UNIVERSIDAD POLITÉCNICA DE CARTAGENA

*DEPARTAMENTO DE TECNOLOGÍAS DE LA INFORMACIÓN Y LAS
COMUNICACIONES*

***CONTRIBUTION TO THE INTEGRATION,
PERFORMANCE IMPROVEMENT, AND SMART
MANAGEMENT OF DATA AND RESOURCES IN
THE INTERNET OF THINGS***

PHD THESIS

Rubén Martínez Sandoval

Supervised by:
Joan García Haro
Antonio Javier García Sánchez

July 2019

Universidad
Politécnica
de Cartagena

DT-16

**CONFORMIDAD DE SOLICITUD DE AUTORIZACIÓN DE DEPÓSITO DE
TESIS DOCTORAL POR EL/LA DIRECTOR/A DE LA TESIS**

D. Joan García Haro Director de la Tesis doctoral "Contribution to the Integration, Performance Improvement, and Smart Management of Data and Resources in the Internet of Things".

INFORMA:

Que la referida Tesis Doctoral, ha sido realizada por D. Rubén Martínez Sandoval, dentro del Programa de Doctorado "Tecnologías de la Información y las Comunicaciones", dando mi conformidad para que sea presentada ante el Comité de Dirección de la Escuela Internacional de Doctorado para ser autorizado su depósito.

La rama de conocimiento en la que esta tesis ha sido desarrollada es:

✓ Ingeniería y Arquitectura

En Cartagena, a 8 de junio de 2019

EL/LA DIRECTOR/A DE LA TESIS

Fdo.: Joan García Haro

Universidad
Politécnica
de Cartagena

DT-16

**CONFORMIDAD DE SOLICITUD DE AUTORIZACIÓN DE DEPÓSITO DE
TESIS DOCTORAL POR EL/LA DIRECTOR/A DE LA TESIS**

D. Antonio-Javier García Sánchez Co-director de la Tesis doctoral "Contribution to the Integration, Performance Improvement, and Smart Management of Data and Resources in the Internet of Things".

INFORMA:

Que la referida Tesis Doctoral, ha sido realizada por D. Rubén Martínez Sandoval, dentro del Programa de Doctorado "Tecnologías de la Información y las Comunicaciones", dando mi conformidad para que sea presentada ante el Comité de Dirección de la Escuela Internacional de Doctorado para ser autorizado su depósito.

La rama de conocimiento en la que esta tesis ha sido desarrollada es:

✓ Ingeniería y Arquitectura

En Cartagena, a 8 de Julio de 2019

EL/LA CO-DIRECTOR/A DE LA TESIS

[Redacted signature area]

Fdo.: ANTONIO J. GARCÍA SÁNCHEZ

Universidad
Politécnica
de Cartagena

DT-17

CONFORMIDAD DE DEPÓSITO DE TESIS DOCTORAL
POR LA COMISIÓN ACADÉMICA DEL PROGRAMA

D/D^a. Jorge Larrey Ruiz, Presidente/a de la Comisión Académica del Programa de Doctorado Tecnologías de la Información y las Comunicaciones.

INFORMA:

Que la Tesis Doctoral titulada, "Contribution to the Integration, Performance Improvement, and Smart Management of Data and Resources in the Internet of Things", ha sido realizada, dentro del mencionado Programa de Doctorado, por D. Rubén Martínez Sandoval, bajo la dirección y supervisión del Dr. Joan García Haro.

En reunión de la Comisión Académica, visto que en la misma se acreditan los indicios de calidad correspondientes y la autorización del Director/a de la misma, se acordó dar la conformidad, con la finalidad de que sea autorizado su depósito por el Comité de Dirección de la Escuela Internacional de Doctorado.

La Rama de conocimiento por la que esta tesis ha sido desarrollada es:

- Ingeniería y Arquitectura

En Cartagena, a 4 de Julio de 2019

EL PRESIDENTE DE LA COMISIÓN ACADÉMICA

Fdo: Jorge Larrey Ruiz

COMITÉ DE DIRECCIÓN ESCUELA INTERNACIONAL DE DOCTORADO

Universidad
Politécnica
de Cartagena

Sr. D. Rubén Martínez Sandoval

Visto el informe favorable del Director de Tesis y el Vº Bº de la Comisión Académica del Programa de Doctorado “Tecnologías de la Información y las Comunicaciones” para la presentación de la Tesis Doctoral titulada: **“Contribution to the integration, performance improvement, and smart management of data and resources in the Internet of Things”** solicitada por D. RUBÉN MARTÍNEZ SANDOVAL, el Comité de Dirección de la Escuela Internacional de Doctorado de la Universidad Politécnica de Cartagena, en reunión celebrada el 25 de julio de 2019, considerando lo dispuesto en el artículo 23 del Reglamento de Estudios Oficiales de Doctorado de la UPCT, aprobado en Consejo de Gobierno el 17 de diciembre de 2015,

ACUERDA

Autorizar la presentación de la Tesis Doctoral a D. Rubén Martínez Sandoval en la modalidad de “compendio de publicaciones”.

Contra el presente acuerdo, que no agota la vía administrativa, podrá formular recurso de alzada ante el Sr. Rector-Magnífico de la Universidad Politécnica de Cartagena, en el plazo de un mes a partir de la notificación de la presente.

Cartagena, 25 de julio de 2019

EL DIRECTOR DE LA ESCUELA
INTERNACIONAL DE DOCTORADO

Pdo.: Pablo S. Fernández Escámez

Escuela Técnicas Superior de Ingeniería de Telecomunicación (ETSIT)

This Thesis is presented as a compilation of the following articles:

1. **R. M. Sandoval**, A.-J. J. Garcia-Sanchez, F. Garcia-Sanchez, and J. Garcia-Haro, "Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz," *Sensors*, vol. 17, no. 1, p. 76, Dec. 2016. [1].
2. **R. M. Sandoval**, A.-J. J. Garcia-Sanchez, J.-M. M. Molina-Garcia-Pardo, F. Garcia-Sanchez, and J. Garcia-Haro, "Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band," *IEEE Trans. Wirel. Commun.*, vol. 16, no. 2, pp. 1294–1307, Feb. 2017. [2].
3. **R. M. Sandoval**, A. J. Garcia-Sanchez, and J. Garcia-Haro, "Improving RSSI-based path-loss models accuracy for critical infrastructures: A smart grid substation case-study," *IEEE Trans. Ind. Informatics*, vol. 14, no. 5, pp. 2230–2240, 2018. [3].
4. **R. M. Sandoval**, A.-J. Garcia-Sanchez, J. Garcia-Haro, and T. M. Chen, "Optimal policy derivation for Transmission Duty-Cycle constrained LPWAN," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 1–1, Aug. 2018. [4].
5. **R. M. Sandoval**, S. Canovas-Carrasco, A. Garcia-Sanchez, and J. Garcia-Haro, "Smart Usage of Multiple RAT in IoT-oriented 5G Networks: A Reinforcement Learning Approach," in *2018 ITU Kaleidoscope: Machine Learning for a 5G Future (ITU K)*, 2018, pp. 1–8. [5].

Mención internacional

1. Estancia en City, University of London (Londres, Reino Unido). Periodo 01/09/2017 - 01/12/2017 (3 meses).
2. Estancia en Cambridge University (Cambridge, Reino Unido). Periodo 01/07/2018 - 01/09/2018 (2 meses).

Agradecimientos

No podría esta sección empezar de otra forma que agradeciendo a mis tutores, Antonio y Joan, su trabajo y esfuerzo durante estos últimos 4 años.

Así mismo, quiero dar las gracias a mis compañeros de laboratorio y amigos por “ser”, pero sobre todo por “estar”. Esta tesis tiene un poco de cada uno de ellos.

Me gustaría también agradecer a mi padre el haberme inculcado el gran don de la curiosidad y las ganas de aprender, fundamentales para ser un buen Doctor. A mi madre, el haberme enseñado a perseverar y a *querer*, ambas capacidades necesarias para llegar hasta el final. A mi hermana, le estaré siempre agradecido por haberme acompañado en los primeros baches de la vida. Sin ella no habría abierto mis ojos al mundo y a la investigación.

Por supuesto, a Raquel por haberme acompañado y haber hecho suyo también cada paso de este camino. Gracias por haberme enseñado que en la vida todo lo bueno requiere su esfuerzo, y esta tesis no es ninguna excepción.

Abstract

The IoT has seen a tremendous growth in the last few years. Not only due to its potential to transform societies, but also as an enabling technology for many other technological advances. Unfortunately, the IoT is a relatively recent paradigm that lacks the maturity of other well-established (not so recent) revolutions like the internet itself or Wireless Sensor Networks; upon which the IoT is built.

The presented Thesis contributes to this maturation process by researching on the underlying communication mechanisms that enable a truly ubiquitous and effective IoT. As a *Thesis by compilation*, 5 relevant articles are introduced and discussed. Each of such articles delve into different key aspects that, in their own way, help closing the gap between what the IoT is expected to bring and what the IoT actually brings.

As thoroughly commented in the Introduction section of this document, the comprehensive approach taken in this Thesis ensures that multiple angles of the same plane –the communication plane– are analyzed and studied. From the mathematical analysis of how electromagnetic waves propagate through complex environments to the utilization of recent Machine Learning techniques, this Thesis explore a wide range of scientific and researching tools that are shown to improve the final performance of the IoT.

In the first three chapters of this document, the reader will be introduced to the current context and state-of-the-art of the IoT while, at the same time, the formal objectives of this Thesis are outlined and set into such a global context. In the next five chapters, the five corresponding articles are presented and commented. For each and every of these articles: a brief abstract, a methodology summary, a highlight on the results and contributions and final conclusions are also added. Lastly, in the two last chapters, the final conclusions and future lines of this Thesis are commented.

Contents

Contents	1
I Introduction, Objectives, and Context of this Thesis	5
1 Introduction	7
2 Objectives	11
2.1 General objectives	11
2.2 Specific objectives	13
3 State of the Art: Past and Present	15
3.1 The IoT as a (cutting-) edge technology	15
3.2 The IoT applied to Smart Grids	18
3.3 The IoT applied to Smart Cities and Industries	20
II Original Articles	23
1 Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz	25
2 Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band	41
3 Improving RSSI-Based Path-Loss Models Accuracy for Critical Infrastructures: A Smart Grid Substation Case-Study	57
4 Optimal Policy Derivation for Transmission Duty-Cycle Constrained LPWAN	69
5 Smart Usage of Multiple RAT in IoT-oriented 5G Networks: A Reinforcement Learning Approach	83

III	Summary of Articles	93
1	Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids	95
1.1	Brief summary	95
1.2	Methodology and tools	96
1.3	Results and Contributions	97
1.4	Conclusions	99
2	Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band	101
2.1	Brief summary	101
2.2	Methodology and tools	102
2.3	Results and Contributions	104
2.4	Conclusions	106
3	Improving RSSI-Based Path-Loss Models Accuracy for Critical Infrastructures: A Smart Grid Substation Case-Study	109
3.1	Brief summary	109
3.2	Methodology and tools	110
3.3	Results and Contributions	111
3.4	Conclusions	113
4	Optimal Policy Derivation for Transmission Duty-Cycle Constrained LPWAN	115
4.1	Brief summary	115
4.2	Methodology and tools	116
4.3	Results and Contributions	119
4.4	Conclusions	121
5	Smart Usage of Multiple RAT in IoT-oriented 5G Networks: A Reinforcement Learning Approach	123
5.1	Brief summary	123
5.2	Methodology and tools	124
5.3	Results and Contributions	128
5.4	Conclusions	129
IV	Conclusions and Future Lines	131
1	Conclusions	133
2	Future Lines	137

<i>CONTENTS</i>	3
V Appendices	139
VIReferences	143
Bibliography	145

Part I

Introduction, Objectives, and Context of this Thesis

Chapter 1

Introduction

The Internet of Things can be understood as a system of interrelated computing devices that connects the physical and virtual world through ubiquitous communications. This system extends to quotidian objects, providing them with communication and computing capabilities. Although people are more familiarized with the concept of IoT in contexts like home automation or Smart Cities, the truth is that the IoT encompasses many other environments, including productive sectors (like industries) or critical infrastructures (like electrical grids). However, it is precisely in this kind of environments where the reliability, performance, and cost of communications matters the most. When e.g. human lives (IoT monitoring civil infrastructures), production chains (industries) or the true cornerstone of modern societies (the electrical grids) are at risk, reckoning with a robust, efficient and reliable communication network is of paramount importance.

In that crucial context, this Thesis was conceived. The improvement of such an overly complex network (the IoT) can be tackled from a wide range of different perspectives. In fact, if we observe the IoT from a purely “telematic” perspective, we could simply regard it as a stack of protocols that work collaboratively and in a perfect balance. From that angle, we could aim to optimize one of such stack levels, trying to contribute with significant enhancements that could lead to a global improved IoT operation. However, by focusing our attention on a rather limited *action point*, we might as well simply translate the bottleneck from one point to another. Therefore, the approach followed in this Thesis has been a multi-level, holistic approach, in which several of these levels (of the aforementioned stack) have been covered and improved.

Shifting away from this multi-level perspective, and from a much more comprehensive point of view, one can also focus his/her efforts on directly achieving the various goals set for the IoT:

1. The IoT should intelligently and automatically orchestrate the different network resources required to make the physical world seamlessly blend with its virtual counterpart. That is, the IoT must be capable of integrating different network resources and technologies (such as different

communication protocols, IoT end devices of different technologies, etc.) with minimum human intervention. This desirable property is integral to this Thesis and included in the first part of its title: "Contribution to the Integration...". It is in the fifth article of the presented thesis where we have mainly focused on achieving a truly seamless integration of different IoT technologies.

2. Also, this orchestration must take place in an optimal way, unleashing the true potential of modern IoT technologies, and taking the most of them. For instance, in some environments, like industrial plants, reducing the latency of communications has a dramatic impact on fault prevention and quality control activities. Therefore, since the IoT must not be thought of as the final goal, but rather as a means to an end, we must ensure that the true underlying productive activity is not only undisrupted but enhanced. To this end, the best IoT-related goal to seek is to increase its raw performance. We have pursued this goal via (i) direct improvements (like increasing the data rate of IoT networks) and (ii) indirect improvements (like increasing the accuracy of simulators that can ultimately lead to a better planning of IoT networks). This important goal is reflected in the second part of the title: "Contribution to the [...] Performance Improvement", and mainly elaborated on in the first, second, and third articles presented in this Thesis.
3. We live in a world where Data has become the new Gold [6], companies like Google and Facebook let people use their platforms for free in exchange for their precious information. This is not different in the IoT arena. In industrial environments or critical infrastructures, it is even more important to timely receive the information that may save a life or prevent the malfunction of an important asset. Not only must this data be correctly delivered when the network is operating in ideal condition, but also when network performance degrades (e.g. due to worse propagation conditions or when resources are scarce). Therefore, the IoT must be smart enough to discard less important events. The correct management of Data is crucial in current societies and we have aimed at reflecting that in the title: "Contribution to the [...] Smart Management of Data". This topic has been mainly addressed in the fourth and fifth articles derived from this thesis.
4. However, none of the above goals can be attained if the scarce resources of the IoT are wasted. It is very well-known that IoT networks are designed with ease of management and cost in mind. As a consequence, IoT nodes (the constituent element of the IoT) are normally battery-powered, resource-constrained devices. They are battery powered to eliminate the need for costly inexhaustible energy source and are resource-constrained (in terms of CPU, memory, bandwidth, time to use the band, duty cycle, etc.) to reduce manufacturing and maintenance costs. Therefore, whatever algorithm these IoT devices implement, they must surely ac-

knowledge their limitation and constraints. Article first, fourth, and fifth explore the impact and potential solutions to this issue. Finally, the importance of proper resource management is also covered in the title: "Contribution to the [...] Smart Management of Resources".

Although the above four goals does not form a comprehensive list of all the relevant goals set for the IoT, it is true that attaining them will surely pave the way for effective and efficient IoT networks –and that is the reason why they are an integral part of this work–. In a nutshell, they are extremely relevant because: ensuring a correct, automatic integration of multiple technologies and resources –first goal– enables a scalable and robust infrastructure, where devices can accommodate to changes in the environment and network operators can easily allocate further resources if needed. If this *integration* goal is not achieved, the IoT will break down in isolated, manufacturer-dependent islands, incapable of growing and of providing those added services that characterize the IoT.

The second goal, ensuring a correct network performance, guarantees that the IoT can live up to the requirements, becoming a new virtual system over which services (e.g. monitoring, controlling, alerting, etc.) can be transparently offered to users and other machines. Failing to do so will make the IoT a technological solution incapable of living up to the requirements of current societies.

The third goal, ensuring a smart management of data, guarantees that the aforementioned islands of information are broken. This way, information flows freely, becoming available to those entities that need it the most and prioritizing such information if required. In times of Wireless Sensor Networks (regarded as the predecessor of the IoT), nodes were considered *dumb* agents that would be simple sources of raw data. This data was expected to –normally– be blindly sent to data sinks (i.e. gateways). However, thanks to the advances in electronics and computing hardware, IoT nodes are now embedded with enough algorithmic intelligence to discriminate between useless and relevant data, pre-process, and convert them into actual information before even transmitting them.

Finally, the last goal, smartly managing resources, is the necessary step to ensure that these limited nodes are capable of timely and effectively carry out their task. Although, traditionally, authors have thought of IoT nodes are being mainly CPU-limited, the truth is that other constraints (such as the time the ISM band can be used) are proven in this Thesis to also have a dramatic impact on network performance. Not fully acknowledging the multiple limitations of IoT nodes leads to unexpected results. Hence, the *raison d'être* of this goal.

As commented above, the IoT is not the final objective by itself, but rather a means to an end. Therefore, these goals –when attained– must be translated into a positive impact on whatever physical objects are augmented with the IoT. For instance, when deploying an IoT network in a city (transforming it into a so-called Smart City), the above four goals, will ensure a capable-enough underlying information network (i.e. the IoT) that provides extended services

and enriches citizens' lives. The extent of this positive impact is directly proportional to the need for communication and computing capabilities of the physical objects being augmented. In critical and time-sensitive environments (like power grids), reckoning with a sensing and control network that ensures the correct operation of the different constituent elements (e.g. transformers, switches, etc.) is crucial and can involve enormous operational savings and important risk reductions.

However, some of the environments that could benefit the most from the IoT may also present elements that can potentially disrupt the well-functioning of such communication networks. For instance, while power grids can truly benefit from ubiquitous sensing and communicating networks, the presence of many obstructing metallic infrastructure can lead to a harsh multi-path effect. The multi-path effect (thoroughly studied in the second article of this Thesis) promotes the emergence of delayed interfering wavefronts that can cause detrimental effects on the performance of the deployed network. Therefore, we, as engineers, must deploy the required countermeasures to prevent the above from happening. In a similar way, although much has been said about the potential benefits of the IoT in cities (again, giving rise to the concept of Smart City), the reality is that the very large areas to be covered may render IoT deployments unfeasible. Therefore, engineering efforts should be devoted to enable long-range, robust communications that can enable devices to seamlessly communicate with their peer at 1 or 10kms.

As a result of the aforementioned multi-level/holistic approach pursued in this Thesis, we also dedicated part of our efforts to investigate the effects of the propagation environment in IoT networks; focusing on a rather physical analysis of the IoT. We believed (and later corroborated) that reckoning with a precise propagation model was strictly necessary to anticipate and optimize the performance of these networks. When IoT nodes are deployed in harsh environments (like power grids) it is obvious that the physical propagation of waves will play an important role in the final network performance. However, in rather simple environments (like Cities), it is the sheer number of deployed smart *things* which complicates the propagation plane. As more and more nodes are deployed and expected to communicate through long-distance links, interference and propagation dynamics will, again, determine the final network performance. To enable researchers run more precise simulations (that can anticipate such a performance, and later optimize it), we developed a method by which accurate propagation models can be derived in a very low-cost manner.

For the reasons outlined in the above paragraphs, the presented Thesis is focused on Smart Grids on the one hand (due to the particular propagation environment and to the potential benefits of smartening the power grids), and Smart Cities/Industries on the other hand (due to the challenging long-distances to be covered, the large number of constituent devices –which may cause coordination problems–, and similarly, the potential impact of these two paradigms on current societies). Nonetheless, the arguments, algorithms, and analyses presented in this work are applicable to any other environment that aligns with the four goals aforementioned.

Chapter 2

Objectives

2.1 General objectives

Although the global goals to be pursued for the IoT have been described in the previous paragraphs, in this second section, the general and specific objectives of this Thesis are going to be detailed. As one could expect, the general objectives of this work are perfectly aligned with the goals set to be attained in the IoT arena. This guarantees that all the efforts devoted in this Thesis are in consonance with global and international efforts.

In total, six global objectives were pursued in this Thesis, four strongly related to the goals set for the IoT and two related to the two scenarios on which this Thesis is focused. Also, integral to these six objectives, there is an ethic commitment that has been pursued throughout the entire Thesis: the reproducibility of results. All contributions presented in this document have been supported by the release of the code, data, and instructions required to reproduce them. We believe that: (i) failing to commit to this high reproducibility standard would invalidate any claims made in scientific papers and (ii) that all scientific community should stick to such a practice to truly contribute to science.

Regarding the global objectives related to the goals set for the IoT (commented in the first Section):

1. General Objective 1: To positively contribute to the integration of different IoT technologies into a global network infrastructure. Described above in 1. Mainly pursued in the fifth article here presented (see Section 5).
2. General Objective 2: To positively contribute to the performance improvement of IoT networks (directly or indirectly as explained in the first section). Described above in 2. Mainly pursued in the first, second, and third articles here presented (see Sections 1, 2, and 3 respectively).

3. General Objective 3: To positively contribute to the management of Data in the IoT. Described above in 3. Mainly pursued in the fourth and fifth papers here presented (see Sections 4 and 5).
4. General Objective 4: To positively contribute to the management of scarce resources in the IoT. Described above in 4. Mainly pursued in the first, forth, and fifth articles here presented (see Sections 1, 4, and 5).

Regarding the way these four general objectives are pursued in this work, it is worth noting that, as previously indicated in the Summary, this Thesis aims to contribute to the IoT arena from a holistic approach. This is, not focusing on just one of the layers defined in the classic OSI protocol stack (physical layer, data link layer, network layer, etc.) On the contrary, we first established a set of general objectives that had an unarguably positive impact on the IoT, and then, geared article towards contributing to such general objectives via their own means and specific objectives. Nevertheless, due to the nature of IoT communications, to study them we had to first acquire an in-depth knowledge of how they took place from a physical point of view. Therefore, the first articles are mainly focused on the first layers of the aforementioned stack. However, in all of them, to not loose the *holistic* perspective, a final analysis of the impact of the physical phenomena on the higher layers is also carried out.

Given the tremendous impact of the IoT on a wide range of different environments, from the perspective of the general objectives, this Thesis is indeed focused on a subset of such environments. This is so, because we understand that not all contexts are aligned with the four IoT general objectives described in the first section. For instance, with regard to the fourth objective (the management of scarce resources), from a “home automation” perspective, the battery consumption may not be a performance limiting factor (due to the presence of wall sockets or thanks to power transference techniques –feasible due to closer distances–), whereas for cities or industrial environments, battery management is unarguably one of the most performance affecting factors.

