network rates resulting in 1 packet (50 bytes) per second on CWSNs and 50 packets (200-2000 bytes) per second on Wi-Fi. In order to simulate new Wi-Fi configurations or the appearance of new Wi-Fi networks or nodes in the area, the simulated Wi-Fi nodes change their communication channel every 10 s.

To validate this assumption, a long term simulation is performed (simulation time 1000 s, 0.1 packet per second for CWSNs and 5 packets per second for Wi-Fi communication) showing similar results to those presented in the next section.

In all the results presented, figures show the energy consumption in accumulated Joules over time. For a real reference, the typical 2AA batteries for CWSN nodes having a total energy of 18000 J are considered. The results show the energy consumption for two types of CWSN nodes, a router and an end device.

We have implemented different noise configuration in order to validate the strategy under different scenarios. These configurations are named uniform, region, fixed, changing and noNoise. The two firsts implies spatially distributed noise while fixed and changing denotes temporally changes. Scenarios marked as noNoise shows configurations in absence of Wi-Fi noise. Figure 5-13 depicts examples of uniform and region changing schemes.

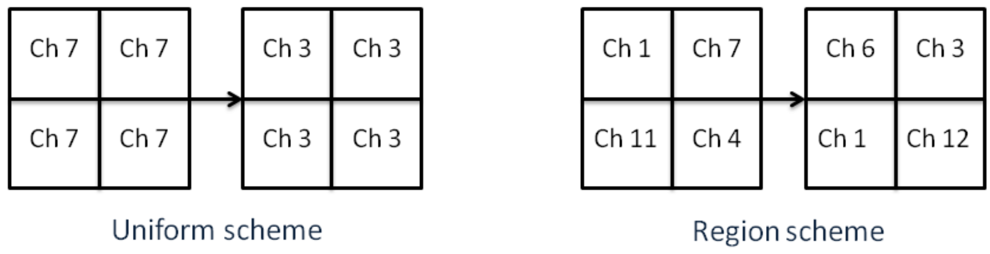


Figure 5-13. Uniform and region changing noise schemes for simulation.

Again, no distinction is made between PUs and SUs given that CWSNs operate on unlicensed bands.

As a summary of the values chosen for this scenario, we present the Table 5-3:

Parameter	Value
Area (m)	60x60
CWSN nodes	100
CWSN topology	Cluster Tree
CWSN tx/rx current consumption (mA)	20
CWSN stand-by current consumption (mA)	Below 1
CWSN available energy (J)	18000
CWSN packet size (Bytes)	50
CWSN transmission power (dBm)	-5
CWSN frequency band (MHz)	2400
CWSN bandwidth (MHz)	3
CWSN data rate (bps)	40
Wi-Fi nodes	100
Wi-Fi packet size (Bytes)	200-2000
Wi-Fi transmission power (dBm)	-3
Wi-Fi frequency band (MHz)	2400
Wi-Fi bandwidth (MHz)	22
Wi-Fi data rate (bps)	8000-80000

Table 5-3. Baseline scenario configuration for the collaborative strategy.

5.2.2 RESULTS

In this section the results of different simulations are discussed. Even if the simulations do not last as long as the battery life, an energy consumption reduction can be appreciated.

In order to test the performance of the proposed strategy, it is compared with the previous strategy. This previous strategy is marked as P2P in the graphs and the new strategy presented in Section 3.5 is named collabGTh. It has been proven that the previous strategy does not depend on the threshold values for the RSSI or the number of samples taken into account.

The first simulation presented in Figure 5-14 compares the performance of these two strategies for end devices in the baseline scenario with a uniform noise scheme (every Wi-Fi device communicating in the same channel) with two different packet sizes (2000 Bytes and 200 Bytes).

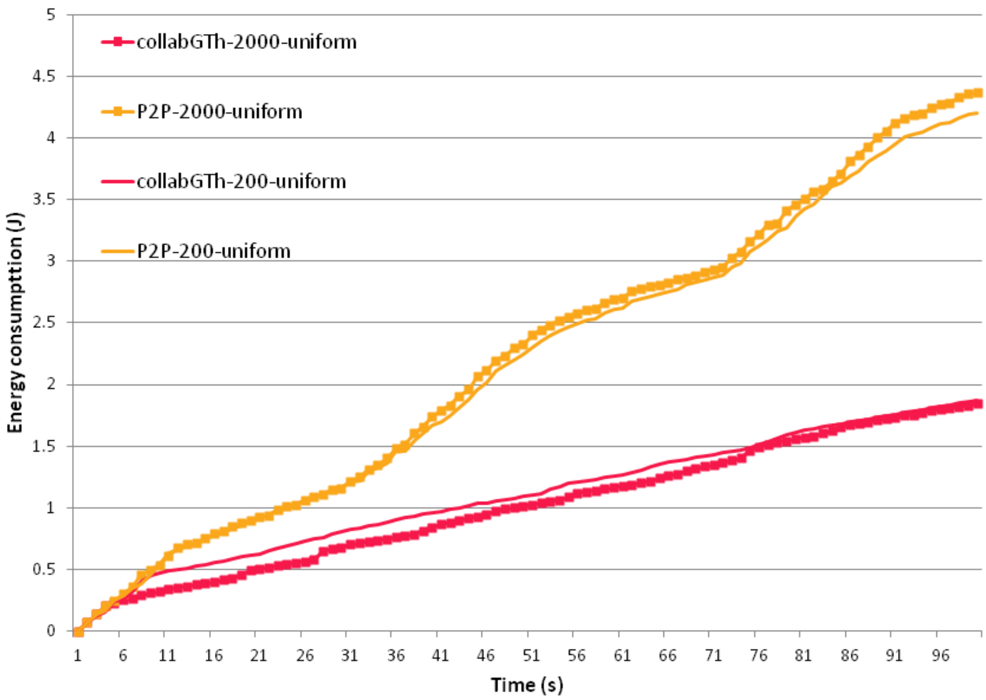


Figure 5-14. Baseline scenario in a uniform noisy scheme (end device).

Results presented in Figure 5-15 compares the performance of these two strategies also for end devices but with another noise scheme. In this case, the 4 Wi-Fi access points communicate in different channels. That means that there are 4 different channels occupied by Wi-Fi communications. In both cases the Wi-Fi channels change every 10 seconds.

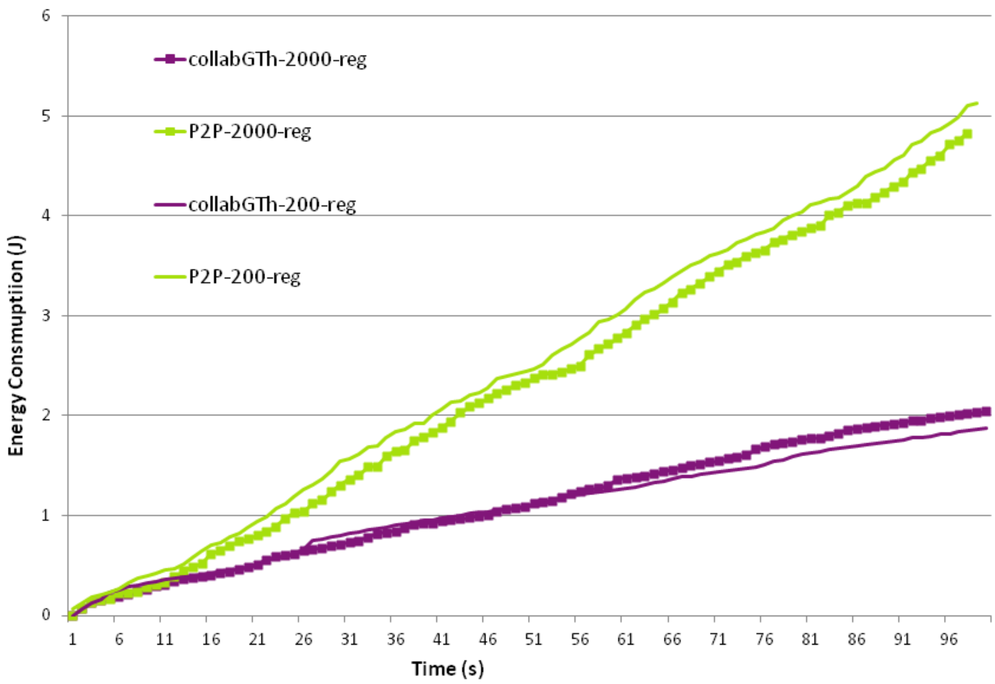


Figure 5-15. Baseline scenario in a region noisy scheme (end device).

In both figures, we can see that the results are quite similar for each strategy, independently of the noise level. It is important to observe the improvement in the energy consumption of the nodes which use the new collaborative approach.

In the case of the uniform noise, we can see that the energy consumption of both algorithms is lower than the case with different regions. However, the adaptation of the new strategy to the noise in different regions gives results similar to the case with uniform noise while the previous strategy performs worse. Therefore we can say that the new collaborative strategy perform equally in more difficult scenarios where the previous strategy fails.

Another conclusion obtained through these simulations is that variation due to the noise level (between packets from 200 to 2000 bytes) has not a big influence in the results.

We present in Figure 5-16 the results obtained for the routers devices, but only for the case where the Wi-Fi nodes transmits packets of 200 bytes, while the variation caused by the level of noise is not very significant.

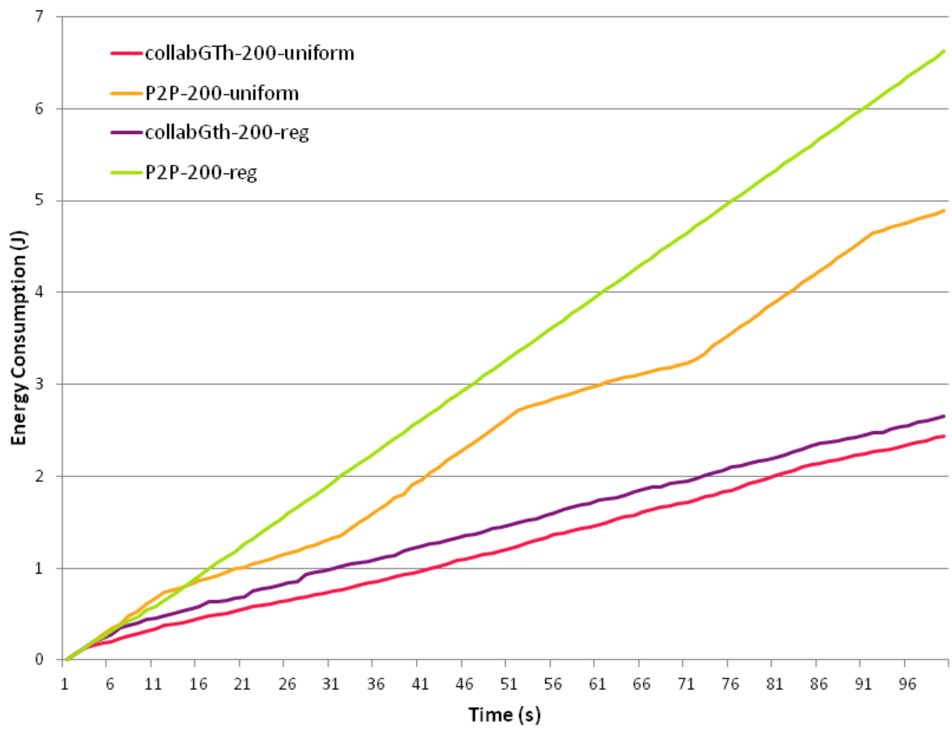


Figure 5-16. Baseline scenario in different noisy scheme (router).

In this case, routers implementing the non-collaborative approach are not able to adapt to the changing channel because finding a free channel to communicate without collaboration it is quite improbable. The routers performance is much more damaged than those of end devices because their data rate is higher than that of the end devices (routers send acknowledgment messages to each end device after a received measurement). The router results confirm that both noise patterns have a similar effect in the case of the collaborative algorithm.