Therefore, from the point of view of “where the IoT network is deployed”, and complementing the four general objectives of this Thesis:

1. General Objective 5: To positively contribute to IoT networks deployed in Smart Grids. We have focused on this environment due to the large number of demonstrated benefits for societies of Smart Grids and thinking of them as a cornerstone for the rest of critical infrastructures. Also, and as commented in several of the articles here presented, the number of academic works devoted to (some of the areas of) the Smart Grid is small due to the difficulty of physically accessing such environments and their strict regulations.
2. General Objective 6: To positively contribute to IoT networks deployed in Smart Cities and Industries. We have focused on this environment

as a catalyst for economical growth as well as a cornerstone in risk mitigation plans. Also, for Smart Cities we found that the sheer number of devices to be deployed make network planning a much harder task, whereas for Smart Industries the difficulties come from the propagation environment. Therefore, we believed (and later demonstrated) that the *holistic* approach was particularly well-suited.

2.2 Specific objectives

Once the general objectives pursued in this thesis are introduced, we shall continue with a detailed description of how they are attained through the five presented articles. Although each of these articles seek the achievement of their respective specific objectives, all of them are in line with the 6 general objectives –which underpin this work–.

To understand how each article contributes to this thesis, in the paragraphs below, the specific objectives attained by each article are detailed as well as how they contribute to each of the 6 general objectives.

First Publication: Evaluating the more suitable ISM frequency band for IoT-based Smart Grids: a quantitative study of 915MHz vs 2400MHz

- Specific Objective 1A: Determine which frequency band is best suited for the Smart Grid (in terms of performance impact) and under which conditions. Related to General Objectives 2 and 5.
- Specific Objective 1B: Determine which frequency band leads to a best management of the available resources: battery and frequency bandwidth. Related to General Objectives 4 and 5.
- Specific Objective 1C: Determine the impact of background noise on IoT communications for 915MHz and 2400MHz bands. Related to General Objectives 2 and 5.
- Specific Objective 1D: Determine the impact of visibility conditions on IoT communications. Related to General Objectives 2 and 5.

Second Publication: Radio-Channel Characterization of Smart Grid Substations in the 2.4GHz ISM Band

- Specific Objective 2A: Perform an in-depth characterization of Smart Grids; specifically, substations of such environment. Related to General Objectives 2 and 5.
- Specific Objective 2B: Raise awareness of the importance of accurate propagation models in complex IoT environments. Related to General Objectives 2 and 5.

- Specific Objective 2C: Demonstrate the impact of inaccurate propagation models (based on non-corrected raw RSSI readings) on IoT simulations. Related to General Objectives 2 and 5.

Third Publication: Improving RSSI-based path-loss models accuracy for critical infrastructures

- Specific Objective 3A: Enable the derivation of accurate propagation models via low-cost RSSI readings. Related to General Objectives 2, 5, and 6.
- Specific Objective 3B: Determine the impact of accurate propagation models (based on corrected RSSI readings) on IoT simulations. Related to General Objectives 2, 5, and 6.

Fourth Publication: Optimal policy derivation for Transmission Duty-Cycle constrained LPWAN

- Specific Objective 4A: Mathematically model Duty-Cycle constrained LPWANs, this ensures that the ISM band regulations are enforced. Related to General Objectives 4, 5, and 6.
- Specific Objective 4B: Integrate data priority into the process of determining optimal transmission policies. Related to General Objectives 3, 5, and 6.
- Specific Objective 4C: Optimize the mathematical models to guarantee that battery efficiency is maximized. Related to General Objectives 4, 5, and 6.

Fifth Publication: Smart usage of multiple RAT in IoT-oriented 5G networks: a reinforcement learning approach

- Specific Objective 5A: Derive optimal policies that determine the optimal Radio Access Technology to be used when considering usage quotas. Related to General Objectives 4 and 6.
- Specific Objective 5B: Integrate data priority and length into the process of determining optimal transmission policies. Related to General Objectives 3, 5, and 6.
- Specific Objective 5C: Ensure an efficient usage of battery in battery-powered IoT nodes. Related to General Objectives 4, 5, and 6.

Chapter 3

State of the Art: Past and Present

Due to the large impact of the IoT on numerous aspects of our societies, when reviewing the state of the art of this new suite of technologies, it is advisable to set the focus on a sub-set of all IoT-affected environments. As commented in previous sections, this Thesis mainly revolves around enhancing IoT networks deployed in: Smart Grids, Smart Cities, and Smart Industries. Therefore, after a subsection that elaborates on the past, present and future of the IoT (as a concept), the utility of the IoT in Smart Grids, Cities, and Industries will be addressed. However, as every of the five articles that composes this Thesis has its own review of related works, this section aims at providing a more general perspective on the application of IoT to each environment.

3.1 The IoT as a (cutting-) edge technology

The IoT has become one of the most hyped concepts in the Information and Communication Technologies (ICT) arena. This is true not only for the industrial and academic communities, but also for the general public as the Google Trend graph below demonstrates. This graph tracks the relative interest of a word (relative to the site's total search volume) over a given period of time. As shown in Fig. 3.1, since 2014 (when Google Trends was introduced), the interest in IoT has steadily grown over the years. This clearly indicates that the IoT, as a paradigm, is not just a passing fad, but a new way of thinking communications that will stay with us for a long time.

In fact, the prestigious technology firm Gartner in its latest annual report *Hype Cycle for Emerging Technologies* [7] –shown in Fig. 3.2–, indicates that IoT platforms are at the top of this hype cycle, and will stay as such for 5 to 10 years more. Being at the top of a hype cycle means that there *are* indeed inflated expectations but it also means that huge research efforts are devoted to the IoT. There are more than 25 thousand IoT-related articles indexed in the IEEEExplore [8] library, more than half of them having been published in

Figure 3.1: Interest over time of the “IoT” term in Google Search

the last two years. This tremendous *momentum* in the IoT research community has translated into a real consolidation and extraordinary level of maturity of this technology. Smart *things* are now part of: natural disaster detection systems [9], animal [10] and goods tracking mechanisms [11], smart water management processes [12], smart homes and buildings [13], crop field monitoring automatism’s [14], etc. This list could –literally– take pages and still be incomplete. From this small list of examples what we can derive is that the IoT now represents a way of bringing intelligence to where it is needed; a way to generate value from inanimate objects, a way to make –from an information perspective– things come to life.

Figure 3.2: Hype Cycle for Emerging Technologies 2018 – By Gartner

To better understand this revolutionizing process, the reader must first understand the origin of the IoT. The term “Internet of things” was coined by Kevin Ashton to describe the result of integrating radio frequency identification (RFID) and any other sensors to industrial goods [15]. Although later on it was extended to everyday objects, originally, it was conceived as a way to track and process information about goods traveling worldwide. The concept of letting *things* automatically generate, process and send information was quite disruptive at that time (1999). There is also an interesting underlying idea that has

been maturing, in parallel, throughout these years: the shift from centralized computing (back in the eighties and nineties, popularized by mainframes) to decentralized, distributed computing, which brings the intelligence to the edge of the network; that is, to the end devices (smart things) that conform such a network.

The IoT allows everyday objects to generate and process information, moving the *brain* of the networks to the edge. This, known as edge or fog computing [16], reduces delays and energy consumption (as information does not flow from the point of creation to distant clouds). The miniaturization of electronic circuits (with IBM leading this process [17]) has allowed the emergence of smaller, more energy efficient, inexpensive computing devices, that can now be embedded in almost every *thing* (from tracked goods in factories [18] to nano-networks inserted in humans [19, 20]).

Figure 3.3: Elements of the IoT: sensing, processing, and communicating.

Generally speaking, the key for success of this IoT-based smartening process (and for a true generation of information in the edge of the network) lies within three key ingredients (illustrated in Fig. 3.3): **sensors** (which constitute the input/source of information), **processing and connectivity** capabilities (which transform and distribute such information), and **people & processes** (which pertain to how the output or outcome is offered). Through sensing capabilities, things can now become aware of their surroundings, their position or their state (and, precisely, context-aware computing is a renowned sub-field of IoT [21]). Now, things can *know*. This knowledge can be pre-processed, transformed (as indicated above thanks to the inclusion of computing capabilities), and offered. This offering is made (normally) via wireless communications. Although the IoT was conceived to communicate via RFID, nowadays IoT devices are fitted with a myriad of different communication technologies: traditional cellular radios (GSM/3G/4G/5G) [22, 23], long-range low-power technologies like LoRa [24], old WSN standards like 802.15.4/Z-Wave [25], or short-range communication schemes like WiFi, Bluetooth, [26] etc. These networks of knowledge (acquired through sensors) and processed/offered information must encompass not only people but also processes. The former is very well accepted (services offered by the IoT must improve, in some direct way, peoples' lives), however, the latter (the fact that IoT must encompass other processes) is an interesting

reflection. Through Machine-to-machine (M2M) communications (expected to account for 20% of all generated traffic by the year 2022 ¹) *things* can interchange information to offer compound, complex services. For instance, in food chains, conveyor belts can adjust their pace according to how fast the goods are being produced. In homes, the heater can preemptively increase the temperature based on the weather forecast (offered by a smart weather station). Clearly, it is the cooperation of different *things* what truly creates an Internet of Things. If things remained disconnected from one another, we will not reach the Plateau of Productivity –illustrated in the bottom right part of Fig. 3.2– and we are in risk of returning back to the Wireless Sensor Network era (where devices did not offer information to their peers). Therefore, although every IoT-based service must eventually come as enhancement of peoples’ lives (via improvement of cities, industries, infrastructures, homes, etc.), simple services must be aggregated and shared among devices (first) to create composed, complex offers [27].

3.2 The IoT applied to Smart Grids

The Smart Grid (SG) is the technological evolution of current power grids and represents a big leap in terms of flexibility, efficiency and reliability of such grids. As thoroughly investigated in the papers that compose this Thesis, with the introduction of the IoT in this critical infrastructure (electrical network), many and crucial benefits are attained: from a safer and more robust power delivery, to a cheaper and greener electricity [28].

Figure 3.4: Smart Grid elements and segments. The power flow is matched by the information flow (provided by the IoT through different technologies) – Image reproduced from [29].

To understand the impact of the SG paradigm, one should first have a complete overview of the segments that constitute the SG. As depicted in Fig. 3.4, the SG is composed of four distinct segments:

¹<https://www.networkworld.com/article/3341099/wi-fi-6-5g-play-big-in-ciscos-mobile-forecast.html>

1. The Generation Segment, where energy is produced (ideally from renewable sources) and stored (if required).
2. The Transmission Segment, where energy is basically transported from distant generation plants to the *last mile*; near to consumers.
3. The Distribution Segment, where electricity is adapted to the requirements of consumers (normally to a lower voltage).
4. The Consumption Segment, where we find consumers (whether it be regular users, companies or institutions) and energy is finally consumed.

Note that behind these four segments, there is a parallel ubiquitous information plane that goes along the power flow plane, providing real-time communications and accurate control. Although most Smart Grid works reflect upon the Advance Metering Infrastructure [30] (due to its potential to improve metering precision, inform about pricing in real time, identify outages, etc.), this is just the tip of the iceberg. Communication systems can increase efficiency, robustness and provide enhanced services across any segment of the Smart Grid.

The United Nations (UN) estimated that, by the year 2050, more than 68% world's population will live in cities [31]. This means that cities (and their infrastructures) must be able to absorb large population influxes. To accomplish that, such infrastructures must achieve high efficiency levels, doing more with less. In this performance improvement process, power grids play a crucial role. Not only is the electricity the cornerstone upon which the rest of infrastructures rely (including telecommunication networks), but also, a temporary failure of such grids has been shown (in many power outage episodes) to have nefarious consequences to economies [32, 33].

To prevent power outages, ubiquitous communication networks (i.e. the IoT) are deployed along the power infrastructure. These networks ensure that complete reports on the health status of the grid can be timely delivered to control centers [34]. In such control centers, decisions, like disconnecting certain parts of the grid, can be taken to protect the rest of the network. Besides this improvement of robustness of the electrical grid, remotely and timely monitoring such a grid have many additional proven benefits:

- Improved Network Congestion Reduction: Substations, transformers and other power assets are better utilized if better resource balance schemes are used. When we have real time information about the usage of power assets, we can re-direct the power flow through infra-utilized routes or ask big players (industries) to stop power-hungry processes ([35, 36]).
- Enabling Real Time Pricing: Thanks to a better monitoring of the Generation Segment, and a comprehensive communication network (that encompasses homes and industries), information about the electricity price can be offered to smart appliances. These appliances can choose whether to activate themselves or not given the current price (e.g. business can

choose to run power-demanding processes when electricity prices are at its lowest point) [37].

- Match energy production and consumption: Thanks to detailed historical data of data-generation facilities (like wind or solar farms), Smart Grids can predict when the generation (and consumption) peaks will take place. This way, Electrical Grid managers can activate/deactivate temporary energy producing facilities (that depend, e.g., on fossil fuels) [38].
- Reduced operating costs: Thanks to a better health monitoring [39], Smart Grids can provide larger error-free running times. This translates to reduced maintenance costs and hence, a reduction on final operating costs (which in turn would have an impact on electricity price).

Ultimately, all these applications depend on having a robust communication network that can efficiently transmit valuable information from power assets to the internet. As commented on the Introduction (Section 1) of this Thesis, most IoT operate making use of wireless communications. Despite their improved flexibility and lower installation costs, communicating wirelessly in some Smart Grids contexts can be challenging. As many authors have indicated, the harsh radio propagation environment of Smart Grids may have a detrimental effect on wireless communications [40–42]. Therefore, to enable a true real-time, effective monitoring network, it is important to characterize and study such an environment.

In line with this proposal (to first characterize the propagation environment so we could later optimize the communication network), recent works have focused their efforts on the consumer segment [42, 43] due to its easier access. However, the Transport and Distribution segments were unexplored in this sense and thus, our decision to focused our efforts on this issue. Articles 1 and 2 (included below) try to deal with this problem.

3.3 The IoT applied to Smart Cities and Industries

When the IoT is applied in cities, it has the potential to transform many aspects of them. As with Smart Grids, having an ubiquitous monitoring network that can inform on the status of multiple assets in real time is very beneficial. For the potential readers to better understand the different ways in which IoTs deployed in Smart Cities could impact their lives, a brief list with some examples is included below:

- Smart Homes: By employing the data freshly acquired by a myriad of different sensors, homes become smart entities. For instance, smart thermostats can automatically regulate homes temperature based on weather forecasts or on pollution levels (e.g. closing windows and activating filtering when CO2 levels raise) [44]. Similarly, the inclusion of Machine Learning techniques can bring significant benefits to areas where tornadoes or other natural disasters are frequent [45]. In such conditions, a

Smart Home could raise an alert and immediately close windows and other physical accesses.

- **Smart Parking:** According to the Parking Network Association [46], in metropolitan cities and business centers, 30% of the traffic slowdowns are caused by traffic difficulties. These difficulties can be reduced by introducing smart systems that can re-direct drivers to parking slots, effectively cutting down parking times [47]. Also, one of the most beneficial byproducts of reducing parking times is decreasing CO emissions, which lead to major health benefits in dense cities.
- **Health Care:** Thanks to the miniaturization of electronics, the inclusion of sensing and communicating capabilities within patients becomes a reality. This way, they could be better monitored, for instance via implants reporting health status in real time [48]. Also, geolocation devices could also be embedded in ambulances to reduce response times [49] or falls among elderly people could be instantly reported to health centers [50].
- **Smart Transportation:** As with ambulances, cars and public means of transportation (buses, trains, etc.) could also be monitored. For instance, the inclusion of the IoT within private transports is known to be a key step for the autonomous driving systems [51]. Similarly, major cities around the globe already reckon with fully tracked public buses that reduce waiting times and increase efficiency. [52].
- **Smart Buildings:** Integral to this process of making *things* come to life is making buildings come to life. According to the Environmental Protection Agency [53], the average citizen spends 87% of his/her life indoor. This means that smartening up buildings is a worthy effort. Among recent efforts, it should be mentioned works devoted to increase energy efficiency at the same time that the ecological footprint is reduced [54], or works focused on increasing the comfort of residents in a fair and impartial way [55].
- **Smart Industries:** The Industrial Internet of Things (IIoT) is the last wave of the technological revolution that is known as Industry 4.0 [56]. IoT will combine the global reach of the internet with modern automation techniques, simplifying the operation and maintenance of industries. Among the opportunities that Smart Industries bring to modern societies we could highlight: Improved operational efficiency (as many recent works have proved, this new paradigm brings improved uptimes and asset utilization [57]), collaboration between machines and humans (which, according to a recent report from the World Economic Forum [58], will result in unprecedented levels of productivity and more engaging work experiences), and of course, a reduction of human safety risks by promptly stopping machinery when an emergency situation has been detected [59].

However, all of these advancements depend on reckoning with a robust wireless communication infrastructure, as no IoT algorithm can truly impact any of the aforementioned scenarios when working in isolation. In cities, industries and other large-scale environments, these links must be robust and, in most cases, of a long distance nature; complicating their feasibility. In this line, Low-Power Long-Range communications standards (like LoRa, Sigfox, etc.) has gained in popularity [60] due to its low maintenance cost and (obviously) long range nature.

Unfortunately, in European countries (and other countries like China, Japan, etc.) this long-range standards operate under severe regulatory constraints since they make use of the license-free Industry, Scientific, and Medical (ISM) frequency bands. As many authors have highlighted in the past few years [4, 61], such regulations can hinder the performance and, ultimately, the applicability of this paradigm. These constraints basically restrict the amount of time IoT nodes can access the wireless ISM bands, This time is known as Transmission Duty Cycle or TDC for short. In fact, many works have recently highlighted the importance of TDC-aware networks and the impact of such a limitation on several network Key Performance Indicators. Particularly, these two works ([62, 63]) illustrated this problem by trying to transmit real-time video in a Long-Range IoT deployment. Although interesting from a research point of view, both works deliberately break the TDC regulations by only complying with them in an aggregated point of view (the network does comply with regulations –when TDC is averaged over all devices–, but not individual devices). Given the importance of these regulatory constraints, we have focused the fourth article to circumvent some of the derived limitations. The final goal is to allow these long-range communication standards to serve as the enabling technology for all the advancements commented above.

Another interesting problem that arise in environments like Smart Cities or Industries is how to manage the vast amount of required communications [60]. Since most IoT devices communicate via wireless links, much effort is being devoted to the development of new Radio Access Technologies (RATs) –or a better combination of them– that can alleviate the expected network congestion. According to the prediction of Cisco [64], by the year 2022 there will be 14.6 billion of IoT-originated connections. This implies an enormous congestion of the wireless spectrum. Hence the need to increase the number of available RATs or to come up with a way to better coordinate them. In this sense, many IoT subfields have emerged, from heterogeneous IoT networks [65, 66], cognitive IoT networks [67] (mainly focused on how to offer the licensed cellular spectrum to secondary users), to Multi-RAT approaches [68]. All these papers ultimately aim at attaining the same objective: reducing congestion and increase radio efficiency. In this line, in our fifth paper, we investigated how multiple RAT can be combined (e.g. 5G and LoRa) to attain higher efficiency levels and extend IoT node lifetimes.

Part II

Original Articles

Chapter 1

Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz

Article

Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz

Ruben M. Sandoval, Antonio-Javier Garcia-Sanchez *, Felipe Garcia-Sanchez and Joan Garcia-Haro

Department of Information and Communication Technologies, Universidad Politécnica de Cartagena (UPCT), Campus Muralla del Mar, E-30202 Cartagena, Spain; ruben.martinez@upct.es (R.M.S.); felipe.garcia@upct.es (F.G.-S.); joang.haro@upct.es (J.G.-H.)

* Correspondence: antoniojavier.garcia@upct.es; Tel.: +34-968-326-538; Fax: +34-968-325-973

Academic Editor: Gonzalo Pajares Martinsanz

Received: 15 November 2016; Accepted: 28 December 2016; Published: 31 December 2016

Abstract: IoT has begun to be employed pervasively in industrial environments and critical infrastructures thanks to its positive impact on performance and efficiency. Among these environments, the Smart Grid (SG) excels as the perfect host for this technology, mainly due to its potential to become the motor of the rest of electrically-dependent infrastructures. To make this SG-oriented IoT cost-effective, most deployments employ unlicensed ISM bands, specifically the 2400 MHz one, due to its extended communication bandwidth in comparison with lower bands. This band has been extensively used for years by Wireless Sensor Networks (WSN) and Mobile Ad-hoc Networks (MANET), from which the IoT technologically inherits. However, this work questions and evaluates the suitability of such a “default” communication band in SG environments, compared with the 915 MHz ISM band. A comprehensive quantitative comparison of these bands has been accomplished in terms of: power consumption, average network delay, and packet reception rate. To allow such a study, a dual-band propagation model specifically designed for the SG has been derived, tested, and incorporated into the well-known TOSSIM simulator. Simulation results reveal that only in the absence of other 2400 MHz interfering devices (such as WiFi or Bluetooth) or in small networks, is the 2400 MHz band the best option. In any other case, SG-oriented IoT quantitatively perform better if operating in the 915 MHz band.

Keywords: smart grid; internet of things; wireless sensor networks; evaluation; propagation

1. Introduction

The Internet of Things (IoT) has emerged as a potential game changer for the way people interact with technology on a daily basis, seamlessly connecting the physical and digital worlds by using the Internet. Although the general public strongly associates the IoT with concepts such as “home automation” or “home appliances”, the truth is that the IoT aims at being (and has the potential to be) employed pervasively in many other environments—from industrial machinery to the water supply chain, Smart Cities (SC), Smart Grids (SG), etc. One of the main additional advantages of applying IoT technologies to these industrial fields is that we can rapidly improve infrastructure or industry performance in an affordable and cost-effective way [1].

Among these industrial fields, one particularly excels for its potential to have a particularly positive impact on the society via the application of the IoT: the SG [2]. The SG is called to revolutionize the way electricity is generated, distributed and finally consumed by every of us. By the inclusion of two-way communication systems, the electricity grid will become a more efficient, reliable, and flexible infrastructure [3], and although there are other technologies that could also be applied in the

SG (like traditional centralized, wired communications), inexpensive deployment costs and the flexible and easy-to-configure nature of the IoT make it one of the most appropriate approaches for renovating the traditional power grid [1].

Nonetheless, like most Information and Communication Technologies (ICTs), the IoT strongly relies on wireless communications as its main enabling technology. Thus, deep insights into this form of transmission are of paramount importance to unleash the true potential of the IoT – and this is even more so in the SG where the complex and heterogeneous environments they operate in play a major role in the communication process. Many of these underlying wireless technologies that IoT systems employ, have been directly borrowed from Wireless Sensor Networks (WSN) or Mobile ad hoc Networks (MANET), as they originally paved the way for the emergence of these new paradigms [4]. Thus, communication technologies employed by most IoT devices are those used in WSNs or MANETs—either Mobile Telecommunications Technologies (MTT), such as 3G/4G [5,6], Cognitive Radio (CR)-based solutions [7–9] or technologies operating in the 2400 MHz ISM unlicensed band, such as WiFi, ZigBee or Bluetooth [10–12].