The new collaborative strategy provides energy consumption savings of around 50% compared to the P2P strategy in the worst case (with different noise schemes in each region and for the routing devices). Summarizing the last results, energy consumed after 100 s of simulations under different noise schemes for routers and end devices is shown in Figure 5-17.

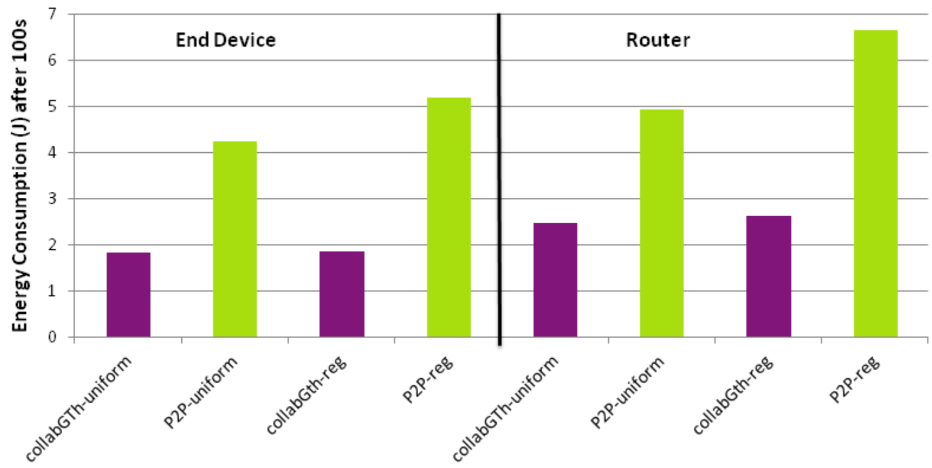


Figure 5-17. Energy consumption after 100 s for different configuration.

To verify the uniform performance of the strategy with different noise patterns, the results shown in Figure 5-18 (end devices) and Figure 5-19 (router devices) compares scenarios where the Wi-Fi communication stays in the same channel for the whole simulation with dynamic scenarios.

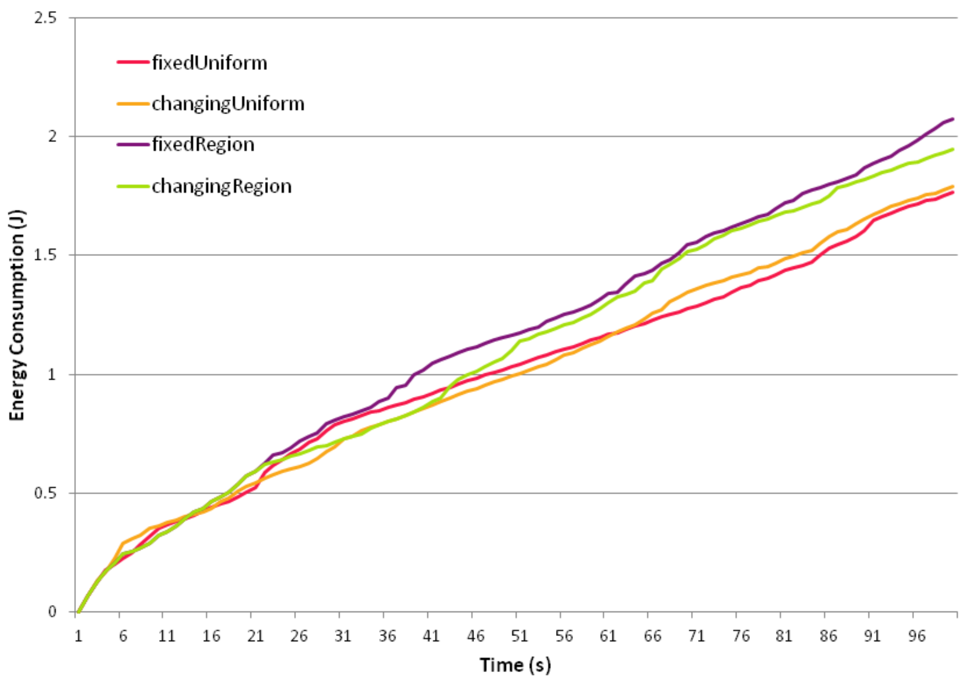


Figure 5-18. Collaborative strategy performance under different noise schemes (end device).

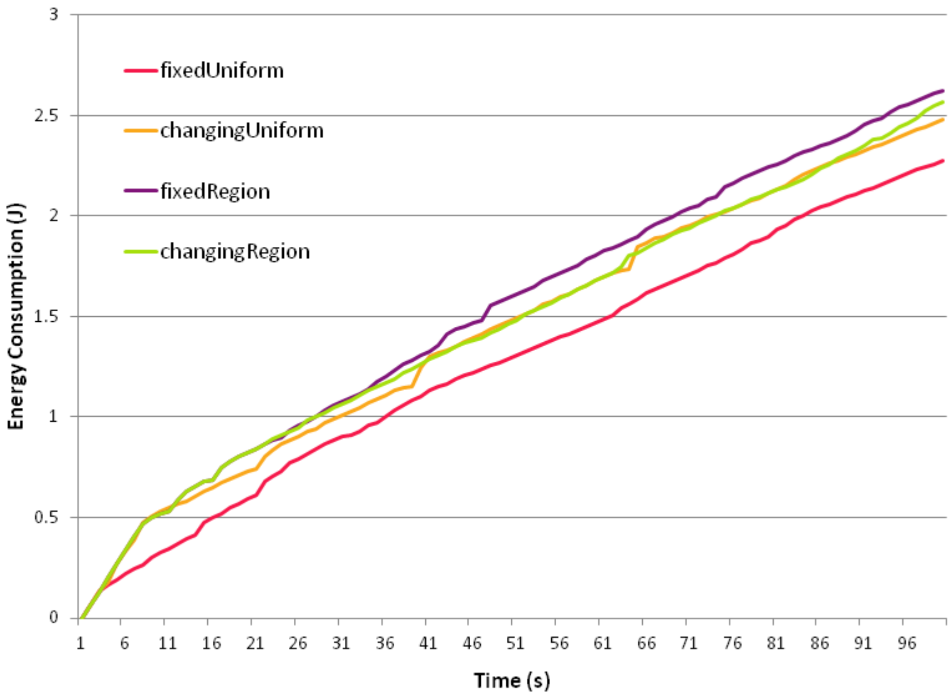


Figure 5-19. Collaborative strategy performance under different noise schemes (router).