Since IoT-based SG should strive for high levels of self-independence and cost-effectiveness, it is not generally advisable to rely on private or licensed bands (such as those used in MTT). Unexpected and uncontrolled MTT failures or high expenditure costs can make deployments economically or technically unfeasible. On the other hand, although wideband Cognitive Radio (CR) approaches have also been thoroughly studied in the literature, the increased cost multi-band transceivers makes this approach unfeasible if intended to be used in every device of an IoT network – note that the IoT is envisaged to consist of more than hundreds or thousands of devices [13]. For these reasons, most battery-powered IoT devices that are conceived to operate in SG use ISM bands [14], generally the 2400 MHz one, and employ low-power standards such as the 802.15.4, 6LoWPAN or ZigBee [15–17].

Although there are other ISM unlicensed bands that have also been exploited since the emergence of the WSN (apart from the 2400 MHz), the evolution to the IoT left them practically unused. The reason to do so was the higher transmission rate that the aforementioned standards provide for the 2400 MHz band (250 Kb/s) along with lower power consumption (orders of magnitude smaller than other non-low-power 2400 MHz standards, such as WiFi, or other ISM bands such as the 5 GHz).

Another key aspect known by the research community is that most of IoT-based SGs do not make extensive use of the network; they transmit information very occasionally [18]. This is particularly true in some segments of the SG such as substations or solar plants/wind farms. There, the different elements are monitored (via IoT devices) and their information aggregated (once sent to a gateway) before being transferred to a central processing station (through wired internet networks), where data are stored and analyzed. Therefore, the work cycle of IoT devices operating in such environments, generally boils down to sensing some physical parameter (s) (temperature, pressure, humidity, etc.), interact with other devices periodically or on demand, and finally, provide some form of added-value service (such as a complete report on the status of a specific transformer or the energy generation rate of some windmills). This gives rise to a very relaxed duty cycle; allowing devices to remain silent and dormant most of the time in order to reduce their power consumption. Therefore, in some IoT networks deployed in SG, there is no pressing need to employ “high” data rates, and it seems logical to explore the advantages and disadvantages of using other unlicensed standardized ISM bands with smaller bandwidth.

Off-the-shelf IoT devices that make use of the 802.15.4/6LoWPAN/ZigBee low-power standards operate in one of the three following bands: 2400, 915 or 868 MHz [19]. While the two former bands have more than ten channels in which IoT devices may work; the 868 MHz band only offers one channel. This issue may represent an unsurmountable obstacle in scenarios where the large number of IoT devices may force the use of channel-assigning algorithms to prevent an increase of interferences and collisions [20–22]. Therefore, as a smaller-bandwidth alternative to the 2400 MHz band, the 915 MHz one may represent an option for IoT-based SGs worth studying. As a matter of fact, although such a

band works at slower rates (40 Kb/s), it has some appreciable benefits; among them, we should note two that are crucial in the SG arena: longer coverage and less power consumption.

In this context, the main contribution of this paper is an exhaustive and quantitative analysis of the impact of the working frequency band (915 MHz or 2400 MHz) on an SG-oriented IoT network. We have focused our study on an SG's generic-enough substation for two reasons: firstly, it is a representative scenario in which the SG may benefit from smaller transmission bandwidths. And secondly, very few works have studied this environment in depth from the wireless communication perspective [23]. Given the complex nature of such a scenario (full of large metallic structures and high levels of electromagnetic noise), we have characterized it for the two aforementioned bands. Hence, the second contribution of this work: a dual-band propagation model focused on IoTs operating in SG's substations. This second contribution is critical as reckoning with an accurate propagation model is of paramount importance in evaluating different IoT environments with high precision.

To evaluate both bands, we have incorporated this propagation model in TOSSIM [24], a very well-known and extensively employed simulator for IoT/WSN networks. We have also extended TOSSIM with the ability to simulate the 915 MHz band and the ability to support different line-of-sight visibility conditions for IoT devices deployed in the same network. This way, and with the help of several information-extraction scripts programmed for this work, we have analyzed and derived valuable information from different simulated environments. Both, the propagation model and the extensions/tools for the TOSSIM simulator have been made publicly available in [25].

It is worth mentioning that although this paper is focused on analyzing and quantifying the performance of the 915 MHz and 2400 MHz bands, the results derived for the 915 MHz band are translatable to the 868 MHz one. This is due to the small frequency gap between these two bands (60 MHz in the worst case) and the relatively large coherence bandwidth (CBW) of the channel (in average, 94.20 MHz). The coherence bandwidth is defined as the range of frequencies over which two frequency components are likely to experience similar amplitude fading [26]. Hence, two bands with a maximum frequency gap smaller than the channel's CBW will be strongly correlated (in terms of the propagation phenomena experienced).

The final aim of this work is thus, to empower the process of choosing the working frequency band for SG-oriented IoT networks with enough quantitative metrics (such as battery consumption or network delay) to shift it from a premade industry decision to a requirements-based decision. The rest of the paper is organized as follows. Section 2 reviews previous related work. Section 3 details the propagation model, the methodology followed and the improvements made on the TOSSIM simulator. In Section 4 we present and discuss the results obtained for different configurations of interest. Finally, Section 5 summarizes the main conclusions.

2. Related Work

The application of the IoT to the SG is a relatively new field, nonetheless underpinned by the wide experience of the academic community in WSN and MANET [4,16]. Parikh et al. [14] looked into different enabling technologies available for the SG, paying special attention to the benefits and drawbacks of each one, whereas [1] directly explored the architecture of the future IoT-based power grids as well as the key technologies that make this possible. Similarly, [27] analyzed the positive impact of the IoT on the energy domain, highlighting the sheer potential of such innovation in our daily lives. Finally, [28] elaborated on the positive impact that Fog Computing—a computing paradigm closely related to the IoT—may have on the Smart Grid arena. All in all, although these works study the enabling technologies in depth, they do not address the actual impact on the SG-oriented IoT of communication issues (such as the working frequency band).

Regarding the study of wireless propagation, Kusy et al. [29] studied the effects on the percentage of packet losses of incorporating two radio interfaces in WSN nodes: one working at 2400 MHz and another in the 915 MHz band. Although very accurate and illustrative, the work was focused on WSNs

operating in forests, which does not share many similarities with the IoT for SGs. Hrovat et al. [30] analyzed two Smart City critical infrastructures' propagation environments in the 400 MHz, 868 MHz and 2400 MHz bands. However, this study concentrates on elaborating empirical propagation models and does not evaluate/quantify their work with any figure of merit that may demonstrate the impact of the obtained models on actual IoT networks. Along the same lines, reference [31] proposed an accurate industrial propagation model capable of predicting low-level propagation characteristics with high accuracy in different frequency bands, whereas reference [32] provided near-ground path loss measurements for wireless deployments in indoor corridors for the different working frequencies. In general terms, the available literature—and these two studies in particular—focus on studying the low-level propagation phenomena applicable to different frequency bands, irrespective of the impact of such phenomena to the upper technologies (802.15.4, WiFi, Bluetooth, etc.) or the overall context (WSN, IoT, etc.).

To the best of our knowledge, there is no scientific literature that jointly analyzes, quantifies and compares the effects of different working frequencies on an IoT deployment. Similarly, we have not found any study that proposes a dual-band propagation model for the Smart Grid.

3. Methods and Tools

In this section we elaborate on the methods and tools required to evaluate the impact of the working frequency band on an IoT-based SG. The process followed is sketched in Figure 1, which synthesizes the six steps (blocks) required to quantitatively simulate the wireless network under study with high accuracy.

Figure 1. The six-step process followed to extract the propagation data, model the environment, define the network and finally, simulate and evaluate it.

3.1. Selected Variables and KPIs

In order to quantify the impact of the frequency band on an IoT network operating in an SG scenario, we consider three Key Performance Indicators (KPIs): the Packet Reception Rate (PRR), the Mean Network Delay (MND), and the Power Consumption per Packet Transmission (PCPT). PRR computes the percentage of issued packets that reach the receiver, illustrating how lossy the network is at that frequency. MND accounts for the mean time a given packet takes to arrive to the final receiver; if such a packet gets lost, retransmissions will be issued until it is received and accounted in the MND (the retransmission protocol employed is a simple stop-and-wait Automatic Repeat request or ARQ algorithm [33] which makes use of ACKs and timeouts to ensure packet reception). This metric reflects the average response time (or responsivity) of the network. Regarding the PCPT, only the consumption derived from the network interfaces was considered. Thereby, we separated the CPU consumption (which is technology-dependent, and thus, not relevant to this work) from the radio consumption (which is highly band-dependent). To evaluate this figure, we have considered the currents drawn (as per specified in their respective datasheets) of two devices that have been

extensively employed in the literature: the CC2420 (a radio transceiver for the 2400 MHz band) and the CC1000 (working in the 915 MHz band), both making use of the low-power 802.15.4 standard.

By defining these three KPIs, we can fully evaluate the performance of the network under several different situations. To study how each band responds to such conditions, three variables have been considered in the analysis: (i) level of background noise in the working band, (ii) packet length, and (iii) mean distance between nodes ($\bar{D}_{in}$). With regard to the noise, it is widely known that the 2400 MHz band is heavily used by many other wireless technologies apart from the 802.15.4 standard: Bluetooth, WiFi, cordless phones, etc. Thus, to study the effects of this phenomenon we have considered two scenarios: one in which the network is operating in a relatively interference-free area (hereinafter referred as Scenario 1) and one surrounded by many other 2400 MHz wireless devices (Scenario 2). Also, the packet size has been varied by modifying the payload length. By increasing it from 6 to 12, 18, and 24 bytes, we obtain a total packet length of 25, 31, 37, and 43 bytes, respectively (we considered the overhead of the IEEE 802.15.4 standard valued in 19 bytes). Finally, the mean distance between nodes has been controlled by a scaling factor α that multiplies the default distance between pairs of nodes, thus varying the mean inter-node distance ($\bar{D}_{in}$). A scaling factor of one ($\alpha = 1$) corresponds to the base network (see Figure 2a) that presents a $\bar{D}_{in}$ of 7.73 m.

Figure 2a represents the base network on which the variations described above have been tested. Such a network consists of eight devices in charge of monitoring different aspects of an SG's substation and of providing added-value services by exchanging information among them (e.g., notifications of an unexpected global increase in temperature). Devices are arranged under different line-of-sight conditions: line-of-sight visibility (LOS, blue line), obstructed line-of-sight visibility (OLOS, green line) and non-line-of-sight visibility (NLOS, red line). Furthermore, they are deployed following a star topology with the explicit objective of not considering the effects of multi-hop algorithms on final results. This decision makes our conclusions much more algorithm-independent. Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) interferences produced by other neighboring devices (neglected in many other works) have also been studied and accounted for.

Figure 2. (a) Simulated base network (b) SG substation where the data was acquired.

3.2. Propagation Model

To be able to evaluate the behavior of the communication network presented above, we derived and implemented an accurate propagation model that was finally programmed in the TOSSIM simulator. This task was decomposed into two steps: first, we acquired real propagation data in an SG substation (a Spanish energy provider; see Figure 2b) by means of a high-end Vector Network Analyzer (the E5071B – VNA, Agilent Technologies®, Santa Clara, CA, USA). Finally, a mathematical model that approximates the propagation behavior of the SG was chosen

(see Equations (1) and (2)) and fitted to the acquired data. This two-fold approach guarantees that if the fitting process is thorough, the propagation model will replicate the original data, and thus, an SG environment.

Arguably, the most important propagation phenomenon when simulating narrow-band communications (such as the 802.15.4 standard) is the relation between the received power and distance to the transmitter. Thus, we have focused on accurately replicating this relation. To do so, we distinguish three visibility conditions between device pairs: LOS, OLOS and NLOS. Differentiating these scenarios is of paramount importance as propagation losses have been proven to be strongly influenced by the visibility conditions of communication links [17,31,34]. In order to model this phenomenon, we have first obtained a series of measures (via the VNA) under the aforementioned visibility conditions: the VNA generates a known signal that travels the wireless medium before reaching the receiver. Then, the differences between the transmitted and the received signal are analyzed and lastly fitted to a propagation model. This procedure is repeated for the following distances: 1, 2, 5, 10, 15, 20, 25, and 30 m. In order to gain statistical confidence, for each distance, we have acquired up to 30 individual measurements over an area of $\lambda/2$ (i.e. half of the wavelength, which translates to 32.8 cm and 12.5 cm for the 915 MHz and 2400 MHz respectively). This is a fairly common method in characterizing propagation environments [31,35] and is carried out with the intention of make the derived propagation model as much general as possible.

This procedure is rerun for both bands: the 915 MHz and the 2400 MHz ones. Figure 3 above shows the received power vs distance for the different visibility conditions and frequency bands (along with the 95% confidence intervals).

Figure 3. Received power vs. distance for (a) LOS, (b) OLOS, and (c) NLOS visibility conditions in an SG environment. 95% confidence intervals are also included.

As explained before, the main purpose of the propagation model is to replicate the behavior of the acquired data (presented in Figure 3) under the three different visibility conditions. The first significant phenomenon in Figure 3a–c to reproduce is the progressive deterioration of communication as the receiver moves away from the transmitter (i.e., less power is received when the distance increases $\bar{D}_{in}$ grows). This and other important phenomena, such as the presence of greater losses in NLOS than OLOS/LOS or larger losses in higher frequencies, can be adequately characterized by a very well-known propagation model: the log-normal shadowing path-loss model (LNSPL) [36].

The LNSPL (Equation (1)) models the dependency of received power on distance by considering the distance d at which we evaluate the path losses. It permits modulating the effect of this phenomenon (the rate at which the received power decays with distance) by adjusting the path loss exponent n for different scenarios, frequencies and visibility conditions. Furthermore, the variance over the mean received power is adjusted for each situation by a zero mean Gaussian random variable (X_σ) – which represents the variability of the received power over the expected value. Finally, in Figure 3 it can also be observed that the received power at the first measured distance is not zero, but it has an offset that depends on the conditions evaluated. This effect is considered in the LNSPL model by the base path losses (BPL) at a reference distance d_0 . These base path losses are generally calculated by the Free Space Path Loss (FPSL) formula (Equation (2)) where d_0 takes the value of 1 m for convenience and comparability of results and λ is the wavelength of the working frequency [36]:

$$PL(d, n, \sigma)_{dB} = BPL(d_0) + 10 n \log_{10} \left(\frac{d}{d_0} \right) + X_\sigma \quad (1)$$

$$FSPS(d_0, \lambda) = 10 \log_{10} \left(\frac{4 \pi d_0}{\lambda} \right)^2 \quad (2)$$

Once the appropriate propagation model is chosen, it is adjusted to replicate the acquired data (Figure 3). To do so, we have minimized the sum square error (SSE) between the real data and the propagation model (Equation (3)). Mathematically the SSE is defined as follows:

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

where y_i represents the real data and $\hat{y}_i$ the predicted data for a given measure i . In turn, $\hat{y}_i$ is computed by Equation (1) and y_i is obtained by calculating the difference between transmitted and received signal's power in the VNA. The value of Equation (3) is then minimized by Gradient Descent, a well-known iterative optimization algorithm extensively used in the IoT and WSN arena [37–39]. Such an algorithm is able to find (in this case) a pair of n and σ that reduces the differences between predicted and real data. This approach is particularly suitable for the LNSPL model as it exhibits good mathematical properties such as differentiability and convexity (features desirable to reach the global minimum of the SSE in the network under study). Table 1 shows the exact values of the LNSPL model for the three visibility conditions and the two working frequency bands as well obtained following the described procedure.

Table 1. Obtained propagation model's parameters for both frequency bands and different visibility conditions.

Scenario	LNSPL Model
915 MHz – LOS	$PL(d)_{dB} = 31.67 + 10 \cdot 1.642 \cdot \log_{10}(d) + X_{2.876}$
915 MHz – OLOS	$PL(d)_{dB} = 31.67 + 10 \cdot 1.924 \cdot \log_{10}(d) + X_{3.131}$
915 MHz – NLOS	$PL(d)_{dB} = 31.67 + 10 \cdot 2.520 \cdot \log_{10}(d) + X_{3.033}$
2400 MHz – LOS	$PL(d)_{dB} = 40.05 + 10 \cdot 1.888 \cdot \log_{10}(d) + X_{4.775}$
2400 MHz – OLOS	$PL(d)_{dB} = 40.05 + 10 \cdot 2.346 \cdot \log_{10}(d) + X_{4.582}$
2400 MHz – NLOS	$PL(d)_{dB} = 40.05 + 10 \cdot 2.788 \cdot \log_{10}(d) + X_{3.962}$

It is worth mentioning that, as expected, the path-loss exponents are greater for the NLOS than OLOS or LOS communications. On the other hand, the 915 MHz frequency band, gives rise to more predictable links (lower values of σ) in comparison with the 2400 MHz band.

Figure 4 shows the good fit of the LNSPL model to the data. The depicted markers represent the acquired data (i.e. the average values of Figure 3) whereas the continuous lines illustrate the fitted model (whose formulae for each scenario are detailed in Table 1).

Figure 4. Acquired data and obtained model for (a) LOS, (b) OLOS, and (c) NLOS and both frequency bands.

Aside from the received power at a specific distance, the presence of electromagnetic interferences (EMI) has also been analyzed for both frequency bands. This is of paramount importance as EMI plays an important role in scenarios like substations where there are many potential sources of background noise (such as switchgears, transformers, etc.) [40,41]. A FSH3 spectrum analyzer (Rhode & Schwarz®, Munich, Germany) has been used to this end.

Although each medium/high voltage substation might be different, most of them share many common features such as the presence of big-sized metallic structures (transformers, switchgears, etc.) at both sides of clear corridors (passageways) with overhead metallic wires (the bus bars, overhead lines, etc.) all along them. Furthermore, the minimum distance between energized structures (such as transformers) and the passageways are defined by strict security regulations (such as the High Voltage Protection Action initiative of PSEG [42], the HV design considerations of the IEEE Houston Section [43], etc.). These two key aspects make many substations' layout share, indeed, common

features. And, although the specific disposition of certain elements may have an impact on propagation parameters, the rough propagation numbers in such substations will remain approximately the same.

3.3. Improvements on the TOSSIM Simulator

Traditionally, the TOSSIM simulator has been used to evaluate well-defined, homogeneous scenarios, i.e., ones where all nodes experience the same propagation phenomena. However, in complex and heterogeneous settings like SG's substations, different visibility conditions and propagation phenomena may be experienced. These differences lead to variations in propagation losses and/or noise conditions that cannot be neglected by modern simulations. Another issue worth looking into it is the fact that TOSSIM has always been geared towards the evaluation of 2.4 GHz links; and hence, it lacks the necessary mechanisms to evaluate other WSN/IoT working frequencies.

Therefore, to accurately evaluate the network under study, we have extended the TOSSIM simulator to: (i) be able to embrace the heterogeneous nature of a SG and (ii) allow different working frequencies for deployed IoT devices.

The first task translates into modifying TOSSIM to permit the presence of different nodes working under various visibility conditions (e.g., the node pairs 0-4 of Figure 2a work under line-of-sight, whereas 0-3 may operate under NLOS conditions). By modifying TOSSIM's architecture, we enabled each node pair to have its own combination of n (path-loss exponent) and σ (standard deviation). This makes the simulation environment more flexible. Furthermore, in order to simulate different frequencies, it is also required to generate distinct BPL values according to the working frequency under use. The second issue is addressed to provide the appropriate signal modulation scheme in accordance with the frequency band. The reason is obvious; 915 MHz transceivers usually employ different modulation schemes than 2400 MHz transceivers. Hence, when the 915 MHz band is under use, the frequency-shift keying (FSK) modulation scheme is utilized (the one typically exploited by transceivers operating in such a band), whereas when transmitting in the 2400 MHz band, the OQPSK (offset quadrature phase-shift keying) modulation scheme is used. Both, FSK and OQPSK, have been implemented into TOSSIM simulator. The full modifications carried out in the TOSSIM simulator, along with the automatization scripts are at the disposal of interested readers in [25].

4. 915 MHz/2400 MHz Bands' Performance in SG-oriented IoTs

In this section, we present and discuss the performance results, in terms of the three key performance indicators, of the two scenarios evaluated. We start by listing the variables employed in the Scenario 1 (the one with 2.4 GHz co-existing devices) and the obtained results. Then, the noise conditions are altered (Scenario 2) to show a different condition on which an SG-oriented IoT may operate.

Both scenarios share some common parameters: the payload lengths assessed (6, 12, 18, and 24 bytes), the scaling factors (α) evaluated (0.5 to 1.5 in steps of 0.05), the transmission rate of each band (40 Kbps for the 915 MHz band and 250 Kbps for the 2400 MHz one, as defined by the 802.15.4 standard), and the packet generation rate (modeled via a random uniform distribution which generates a packet every 1 to 3 s). Data generation rate, payload length and α ranges are in line with the nature of SG-oriented IoT services and are chosen so as to effectively illustrate when it is more beneficial to work in one band or another. Furthermore, the above packet lengths reproduce the wide variety of services that SG-oriented IoT may offer: from very limited reports that may fit in payloads of six bytes, such as informing of a particular switchgear temperature, to more complex ones that may need (one or more) 24-byte packets, such as a complete report of a transformer status.

4.1. Scenario 1: Presence of 2400 MHz Co-Existing Devices

In this scenario, we consider an environment in which the 2400 MHz band is extensively employed by many other devices and hence, suffers moderate interference levels with an average noise floor of -87.4 dB. The 915 MHz band, on the other hand, as it is not usually shared with other technologies

nowadays, remains relatively free from interference, presenting an average noise floor of -93.85 dB. These exact noise values have been obtained from the real SG under consideration using the Rhode & Schwarz® FSH3 spectrum analyzer and are incorporated in the TOSSIM simulator.

The results obtained are shown in Figure 5a for the packet reception rate (PRR), Figure 5b for the mean network delay (MND), and Figure 5c for power consumption per packet transmission (PCPT).

Figure 5. Results of the Scenario 1 for different packet sizes and resizing factors. (a) PRR, (b) MND, and (c) PCPT.

The first and most notable highlight of Figure 5a is the good behavior of the 915 MHz band (blue, upper lines) compared with the 2400 MHz band (red, lower lines) in terms of PRR. The reason for this is threefold: firstly, differences in LNSPL models (presented in Table 1) reveal the tendency of the 2400 MHz band to attenuate signals more than the 915 MHz band. Secondly, the 2400 MHz band experiences a higher noise floor level due to the presence of other co-existing devices. Finally, the OQPSK modulation (employed in the 2400 MHz band) tends to perform slightly worse in terms of PRR versus signal-to-noise ratio than the FSK modulation (used in the 915 MHz band) [44].

Both bands face the typical effects of the distance on the PRR. When α (and thus $\bar{D}_{in}$) increases, the received power decreases, leading to a larger number of packet losses and a decrease of the PRR. However, this KPI is not affected evenly in both bands, as the 2400 MHz band deteriorates slightly faster than the 915 MHz band due to higher path-losses. Regarding the packet size, larger packets produce smaller PRR values; given a certain bit error rate, an increment of the payload length always implies a smaller PRR. However, we can claim that packet size is not a crucial variable as it entails a PRR drop of less than 5%, on average, when increasing the payload length from 6 bytes to 24 bytes.