In both cases the difference found in energy consumption between the different scenarios is barely noticeable, so we can ensure that the proposed collaborative strategy can perform stabilized with different noise patterns.

Finally, to evaluate the energy cost of performing this strategy even in a scenario without noise, we simulate this behavior: the same CWSN is deployed without introducing the Wi-Fi nodes. The results are shown in Figure 5-20.

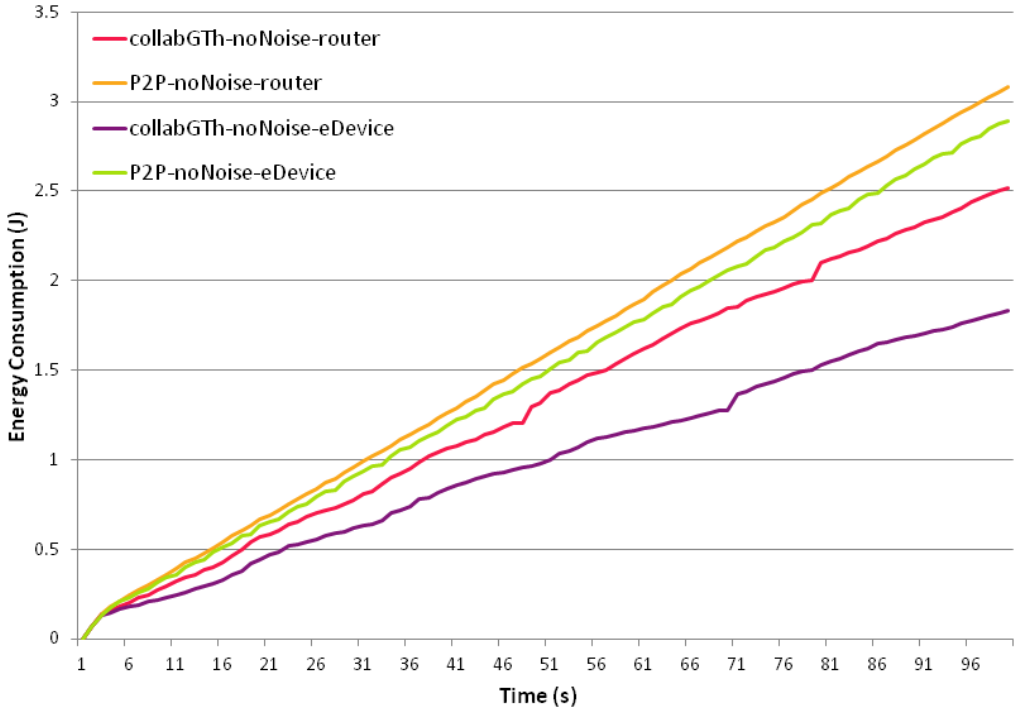


Figure 5-20. Comparison in a noise-free environment.

As shown in the Figure 5-20, the energy cost of performing this strategy is even lower. This is because CWSN nodes can interfere with the communications in their own network. The new collaborative strategy is able to adapt its transmission channel to decrease the noise level perceived by the other nodes of the network with which it does not communicate. This is possible thanks to the weighing done in the utility function calculation, which takes into account the messages exchanged between nodes.

In order to complete a general depict and looking to test if the developed strategies have some negatives aspects related to the network packet rate or the achieved data latency we have performed some tests. The first one, related to achievable network packet rate aims to verify that the introduction of the GTh strategies does not degrade this network parameter. The Figure 5-21 depicts the achieved data rates for the two energy efficient developed strategies and a classical WSNs without cognitive capabilities under the five noise schemes presented before.

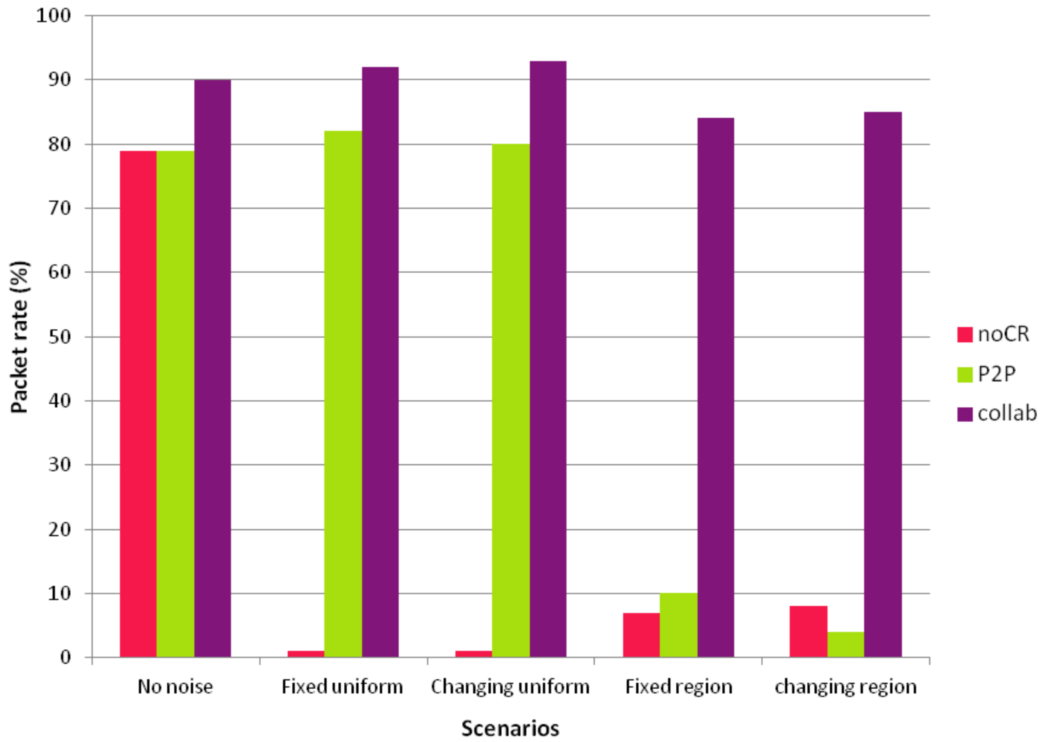


Figure 5-21. Packet rate under the 5 noise schemes.

As shown in the figure, the packet rate is acceptable (considering a MAC layer not optimized for the network) and similar for the three network configurations in absence of noise. The collaborative strategy provides better packet rates than noCR and P2P strategy that are similar among them. This fact can be explained due to the topologies used in the scenarios. As noCR and P2P use a star topology where every node send its data to a coordinator, this node is more saturated than in the cluster-tree topology used in the collaborative simulation. Nevertheless, as the noise scheme become more complex (from left to right), the noCR and the P2P strategy turn into useless configurations as they provide data rates below 10%. That is the case for any noise configuration for noCR networks and for the spatially distributed noise in different regions for the P2P optimization strategy.

Next verification is related to data latency, for measuring the delay introduced by the energy efficient strategies developed. Results are shown in Figure 5-22, but only for packet rates above 10%, as below this threshold data is not significant.

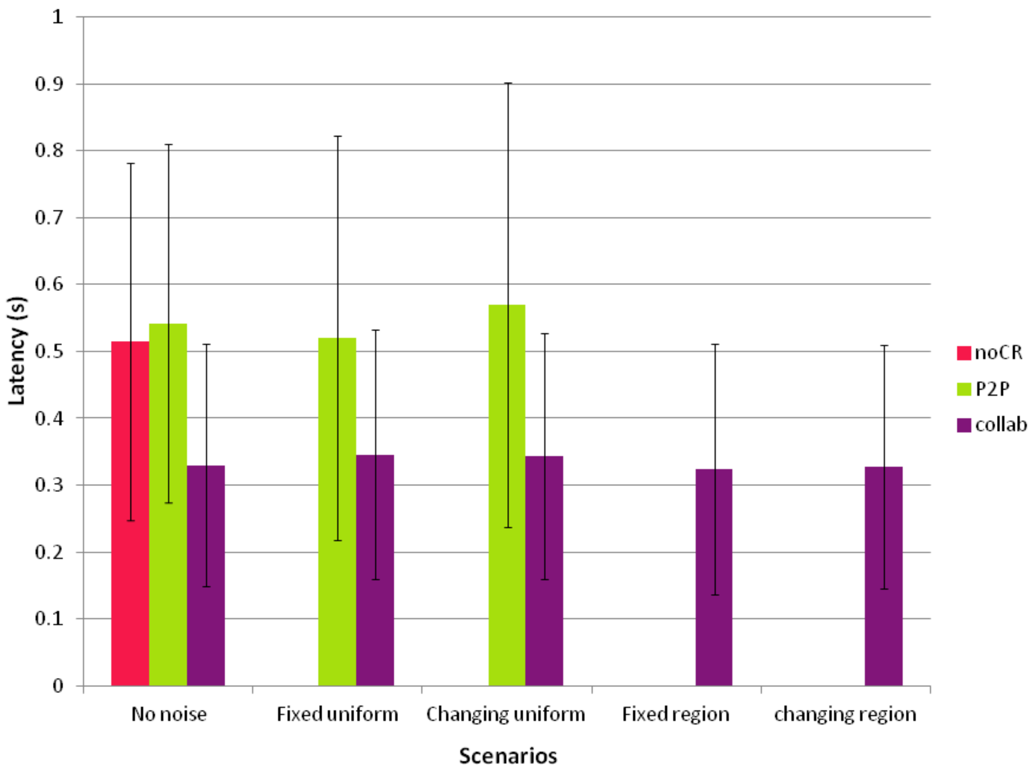


Figure 5-22. Latency comparison for the 5 noise schemes.

In the figure above we can see the average latency for an end device in bars and the standard deviation marked also over the bars.

Even if the network topology and the scenarios definition have some impact in the latency comparison because of spatial nodes distribution and the use of routers in the collaborative strategy (where latency has been measure as routers keeps the data packet until they collect 10 measures), we can extract some conclusions. The complexity of the noise scheme does not affect to the latency for the different strategies, keeping almost constant for the different scenarios, which denote the adaptation of the algorithm to different noise contexts. On the other hand, we can compare the noCR latency results in absence of noise with the P2P strategy and we can see that the differences are not pronounced, which implies that the strategy overload is not harmful. In the same way, we can expect that in the noNoise scenario the data latency is similar to not execute any CR strategy as the nodes do not enter into the game theory evaluation. With this premise, we can compare the no noise scenario for the collaborative strategy with the rest of noise configuration. This comparison shows also not remarkable differences among them, denoting the fast convergence for the collaborative strategy.

5.2.3 DISCUSSION

This new strategy based on game theory and collaboration for reducing energy consumption in CWSNs presents improvements compared to the previous strategy in terms of noise protection when the noise scheme is more aggressive. Nevertheless, this strategy is still a light optimization that can be implemented in CWSNs although the computing resources of the nodes are limited. The optimization of this strategy relies on the modeled game improved with collaborative behavior.

The developed strategy is tested and compared with a previous non-cooperative strategy in the B105 Lab developed framework. As seen in the results section, the strategy shows improvement rates of over 50% compared to the previous non-cooperative strategy. This strategy behaves similarly even with significant variations in the level of noise. Likewise, the results of every node in the network independently of their role (both routers and end devices) are improved.