When the number of packet losses increases (and hence, the PRR decreases) a higher number of retransmissions is issued. This leads to an increment of the MND as this KPI takes into account the extra time taken by retransmissions (Figure 5b). Therefore, it should be noted that even though the

transmission rate of the 2400 MHz band is higher, due to big differences in terms of PRR, the MND of the 2400 MHz band is, on average, four times larger than that obtained for the 915 MHz band. Under these circumstances, this phenomenon makes the 2400 MHz band less adequate for delay-sensitive applications. As with the PRR, an increment of the scaling factor (α) negatively affects the MND in both bands. Again, due to differences in path-losses, the 2400 MHz band is much more sensitive to α than the 915 MHz band. Considering the dependency of MND with α , the 2400 MHz band grows seven times faster than the 915 MHz band.

Figure 5c illustrates the PCPT. The very low value for the 2400 MHz band is, again, produced by the large volume of retransmissions, which greatly increases the power consumption. The 2400 MHz-band consumption is up to 120 times larger than the 915 MHz one (1187 joules versus 9.7 joules per packet transmission for a packet length of 24 B and $\alpha = 1.5$). Therefore, the latter band should become the preferred choice for energy-constrained IoT deployments.

4.2. Scenario 2: Absence of 2400 MHz Co-Existing Devices

A capital factor in the performance of wireless networks is their coexistence with other devices operating in the same frequency band. This second scenario evaluates the situation in which an IoT is deployed in an environment that presents the same amount of interference in both bands (set to -93.85 dB).

This will generally be the case in which the SG is placed in a remote area—hence, the absence of other interfering 2400 MHz devices. The rest of the variables will remain unaltered. As in the previous scenario, the PRR is greater for the 915 MHz band than for the 2400 MHz one (Figure 6a). However, the sheer differences that appeared in Scenario 1 are no longer present when both bands are subject to the same noise conditions. Nevertheless, the PRR for the 2400 MHz band is still much more affected by the resizing factor due to, mainly, a larger path loss, decreasing 2.25 times faster with α than for the 915 MHz band.

Figure 6b shows a general outlook of the MND results, whereas Figure 6c depicts a close-up of the first α points. The results reveal a very interesting fact: in terms of MND, there are distances for which the 2400 MHz band is better suited than the 915 MHz one (and vice versa). When communicating devices are relatively far apart (e.g., greater than $\alpha = 0.996$ or $\bar{D}_{in} = 7.7$ m for a packet length of 6 B), the increment of path losses in the 2400 MHz band cannot be compensated by the higher transmission rate, thus resulting in larger MND values in this band. Conversely, when the resizing factor is small, the short number of packet losses does not play a major role in the MND, since the transmission rate is a more determining factor and presents a smaller value for the 915 MHz band. Therefore, when designing delay-sensitive networks, one should consider not only the transmission rate of the chosen band but also the $\bar{D}_{in}$ of the deployment, incorporating it as a key design parameter.

Since both the MND and the PCPT are affected by the number of retransmissions, they are strongly influenced by the packet losses, evaluated by the PRR. Therefore, the PCPT shows a similar tendency with α than the MND. Again, there are specific values of α for which SG-oriented IoT operating in the 2400 MHz band will benefit from a lower power consumption and vice versa. For example, for 6-byte long payloads, devices working in the 2400 MHz band will consume less energy if the network presents a small $\bar{D}_{in}$ (specifically, values of $\bar{D}_{in}$ smaller than 6.96 m or $\alpha = 0.9$). This is explained by the behavior of the PRR along with the time that the transceiver requires to transmit a packet. When the PRR is relatively high for both bands, the much shorter transmitting times of the 2400 MHz band make the total power consumption smaller; power consumption strongly depends on the time the device is actively sending a packet. However, when the PRR drops abruptly ($\alpha > 0.9$), these shorter times cannot compensate for the large number of losses.

Furthermore, since bigger packets take longer times, the 2400 MHz especially benefits from a faster transmission rate when transmitting larger payloads. Finally, as α grows, the power consumption in the 2400 MHz band greatly increases due to a corresponding decrease of the PRR. This increment

leads to a PCPT up to 12 times higher for the 2400 MHz band than for the 915 MHz one for a 24-byte long payload.

Figure 6. Results of Scenario 2 for different packet sizes and resizing factors. (a) PRR, (b) MND, (c) Zoom of MND, (d) PCPT, and (e) Zoom of PCPT.

5. Conclusions

A comprehensive study of how the working frequency band (915 MHz or 2400 MHz) affects IoT networks operating in SGs has been conducted. To do so, we have proposed a dual-band propagation model based on the well-established LNSPL model. Our model implementation has been geared towards IoT-based SG networks and with a special focus on radio propagation visibility conditions (LOS/OLoS/NLOS). Accordingly, we have extended the TOSSIM simulator to incorporate this new propagation model and developed a set of tools to efficiently extract data from a series of simulations.

By defining specific KPI (PRR, MND, and PCPT), we have quantified the performance of the IoT network under different scenarios. In general terms, we can unexpectedly affirm that in SG scenarios where the 2400 MHz band is used by other devices, the 915 MHz band is always the best option in terms of the three analyzed KPI, regardless of the packet length, and $\bar{D}_{in}$ (mean inter-node distance). However, when both bands are equally affected by a similar noise level, there are particular values

CHAPTER 1. EVALUATING THE MORE SUITABLE ISM FREQUENCY BAND FOR IOT-BASED SMART GRIDS: A QUANTITATIVE STUDY OF 915 MHZ VS. 2400 MHZ

Sensors 2017, 17, 76

13 of 15

of $\bar{D}_{in}$ for which each band is better suited: the 2400 MHz band is the preferred option for small size networks, whereas for large size networks the 915 MHz band is the best choice.

Although the exact values of when to use one or another band will depend on the specific environment and network layout, the models and figures presented here seek to raise awareness and set ground rules for when to consider the proper standardized ISM band in SG environments as the best option.

Acknowledgments: This research was supported by the MINECO/FEDER project grants TEC2013-47016-C2-2-R (COINS) and TEC2016-76465-C2-1-R (AIM). The authors would like to thank Juan Salvador Perez Madrid and Domingo Meca (part of the Iberdrola staff) for the support provided during the realization of this work. Ruben M. Sandoval also thanks the Spanish MICINN for an FPU (REF FPU14/03424) pre-doctoral fellowship.

Author Contributions: Ruben M. Sandoval and Antonio-Javier Garcia Sanchez conceived the idea, proposed the scientific methodology and performed the measurements campaigns. Ruben M. Sandoval conducted the simulations. Felipe Garcia-Sanchez and Joan Garcia-Haro contributed to the technical improvements. All authors participated in the review of the related works, analysis of the results, elaboration of the manuscript and its revision.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Yun, M.; Yuxin, B. Research on the architecture and key technology of Internet of Things (IoT) applied on smart grid. In Proceedings of the International Conference on Advances in Energy Engineering, Beijing, China, 19–20 June 2010; pp. 69–72.
2. Blumsack, S.; Fernandez, A. Ready or not, here comes the smart grid! *Energy* **2012**, *37*, 61–68. [\[CrossRef\]](#)
3. Martinez-Sandoval, R.; Garcia-Sanchez, A.J.; Garcia-Sanchez, F.; Garcia-Haro, J.; Flynn, D. A comprehensive WSN-based approach to efficiently manage a smart grid. *Sensors* **2014**, *14*, 18748–18783. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Bellavista, P.; Cardone, G.; Corradi, A.; Foschini, L. Convergence of MANET and WSN in IoT urban scenarios. *IEEE Sens. J.* **2013**, *13*, 3558–3567. [\[CrossRef\]](#)
5. Hossen, M.; Jang, B.J. Extension of wireless sensor network by employing RoF-based 4G network. In Proceedings of the 11th International Conference on Advanced Communication Technology, Phoenix Park Gangwon-Do, Korea, 15–18 February 2009; Volume 1, pp. 275–278.
6. Eddabbah, M.; Moussaoui, M.; Laaziz, Y. A flexible 3G WebService based gateway for wireless sensor networks in support of remote patient monitoring systems. In Proceedings of the 2014 Mediterranean Microwave Symposium (MMS2014), Marrakech, Morocco, 12–14 December 2014; pp. 1–5.
7. Akyildiz, I.F.; Lee, W.-Y.; Vuran, M.C.; Mohanty, S. NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Comput. Netw.* **2006**, *50*, 2127–2159. [\[CrossRef\]](#)
8. Akan, O.B.; Karli, O.B.; Ergul, O. Cognitive radio sensor networks. *IEEE Netw.* **2009**, *23*, 34–40. [\[CrossRef\]](#)
9. Yang, Z.; Shi, Z.; Jin, C. SACRB-MAC: A High-Capacity MAC Protocol for Cognitive Radio Sensor Networks in Smart Grid. *Sensors* **2016**, *16*, 464. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Gharghan, S.K.; Nordin, R.; Ismail, M. Energy-Efficient ZigBee-Based Wireless Sensor Network for Track Bicycle Performance Monitoring. *Sensors* **2014**, *14*, 15573–15592. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Lopez-Iturri, P.; Aguirre, E.; Azpilicueta, L.; Astrain, J.J.; Villadangos, J.; Falcone, F. Implementation and Analysis of ISM 2.4 GHz Wireless Sensor Network Systems in Judo Training Venues. *Sensors* **2016**, *16*, 1247. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Tuwanut, P.; Kraijak, S. A survey on IoT architectures, protocols, applications, security, privacy, real-world implementation and future trends. In Proceedings of the 16th International Conference on Communication Technology, Hangzhou, China, 18–20 October 2015; pp. 26–31.
13. Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Gener. Comput. Syst.* **2013**, *29*, 1645–1660. [\[CrossRef\]](#)
14. Parikh, P.P.; Kanabar, M.G.; Sidhu, T.S. Opportunities and challenges of wireless communication technologies for smart grid applications. In Proceedings of the 2010 IEEE Power and Energy Society General Meeting, Minneapolis, MN, USA, 25–29 July 2010; pp. 1–7.
15. Ma, R.; Chen, H.H.; Huang, Y.R.; Meng, W. Smart grid communication: Its challenges and opportunities. *IEEE Trans. Smart Grid* **2013**, *4*, 36–46. [\[CrossRef\]](#)

16. Fadel, E.; Gungor, V.C.; Nassef, L.; Akkari, N.; Maik, M.G.A.; Almasri, S.; Akyildiz, I.F. A survey on wireless sensor networks for smart grid. *Comput. Commun.* **2015**, *71*, 22–33. [[CrossRef](#)]
17. Kilic, N.; Gungor, V.C. Analysis of low power wireless links in smart grid environments. *Comput. Netw.* **2013**, *57*, 1192–1203. [[CrossRef](#)]
18. Palattella, M.R.; Accettura, N.; Grieco, L.A.; Boggia, G.; Dohler, M.; Engel, T. On Optimal Scheduling in Duty-Cycled Industrial IoT Applications Using IEEE802.15.4e TSCH. *IEEE Sens. J.* **2013**, *13*, 3655–3666. [[CrossRef](#)]
19. Molisch, A.F.; Balakrishnan, K.; Chong, C.; Emami, S.; Fort, A.; Karedal, J.; Kunisch, J.; Schantz, H.; Schuster, U.; Siwiak, K. IEEE 802.15.4a Channel Model. Available online: <http://www.ieee802.org/15/pub/2004/15-04-0662-00-004a-channel-model-final-report-r1.pdf> (accessed on 29 December 2016).
20. Subramanian, A.P.; Gupta, H.; Das, S.R.; Cao, J. Minimum Interference Channel Assignment in Multiradio Wireless Mesh Networks. *IEEE Trans. Mobile Comput.* **2008**, *7*, 1459–1473. [[CrossRef](#)]
21. Wu, D.; Bao, L.; Liu, C.H. Scalable Channel Allocation and Access Scheduling for Wireless Internet-of-Things. *IEEE Sens. J.* **2013**, *13*, 3596–3604. [[CrossRef](#)]
22. Kim, H. Low power routing and channel allocation method of wireless video sensor networks for Internet of Things (IoT). In Proceedings of the IEEE World Forum on Internet of Things (WF-IoT), Seoul, Korea, 6–8 March 2014; pp. 446–451.
23. Güzelgöz, S.; Arslan, H.; Islam, A.; Domijan, A. A Review of Wireless and PLC Propagation Channel Characteristics for Smart Grid Environments. *J. Electr. Comput. Eng.* **2011**, *2011*, 1–12. [[CrossRef](#)]
24. Levis, P.; Lee, N.; Welsh, M.; Culler, D. TOSSIM: Accurate and Scalable Simulation of Entire TinyOS Applications. In Proceedings of the 1st International Conference on Embedded Networked Sensor Systems, Los Angeles, CA, USA, 5–7 November 2003; ACM: New York, NY, USA; pp. 126–137.
25. Sandoval, R.M.; Garcia-Sanchez, A.-J.; Garcia-Sanchez, F.; Garcia-Haro, J. Propagation Model and Tools. Available online: <http://labit501.upct.es/~rmartinez/915vs2400/> (accessed on 30 December 2016).
26. Instruments, N. National Instruments—Coherence Bandwidth. Available online: <http://www.ni.com/white-paper/14910/en/> (accessed on 16 December 2016).
27. Karnouskos, S. The cooperative internet of things enabled smart grid. In Proceedings of the 14th IEEE international symposium on consumer electronics (ISCE2010), Braunschweig, Germany, 7–10 June 2010; pp. 7–10.
28. Bonomi, F.; Milito, R.; Zhu, J.; Addepalli, S. Fog Computing and Its Role in the Internet of Things. In Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing, Helsinki, Finland, 17 August 2012; ACM: New York, NY, USA; pp. 13–16.
29. Kusy, B.; Richter, C.; Hu, W.; Afanasyev, M.; Jurdak, R.; Brunig, M.; Abbott, D.; Huynh, C.; Ostry, D. Radio diversity for reliable communication in WSNs. In Proceedings of the 10th ACM/IEEE International Conference on Information Processing in Sensor Networks, Chicago, IL, USA, 12–14 April 2011; pp. 270–281.
30. Hrovat, A.; Javornik, T. Radio channel models for wireless sensor networks in smart city applications. In Proceedings of the 2013 International Conference on Electronics, Signal Processing and Communication Systems, Gold Coast, Australia, 16–18 December 2013; pp. 95–99.
31. Ferrer Coll, J.; Dolz Martin de Ojeda, J.; Stenumgaard, P.; Marzal Romeu, S.; Chilo, J. Industrial indoor environment characterization—Propagation models. In Proceedings of the 10th International Symposium on Electromagnetic Compatibility, Long Beach, CA, USA, 26–30 August 2011; pp. 245–249.
32. Rao, T.R.; Balachander, D.; Nishesh, T.; Prasad, M. Near ground path gain measurements at 433/868/915/2400 MHz in indoor corridor for wireless sensor networks. *Telecommun. Syst.* **2014**, *56*, 347–355.
33. Tanenbaum, A.S. Computer Networks. In *Computer Networks*; Prentice Hall PTR: Upper Saddle River, NJ, USA, 2003.
34. Tanghe, E.; Joseph, W.; Bruyne, J.D.; Verloock, L.; Martens, L. The industrial indoor channel: Statistical analysis of the power delay profile. *AEU Int. J. Electron. Commun.* **2010**, *64*, 806–812. [[CrossRef](#)]
35. Rappaport, T.S. Characterization of UHF multipath radio channels in factory buildings. *IEEE Trans. Antennas Propag.* **1989**, *37*, 1058–1069. [[CrossRef](#)]
36. Rappaport, T.S.; MacCartney, G.R.; Samimi, M.K.; Sun, S. Wideband Millimeter-Wave Propagation Measurements and Channel Models for Future Wireless Communication System Design. *IEEE Trans. Commun.* **2015**, *63*, 3029–3056. [[CrossRef](#)]

CHAPTER 1. EVALUATING THE MORE SUITABLE ISM FREQUENCY
BAND FOR IOT-BASED SMART GRIDS: A QUANTITATIVE STUDY OF
40 915 MHZ VS. 2400 MHZ

Sensors 2017, 17, 76

15 of 15

37. Latsoudas, G.; Sidiropoulos, N.D. A Fast and Effective Multidimensional Scaling Approach for Node Localization in Wireless Sensor Networks. *IEEE Trans. Signal Process.* **2007**, *55*, 5121–5127. [[CrossRef](#)]
38. Garg, R.; Varna, A.L.; Wu, M. An Efficient Gradient Descent Approach to Secure Localization in Resource Constrained Wireless Sensor Networks. *IEEE Trans. Inf. Forensics Secur.* **2012**, *7*, 717–730. [[CrossRef](#)]
39. Yao, L.; Sheng, Q.Z.; Ngu, A.H.H.; Ashman, H.; Li, X. Exploring Recommendations in Internet of Things. In Proceedings of the 37th International ACM SIGIR Conference on Research & Development in Information Retrieval, Gold Coast, Australia, 6–11 July 2014; ACM: New York, NY, USA; pp. 855–858.
40. Shapoury, A.; Kezunovic, M. Noise Profile of Wireless Channels in High Voltage Substations. In Proceedings of the 2007 IEEE Power Engineering Society General Meeting, 24–28 June 2007; pp. 1–8.
41. Sallabi, F.M.; Gaouda, A.M.; El-Hag, A.H.; Salama, M.M.A. Evaluation of ZigBee Wireless Sensor Networks Under High Power Disturbances. *IEEE Trans. Power Deliv.* **2014**, *29*, 13–20. [[CrossRef](#)]
42. PSEG—High Voltage Protection Action. Available online: https://www.pseg.com/business/local_government/safety/pdf/HighVoltageProximityActGov.pdf (accessed on 19 December 2016).
43. IEEE Houston Section—High Voltage Substation Application Design. Available online: <http://sites.ieee.org/houston/files/2016/04/2012-10-02-HV-Substation-Application-Design-Oct-2-3.pdf> (accessed on 19 December 2016).
44. Vuran, M.C.; Akyildiz, I.F. Error Control in Wireless Sensor Networks: A Cross Layer Analysis. *IEEE/ACM Trans. Netw.* **2009**, *17*, 1186–1199. [[CrossRef](#)]

© 2016 by the authors; licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license (<http://creativecommons.org/licenses/by/4.0/>).

Chapter 2

Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band

Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band

Ruben M. Sandoval, *Member, IEEE*, Antonio-Javier Garcia-Sanchez, Jose-Maria Molina-Garcia-Pardo,
Felipe Garcia-Sanchez, and Joan Garcia-Haro, *Member, IEEE*

Abstract—The smart grid (SG) represents the present and the future of electric power grids. Wireless networks (WNs) are a key technology for this updating process, empowering electric networks to be easily managed in a flexible and cost-effective way. However, as with any wireless technology and especially in a harsh multipath environment such as the SG, reckoning with an extensive channel characterization is crucial. This paper presents an exhaustive characterization of two representative scenarios, both in the transport and distribution segment of an SG: a 400-kV outdoor substation and a main power room. The 2.4-GHz ISM band—in which most wireless communication technologies applied to SG operate—is examined in depth to characterize the radio-propagation phenomena. Large and small-scale fading, RMS delay, coherence bandwidth, and electromagnetic interferences are studied under different line-of-sight, polarizations, and frequency conditions to derive empirical models allowing to estimate the aforementioned parameters in other SGs of a similar nature. Finally, to further evaluate and compare our channel characterization, a WN was simulated in a substation to examine the channel modeling impact on its suitable design and operation.

Index Terms—Channel characterization, network simulation, propagation model, smart grid, wireless sensor networks.

I. INTRODUCTION

THE Smart Grid (SG) represents a modernization in the way electricity is generated, distributed and consumed in twenty-first-century society through the convergence of a wide variety of information and communication technologies (ICT), ranging from sensing to communicating. Some of the most important benefits that the SG can provide include: a real shift from fossil fuels to renewable energies, a steep increase in energy efficiency and a reduction in the greenhouse gas emissions and electricity prices. These advantages are making the general public aware of the immense potential of this relatively new paradigm.

Manuscript received April 4, 2016; revised July 30, 2016, October 24, 2016 and December 5, 2016; accepted December 19, 2016. Date of publication December 23, 2016; date of current version February 9, 2017. This work was supported in part by the MINECO/FEDER under Project TEC2013-47016-C2-2-R (COINS) and Project TEC2016-76465-C2-1-R (AIM) and in part by Spanish MICINN for an FPU through a Pre-Doctoral Fellowship under Grant REF FPU14/03424. The associate editor coordinating the review of this paper and approving it for publication was G. D. Durgin.

The authors are with the Department of Tecnologías de la Información y Comunicaciones, Antigo Hospital de Marina, Universidad Politécnica de Cartagena, 30202 Cartagena, Spain (e-mail: ruben.martinez@upct.es; antoniojavier.garcia@upct.es; josemaria.molina@upct.es; felipe.garcia@upct.es; joang.haro@upct.es).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TWC.2016.2644610

Although the existing electrical grid is the most complex and sophisticated engineering system of the 20th century [1], the electric utility has not yet been able to leverage the potential of the advances in ICT [2]. Cutting-edge innovations in sensing, communication and control must become standard practice in the future grid and a more reliable two-way communication architecture is clearly needed to overcome, for instance, current and unpleasant shortfalls (such as blackouts or lack of real-time information on households consumption). In short, the SG will improve the traditional electrical grid to be more cooperative, economical, intelligent, trustworthy and responsive [3]. After this renovating process, the electricity grid will turn into a more reliable and secure infrastructure, increasing its role as a cornerstone of the information society in which we live and, at the same time, helping the remaining infrastructures to unleash their true potential (water supply, transportation, telecommunications, etc.).

To fully understand this process of renovation from an academic perspective, we must first understand the core components of the SG. The SG basically encompasses three distinct segments: the Generation Segment (where power plants and storage systems lie), the Transmission and Distribution Segment (T&D; where substations, transformers and power lines can be found), and the Consumer Segment (including consumers' premises) [4]. Great research effort has been devoted to the study of the Consumer Segment and its context since it is clearly the easiest and most available environment [5]–[7]. Thanks to this academic effort, many initiatives have been proposed and are being deployed, such as the automatic metering infrastructure [8], [9], dynamic pricing initiatives [10], [11], and demand response systems [12], among others. The Generation Segment has also been widely studied from the automation, control and communication perspective, and SCADA-like (Supervisory Control And Data Acquisition) approaches have become popular due to their reliability and good results [13], [14]. These two segments (consumer and generation) are very well known and, as we observed, extensively investigated by the scientific community, but both ultimately rely on the proper operation of the intermediate segment: the T&D segment. This segment has attracted much less attention from the technology and communication perspective due to its difficult physical access and its extremely harsh environment. This can raise concerns, negatively affecting the remaining segments, especially when many current and future SG works are supported by wireless communication-based technologies [4], [15], [16].

When designing SG initiatives that make extensive use of communications, and particularly wireless communications, it is of paramount importance to have an in-depth knowledge of the signal propagation medium. This is even more so when the working environment is full of electromagnetic interferences and complex metallic structures that will affect communications [17], like those in substations located in the T&D segment. In this sense, some papers have highlighted the pressing need to study channel characteristics of the SG specific communication environment since they are a crucial factor in determining the ultimate performance of any communication system [17]–[20]. Unfortunately, and this has also been pointed out in previous works [17], [21], the academic community lacks an exhaustive channel characterization of many of these complex environments, especially in the T&D segment. Therefore, current SG-wireless technologies operating in the T&D segment cannot be appropriately simulated or their performance fully anticipated and optimized.