The strategy is also validated in different noise scenarios. The strategy presents promising results and seems useful both for scenarios in which the noise stays constant in the same channel and for those in which the noise patterns change. Moreover, the spatial distribution of noise is also changed from a uniform noise in the whole area to multiple noisy zones in different channels. Even more, as shown in Figure 5-20 where the scenario is simulated in the absence of noise, the strategy presents better results than the previous one. These data provide an idea of the lightness of the designed strategy. Also, they could be used in order to avoid interferences within the same network. Results about packet rates shows that the strategy behaves at least equal for the simple noise configuration and better for the complex ones than the previous P2P strategy improving the network performance. Latency results verify the fast convergence of the collaborative strategy. We can state that the introduction of these strategies does not degrade the performance of the network.

As in the previous strategy, this collaborative strategy could be implemented together with other energy consumption optimizations. In this way, the results can be enhanced further by incorporating efficient routing or MAC implementations.

This strategy has been demonstrated to perform better than the previous one in complex noise-environments. This is a progress to assure protection of the CWSN when it is deployed in very crowded spectrum areas. However, the simplicity and lightness of the strategy has not increased a lot. Even though the collaborative strategy implies more communication and calculation, it is still suitable for CWSN scenarios.

This strategy could provide even better energy optimization results in a scenario with several heterogeneous CWSN deployments. With this strategy implemented in every CWSN collaborating only within the same network and without any communication with the rest of the networks, the CWSNs could adapt their communication channel for optimizing their performance. This would result in an optimized channel selection for every network and improve the energy consumption. Applying this strategy would improve energy consumption by avoiding the implementation of complex standards for heterogeneous communications.

Despite the good results revealed by this strategy, we can depict some scenarios where the previous strategy could have a better performance. We can imagine the deployment of a very simple CWSN consisting of a few nodes (around 10). This CWSN communicates with a star topology and under a uniform noise scheme (this situation is usual in a CWSN house-monitoring scenario where the house's Wi-Fi router is fixed). In this situation, the decision about the channel has to be common and it used to be the same for every CWSN node. In this particular scenario, introducing more complexity to the strategy has no benefits and increases the communication demands.

5.3 TEST IN REAL DEVICES

Next step, according to the methodology exposed in Section 1.2, is testing in real devices. As noted in Chapter 4, we are currently in the testbed deployment. Because of this work in progress we have not enough nodes deployed in order to provide significant results.

Nevertheless, in order to validate that the strategies design fit the resources constraints of the CWSN nodes, we have implemented and run the strategies in two nodes choosing the 2.4 GHz interface for data communication and the 433 MHz for the implementation of the VCC. We have compared the performance of the strategies in physical nodes with the simulated performance and they are similar in behavior. When data packets began to be retransmitted the node launched the strategy and the evaluation of the game. The implementation for the cNGD fits memory, computational capabilities, and energy consumption constraints denoting the lightness of the strategy and the its adequacy for CWSNs.

As said in Section 1.2 feedback is an important feature of the methodology. We implement this feedback too when design the tools, and for that purpose we have measure sensing time and changing channel required time in order to introduce these measures in Castalia for more accuracy simulated results. These times are 200 ms for sensing the 2.4 GHz available channels and 0.15 ms for channel shifting in 2.4 GHz band.

Now that the results have been presented and discussed, we can extract the main conclusions of the work and propose future research lines.

Reserve your right to think, for even to think wrongly is better than not to think at all

Hypatia

6 CONCLUSION AND FUTURE WORK

This chapter presents a full review of the thesis aimed at the design of strategies to reduce energy consumption based on cognitive capabilities for CWSNs. A general description of the work is presented together with the main conclusion and future lines of research.

The goal of this thesis is to reduce energy consumption in CWSNs by exploiting the new capabilities introduced by the cognitive radio concept. Due to the number of nodes, the new cognitive features introduced, their wireless nature, and their deployment in difficult access areas, energy consumption in CWSNs is one of the more important problems when designing these networks.

The introduction of CR capabilities into WSNs provides a new paradigm for energy consumption reduction, but it also implies some challenges. This reduction of energy consumption is a task that must be considered during the whole network definition process in order to make it sustainable.

To achieve the main contributions of this work, several tasks have been performed in order to enclose the research area. The first contribution corresponds to a complete analysis of the possibilities introduced by incorporating cognitive abilities into the network. We have exposed and discussed these possibilities by dividing them into three main groups according to which CR feature they belong.

After the first stage of the analysis, we have completed a review of the state of the art focused on different cognitive techniques for energy efficiency in CWSNs. As a result of this process of reviewing previous works, we can draw some conclusions. First, the state of the art is still in the early stages. Next, while several authors emphasize the advantages of incorporating cognitive capabilities into WSNs, specific CWSN research related to energy optimization began to arise after 2012.

We have divided the reviewed optimizations into three different categories as in the analysis section. The first category is responsible for optimizing the spectrum sensing stage. As a major cornerstone, it has attracted the efforts of several research groups and several solutions exist. The second group corresponds to those related to the ability to change the communication parameters. Some works optimizing different parameters such as modulation, transmission power, packet size, and frequency channel have arisen over the last years. Nevertheless, the optimizations are envisaged for CWSNs capable of accessing licensed spectrum bands, which is not the typical WSN scenario. The third main group is composed of traditional energy consumption optimization methods, which use the spectrum sensing information to enhance energy efficiency strategies. Given the similarities between the constraints of CWSNs and the constraints of traditional WSNs, we have also revised energy optimization methods for WSNs that we can use in the design of our strategies. Likewise, although the limitations of the CNs are not the same as those of CWSNs, the cognitive opportunities are similar, so we have also performed a review on CN energy efficiency techniques that can inspire us when designing new CWSN strategies.

After the analysis and the state of the art review, we have concluded that the group of strategies corresponding to the capability of change communication parameters is an interesting starting point. The designed energy efficiency strategies must keep in mind the resources offered by a CWSN and try to adapt transmission parameters according to the hardware associated with these nodes. Among the available parameters, the contribution of this thesis is focused on optimizing the communication channel and thus meeting the main objective of reducing energy consumption. This parameter is easily accessible in every CWSN node.