To the best of our knowledge, just one work has attempted to address this shortage. Gungor *et al.* [22] modeled the wireless channel of three distinct scenarios of the T&D segment using the log-normal shadowing path-loss model (LNSPL model). To achieve this, they made use of wireless sensor nodes and their ability to measure the received power (via the RSSI indicator) in order to estimate the parameters of the aforementioned propagation model. This approach, although straightforward, raises three concerns: firstly, the RSSI indicator can only be obtained from successfully received packets, and hence, those packets received with a power less than the fairly limited sensitivity threshold of the WSN nodes will not be accounted for. This may lead to biased results, because only a certain part of the transmitted packets are considered when computing the path-loss model. Secondly, the LNSPL model is a large-scale propagation model and does not reflect precise changes in signal power when sensor nodes are moved within a small area (it is a “coarse-grain” approximation). Finally, many other indicators, aside from the two variables of the LNSPL model (path loss and standard deviation), are needed to fully characterize a radio channel; e.g., power delay profiles, root mean square (RMS) delays, coherence bandwidth, measurements of the polarization effects, among others.

To tackle these concerns, the main objective of this paper was to present an in-depth analysis of the propagation phenomena that a wireless network operating in an SG may have to deal with. Large and small-scale fading, RMS delay, coherence bandwidth and electromagnetic interferences have been studied under different line-of-sight, polarization, and frequency conditions. In this line, a mathematical model has also been provided to allow for estimating them in other SGs of a similar nature.

This paper analyzed a bandwidth (BW) of 800MHz centred at the 2.4GHz band due to the large amount of WSN technologies that operate on the 2.4GHz ISM band (e.g., Bluetooth, ZigBee, Wi-Fi, etc.). At the same time, considering a large enough BW of 800MHz yields a better time resolution, which, as will be shown in the third section of this paper, is crucial to the accuracy of the data collected.

We believe that the results presented in this work are relevant for the design of future SG wireless systems and for accurately measuring and optimizing the performance of current developments. It is worth mentioning that the results of this study (including raw measured data) are made publicly available to support the research in this area [23].

The rest of this paper is organized as follows. Section II explains the main mathematical and physical concepts behind radio channel characterization. The third section introduces the methodology employed in this research and details the scenarios under consideration. Then, the following section presents the results and figures of the measurements carried out. The fifth section elaborates on the results and explores the impact of such figures on an actual Wireless Sensor Network deployed in an SG. Finally, section VI summarizes the main conclusions.

II. CHANNEL CHARACTERIZATION PARAMETERS

As stated in the previous section, characterizing the radio propagation channel is of paramount importance in the development and evaluation of proper wireless-based technologies. Furthermore, having an accurate model of the radio environment (as the one proposed in this work) is equally important and some works have pointed out that, even when simulating the simplest communication protocols, results may greatly differ when using inaccurate models [19], [24].

Characterizing the propagation environment is an extremely hard task due to the large number of phenomena that may affect transmitted signals. Well-established approaches deal with this problem by firstly obtaining the channel impulse response (CIR) of the propagation environment and lastly deriving valuable numeric figures from it [25]. One of the most significant parameters obtained from the CIR is the power delay profile (PDP), which represents the distribution of signal power as a function of propagation delays [26]. The PDP is of particular interest when the communication channel is within a rich multipath environment. Multipath interferences have proven to be the major cause of signal degradation in such scenarios [27] by promoting the emergence of delayed interfering wavefronts. The T&D segment of the power grid, with its many sharp metallic structures of variable size (e.g., transformers, circuit switchers, steel towers, etc.), is a good example of a harsh multipath environment.

To characterize the multipath nature of the T&D segment, two parameters were analyzed: the root mean square delay spread (RMS delay spread or simply σ_t) and the coherence BW, both derived from the PDP [28]. The RMS delay spread is the square root of the second moment of the PDP. Furthermore, the RMS delay spread is thought to be one of the most useful figures in quantifying the impact of multipath channels since it sets an upper limit to the communications modulation rate [29]. The coherence BW determines the range of frequencies over which the frequency response of the channel can be considered flat, hence characterizing the frequency selectivity behavior of the channel. Having a wide enough coherence BW prevents the intersymbol interference (ISI) from occurring, which enormously degrades the quality of the channel and

sets an upper bound to the communication speed (bit rate) achievable.

The following lines describe the procedure to obtain the aforementioned parameters. The instantaneous PDP (IP) is defined as the square magnitude of the CIR:

$$IP(\tau, t, x) = |h(\tau, t, x)|^2, \quad (1)$$

where τ represents the propagation delay, t is the instant at which the IP was obtained, and x the spatial position. The CIR is, in turn, obtained by calculating the inverse Fourier transform of the frequency response of the channel acquired by a network analyzer [25]; the equipment used and the measuring procedure is explained in the next section. To reduce side lobes and to get a much smoother response, a common technique is to multiply the frequency response by a Hanning window of the same size. To prevent this process from affecting the absolute value of the PDP, the correction technique introduced by Molina-Garcia-Pardo *et al.* [30] was applied as follows:

$$\widehat{IP}(\tau, t, x) = \frac{IP(\tau, t, x)}{K^2}, \quad (2)$$

where K is the inverse Fourier transform of the Hanning window used in the windowing process described above and $\widehat{IP}$ defines the corrected (smoother and with smaller side lobes) expression of the instantaneous PDP. Finally, if the radio channel is assumed to be ergodic and to exhibit wide sense stationarity (WSS) properties over space, which is fairly common [31]–[33], the value of the PDP can be expressed by:

$$\widehat{P}(\tau) = E[\widehat{IP}(\tau, t, x)], \quad (3)$$

where $E[\cdot]$ denotes the spatial average value. Therefore, several IPs must be obtained over a small static area to attain the final PDP. Once the PDP is achieved, the RMS delay spread can be calculated as follows:

$$\sigma_\tau = \sqrt{\frac{\sum_k \widehat{P}(\tau_k) \cdot \tau_k^2}{\sum_k \widehat{P}(\tau_k)} - \left(\frac{\sum_k \widehat{P}(\tau_k) \cdot \tau_k}{\sum_k \widehat{P}(\tau_k)} \right)^2}, \quad (4)$$

where $\widehat{P}(\tau)$ denotes the value of the PDP at time τ . To prevent the background noise from altering the results, only those values of the PDP that exceed a defined threshold will be taken into account (e.g., -30 dB with respect to the maximum value of the PDP, assuming a dynamic range greater than 30 dB). The coherence BW in turn, is obtained from the Fourier transform of the PDP. The relative power in frequency is calculated as follows (expressed in logarithmic units ranging from $-BW/2$ to $BW/2$ hertz) [30]:

$$\widehat{P}(f) = 10 \cdot \log_{10} \left(\sum_{n=1}^M \widehat{P}(\tau) \cdot e^{-j \cdot 2\pi \cdot f \cdot n \cdot \Delta\tau} \right). \quad (5)$$

If we normalize the above function with respect to its maximum value, the width of the fraction of the function exceeding -3 dB corresponds to the 3 dB-coherence BW [30].

The several interfering wavefronts created by the rich multipath environment lead to another phenomenon worth looking

into: the behavior of the signal power with respect to distance. Path-loss models express how signal power decays as the distance between the transmitter and receiver increases. Most of these models reflect the statistical nature of the variation in the signals power. For instance, the LNSPL (6) calculates the losses as a function of a fixed amount at a reference distance d_0 , a factor n representing the power decay (path loss exponent) and a zero mean Gaussian random variable (X_σ) with standard deviation of σ . This random variable helps to account for fluctuations of the mean received power as we move over long distances, which we call large-scale shadowing.

$$PL(d)_{dB} = PL(d_0) + 10 \cdot n \cdot \log_{10} \left(\frac{d}{d_0} \right) + X_\sigma. \quad (6)$$

In this work, we also studied the deviations of the signal amplitude with respect to its mean value as the separation of the transmitter-receiver (TX-RX) varies within a small area, namely, small-scale fading. This mean value, or average path loss, is mathematically represented by the first two elements of the path-loss formula presented above and it is directly calculated from the PDP by summing all its samples:

$$\overline{PL} = -10 \cdot \log_{10} \left(\sum_{i=1}^M \widehat{P}(\tau_i) \right). \quad (7)$$

Therefore, this represents a way by which given a certain frequency band, we can study the nature of the signal strength from two different approaches depending on the scale: large and small (with the former scale in the order of magnitude of meters or dozens of meters and the latter one in the order of centimeters or a couple of meters). This study can be carried out via the CIR and will be further discussed in the following sections.

To finish up characterizing the radio environment and to be able to obtain valuable parameters such as the signal to noise ratio (S/N), the electromagnetic/background noise present in the channel must be captured and analyzed.

III. MEASUREMENT SYSTEM, ENVIRONMENT AND METHODOLOGY

A. Measurement System

The previous section presented key aspects of great relevance in characterizing and modeling a propagation environment. Ultimately, most of them rely on obtaining the frequency or time response of the channel with high accuracy. To this end, an Agilent Technologies E5071B [34] network analyzer was employed. Network analyzers, among many other functionalities, transmit a known signal that sweeps the desired frequency range and measure the received waveform in order to calculate the frequency response of the channel in amplitude and phase (i.e. the complex channel transfer function). The frequency range and the fineness of the sweep (number of measurement points taken) determine the resolution and distance range of the measures respectively. The measured frequency range actually used was 2.0 GHz to 2.8 GHz divided

Fig. 1. Measurement setup used to characterize the environment. The transmitted signal is sent through an optical fiber and a 30dB amplifier to reduce perturbations and increase the transmitted signal's power.

into 410 points (frequency step of 1.95MHz). These values yield a 1.25ns resolution (37.5 centimeters) and a maximum accountable delay of $0.512\mu\text{s}$ (153 meters) in the PDP metric. This distance resolution was proven to be enough due to the high density of obstacles in the scenarios under consideration, which will produce quantifiable reflections in distances smaller than 153m.

Alongside the network analyzer, two biconical antennas were used (Microwave Biconical Antenna SBA 9113) as transmitter and receiver respectively. These antennas present a working frequency range of 500MHz to 3GHz and a gain of up to 1.5dBi. To allow measuring distances of dozens of meters, the signal generated by the network analyzer was sent to the transmitter antenna through an optical fiber (and an Ortel 3540A/4510B optical transmitter and receiver) and amplified just before being radiated (a 30dB low-noise amplifier powered by an independent +12V power source was used). The network analyzer was calibrated to account for the variation in the transmitted signal once the setup was completed using what is commonly called a *through calibration* [35]. Furthermore, the wideband measurements of the antennas' radiation patterns in an anechoic chamber (provided by the manufacturer) were considered to correct for potential undesired effects. Fig. 1 depicts the setup employed for the channel characterization process.

Furthermore, a Rohde & Schwarz FSH3 spectrum analyzer was also used to assess the impact of the electromagnetic noise on the 2.0-2.8GHz band. This is extremely important since communication quality will ultimately depend on the effects experienced by the emitted signal (distortion, power losses, etc.) as well as on the presence of electromagnetic noise.

B. Test Scenarios

Two different scenarios have been studied. The first one was an outdoor 400kV substation under three different communication conditions, namely: line-of-sight communication (LOS), obstructed line-of-sight communication (OLOS), and non-line-of-sight communication (NLOS). LOS communications are those in which the direct ray (line-of-sight) is not blocked and the first Fresnel zone is 80% clear (free from obstacles or reflecting surfaces). OLOS communications present the main direct ray blocked or the first Fresnel zone is between 50% and 80% clear. Finally, NLOS communications represent the scenario in which the direct ray is blocked and the first Fresnel zone is more than 50% blocked by obstacles or

Fig. 2. Outdoor 400kV substation scenario. The big switchgears and other metallic structures cause the communication to be ruled by the multipath propagation.

Fig. 3. Picture of the main power room used to control the substation. Control cabinets are present at both sides, which boosts the multipath phenomenon.

reflecting surfaces. The second test scenario was a main power room in which only LOS communications were considered due to the unavailability of any other form of communication (an indoor environment with little or no obstructing objects). Both scenarios were found in a substation located in the South-West of Spain owned by Iberdrola, the leading energy provider in Spain.

In our interest to seek generality, it should be noted that these are two quite common scenarios in any big or midsize substation. Therefore, the characterization of such environments would allow for a wide range of possibilities in simulating the T&D segment of an SG. Fig. 2 and 3 show a picture of the chosen test areas.

C. Methodology

In order to calculate the PDP (which requires spatial averaging) and to characterize the large and small-scale fading behavior of these two scenarios (400kV substation and main power room), the receiver/transmitter antennas were positioned in up to 30 different positions within an area of radio from 2 to 3 times the wavelength of the signal ($2-3\lambda$), and a

Fig. 4. Floor plan of the 400kV substation. Crosses depict where the receivers were placed, whereas straight lines show the different positions taken by the transmitters. Surrounding structures produce a rich multipath environment due to their metallic nature. Elements in the figure depict: 1. Transformer, 2. Control building, 3. Busbar, 4. Current transformer, 5. Surge arrester.

minimum separation of $\lambda/2$ between them. This translates to an area of 45cm of radius and a minimum separation of 7.5cm for the lowest frequency (2GHz) under consideration. This separation has been proven to eliminate correlation in the channel responses [25], [36] while still experiencing the same propagation effects on the signal.

To calculate the effects of the path-loss, the above procedure was repeated for a TX-RX separation of: 1, 2, 5, 10, 15, 20, 25 and 30 meters. The crosses depicted in Fig. 4 represent where the receivers were placed, whereas the continuous straight lines show the different positions taken by the transmitters at the distances mentioned above (the blue line in the middle stands for LOS communication, the green upper line for OLOS and the red lower line for NLOS respectively). The antennas were placed 1 meter above the ground (to prevent the ground effect from affecting communications) and the horizontal and vertical polarization were also analyzed to search for the presence of any influence on the communications. The transformers present in Fig. 4 are 6.5 meters high, whereas the bus bars and the overhead cables are 10 meters above the ground. A very similar procedure was conducted in the main power room (Fig. 5). But due to the limited size of the place the TX-RX distances selected were as follows: 1, 2.5, 4, 5.5, 7, 8.5 and 9 meters. Furthermore, since the main power room was also used as a warehouse, the TX-RX could only be placed on the depicted blue line and hence, only the LOS condition for the indoor case could be tested. In both scenarios, the propagation channel could be considered static and the area was cleared before the measurements took place.

Electromagnetic noise traces were obtained with the spectrum analyzer for both types of polarization and for the two test scenarios (using the same antenna as in the procedure explained above and a resolution bandwidth of 1MHz), thus yielding information on how noisy the environment was in the 2.0-2.8GHz band. Ten different noise traces were obtained in different spots of the substation (5 outdoor and 5 indoor), where the channel characterization took place. The results

Fig. 5. Floor plan of the main power room. The cross depicts where the receiver was placed, whereas the straight line shows the different positions taken by the transmitter. Only LOS communications were measured.

presented in the following section take into consideration the 10 noise traces to analyze the impact of the electromagnetic noise on wireless communications.

IV. RESULTS

In this section, the measurement results regarding the metrics of interest: 1) RMS delay, 2) coherence BW, 3) large-scale fading, 4) small-scale fading, and 5) background noise are presented and analyzed. Different models are proposed and discussed with the particular objective of being able to estimate such parameters in other SG environments of the same nature.

A. PDP and Derived Parameters

The RMS delay was calculated considering only the fraction of the PDP that surpasses the -30dB with respect to the strongest delay bin (the sum of all energy received over the duration of that bin) in the PDP. Having a S/N over 30dB and applying this thresholding technique, we can ensure that the VNA noise floor was not considered when calculating the propagated signal properties. On the other hand, the -3dB coherence BW was analyzed as explained in the second section.

For each scenario and polarization, we present the RMS delay and coherence BW calculated from the PDP (which takes into account up to 30 individual impulse PDPs) along with a linear regression model. This model minimizes the differences between the measured and estimated RMS delay in a mean squared error (MSE) sense and could be employed in estimating the value of such figures in other scenarios with similar characteristics. To calculate the PDP, the various impulse PDPs were averaged as per the procedure explained in section II.

Fig. 6a and 6b show the values of the RMS delay in the 400kV substation and the main power room respectively. There is a clear dependency of such value on the distance, leading to a general increase of the RMS delay as the TX-RX distance grows. As one might expect, LOS communications suffer from much smaller RMS delays than OLOS or NLOS, with the latter being the most affected (13.93ns, 24.57ns and 46.15ns in average for the LOS, OLOS and NLOS scenarios respectively). In the outdoor environment,

Fig. 6. RMS delays for different configurations and polarizations vs distance. (a) 400kV substation and (b) Main power room. Straight lines depict the proposed linear regression model, whereas markers show the mean values obtained for each distance. Note that scales are different.

Fig. 7. Coherence bandwidth for different configurations and polarizations vs distance. (a) 400kV substation and (b) Main power room. Straight lines depict the proposed linear regression model, whereas markers show the mean values obtained for each distance.

we observed that horizontally polarized communications, in general terms, experienced less RMS delays than vertical polarization (9.37ns vs 15.6ns). This can be explained by the overhead cables that run horizontally over the entire substation. These cables provide a reflective surface only for horizontally polarized waves, thus, minimizing the proportion of power that reflects in distant obstacles (or does not reflect at all). Closer and hence faster reflections imply a reduction of the RMS delay. The indoor scenario shows even smaller RMS delays due to its confined nature, i.e. the reduced dimensions of the room make propagated waves reflect and reach the receiver

faster. For this scenario, there is also a clear positive correlation of the RMS delay with distance for both polarizations.

Fig. 7a and 7b reproduce the values obtained for the coherence BW (at -3dB) along with the calculated linear regression models (following the same MSE minimization process) for the 400kV substation and the main power room respectively. In general, we cannot identify a direct link between distance, visibility condition and coherence BW but, generally speaking, we can state that horizontal polarization tends to perform better in terms of this metric (in average, 496.7MHz vs 409MHz for the horizontal and vertical

polarization respectively in the outdoor scenario). As expected, the main power room, due to its reduced size and large amount of reflecting objects (which dramatically increases the number of multipath components), presents a much smaller coherence BW (in average, 204.35MHz vs 452.84MHz for the indoor and outdoor scenarios respectively). This poses some challenges to the use of wide-band wireless communications in control rooms of this nature. However, MIMO (multiple input multiple output) receivers have traditionally been used in scatter-rich environments (such as the one under consideration) and have proven to be of great help [37].

B. Path Loss and Large-Scale Shadowing

Path loss is calculated by summing all the delay bins of the PDP, as explained above in the second section. However, since the amplitude of the PDP depends on the antennas, and the measuring system in general, calibration is of paramount importance in this part. Corrections to antennas' radiation patterns were made as per the anechoic chamber measures and the entire "network analyzer - transmitter/receiver - cables - amplifier" system was calibrated using the in-built through calibration function of the E5071B network analyzer [35].

The LNSPL model introduced in section II was studied so as to provide a solid model that could be regarded as a point of reference in simulating other SG substation environments. Nonetheless, the exact model's parameters may vary depending on specific propagation characteristics of other scenarios. $PL(d_0)$ was set to the free space path losses (FSPL) in decibels at a distance of d_0 meters (calculated using (8)). In our work we considered a reference distance (d_0) of 1 meter since it is common practice and a sound value for SG wireless networks with a required coverage range in the order of tens of meters. The wavelength λ was calculated using the central frequency of the studied band: 2.4GHz.

$$FSPL = 10 \cdot \log_{10} \left(\frac{4 \cdot \pi \cdot d_0}{\lambda} \right)^2. \quad (8)$$

By using (6) and taking a best-fit approach of the acquired data (minimum mean squared error, precisely – MMSE), the obtained n and σ parameters (of (6)) become, respectively, a good characterization of "how lossy" the environment is and how "dispersed" the measures are around the mean path loss. It is worth mentioning that this holds true only when $PL(d_0)$ is defined using (8), called the fixed intercept model, and not when it is obtained as the result of minimizing the MMSE, considering such value as a second variable [38]. The model which accepts $PL(d_0)$ as a second variable is known as a non-fixed intercept model and reduces the σ parameter at the expense of losing the physical basis and leading to not easily comparable propagation models [38].

By employing the fixed intercept model and minimizing the MMSE, we have obtained the n and σ parameters for each scenario, configuration and polarization. To increase the accuracy of the model, the whole 800MHz band (from 2.0GHz to 2.8GHz) was divided into 30 overlapped chunks of 100MHz each, yielding 30 pairs of n and σ . In this way, one can precisely estimate the path losses at a certain

Fig. 8. Path loss exponent vs frequency for 100MHz chunks when a fixed intercept model is employed. Different environments, configurations and polarization are considered.

frequency and distance in the modeled environments under LOS/OLOS/NLOS configuration and employing horizontal or vertical polarization. The 100MHz band guarantees that the considered frequency points experience the same propagation effects while still having a considerably large BW, thus providing a good time and frequency resolution. Lowering this value may lead to inconsistent parameters (due to the reduced number of points taken into account), whereas increasing it would assume a much flatter frequency response.

Fig. 8 depicts the path loss exponent obtained as a result of the process of minimizing the mean squared error over the entire data set. In general terms, LOS communications suffer from less attenuation (smaller n parameter) than OLOS or NLOS communications, with the latter being the most affected by propagation losses (in average, an n of 1.62, 1.97 and 2.43 for the LOS, OLOS and NLOS conditions respectively). Generally speaking, vertically polarized communications show stronger losses than horizontally polarized ones. Again, this can be explained by the specific arrangement of the overhead cables that increases the proportion of power that reflects and reaches the receiver for the horizontally polarized waves. Another phenomenon which fits well with the physics of propagation is the presence of higher losses at higher frequencies (n and $PL(d_0)$ go up when the frequency increases). In every scenario, the obtained n parameter is greater than zero, representing the positive correlation between losses and distance. Similarly, in many occasions, the path-loss exponent is smaller than 2 –the value for free-space conditions– showing the presence and significance of the multipath effect, which helps reducing the propagation losses. It is worth mentioning that the main power room exhibits smaller losses than any other scenario due to its particular nature: a closed, well-isolated room mostly surrounded by metallic components (which do not absorb, but reflect, incident rays). Furthermore, we have also computed the 95% confidence intervals of the estimated n parameters and found them to be almost invariant

Fig. 9. Standard deviation vs frequency for 100MHz chunks when a fixed intercept model is employed. Different environments, configurations and polarization are considered.

to the frequency and quite small; therefore they have not been included in the figure (they are, on average, less than 0.262). Fig. 9 shows the standard deviation (σ) of the Gaussian random variable used to model the path loss. Indoor communications are revealed to be more predictable than outdoor ones, showing smaller values of σ (in average, a σ of 0.90 vs 2.76 for the indoor and the outdoor scenarios respectively). This phenomenon is explained by the homogeneous distribution of metallic surfaces, which, unlike in the outdoor scenario, are evenly distributed along the measured spots. The dependency of σ on frequency is specific to each environment and no general rule can be extracted. However, this metric (and therefore, its corresponding Fig. 9) has been intentionally included to allow future works to use and reproduce the model proposed in this paper, for which n and σ parameters are required. It is worth noting that if a non-fixed intercept model were used to model the acquired data, the reduction of σ would be, on average, less than 0.51. With the mean path-loss of the order of several tens of decibels, a reduction in the variance of 0.51 is not worth losing the ability to compare different propagation models. Hence, the utility of a model with no physical basis such as the non-fixed intercept was not justified in this work.

C. Small-Scale Fading

To analyze the small-scale fading behavior of each environment, several probability distributions were first studied in order to find out which one best fits each data set under a certain criterion. Then, a model able to estimate the distribution parameters was proposed and used to obtain such parameters. Finally, results were presented so as to help in the process of modeling future propagation channels.

The process of finding out which probability density function (PDF) best fits the data may be achieved by following different mathematical approaches. The first step is usually the

estimation of a certain PDF's parameters so as to maximize some figure of merit. In this sense, the Maximum-Likelihood Estimation (MLE) has proven to be an excellent tool by obtaining the PDF's parameters that maximize the likelihood of the data coming from such PDF (which is, basically, the idea under consideration). Once the parameters of each PDF have been obtained, one needs to decide which PDF must be chosen as a generalization of the physical nature of the underlying small-scale fading phenomenon. In doing so, there is no "silver bullet" that works well under any condition but, instead, several methods may be considered and the result of each of them evaluated in making the final decision.

Rician, Normal, Log-Normal, Nakagami, Rayleigh and Weibull distributions are among the most popular PDFs used to describe small-scale fading in wireless communications [29], [36], [39], [40]. Therefore, all of them have been considered in this work. Once their corresponding parameters were obtained using the MLE method, three different mathematical approaches were used to select the most adequate PDF for each scenario: A Generalized Likelihood Ratio Test (GLRT) [41], a Kolmogorov-Smirnov (KS) test [42], and a comparison of the mean squared error (MSE) between each pair of cumulative distribution functions (CDF) obtained from each PDF.

We have analyzed the small-scale statistics of the data set in the frequency domain. For each frequency step we have considered all data within a frequency BW of 10MHz (7 frequency points) which corresponds to the lowest coherence BW found for every scenario. In this way, both the data of the exact frequency under consideration and the information yielded by the adjoining frequency points were of relevance in this analysis. The 10MHz BW ensured that the considered frequency points not only experienced the same propagation effects but also showed the same statistical distribution. The effect of considering larger BWs has also been studied and results have shown that values greater than 10MHz produce an undesired instability that leads to abrupt variations of the estimated PDF. Having up to 30 measures of signal amplitude for each distance and allowing a 10MHz BW, the total number of points used to determine the small-scale statistics expands up to 210 (30 measures per frequency multiplied by 7 frequency points).

The results were conclusive; the most suitable PDF to approximate the small-scale fading phenomenon in every scenario, polarization and configuration is the Weibull distribution (9). We obtained more than 97.5% positive results when applying the KS test (i.e., only 2.5% of the tests could reject the hypothesis that the small-scale fading phenomenon could be modeled by a Weibull distribution). Furthermore, the GLRT and MSE tests prove that, among all the tested PDFs, the Weibull distribution models the aforementioned phenomenon with the greatest accuracy (by showing the highest likelihood and the least mean squared error respectively). The following equation describes the Weibull distribution:

$$f(x; \lambda, k) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}. \quad (9)$$

Once the k and the λ parameter (shape and scale parameters respectively) of the Weibull distribution were obtained for each

TABLE I
PARAMETERS TO ESTIMATE λ

400kV Substation	$\lambda_0 \cdot 10^{-3}$	$n_\lambda^d \cdot 10^{-3}$	$n_\lambda^f \cdot 10^{-3}$	NRMSE
Vertical Polarization – LOS	0.013	0.637	1.050	0.088
Horizontal Polarization – LOS	0.011	0.639	0.414	0.111
Vertical Polarization – OLOS	0.006	0.234	0.674	0.101
Horizontal Polarization – OLOS	0.003	0.075	0.415	0.159
Vertical Polarization – NLOS	0.002	0.091	0.186	0.124
Horizontal Polarization – NLOS	0.002	0.063	0.097	0.115
Main power room	$\lambda_0 \cdot 10^{-3}$	$n_\lambda^d \cdot 10^{-3}$	$n_\lambda^f \cdot 10^{-3}$	NRMSE
Vertical Polarization – LOS	0.017	0.913	1.475	0.083
Horizontal Polarization – NLOS	0.011	0.435	0.712	0.175

TABLE II
PARAMETERS TO ESTIMATE k

400kV Substation	k_0	$n_k^d \cdot 10^{-3}$	$n_k^f \cdot 10^{-3}$	NRMSE
Vertical Polarization – LOS	4.876	-21.143	534.733	0.175
Horizontal Polarization – LOS	1.480	-100.237	-573.017	0.148
Vertical Polarization – OLOS	4.788	19.901	498.544	0.168
Horizontal Polarization – OLOS	4.831	-72.768	657.647	0.200
Vertical Polarization – NLOS	5.340	112.086	323.789	0.159
Horizontal Polarization – NLOS	3.600	78.283	94.662	0.147
Main power room	k_0	$n_k^d \cdot 10^{-3}$	$n_k^f \cdot 10^{-3}$	NRMSE
Vertical Polarization – LOS	3.332	30.490	125.636	0.123
Horizontal Polarization – NLOS	1.864	9.948	-197.299	0.142

distance and frequency (considering the allowed BW and by means of the MLE), we proposed the following empirical model as an estimator of such parameters in other SGs with the same characteristics and nature:

$$\lambda = \lambda_0 - 10 \cdot n_\lambda^d \cdot \log_{10}(d) - 10 \cdot n_\lambda^f \cdot \log_{10}(f), \quad (10)$$

$$k = k_0 - 10 \cdot n_k^d \cdot \log_{10}(d) - 10 \cdot n_k^f \cdot \log_{10}(f), \quad (11)$$

where d is the distance expressed in meters and f is the frequency in GHz. n_λ^d and n_λ^f model the dependency of the λ parameter on distance and frequency respectively. Similarly, n_k^d and n_k^f characterizes the dependency of the k parameter with distance and frequency. λ_0 and k_0 are the offset values for the scale and shape models respectively. This model has been chosen to minimize the MSE; other linear and quadratic equations as an alternative to (10) and (11), such as the ones proposed in [39] or [36], have also been considered, but with worse results. Furthermore, the fitness of the model has also been computed in terms of the normalized root-mean-square error (12) (NRMSE), which is the square root of the MSE normalized to the range of the parameter being modeled (defined as the difference between the maximum and the minimum value). This error figure gives a clear representation of the goodness of the model regardless of the scale of the parameter and the size of the data (N).

$$NRMSE = \sqrt{\frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N(y_{max} - y_{min})^2}}, \quad (12)$$

where $\hat{y}_i$ is the estimation of the parameter (either λ or k) for the i -th sample, y_i is the i -th measured parameter

(obtained via MLE), and y_{max} and y_{min} are the maximum and minimum values of the MLE-obtained parameter respectively. Tables I and II specify the results achieved for each scenario, configuration, and polarization.

For n_k^d and n_k^f , up to three orders of magnitude smaller than its respective "base" value, (k_0) indicated the small dependency of the shape parameter on distance or frequency once modeled by (11). The low NRMSE values attained indicate that the proposed models predict reasonably well the λ and k parameters for the different frequencies and distances. It is worth mentioning that the variance of the NRMSE values is 0.0011, reflecting the good behavior of the proposed model regardless the specific configuration of visibility and environment.

D. Interferences

The presence of electromagnetic interferences (EMI) has also been analyzed for both environments (400kV substation and main power room) and for both polarizations (horizontal and vertical) by means of 10 noise traces evenly distributed throughout each environment. It is worth noting that the potential effects of the antennas employed on the measures have been corrected before being shown in this section, following the same procedure explained before.

It has not been possible to establish any clear correlation between polarization and the strength of EMI, showing similar values for each scenario. Furthermore, we could not clearly determine that there were sources of EMI for the working frequency band inside the substation (i.e. switchgears do

Fig. 10. Simulated WSN. 6 nodes are placed following a star-topology to control the following substation elements: Nodes 1 and 2 control the two transformers. Nodes 3 and 5 govern the current of the busbars. Node 4 reports the status of the control building, and node 0 acts as a sink.

not act as a 2400MHz band EMI sources). Therefore, the 10 measures obtained showed similar values within each environment. In the outdoor 400kV substation, the different traces exhibit a similar noise floor value around -97dBm , with the exception of the 2100MHz band, which is currently used for the 3G mobile communication systems. In such a band, the noise power shows a peak of -82dBm . On the other hand, the noise floor in the main power room remains mainly flat with a value around -97.5dBm , whereas noise power rises up to -92dBm in the 2100MHz band. However, since the 2.4GHz ISM band extends from 2.4GHz to 2.5GHz, interferences around 2100MHz will not cause any significant inconvenience.

V. SYSTEM AND MODEL ANALYSIS

In this section we present the results of a WSN-based simulation deployed in an SG 400kV substation. The objective of this section was twofold: firstly, to prove the importance of model's parameters when simulating a WSN. And secondly, to do so by comparing the results obtained employing our proposed model's parameters to those yielded making use of a previous, heavily referenced work [22].

A. The Simulated Network

The purpose of the simulated WSN, as in most of the sensor networks deployed in an SG, was to monitor, control and actuate over the substation's elements. The network under consideration comprised 6 nodes following a star topology, all of them being powered by batteries and operating under different line-of-sight configurations. The specific position of each node is chosen to satisfy the needs of controlling specific elements of the substation: switchers, transformers, and surge arresters. Fig. 10 illustrates such a network.

As in the majority of WSNs designed to run with limited energy sources for extended periods, the 802.15.4 standard

was considered [4]. The 802.15.4 standard, operating in the 2.4GHz band (ranging from 2400MHz to 2483MHz), divided the spectrum into 16 channels of 2MHz separated by a gap of 5MHz. The maximum bitrate is 250kbps and presents a symbol duration of $16\mu\text{s}$. These values have the following impact:

- All frequency components of the transmitted signal will experience the same magnitude of fading (frequently known as flat fading). This is due to the small BW of the signal (2MHz) compared to the channel coherence BW, which is greater than 10MHz for every scenario, as shown in the previous section. This leads to simpler and more efficient receivers since there is no need to equalize and post-process the signal received. It is worth mentioning that in the case of using other technologies, such as 802.11g (WiFi), MIMO receiver and equalization techniques would have been required.
- There will be no strong ISI. This is due to the large symbol duration ($16\mu\text{s}$) of the 802.15.4 standard compared to the RMS delay spread of the environment (of only 70ns in the worst case). This situation leads to a slow-fading channel and hence the absence of an increase in the bit error rate (BER) because of the ISI phenomenon.

A key indicator of the WSN's performance is the packet reception rate (PRR). This figure of merit indicates the proportion of packets reaching the receiver (at the first transmission attempt) and plays a major role in estimating the power consumption of the devices. To estimate such a parameter, it is crucial to compute the signal to noise ratio (S/N) of the communication as there are expressions that relate these two figures [18]. To calculate the S/N, we considered a 0dBm transmission power (which is fairly common in most WSNs [4], [43], [44]) and a background noise of -97dBm (according to the results achieved in the previous section). To compute the path-loss, the n and σ of the vertically-polarized 2.4GHz (2425MHz precisely) were picked from Fig. 10, attending to the visibility condition under which each pair of nodes operates (e.g., node pair 0-1 works under OLOS configuration so an n of 2.241 is employed in simulations –see Fig. 10–). Vertical polarization was chosen as it represents a worst-case situation in each scenario at the chosen frequency.

To compute the results, a ten-fold simulation of 10000 attempts to send a 28-byte long packet was carried out (these 28 bytes, or 224 bits, needed 0.896ms to be sent at a bitrate of 250kbps). The length of the packet was chosen so as to represent a vibration and temperature reading of sensors placed in different substation elements. If any packet did not reach the destination, the transmitter kept trying until such packet was received by the root node (node 0). The results obtained when using the LNSPL model's parameters suggested in a previous reference work [22] were also included to further highlight the importance of model's parameters when simulating WSNs. Since that work did not include the characterization of the OLOS configuration, an interpolation between LOS and NLOS was performed (this approach fitted our data reasonably well; thus the path-loss exponent and standard deviation of the OLOS situation could be approximated by averaging those of LOS and NLOS). Tables III and IV show the results obtained

TABLE III
RESULTS OBTAINED USING THE CHANNEL PARAMETERS DERIVED FROM OUR MEASUREMENTS

Node Pair	Distance & Configuration	PRR	Total number of packets sent	Parameters employed in the simulation
0-1	4.8m - NLOS	92.11%	10856	$n=2.642, \sigma=3.04$
0-2	10.6m - OLOS	78.44%	12748	$n=2.22, \sigma=3.564$
0-3	15.50m - LOS	93.82%	10659	$n=1.723, \sigma=2.398$
0-4	15.2m - OLOS	70.95%	14095	$n=2.22, \sigma=3.564$
0-5	16.6m - LOS	94.07%	10630	$n=1.723, \sigma=2.398$

TABLE IV
RESULTS OBTAINED USING CHANNEL PARAMETERS FROM [22]

Node Pair	Distance & Configuration	PRR	Total number of packets sent	Parameters employed in the simulation
0-1	4.8m - NLOS	86.15%	11608	$n=3.51, \sigma=2.95$
0-2	10.6m - OLOS	71.03%	14079	$n=2.8, \sigma=3.07$
0-3	15.50m - LOS	69.62%	14363	$n=2.42, \sigma=3.12$
0-4	15.2m - OLOS	55.99%	17861	$n=2.8, \sigma=3.07$
0-5	16.6m - LOS	68.77%	14541	$n=2.42, \sigma=3.12$

and the specific parameters employed in the simulation, for both, our model (Table III) and the model proposed in [22] (Table IV).

The differences between the results provided in Table III and Table IV are quite significant. For instance, the differences between the two simulations in terms of PRR exceed 24% and 25% for node pairs 0-3 and 0-5 respectively. These differences would have a serious impact on the network planning process: e.g., the two aforementioned node pairs would require a battery replacement much less often than the simulation employing the model parameters of [22] suggests (fewer packet retransmissions lead to less battery exhaustion), thus scheduling unnecessary maintenance tasks. For instance, the power estimations using the Avrora simulator [45] (widely used in many WSN works [4], [46], [47]) showed that differences in PRRs led to an increase of 36.8% and 34.7% in the estimation of battery consumption in nodes 3 and 5.

Furthermore, in the second simulation (carried out with the model's parameters suggested in [22]), node pair 0-4 would be considered to have an insufficient PRR; thus, to help reduce the power consumption and as a straightforward solution, an extra node would be required to act as an intermediate to maintain connectivity. This increases not only the capital expenditure, but also the operating cost. Installing and maintaining extra nodes may lead to an additional cost of hundreds or thousands of dollars during the network lifetime (due to battery replacements, interruption of service to install them, etc.).

Moreover, an interesting question to explore arises. Differences in network topology between simulation and reality (due to an inaccurate evaluation of path losses) led to unexpected results in contention-based and multi-hop algorithms. In such algorithms, it was of paramount importance to know how many nodes were sharing the wireless media in advance (determined, for instance, by the PRR) as this had a direct effect on network efficiency.

Finally, we should look deeper into the procedure of deriving the LNSPL model's parameter via the RSSI indicator.

As explained before, other works such as [22], [48], and [49] have derived path-loss models directly from the RSSI readings of nodes without the need of devices like VNAs. In this final paragraphs we want to confirm if the results yielded are, indeed, platform dependent; and therefore, only suitable for simulating the same node platform from which the model was obtained.

To do so, we employed two different node platforms (i.e. Iris and MicaZ) with two different radio interfaces (AT86RF230 [50] and CC2420 [51] respectively) with the objective of testing if the radio interfaces themselves had any impact on the path-loss model derived. By making use of the RSSI indicator we measured the received power (once corrected following their respective manufacturers' instructions [50], [51]) at different distances (1m, 2m, 3m, 5m, 10m, 15m and 20m) in the 400kV substation for the LOS and vertical polarization configuration. For each distance value, and in the same logic explained in subsection III.C, we took 5 different measures of 512 packets each at slightly different spots within an area of $2-3\lambda$. Thereby, we captured 17920 RSSI packets for each platform ($7 \text{ distances} \times 5 \text{ spots} \times 512 \text{ packets}$). Once again, we fit the data to the LNSPL model following a best-fit approach (MMSE). Results are specified in Table V for both, the fixed and non-fixed intercept model.

The first thing to notice is that, given the low-cost nature of the aforementioned platforms, the empirical $PL(d_0)$ is far distant from the theoretical value (-63.28dB for the MicaZ platform vs the theoretical -40.14dB), i.e. relatively large path losses are experienced even at small distances. Therefore, the fixed intercept model, which forces a $PL(d_0)$ of -40.14dB at 2.425GHz , yields imprecise values (measured in terms of σ –see middle column of Table V–). This makes the non-fixed intercept model the only valid choice at the expense of losing the physical basis and making it not directly comparable with the VNA-derived model –it is worth mentioning that for the VNA model, the fixed intercept model increases σ by only

TABLE V
MODEL'S PARAMETER OBTAINED WITH THE MicaZ AND IRIS
PLATFORMS FOR THE FIXED AND THE NON-FIXED
INTERCEPT LNSPL MODEL

Platform	Fixed intercept model	Non-fixed intercept model
MicaZ	$PL(d_0) = -40.136\text{dB}$ $n = 4.40$ $\sigma = 47.5$	$PL(d_0) = -63.28\text{dB}$ $n = 1.99$ $\sigma = 1.07$
Iris	$PL(d_0) = -40.136\text{dB}$ $n = 3.35$ $\sigma = 45.4$	$PL(d_0) = -56.82\text{dB}$ $n = 1.64$ $\sigma = 1.86$

0.51 in average, thus, making such a model a much adequate option—.

Results indicate that there are noticeable differences between the MicaZ and Iris-derived model's parameter: for instance, for the non-fixed intercept model, $n = 1.99$ and $PL(d_0) = -63.28$ vs $n = 1.64$ and $PL(d_0) = -56.82$ for the MicaZ and Iris respectively. This indicates that node-derived models are only valid when simulating the specific platform. Nevertheless, we can affirm that they are a reasonable first approximation to the problem of SG simulation and a better alternative to generic models which tend to omit the rich multipath nature of such environment.

Finally, we would like to note that even though the path loss exponents (n) obtained with the node-based models seem to be close to the value obtained with the VNA (around 1.72 for the frequency under consideration), discrepancies in PL_0 values indicate that there exist great differences among models (-40.14dB for the VNA-based model vs -63.28dB and -56.82dB for the MicaZ and the Iris-based models respectively). Furthermore, and as explained in the Section I, nodes are unable to derive frequency-related parameters such as the Coherence Bandwidth or the RMS delay.

VI. CONCLUSIONS

A comprehensive channel characterization of two key scenarios/environments of the T&D segment of an SG (substations and control rooms) was conducted for the 2.4GHz ISM Band. LOS conditions, polarization, frequency and distance were taken into account to generate an exhaustive propagation model for this kind of environments. RMS delay, coherence BW, and both large and small-scale fading conditions were studied and modeled via the complex frequency response of the channel obtained with a Vector Network Analyzer. Results proved that, for the studied environments, coherence BW and RMS delay spread did not represent insurmountable obstacles to the deployment of future wireless networks as long as small-BW standards are used (such as the 802.15.4 standard). The large-scale nature and path-loss phenomenon of the wireless links fitted a log-normal shadowing model reasonably well and mathematical tools for extracting such model parameters were provided and discussed. The small-scale fading was studied in depth and confirmed to be mostly Weibull-distributed. Empirical formulas were also proposed to estimate small-scale fading under different conditions.

The importance of this work was further highlighted by comparing our model and a well-known and referenced model in terms of PRR and energy consumption. Discrepancies of more than 25% in PRR and 34% in battery consumption were observed in the worst-case scenario. Thus, we showed the importance of model's parameters when simulating SG-oriented WSNs.

We consider that this study represents a step forward in the understanding of radio propagation in Smart Grid's environments and empowers the academic and engineering communities with a general and accurate model that not only permits the testing of currently developed protocols in SGs but also makes it possible to study future 2.4GHz wireless communication proposals in a more precise and realistic manner.

ACKNOWLEDGMENT

The authors would like to thank Juan Salvador Perez Madrid and Domingo Meca (part of the Iberdrola staff) for the support provided during the realization of this work.

REFERENCES

- [1] U. S. A., *The Smart Grid: An Introduction*, accessed on Mar. 1, 2016. [Online]. Available: <http://energy.gov/oe/downloads/smart-grid-introduction-0>
- [2] M. Erol-Kantarci *et al.*, "Energy-efficient information and communication infrastructures in the smart grid: A survey on interactions and open issues," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 179–197, Feb. 2014. [Online]. Available: <http://ieeexplore.ieee.org/ipdcs/epic03/wrapper.htm?arnumber=6861946>
- [3] N. Kayastha, D. Niyato, E. Hossain, and Z. Han, "Smart grid sensor data collection, communication, and networking: A tutorial," *Wireless Commun. Mobile Comput.*, vol. 14, no. 11, pp. 1055–1087, Aug. 2014. [Online]. Available: <http://doi.wiley.com/10.1002/wcm.2258>
- [4] R. Martinez-Sandoval, A.-J. Garcia-Sanchez, F. Garcia-Sanchez, J. Garcia-Haro, and D. Flynn, "A comprehensive WSN-based approach to efficiently manage a Smart Grid," *Basel, Switzerland*, vol. 14, no. 10, pp. 18748–18783, Jan. 2014. [Online]. Available: <http://www.mdpi.com/1424-8220/14/10/18748/html>
- [5] C. Müller, H. Georg, M. Putzke, and C. Wietfeld, "Performance analysis of radio propagation models for smart grid applications," in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Oct. 2011, pp. 96–101.
- [6] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.
- [7] J. J. Shah, M. C. Nielsen, T. S. Shaffer, and R. L. Fittro, "Cost-optimal consumption-aware electric water heating via thermal storage under time-of-use pricing," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 592–599, Mar. 2016.
- [8] H. Y. Tung *et al.*, "The generic design of a high-traffic advanced metering infrastructure using ZigBee," *IEEE Trans. Ind. Informat.*, vol. 10, no. 1, pp. 836–844, Feb. 2014.
- [9] C. Rottondi, G. Verticale, and C. Kraus, "Secure distributed data aggregation in the automatic metering infrastructure of smart grids," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Mar. 2013, pp. 4466–4471.
- [10] X. Liang, X. Li, R. Lu, X. Lin, and X. Shen, "UDP: Usage-based dynamic pricing with privacy preservation for smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 141–150, Mar. 2013.
- [11] G. A. Pagani and M. Aiello, "Generating realistic dynamic prices and services for the smart grid," *IEEE Syst. J.*, vol. 9, no. 1, pp. 191–198, Mar. 2015.
- [12] W. Tushar *et al.*, "Energy storage sharing in smart grid: A modified auction-based approach," *IEEE Trans. Smart Grid*, to be published.
- [13] C. H. Hauser, D. E. Bakken, and A. Bose, "A failure to communicate: Next generation communication requirements, technologies, and architecture for the electric power grid," *IEEE Power Energy Mag.*, vol. 3, no. 2, pp. 47–55, Mar. 2005.
- [14] M. H. Dhend and R. H. Chile, "Innovative scheme for smart grid distribution SCADA system," in *IEEE 2nd Int. Future Energy Electron. Conf. (IFEEEC)*, Nov. 2015, pp. 1–6.