Once we completed the analysis of the possibilities offered by the introduction of cognitive abilities to WSNs, we studied three of the main techniques used in the field of optimization and decision making for communications networks: (a) genetic algorithms, (b) particle swarm optimizations, and (c) game theory. Due to this analysis, we can state that PSO algorithms fit better in our scenario than GAs. Related to GTh, the simplicity of this method is more than acceptable to be implemented in a low resource network and the problem model suits our scenario well. Although both PSO and GTh are good options, we have chosen GTh as a starting point to begin modeling the energy problem in CWSNs because of its capacity to model resource competition systems.

Along with the main objective of this work and with the performed analysis, we have proposed two energy optimization strategies based on the game theory. To test these strategies, a complete CWSN framework has been developed. This framework constitutes the second contribution of this thesis. We have designed and implemented a cognitive layer for a WSN simulator and a real testbed based on a CWSN node also developed in the B105 Lab, the cNGD.

These strategies for energy optimization are the main contributions of this doctoral thesis. After designing and testing them, we present some conclusions in the next section.

6.1 CONCLUSION

We have designed, analyzed, implemented, and validated two strategies based on game theory to achieve the goal of reducing energy consumption in CWSNs by exploiting the new capabilities introduced by the CR concept. After this process, we can draw the following conclusions:

The energy consumption of a WSN can be decreased by designing a strategy based on a non-cooperative game for the choice of the communication channel.

The non-cooperative P2P strategy described in Section 3.4 consists of a non-cooperative game strategy that decides the communication channel and aims to prevent unnecessary retransmissions. The use of less noisy channels avoids extra retransmissions and makes the global reduction of the energy consumption of the network possible. This strategy is based on the ability to sense the spectrum and change the transmission parameters in order to reduce energy consumption. This P2P strategy is composed by different parameters with a non-cooperative game serving as the master piece for decision-making.

The results obtained through the testing of this non-cooperative game theory based strategy are promising. As stated in Section 5.1, the algorithm brings energy improvement rates of over 65% compared to WSNs without cognitive capabilities and energy improvement rates of over 25% compared to sensing strategies for changing channels based on a decision threshold. We have also verified that the algorithm behaves similarly even with significant variations in the level of noise. Likewise, we have concluded that decision thresholds do not influence the operation of the algorithm, which implies certain independence between the strategy and the trigger value. Also, as shown in Chapter 5, the strategy evolves based on the node behavior and the noise scheme, even with different values of the initialization parameters.

Another important statement is that the simplicity and lightness of the strategy makes it very suitable for CWSN scenarios where nodes are very constrained in terms of energy or computational resources. Also, as we have used game theory for the design phase, we can assure an optimal performance of the communication channel in terms of energy consumption. This way, even if the strategy is very simple, it accomplishes the objective of reducing energy consumption through cognitive capabilities while ensuring its implementation in the simplest devices.

Nevertheless, the simplicity and lightness of this strategy could be its main weakness, too, when the network performs in difficult noisy scenarios. If the noise distribution is locally variable, node positioning has a great impact on sensed spectrum information. That scenario could bring different channels assignments, making CWSN communication unfeasible. In this situation, collaboration among nodes could resolve this problem, which leads us to the second main conclusion.

The energy consumption of a CWSN could be diminished by designing a strategy based on a collaborative game for the choice of communication channel. This game will be more resistant to dynamic interference environments (spatially and temporally distributed).

In this case, we state that it is possible to reduce the energy consumption of a CWSN further if the modeled game is collaborative according to the strategy designed in Section 3.5. Named "collaborative strategy", this strategy consists of a collaborative strategy based also on a non-cooperative game. This strategy also takes advantage of the communication channel choice in order to avoid preventable retransmissions. The main difference regarding the previous strategy resides in the strategy’s collaborative approach. Even though the game model is a non-cooperative game, the strategy proposes a collaborative channel decision approach that benefits the overall performance of the nodes when the noise scheme is complex.

This reduction of energy consumption has proved to be very resistant to dynamically changing scenarios in which the interference varies both temporally and spatially as shown in Section 5.2. The reduction of energy consumption compared with the previous strategy is more pronounced the larger the variations in the distribution of the interferences are. According to the results, the developed strategy shows improvement rates of over 50% compared to the previous non-cooperative strategy in noise-aggressive scenarios.

This strategy behaves similarly even with significant variations in the level of noise and the energy consumption of every node in the network independently of their role (routers or devices) is improved. Even more, in the absence of noise, the strategy also presents benefits. This strategy could be used, too, for preventing interference among the same network. Also, if we go one step forward and implement this strategy in different CWSNs, we can assure an optimal channel selection in terms of energy consumption even without collaboration between them and thus avoid complex implementation for heterogeneous networks. Despite being more complex than the previous strategy, this strategy is still a light optimization that can be implemented in CWSNs although the computing resources of their nodes are limited as demonstrated through implementation in real devices. Results about packet rates and latency shows that the strategy behaves at least equal for the simple noise configuration and better for the complex ones than the previous P2P strategy improving the network performance. We can state that the introduction of these strategies does not degrade the performance of the network.

Another important claim related to both strategies is that they could be applicable in conjunction with other energy consumption optimizations. In this way, the results can be improved further by incorporating proved efficient routing protocols or MAC implementations for low power consumption.

Considering the two previous conclusions, we can state that **it is possible to reduce the energy consumed by a wireless sensor network by using the cognitive capabilities available in a CWSN.**

Both of the strategies presented in Section 3.4 and in Section 3.5 use channel allocation in order to avoid unnecessary retransmission based on spectrum information. As the results show, both strategies achieve energy consumption reduction in CWSN. As we stated in Chapter 1, we start from the premise that cognitive features are introduced to solve the existing problems related to spectrum saturation in ISM bands due to the spectral coexistence of WSNs with other WSNs and WLANs that overlap their performance. Therefore, we assume that we start from these CWSNs. From this point we have proved that, thanks to these new introduced capabilities, we are able to reduce energy consumption at least to the level prior to the introduction of CR in WSNs.

According to the presented conclusion, we can say that the hypotheses of this thesis presented in Chapter 2 are validated through the design and testing of two energy efficient strategies.