- [15] W.-Z. Song, D. De, S. Tan, S. K. Das, and L. Tong, "A wireless smart grid testbed in lab," *IEEE Wireless Commun.*, vol. 19, no. 3, pp. 58–64, Jun. 2012.
- [16] P.-Y. Kong and Y. Han, "Cooperative wireless transmissions of dynamic power price and supply information for smart grid," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2013, pp. 410–415.
- [17] S. Güzelgöz, H. Arslan, A. Islam, and A. Domijani, "A review of wireless and PLC propagation channel characteristics for smart grid environments," *J. Electr. Comput. Eng.*, vol. 1, no. 7, pp. 1–12, 2011. [Online]. Available: <http://www.hindawi.com/journals/jece/2011/154040/>
- [18] N. Kilic and V. C. Gungor, "Analysis of low power wireless links in smart grid environments," *Comput. Netw.*, vol. 57, no. 5, pp. 1192–1203, Apr. 2013. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1389128612004136>
- [19] A. Martínez-Sala, J.-M. Molina-García-Pardo, E. Egea-López, J. Vales-Alonso, L. Juan-Llaser, and J. García-Haro, "An accurate radio channel model for wireless sensor networks simulation," *J. Commun. Netw.*, vol. 7, no. 4, pp. 401–407, Dec. 2005. [Online]. Available: <http://ieeexplore.ieee.org/document/6387982/>
- [20] S. Luo, Z. Chen, N. Polu, and M. Morillo, "Iterative method for extracting impulse response of a RF channel with its band-limited transfer function," in *Proc. IEEE Radio Wireless Symp. (RWS)*, Jan. 2010, pp. 645–648.
- [21] S. Güzelgöz, "Characterizing wireless and powerline communication channels with applications to smart grid networks," Ph.D. dissertation, Dept. Electr. Eng., Univ. Florida, FL, USA, 2011. [Online]. Available: <http://scholarcommons.usf.edu/etd/3138>
- [22] V. C. Gungor, B. Lu, and G. P. Hancke, "Opportunities and challenges of wireless sensor networks in smart grid," *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3557–3564, Oct. 2010.
- [23] R. M. Sandoval. (2016). *Smart Grid Measurements—Raw Data*, accessed on Sep. 1, 2016. [Online]. Available: <http://labit501.upct.es/~rmartinez/>
- [24] D. Kotz, C. Newport, R. S. Gray, J. Liu, Y. Yuan, and C. Elliott, "Experimental evaluation of wireless simulation assumptions," in *Proc. 7th ACM Int. Symp. Model., Anal. Simul. Wireless Mobile Syst.*, 2004, pp. 78–82. [Online]. Available: <http://doi.acm.org/10.1145/1023663.1023679>
- [25] T. Rappaport, *Wireless Communications: Principles and Practice*, 2nd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2001.
- [26] N. Moraitis, A. Kanatas, G. Pantos, and P. Constantinou, "Delay spread measurements and characterization in a special propagation environment for PCS microcells," in *Proc. 13th IEEE Int. Symp. Pers., Indoor Mobile Radio Commun.*, vol. 3, Sep. 2002, pp. 1190–1194.
- [27] P. G. Flikkema and S. G. Johnson, "A comparison of time- and frequency-domain wireless channel sounding techniques," in *Proc. IEEE Southeastcon Bringing Together Edu., Sci. Technology.*, Apr. 1996, pp. 488–491.
- [28] J. F. Coll, J. D. M. de Ojeda, P. Stenumgaard, S. M. Romeu, and J. Chilo, "Industrial indoor environment characterization—Propagation models," in *Proc. 10th Int. Symp. Electromag. Compat.*, 2011, pp. 245–249. [Online]. Available: <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6078532>
- [29] A. H. Kemp and E. B. Bryant, "Channel sounding of industrial sites in the 2.4 GHz ISM band," *Wireless Personal Commun.*, vol. 31, nos. 3–4, pp. 235–248, Dec. 2004. [Online]. Available: <http://link.springer.com/10.1007/s11277-004-4169-z>
- [30] J. M. Molina-García-Pardo, J. V. Rodríguez, and L. Juan-Llaser, "Wide-band measurements and characterization at 2.1 GHz while entering in a small tunnel," *IEEE Trans. Veh. Technol.*, vol. 53, no. 6, pp. 1794–1799, Nov. 2004. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1360137
- [31] T. S. Rappaport, "Characterization of UHF multipath radio channels in factory buildings," *IEEE Trans. Antennas Propag.*, vol. 37, no. 8, pp. 1058–1069, Aug. 1989.
- [32] D. Cox, "Delay Doppler characteristics of multipath propagation at 910 MHz in a suburban mobile radio environment," *IEEE Trans. Antennas Propag.*, vol. TAP-20, no. 5, pp. 625–635, Sep. 1972.
- [33] D. Devasirvatham, "Multipath time delay spread in the digital portable radio environment," *IEEE Commun. Mag.*, vol. 25, no. 6, pp. 13–21, Jun. 1987.
- [34] Keysight Technologies. (2016). *E5071B ENA RF Network Analyzer*. [Online]. Available: <http://www.keysight.com/en/pdf-1000004587%3Aeapsg%3Apro-pn-E5071B/>
- [35] Agilent Technologies. (2007). *E5071B User's Guide*. [Online]. Available: <http://cp.literature.agilent.com/litweb/pdf/E5070-90430.pdf>
- [36] J. Karedal, S. Wyne, P. Almers, F. Tufvesson, and A. F. Molisch, "A measurement-based statistical model for industrial ultra-wideband channels," *IEEE Trans. Wireless Commun.*, vol. 6, no. 8, pp. 3028–3037, Aug. 2007. [Online]. Available: <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4290044>
- [37] Y. Mehmood, N. Haider, W. Afzal, U. Younas, I. Rashid, and M. Imran, "Impact of massive MIMO systems on future M2M communication," in *Proc. IEEE Malaysia Int. Conf. Commun. (MICC)*, Nov. 2013, pp. 534–537.
- [38] T. S. Rappaport, G. R. Maccartney, M. K. Samimi, and S. Sun, "Wide-band millimeter-wave propagation measurements and channel models for future wireless communication system design," *IEEE Trans. Commun.*, vol. 63, no. 9, pp. 3029–3056, Sep. 2015.
- [39] J.-M. Molina-García-Pardo, M. Lienard, and P. Degauque, "Propagation in tunnels: Experimental investigations and channel modeling in a wide frequency band for MIMO applications," *EURASIP J. Wirel. Commun. Netw.*, vol. 1, Feb. 2009, Art. no. 7.
- [40] E. Tanghe *et al.*, "The industrial indoor channel: Large-scale and temporal fading at 900, 2400, and 5200 MHz," *IEEE Trans. Wireless Commun.*, vol. 7, no. 7, pp. 2740–2751, Jul. 2008.
- [41] G. Reinsel, *Statistical Theory*, 1st ed. Oxford, U.K.: Oxford Univ., 2009. [Online]. Available: <http://www.stats.ox.ac.uk/~reinsel/stattheory/theoryshort09.pdf>
- [42] N. Smirnov, *Approximate Distribution Laws For Random Variables, Constructed From Empirical Data*, 10th ed. Moscow, Russia: Uspekhi Mat. Nauk, 1944.
- [43] G. Tuna, V. C. Gungor, and K. Gulez, "Wireless sensor networks for smart grid applications: A case study on link reliability and node lifetime evaluations in power distribution systems," *Int. J. Distrib. Sensor Netw.*, vol. 1, pp. 1–11, Jan. 2013. [Online]. Available: <https://www.hindawi.com/journals/ijdsn/2013/796248/abs/>
- [44] H. Liu, Y. Chen, M. C. Chuah, and J. Yang, "Towards self-healing smart grid via intelligent local controller switching under jamming," in *Proc. IEEE Conf. Commun. Netw. Secur. (CNS)*, Oct. 2013, pp. 127–135.
- [45] B. Titzer, D. Lee, and J. Pulsberg, "Avrora: Scalable sensor network simulation with precise timing," in *Proc. 4th Int. Symp. Inf. Process. Sensor Netw. (IPSN)*, 2005, pp. 477–482. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1440978
- [46] A. Somov, I. Minakov, A. Simalatsar, G. Fontana, and R. Passerone, "A methodology for power consumption evaluation of wireless sensor networks," in *Proc. IEEE Conf. Emerging Technol. Factory Autom. (ETFA)*, Sep. 2009, pp. 1–8. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5347152
- [47] O. Landsiedel, K. Wehrle, and S. Götz, "Accurate prediction of power consumption in sensor networks," in *Proc. 2nd IEEE Workshop Embedded Networked Sensors (EmNetS)*, May 2005, pp. 37–44.
- [48] J. H. Yoo, J. H. Lee, and S. H. Cho, "A propagation model in 2.4GHz ISM band using IEEE 802.15.4 systems," in *Proc. 17th Asia-Pacific Conf. Commun. (APCC)*, Oct. 2011, pp. 339–343.
- [49] A. Hrovat and T. Javornik, "Radio channel models for wireless sensor networks in smart city applications," in *Proc. 2013 Int. Conf. Electron., Signal Process. Commun. Syst.*, 2013, pp. 95–99.
- [50] Atmel. (2012). *AT86RF230 Datasheet*. [Online]. Available: <http://www.atmel.com/images/doc5131.pdf>
- [51] Texas Instrument. (2013). *CC2420 Radio Datasheet*. [Online]. Available: <http://www.ti.com/lit/ds/symmlink/cc2420.pdf>

Ruben M. Sandoval (M'12) received the B.S. degree in telematics engineering and the M.S. degree in telecommunication engineering from the Universidad Politécnica de Cartagena, Cartagena, Spain, in 2011 and 2014, respectively, where he is currently pursuing the Ph.D. degree. He took part in the interuniversity student exchange program ERASMUS at Heriot-Watt University, Edinburgh, U.K., where he studied the application of wireless sensor networks to smart grids. His research interest includes the development of efficient wireless networks, the applicability of such networks to the process of power assets management, and embedded systems.

Antonio-Javier Garcia-Sanchez received the M.S. degree in industrial engineering from the Universidad Politécnica de Cartagena (UPCT), Spain, in 2000, and the Ph.D. degree from the Department of Information Technologies and Communications, UPCT, in 2005. He is currently an Associate Professor with UPCT. He has co-authored over 50 conference and journal papers, 15 of them indexed in the Journal Citation Report (JCR). He is also an inventor/co-inventor of seven patents or utility models. He has been the main head on several research projects in the field of communication networks and optimization. His main research interests are in the areas of wireless sensor networks, streaming services, smart grid, and soil data collection. He has been a TPC member and the chair of about 30 international congresses and workshops. He is currently a reviewer of several journals listed in the ISI-JCR.

Felipe Garcia-Sanchez received the M.S. degree in telecommunication engineering from the Universidad Politécnica de Valencia in 2001, and the Ph.D. degree from the Universidad Politécnica de Cartagena in 2005. In 2001, he joined the Universidad Politécnica de Cartagena as an Assistant, where he is currently an Associate Professor. He has authored or co-authored over 50 papers in journals and conferences. He holds nine patents or intellectual properties. His current research areas involve especially Internet of Things, big data processing and performance evaluation in networking. He is a member of different workshop organization committees. He is a Technical Editor of the *International Journal of Digital Broadcasting*. He is a continuous reviewer of different journals, such as *Sensors*, *International Journal of Distributed Sensor Networks* and the *IEEE TRANSACTIONS ON COMPUTERS*.

Jose-Maria Molina-Garcia-Pardo received the degree in telecommunications engineering from the Universidad Politécnica de Valencia, Spain, in 2000, the M.Sc. degree in communication and signal processing from Newcastle upon Tyne, U.K., in 2001, and the Ph.D. degree in telecommunications and the bachelor's degree in business and administration from the Universidad Politécnica de Cartagena (UPCT), Spain, in 2004 and 2008, respectively. In 2001, he joined the Department of Information Technologies and Communications, UPCT, where he has been an Associate Professor since 2007, and accredited as a Full Professor since 2012. He is currently a Coordinator of International Relations at UPCT and leads the SiCoMo Research Group. He is also the lead researcher on some national projects, and participates actively in the European COST action IC-1004 (Radio Communications for Green Smart Environments). He has authored over 60 journals indexed in the JCR, over 100 international conferences, three book chapters, and holds four patents related to telecommunications. His research activities are centered on radio-communications, propagation, channel modeling and experimental channel sounding in different frequency band (300–400 GHz) and technologies, such as GSM, UMTS, LTE, WiFi, WSN, TETRA, mmW, OFDM, MIMO, BAN, and cognitive radio.

Joan Garcia-Haro (M'91) received the M.S. and Ph.D. degrees in telecommunication engineering from the Universitat Politècnica de Catalunya, Barcelona, Spain, in 1989 and 1995, respectively. He has been a Visiting Scholar with Queen's University, Kingston, Canada, from 1991 to 1992, and with Cornell University, Ithaca, NY, USA, from 2010 to 2011. He is currently a Professor with the Universidad Politécnica de Cartagena. He has authored or co-authored over 70 journal papers mainly in the fields of switching, wireless networking, and performance evaluation. He received an Honorable Mention for the IEEE Communications Society Best Tutorial Paper Award in 1995. He served as the Editor-in-Chief of the IEEE *Global Communications Newsletter*, included in the *IEEE Communications Magazine*, from 2002 to 2004. He was a Technical Editor of the *IEEE Communications Magazine* from 2001 to 2011.

Chapter 3

Improving RSSI-Based Path-Loss Models Accuracy for Critical Infrastructures: A Smart Grid Substation Case-Study

Improving RSSI-Based Path-Loss Models Accuracy for Critical Infrastructures: A Smart Grid Substation Case-Study

Ruben M. Sandoval[✉], *Student Member, IEEE*, Antonio-Javier Garcia-Sanchez,
and Joan Garcia-Haro, *Member, IEEE*

Abstract—IoT is rapidly expanding to all productive sectors; however, as thousands of devices are envisioned to be deployed, a careful study of the radio spectrum (and its interferences) must be considered to predict and improve the network performance. In this sense, radio-channel characterization is essential; in particular, path-loss characterization allows to mathematically predict the propagation behavior and interferences of IoT devices with precision. In this paper, we show that by means of a set of mathematical corrections and measuring procedures, we can soundly employ the received signal strength indicator (RSSI), available in most IoT motes, to derive accurate path-loss models of industrial infrastructures. Experimental results reveal that the proposed scheme substantially improves the characterization accuracy of a real smart grid environment. This, in turn, is proven to have a measurable positive impact on the planning stage of an IoT network, whose life-of-time and cost analysis can be better anticipated.

Index Terms—Characterization, IoT, network planning, path-loss model, received signal strength indicator (RSSI), smart grid (SG).

I. INTRODUCTION

INTERNET of Things (IoT) is being increasingly used for the management and control of a wide variety of critical processes and infrastructures in modern societies: first, thanks to its high flexibility, adaptability, and low-cost, and second because of the level of maturity that this type of networks exhibits nowadays. However, and precisely due to the criticality of controlled assets, the environment in which these networks are deployed should be first understood in depth from a radio propagation perspective [1]. In this sense, radio-characterization aims to predict

and optimize the use of the radio spectrum in wireless networks; critical in future IoT deployments, where the envisioned large number of devices will translate to a rapid increase in the amount of interferences—degrading the performance of the network.

The above is particularly true for certain sensitive industrial environments, where the insights provided by channel characterization are of paramount importance and make the characterization a required effort (as indicated by [2]). For instance, in substations of the smart grid (SG), the harsh environment and multipath effect are known to govern the network performance [3]. Reckoning with specific channel characterization allows for accurate simulations and better network planning which, in turn, leads to a good management of the substation; reducing deployment, operational, and maintenance costs while increasing performance [4]. Traditionally, this channel characterization has been carried out with expensive high-end devices (such as VNA—vector network analyzers—or wideband RF generators/receivers) [5]. However, the relatively scarce availability and high acquisition cost of such devices result in a reduction of the number of works that characterize different potential environments. Although these works usually seek generalization, specific characteristics of a given environment may ultimately determine the channel behavior and propagation phenomena (as indicated in [3] and [6]).

Although there are many ways to model a radio channel for IoT networks, the most widely used due to its simplicity and yet, powerful results, is path-loss characterization. Path-loss characterization basically boils down to determining how transmitted signals attenuate with distance, enabling the study of interferences and transmission losses. This straightforward characterization is of special relevance for the IoT, where the small bandwidth of communications generally leads to flat-fading propagation channels (i.e., the transmitted signal experiences the same propagation phenomena across its entire bandwidth) [3]. Furthermore, this approach has the additional benefit of allowing us to focus the study on those parameters of the channel related to transmitted/received power; thus opening the door to simpler methods and cost-effective tools. For instance, by measuring the power received at certain points [via the received signal strength indicator (RSSI)] it is possible to derive a path-loss model for a specific environment (as explored

Manuscript received July 12, 2017; revised September 29, 2017 and October 25, 2017; accepted November 14, 2017. Date of publication November 17, 2017; date of current version May 2, 2018. This work was supported by the project AIM, Ref. TEC2016-76465-C2-1-R (AEI/FEDER, UE). The work of R. M. Sandoval was supported by the Spanish MECO for an FPU Ref. FPU14/03424. Paper no. TII-17-1539. (Corresponding author: Ruben M. Sandoval.)

The authors are with the Department of Tecnologías de la Información y Comunicaciones, Universidad Politécnica de Cartagena, Antiguo Hospital de Marina, Cartagena 30202, Spain (e-mail: ruben.martinez@upct.es; antoniojavier.garcia@upct.es; joang.haro@upct.es).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TII.2017.2774838

in [7], [8], and [9], among others). The RSSI is an indicator available in most modern wireless sensor networks (WSN) and IoT motes that lets us measure the power of a received packet. Basically, the idea is to gradually increase the distance between a pair of transmitter–receiver (TX–RX) nodes while logging the perceived signal power. After this, one will have a rough idea of how a specific environment attenuates transmitted waves [10].

This straightforward procedure presents many advantages in comparison with traditional characterization techniques (namely, cost—compared to off-the-shelf alternatives—, agility, and simplicity); however, it is not problem free: first, the RSSI indicator has been reported to be affected by many factors (such as temperature [11], battery levels [12], and even WiFi or other electronic devices interferences [13]–[15]). Second, models inferred from raw RSSI values reported by different WSN/IoT platforms are substantially different, hence, results must be considered platform-dependent unless corrected [8], [16]. Finally, and although there have been a couple of works that highlight a few tips on how to increase the quality of RSSI readings [17]–[19] and how to detect WiFi-interfered RSSI readings [20], [21]; there is still a notable lack of a *common reproducible procedure* that accounts for the different phenomena, which may affect RSSI readings. These three questions may cause models derived from RSSI readings to differ substantially from, e.g., VNA-derived models [3]. Such discrepancies may lead to inaccurate models and, eventually, errors in the estimation of certain critical network aspects that would render the IoT ineffective. However, the three of them may be properly accounted for and their impact on the final derived model further reduced.

Hence, the contribution of this paper is threefold: first, to conduct an in-depth analysis of the factors involved in the estimation of an RSSI-based model from a physical perspective. Each determined factor is quantified and its respective impact mitigated through a two-sided approach: a set of correction mechanisms, and a specific measuring procedure aimed at effectively limiting the influence of such factors. Second, for an industrial scenario (a substation of the SG), two RSSI-derived models—with and without the proposed corrections—are obtained and compared to a ground-truth VNA-derived model to highlight the value of this work. Finally, these models are fed into a custom-build IoT simulator to quantify their effects on the network planning stage of an 802.15.4-based SG IoT deployment. We will show how, by applying the proposed corrections, one can derive path-loss models that combine the simplicity, cost-efficiency, and agility of RSSI-derived models with the precision of classical high-end tools. Moreover, we would like to note that all the measurements taken and scripts employed in this paper have been made available at [22] to help in the reproducibility of the results presented.

The rest of this paper is organized as follows. Section II describes and quantifies the factors that affect RSSI readings, providing mathematical tools, and reproducible procedures to limit their influence on RSSI-based models. Section III makes use of these tools to derive the accurate RSSI-based path-loss models that are employed in Section IV to run the simulations. Finally, Section V summarizes the main conclusions.

Fig. 1. Elements involved in an RSSI reading.

II. FACTORS IMPACTING RSSI-BASED MODELS

The RSSI indicator of most IoT mote platforms is an 8-bit register that accounts for the strength of the received packet averaged over its first 8 symbols (i.e. 128 μ s) [19]. The RSSI readings, along with the reference of distances at which they were taken, can be used to derive path-loss models that quantify the relation between distance and received signal power. Unarguably, the precision of the obtained RSSI readings directly affects the quality of the model obtained. Therefore, to increase the precision of the model, one should first identify each source of inaccuracy involved in the process of measuring and, either avoid its appearance or reduce its impact. From a physical point of view, a packet from which the RSSI indicator is extracted passes through the elements depicted in Fig. 1.

The packet is crafted in the transmitter IoT mote following a predefined frame format. Then, it is encoded and modulated via the radio transceiver of the mote, converting such a packet into an electromagnetic signal. After the signal goes through a series of connectors and electrical paths, it is then radiated via an antenna. The electromagnetic (EM) waves travel through the wireless medium under study and reach the receiver antenna, where the process is reversed until the packet is read by the receiving mote.

Considering the elements above, we have identified the following sources of potential inaccuracies: two intrinsic factors, i.e., related to the IoT platform itself, and one extrinsic factor, i.e., external to the motes.

- 1) The specific electronics of the motes—intrinsic factor—can be further divided as the following.
 - a) Receiver electronics: How does a certain received signal power translate into an RSSI reading?
 - b) Transmitter electronics: How do the power value set at a software level and the actual power of the transmitted packet relate?
- 2) The connectors and the antennas—intrinsic factor: Do the connectors introduce added losses to the system? How does the radiation pattern of the antennas affect the readings?
- 3) The channel under study—extrinsic factor: This should be the only variable in the system if we want to precisely estimate a path-loss model. However, since such a model represents a simplification of the real scenario, it is necessary to isolate the relation of “distance versus power” while minimizing the impact of external factors (e.g., the effect of temperature, external interferences, etc.).

Fig. 2. RSSI readings—measured at the receiving mote—versus actual received power—measured at the spectrum analyzer—for the three distinct platforms. Along with the measures, a linear regression model is represented and its rms error evaluated.

Section II-A looks into the above three sources of inaccuracies, quantifying them or preventing them from affecting RSSI readings when possible.

A. Mote Transceiver Electronics

1) *Receiver Electronics*: Although there is a plethora of works that aim at deriving the relation between actual received power and reported RSSI for different radio transceivers [12], [23], [24], to the best of the authors' knowledge, none of them has entirely isolated the influence of the radio from the impact of the environment or connectors/antennas. More explicitly, the studied RSSI readings have been obtained by wirelessly transmitting packets and then, obtaining the RSSI values from them. This leads to the consideration of two concerns: first, the effects of connectors and antennas have been neglected (e.g., the radiation patterns of the antennas have been treated as isotropic), and second, the environment has been considered to exhibit free-space properties (i.e., multipath, fading, occlusions, and other complex phenomena have been completely disregarded).