As a side conclusion derived from the previous ones, we can state that game theory is a good tool for decision-making modeling in CWSN scenarios. As shown in Chapter 2, , game theory is widely accepted for resource optimization in a cooperative WSN. Now with cognitive capabilities, it could fit even more. In addition, games can be simplified enough without losing functionality to enable them to be supported by a WSN node, even if the node's processing capability is limited. Considering the presented results, we can ensure that game theory has proved to be a useful, lightweight, and effective modeling tool for decision-making modeling in CWSNs.

Also, the followed methodology described in Section 1.2 has been shown to be valid for the development of these strategies. The advantage of feedback throughout the process has become essential and the amendments introduced at every feedback stage have contributed to obtaining better results. Likewise, the simulation and implementation in the real devices phase is indispensable to conclude the validity of the proposed strategies. Along with the use of feedback, the characteristic of the methodology followed based on progression from the simplest contribution to the most complex has allowed us to implement complex contributions gradually.

The same idea has been followed when developing the testing framework. Both the simulator and the testbed have been built from the most basic characteristic to the most complex ones until a valuable tool has been reached for testing these strategies. We can also conclude that the implemented framework described in Chapter 4 has fulfilled the requirements to test and validate optimization strategies in CWSNs.

Once the main contributions are exposed and the conclusions are extracted, we can depict the future work.

6.2 FUTURE WORK

Some of the proposals for future works related to the development of this thesis are explained below. The realization of the first presented works would be interesting to expand the research into the area of energy consumption reduction in CWSNs. On the other hand, other future works are presented in order to implement joint optimization strategies for testing the possible interactions between them. Finally, works related to the testing in a real CWNS are exposed.

Implementing a cooperative strategy based on a cooperative game for energy consumption reduction could be interesting. After a non-cooperative strategy and a collaborative strategy based on a non-cooperative game, the natural next step is to implement a strategy where the nodes cooperate in order to achieve global results. After the design of the strategy, a formal analysis and test must be performed. Along with this game, the formation of cluster coalitions has to be studied.

Likewise, implementing PSO aimed to improve energy efficiency in CWSNs is another natural need. As we stated in Section 2.3, PSO fits well with the depicted scenario. Developed a strategy based in PSO and compare with the GTh based strategies is interesting in terms of evaluating the best method to accomplish energy sustainable CWSNs.

Related to the area of joint optimization implementations, it would be interesting to implement different spectrum sensing algorithms in order to improve the performance of the strategies. Also, a natural step forward is to jointly optimize power allocated with channel selection aim to reduce intra network interferences.

Related to the interactions with other CWSNs implementations and taking advantage of the knowledge about security research area in the B105 lab, the implementation of combined implementations in order to improve security and energy efficiency could be one of the next steps. In the same line, the coordination of these strategies with a controlled degradation of the network when nodes depleted their batteries is an interesting promising research area.

Finally, a valid testing in a real deployment of CWSN nodes should be performed. Even if the framework is designed as a combination of simulator and real devices features, the implementation in real large CWSNs serves as a deeper validation. For that purpose, as said in Chapter 4, the current work in progress includes the planning for the physical deployment of the CWSN B105 Lab Testbed nodes at the university building.

The more I study, the more insatiable do I feel my genius for it to be

Ada Lovelace

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If you obey all the rules, you miss all the fun

Katherine Hepburn

8 ACRONYMS LIST

API	Application Programming Interface
BER	Bit Error Rate
BR	Best Response
BWRC	Berkeley Wireless Research Center
CAgent	Cognitive Agent
CAGR	Compound Annual Growth Rate
CB	Connectivity Brokerage
CN	Cognitive Networks
cNGD	cognitive New Generation Device
COCRA	Comprehensive Optimal Cooperative Routing Algorithm
CogLEACH	Cognitive Low Energy Adaptive Clustering Hierarchy
Cog-MAC	Cognitive Media Access Control
CPU	Central Processing Unit
CR	Cognitive Radio
CRCN	Cognitive Radio Cognitive Network
C-RICER	Cognitive-Receiver Initiated CyclEd Receiver
CWSN	Cognitive Wireless Sensor Networks

EECUR	Energy Efficient Cognitive Unicast Routing
GA	Genetic Algorithm
GPIO	General Purpose Input Output
GTh	Game Theory
GUI	Graphical User Interface
HAL	Hardware Abstraction Layer
I2C	Inter Integrated Circuit
IEEE	Institute of Electrical and Electronic Engineers
IF	Impact Factor
IoT	Internet of Things
IR	InfraRed
ISM	Industrial Scientific and Medical
JCR	Journal Citation Report
JSCS	Joint Source and Channel Sensing
LEACH	Low Energy Adaptive Clustering Hierarchy
LQI	Link Quality Indicator
M2M	Machine to Machine
MAC	Media Access Control
MCU	Microcontroller Unit
MIMAC	Microchip's Media Access Control
MIMO	Multiple Input Multiple Output
NS	Network Simulator
OTA	Over The Air
P2P	Peer to Peer
PhD	Doctor of Philosophy
PSO	Particle Swarm Optimization
PU	Primary User
QoS	Quality of Service
RAM	Random Access Memory
RF	Radio Frequency
RSSI	Received Signal Strength Indicator
RX	Reception
SDR	Software Defined Radio

SENDORA	SEnsor Network for Dynamic and cOgnitive Radio Access
SPI	Serial Peripheral Interface
SU	Secondary User
TCP	Transmission Control Protocol
TKN	Telecommunication Network Group
TUB	Technical University Berlin
TWIST	TKN Wireless Indoor Sensor Network Test-bed
TX	Transmission
UART	Universal Asynchronous Receiver Transmitter
USB	Universal Serial Bus
VCC	Virtual Control Channel
VT-CORNET	Virginia Tech COgnitive Radio NEtwork Testbed
WBASN	Wireless Body Area Sensor Network
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network
WOR	Wake on Radio
WPAN	Wireless Personal Area Network
WSN	Wireless Sensor Network