To cope with these two aspects, we have designed and implemented an experiment conceived to truly isolate and measure the effects of the mote electronics on RSSI readings. The result of this experiment is a set of curves that precisely quantifies the relation between the power of the signal arriving at the mote electronics and the reported RSSI value.

A transmitter mote generates a packet with a fixed power (defined by software following manufacturer instructions) which passes through a low-loss connector (with a plain frequency response over the working bandwidth) and a variable attenuator. Afterwards, the signal is split and takes two paths: one to a spectrum analyzer, and the other to a receiver mote. In the spectrum analyzer, the ground-truth signal power is registered and compared to the RSSI value reported by the receiving mote, yielding the aforementioned set of curves (see Fig. 2);—the

TABLE I
CONFIGURATION OF THE SPECTRUM ANALYZER

Resolution Bandwidth	300 KHz
Video Bandwidth	1 MHz
Sweep Time	2.5 ms
Integration Span	3 MHz

specific spectrum analyzer configuration used for every experiment described in here is presented in Table I. The experiment has been conducted for three distinct mote platforms (MicaZ, Iris, and Waspote PRO v1.2), each of which is equipped with a different radio transceiver (TI CC2420, AT86RF230, and Digi XBee s1, respectively). To test for variances between motes of the same platform, the analysis has been repeated for three motes from each platform. Furthermore, the procedure is replicated for different values of transmitting powers and attenuations (the latter being set at the variable attenuator). It is worth mentioning that the losses introduced by the splitter, connectors, and the variable attenuator have been considered when computing these relations. This thorough process ensures that, by eliminating the need for radiating waves, the effects of the antennas/connectors of the motes and the uncontrolled environmental variables on the RSSI readings are removed.

Each individual point in Fig. 2 has been obtained by averaging 2048 packets from 3 different motes of each platform (total 6144 packets)—note that the standard deviation of the 6144 packets is also depicted as an error bar for each distinct power value. The *deviation values*, shown in the upper-left legend, indicate the average difference between actual received power (measured with the spectrum analyzer) and mote RSSI reported power; i.e., the expected *loss of precision of the mote platform*. Furthermore, a linear regression model (1) has been fitted [via minimization of the mean square error (MSE)] to the acquired data. This regression model helps us easily correct raw RSSI readings by projecting them to actual received power values; thus, yielding the $RSSI_{corrected}$ value—this will be used in Section III to increase RSSI-derived model precision. The root mean square error (RMSE) of the model has also been provided to illustrate the goodness of fit of the model (the low RMS error indicates, precisely the adequate fit achieved).

$$RSSI_{RAWreadings} = a + b \cdot RSSI_{corrected}. \quad (1)$$

Regarding the results presented in Fig. 2, there are a few aspects worth noting. First, it is quite important to highlight the notable differences between platforms that ultimately lead to platform-dependent RSSI-derived models—also reported in [8], [12], and [24]. Second, the calculated deviation values are relatively large for every platform. These two aspects indicate that, unless corrected, the precision of raw RSSI measurements might not be appropriate to derive path-loss models for the IoT where precision is a must. For instance, a deviation of 5.07 for the MicaZ platform, indicates that the average deviation of a given RSSI reading from the actual received power is around 5 dB. Finally, the relatively large standard deviation (depicted as error bars) for certain power values has been proven to arise

Fig. 3. Expected transmission power (as per datasheets) versus experimentally measured power.

from a large variability in RSSI readings between same-platform motes—which can be as high as 3.23 dB in the case of MicaZ motes. This phenomenon has also been reported by Lui *et al.* [25] and introduces unwanted imprecision on derived models unless various motes of the same platform are employed to smooth out this effect.

2) **Transmitter Electronics:** Some works (see [26], [27]) have reported that transmitters from different manufacturers, even under the same configuration, behave differently in terms of output power. This statement has been taken further by Capriglione *et al.* [12] who stated that, for a given mote transceiver, transmission power always seems to show variability. These potential, nonnegligible variations in transmitted power may lead to inconsistencies in the calculated path-loss and then, in turn, to imprecision in the derived RSSI-based path-loss model. Although it is a common practice to assume that the transmission power indicated in datasheets (and programmed in the IoT motes) is directly translated into actual transmitted signals, we argue that this must be corroborated in order to guarantee an accurate RSSI-derived path-loss model. However, to the best of the authors' knowledge, no attempts have been made to shed any light on this issue. To this end, we have quantified the relation between the actual signal power (measured at the output of the mote transceiver with a spectrum analyzer) and the alleged transmitted power (as per manufacturers' datasheets and programmed at the software level). Fig. 3 presents the results obtained.

Along with the measures, a linear regression model is also provided to correct the deviations observed. Results show that there are great discrepancies between the alleged transmission power and the experimentally measured power that directly affect the precision of derived models. For instance, the studied MicaZ motes generate signals, on average, 7 dB weaker than expected. However, results also reveal that these discrepancies are consistent among motes of the same platform (i.e., the standard deviations of transmitting powers between motes of the same

platform are low—on average, smaller than 0.5 dB); opening the door for the provided linear model to effectively help in the correction of these divergences (it is worth mentioning that the proposed linear models present a good fit to the data; with low RMSE error values −0.42, 0.76, and 0.36 dB for the MicaZ, Iris, and Waspnote, respectively).

B. Connectors and Antennas

The effects of IoT mote connectors and antennas have been studied as a whole in different works [28]–[30] where the radiation pattern of the mounted antennas has been characterized. All the results reflect the same fact: the studied antennas do not exhibit a perfect isotropic radiation pattern. That is, the received signal power depends on the correct pointing/aligning of the TX/RX motes. Wadhwa *et al.* [31] even stated that the antenna orientation has a significant impact on the RSSI, making it crucial to consider this variable in simulations.

Therefore, to achieve the highest accuracy possible in RSSI-derived models, it is necessary to incorporate such an effect on raw RSSI readings. We propose to break down the connector/antenna impact into two distinct effects: 1) an offset, independent of the radiation pattern, and 2) an additional loss that depends on the antenna orientation. The former is determined by the maximum gain of the antennas ($G_{\max}$) minus the losses introduced by connectors (L_{conn}) in dB. In contrast, the latter depends on the miss-aligning of both antennas (TX–RX) and must be minimized by a correct pointing/aligning procedure.

All the studied mote platforms provide a $\lambda/4$ insulated wire as an antenna (known as *quarter-wave monopole antenna*). These antennas have a theoretical maximum gain of $G_{\max} = 5.19$ dBi; but, as empirically measured by [29], and considering the losses introduced by connectors and other electrical paths (L_{conn}), the effective maximum gain of such antennas mounted on IoT motes is approximately 0 dBi.

Thus, the only remaining consideration is the additional losses introduced by the irregularities of the radiation patterns. Such radiation patterns ultimately depend on the antenna mounted and the electrical characteristics/shape of the mote (as it acts as a reflection plane itself). Therefore, as both, Iris and MicaZ have the exact same electrical/shape design and employ the same antenna, we can safely assume that their respective radiation patterns are the same (note that both have been manufactured by Memsic Inc.). Since many specialized works have characterized the effective radiation pattern of the motes under study, we simply reproduce the results they have provided after normalizing such results to their peak value (see Fig. 4; the MicaZ/Iris radiation pattern has been reproduced from [28] whereas the Waspnote radiation pattern has been reproduced from [32]). It is worth noting the large deviations from the peak value (i.e., the nonuniformity) of the Waspnote platform's horizontal diagram in comparison with MicaZ/Iris and the “unusual” orientation of such a peak value (radiating backwards, i.e., 270°). In this horizontal plane, the Iris/MicaZ platforms, on the contrary, present a relatively good nearly-isotropic radiation pattern. This pattern is suitable for deriving RSSI-based models, due to its higher immunity to antenna miss-aligning. Nevertheless, and considering

Fig. 4. Horizontal and vertical radiation patterns of (a) MicaZ/Iris and (b) Wasp mote.

the nonuniformity of the vertical plane, the attenuations caused by the antenna pattern must be accounted for when correcting raw RSSI measurements.

C. Channel: Extrinsic Factors Affecting RSSI Readings

So far, a set of mote-related (i.e., intrinsic) elements that may influence RSSI readings have been analyzed and quantified; however, to precisely characterize how waves attenuate with distance, other environmental factors must be considered. Unfortunately, as remarked in [12], the current specific literature still lacks of methodological approaches aimed at identifying and quantifying the main influential factors involved in RSSI-based processes. To this end, this section presents a series of extrinsic factors that has nonnegligible negative effects on the precision of the derived model, and hence, on the IoT planning stage. The potential impact of such factors is quantified to raise awareness of the importance of an appropriate procedure in the acquisition of RSSI values.

General Considerations: In IoT networks, the most widely employed path-loss model is the log-normal shadowing path-loss model (LNSPL) (2). Such a model owes its popularity to its simplicity and ability to generalize different environments with acceptable precision [4]:

$$PL(d, n, \sigma) = BPL(d_0) + 10 \cdot n \cdot \log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma} \quad (2)$$

The LNSPL model consists of three distinct terms. The first one, the base path losses (BPL) considers the losses that are present at a reference distance d_0 (which usually takes the value of 1 m for convenience and comparability of results). The second term, the so-called path loss exponent n , adjusts the rate at which the power decays with distance. This exponent varies with the environment, frequency, and even visibility condition and determines how prone to loss the environment is. The last term is a zero mean Gaussian random variable which models the multipath nature of complex environments. The σ parameter varies the standard deviation of such random variable and reflects how disperse the losses are around the expected (mean) value.

The idea behind RSSI-based path-loss models is to acquire several RSSI readings (from transmitted probe packets) at

different distances and then fit those readings to an LNSPL model—by, e.g., minimizing the sum of square errors. If the RSSI readings are affected by external uncontrolled factors, the process of fitting will give rise to an imprecise LNSPL model.

1) *Effect of the Number of RSSI Readings Per Distance:* As explained in the last section, a fitting process takes place to derive the parameters of the path-loss model; thus, the quantity of available data readings is a paramount factor. Srinivasan *et al.* [33] argued that employing more than 120 readings is enough to increase the aggregate precision of RSSI readings. We have mathematically modeled a real environment with the help of the LNSPL model ($BPL = 40.23$ dB, $n = 2$, $\sigma = 3$) and have found that 120 readings per distance yields an estimation error of the path-loss exponent of 0.01501 (just 0.75% of the absolute, real value)—note that the exact error value depends on σ . We find this accuracy very acceptable for most critical environments and would require just a few seconds in current IoT platforms (capable of generate more than dozens of probe packets per second).

2) *Effect of Coexisting Devices on RSSI Readings:* Coexisting devices are those that operate in the same working band of frequencies. They do not need to be other IoT motes, but devices that make use of any other widely extended wireless technology (e.g., for 2.4 GHz: WiFi, Bluetooth, cordless phones, etc. [34]) The problem with RSSI readings is that, an increase in the received signal (due to uncontrolled interferences from, e.g., WiFi devices) is directly translated into an increment of the RSSI indicator. This may ultimately cause errors in the estimation of the derived path-loss model.

To cope with this situation, IoT motes operating at 2.4 GHz using the IEEE 802.15.4 standard—the most common scenario—may employ channel no. 26, which is located outside the working frequency band of most WiFi devices. Furthermore, during the RSSI acquisition campaign, the practitioner must ensure that other sources of EM interferences are avoided. If these interferences cannot be removed, their effect must be evaluated in the specific environment under study. We have empirically evaluated this recommendation and found that, in a regular laboratory setting, the average difference in RSSI readings can be as high as 4.2 dB. In other words, when employing channel no. 26, the RSSI readings were, on average, 4.2 dB smaller than those found in channel 23 (where high WiFi interferences were present) for the same distance/environment conditions.

3) *Effect of Temperature on RSSI Readings:* Boano *et al.* [11] studied the impact of temperature on the RSSI indicator, determining that an increase in temperature directly translates into an effective reduction of the RSSI. For devices employing the CC2420 radio transceiver (such as the MicaZ platform), there is a decrease/increase of about 0.18 dB with each additional degree past/below the 22 °C—the reference temperature. Although there is much work left to do in characterizing the impact of temperature on other platforms, unarguably, temperature has proven to be a determining factor and, hence, it is in the interest of the practitioner to compensate its impact on the derived path-loss model. However, since the acquisition of RSSI readings can be carried out in a few minutes, it can be safely assumed that the temperature of the environment will not vary too

much. If this is not the case, one must ensure that both, the TX and the RX are exposed to the same temperature/direct sunlight conditions during the whole campaign, or these differences in temperature must be accounted for in a later stage (e.g., using [11] corrections).

4) *Effect of Transceiver Sensitivity*: As explained in the general considerations, when performing an RSSI acquisition campaign to estimate a path-loss model, the distance between the TX and the RX motes is changed (to capture the relation between signal power and distance). When this distance makes the signal power of received packets close to, or smaller than the sensitivity of transceivers, some of these packets will not be successfully received. Intuitively, it is easy to understand that incoming packets exceeding the sensitivity threshold of the employed receiving transceiver will be effectively received, whereas those with power which falls below such a sensitivity threshold will not be recovered. Since the RSSI indicator is only computed from successfully received packets, the derived RSSI-model will only consider received packets with power above the receiver sensitivity threshold. This effect ultimately leads to an incorrect estimation of the path-loss model.

We have mathematically modeled a real channel with the help of the LNSPL model ($BPL = 40.23$ dB, $n = 2$, $\sigma = 3$). Then, two different path-loss estimations have been derived: one that does not consider the *threshold effect*, and another one that does suffer from it. Results prove that, when the *threshold effect* is not present, the error of the derived model is only 0.25% (an estimated path-loss exponent of $n = 1.995$ is obtained). However, when the transceiver sensitivity plays a major role in the estimation, i.e., the *threshold effect* is present, the error increases to 10.55% (more than 42 times larger, yielding an inaccurate path-loss exponent of $n = 1.789$).

To avoid such an unwanted effect, we propose keeping the maximum distance between the TX and the RX within the so-called *connected region* [35]. This region is characterized by a packet reception rate (PRR) larger than 85% [35] and smaller variations of the RSSI indicator [19]. The specific distance of the connected region depends on the transmitted signal power and attenuation of the channel; therefore, the $PRR > 85\%$ test will be used as an indicator of whether the motes are within the allowed maximum distance.

5) *Effect of Packet Length*: The above effect is aggravated when the size of transmitted packets is large. In fact, the *threshold effect* is not a deterministic process: as the received power gets closer to the sensitivity threshold, the probability of bit error (p_e) increases. This bit error probability is translated into the actual expected packet error probability (p_p) with the following equation:

$$p_p = 1 - (1 - p_e)^L \quad (3)$$

where L is the length of the transmitted packet (in bits) from which the RSSI is calculated. It is easily observed how larger packets lead to higher packet loss probabilities. In turn, higher probabilities imply a larger number of “low power packets” not being accounted for and hence, a more imprecise estimation of the propagation model.

Fig. 5. Quantification of the error in the estimation of the path-loss model when transmitted packet size increases.

To assess this effect, once again, we have simulated a real channel (modeled via the same LNSPL model) and employed the formulae of the OQPSK modulation (the modulation used by most low power 802.15.4 motes such as MicaZ, Iris, Waspmote, etc.) to estimate the p_e given a specific signal-to-noise ratio. Considering a background noise level of -87.4 dBm (a common value found in, e.g., critical infrastructures like SG [4]), Fig. 5 illustrates how the error in the estimation of the channel path-loss exponent relates to packet size. As can be observed, an increment of the packet size leads to an increase in the estimation error. Hence, to keep this effect as insignificant as possible, the smallest packet size must be employed. However, it is worth noting that minimum packet size is determined by the headers/footers of the protocol stack configured (e.g., IEEE 802.15.4 PHY and MAC layers entail a minimum of 14 B in headers/footers [36]).

6) *Effect of Employing Multiple Same-Platform Motes*: As commented in Section II-A2, the RSSI indicator obtained from fixed-power packets depends on the specific mote employed. The standard deviation of these RSSI readings is depicted as error bars in Fig. 2 and can be as high as 3.23 dB for the MicaZ platform. To prevent these specific-mote variations from affecting derived models, it is recommended to use different motes from the same platform. Then, different readings at each distance will be averaged, and such value used to fit the model. The effect of this phenomenon depends on the specific platform. For instance, for the MicaZ, making use of just one mote (instead of averaging the readings of three of them), yields a derived model with an RMSE 21.23% larger. However, for the Iris platform, this value is smaller (15.06%) due to the reduced standard deviation of the RSSI values.

7) *Effect of Battery Charge Status on RSSI Readings or Transmission Power*: Several works such as [12], [37], [38] claim that battery level might reduce the sensitivity of RSSI measurements or the power of wireless transmissions. However, they do not quantify such an effect and, thus, the impact of

it cannot be anticipated. In the interest of evaluating the impact of the battery charge on the RSSI readings, we have powered both, the TX and the RX, with controllable power sources and repeated the experiment of Sections II-A1 and II-A2. Instead of modifying the transmission power, we have varied the supply voltage: from 3 to 1.7 V in steps of 0.1 V for the Iris and MicaZ platforms, and from 3.7 to 2.8 V in steps of 0.1 V for the Waspote.

Our results reveal that, for the platforms under consideration, the supply voltage does not have a measurable effect on either the transmission power or the RSSI readings. When supply voltage drops below a certain threshold (1.7 V and 2.8 V for the MicaZ/Iris and for the Waspote platforms, respectively) the mote would refuse to turn the radio transceiver ON, but when it does, the TX/RX power is unaffected.

8) Effect of Environmental Conditions on RSSI Readings:

In a measurement campaign, when motes are radiating packets, the EM waves suffer from different phenomena depending on the surrounding environment and its configuration. Since the specific layout ultimately determines the scale of path losses, it is in the interest of the practitioner to ensure that the studied environment reasonably presents the same configuration during the lifetime of the IoT network. The IEEE 802.15.4 channel model report [39] asserts that the mere presence of a person close to the antenna of a mote can have an impact on the signal attenuation ranging from 1 dB to more than 10 dB. We have corroborated these results and found that variations from 1 to 8 dB are easily observed when a person crosses—or is near to—a TX–RX link. These variable and uncontrolled attenuations have a direct effect on the standard deviation of the LNSPL model to reflect the uncertainty in the received power. Thus, when carrying out the RSSI acquisition campaign, the scenario under study should present the same characteristics that it will exhibit when the IoT network is deployed (i.e., if people are expected to be around, the RSSI acquisition campaign should be carried out under such conditions).

III. ANALYSIS OF THE IMPROVEMENTS ON AN RSSI-DERIVED MODEL

The objective of this section is to illustrate the impact of the aforementioned factors on a real RSSI-derived model. To this end, we have acquired a set of RSSI readings from a substation of an SG (see Fig. 6) with the three studied mote platforms: MicaZ, Iris, and Waspote. Furthermore, two different visibility conditions are considered when acquiring the RSSI values: line-of-sight (LOS) and non-line-of-sight (NLOS). Such readings are then used to derive two LNSPL models for each platform and visibility condition: one of them is computed from raw acquired RSSI readings (called *base model*), and the other one is calculated after those readings have been corrected (called *corrected model*). The corrections are performed following the recommendations/numerical results of Section II. Once the two models have been obtained, they are compared against a ground-truth LNSPL model derived from high-end VNA measurements. The specific details of this VNA-based characterization are

Fig. 6. Substation where the received signal strength indicator (RSSI) measurements were taken. The substation is located in the south-west of Spain.

TABLE II
GROUND-TRUTH MODELS PARAMETERS

PL_0	40.3308 dB	PL_0	40.3308 dB
n	1.701	n	2.583
σ	2.18 dB	σ	3.061 dB
	LOS		NLOS

Fig. 7. Summary of steps followed to derive the *corrected model*.

covered in [3] whereas the parameters of the LNSPL model are described in Table II.

Fig. 7 summarizes the main steps of the correction method presented in the previous section and indicates the order in which they must be applied. Transmitter and receiver motes are progressively moved away to cover the following distances: 1, 2, 3, 5, 10, 15, and 20 m. 15-byte packets are sent per distance point. Given the nature of the substation, both derived models follow some of the recommendations commented on previous sections: the area remained in its usual standard conditions during the characterization stage and no major interferences were present in the working band (since no other wireless networks were

Fig. 8. Comparison between LOS RSSI-derived and ground-truth models.

Fig. 9. Comparison between NLOS RSSI-derived and ground-truth models.

installed and channel 26 was used)—steps 1 and 2 of Fig. 7. In spite of this, when the intrinsic (and the rest of extrinsic) factors are not considered, *base models* greatly differ from the ground-truth VNA-derived one. The *corrected models* alleviate this situation by considering the rest of the intrinsic and extrinsic factors, which are as follows.

Extrinsic factors (blue squares in Fig. 7)

- 1) A larger number of RSSI measurements are acquired (120 readings per distance instead of 10)—step 3 of Fig. 7.
- 2) Three motes have been used, instead of one, to smooth out the effects of intraplatform RSSI deviations—step 4 of Fig. 7.
- 3) Only readings acquired inside the *connected region* were considered. That is, those distances with $PRR > 85\%$ —step 5 of Fig. 7.
- 4) Corrections due to temperature are taken into consideration (the temperature of the substation was 31°C during the measuring campaign)—step 6 of Fig. 7.

Intrinsic factors (green squares in Fig. 7)

- 5) The deviation in the aligning of the antennas is considered, for both, the horizontal and vertical planes—step 7 of Fig. 7.
- 6) The model presented in Section II-A1 (see Fig. 2) is applied—step 8 of Fig. 7.
- 7) The model presented in Section II-A2 (see Fig. 3) is applied—step 9 of Fig. 7.

RSSI-derived models along with the ground-truth VNA-based model are depicted in Figs. 8 and 9 for the LOS and NLOS conditions, respectively. The RMS errors between the RSSI-based and the ground-truth models are also calculated to quantify the reduction achieved in the estimation error. The large reduction of this figure of merit is remarkable when all the corrections and methodological aspects are considered. For the LOS conditions, this figure of merit lowers from $RMSE = 15.238$ to $RMSE = 1.8447$ (87.89% smaller) for the Iris platform, from $RMSE$

$= 24.1561$ to $RMSE = 0.96706$ (95.99% smaller) for the MicaZ platform and from $RMSE = 10.8306$ to $RMSE = 0.93265$ (91.38% smaller) for the Waspnote platform. Similarly, and under NLOS conditions, the error reduces from $RMSE = 9.0481$ to $RMSE = 0.80593$ (91.09% smaller) for the Iris platform, from $RMSE = 19.8344$ to $RMSE = 1.2986$ (93.45% smaller) for the MicaZ platform and from $RMSE = 6.3397$ to $RMSE = 1.1116$ (82.46% smaller) for the Waspnote platform. The final RMSE obtained for each platform and visibility condition lies within the reasonable deviation of the ground-truth measurements; that is, the inherent variation of received power due to the environment ($\sigma_{\text{environment}} = 2.15\text{ dB}$). Moreover, the correction procedure exhibits a good behavior irrespective of the visibility conditions.

All in all, results indicate that, when both the intrinsic and the extrinsic RSSI-affecting factors are considered, RSSI-based models can be good, straightforward and cost-efficient first-approximations of an environment path-loss characterization for WSN.

IV. ANALYSIS OF THE IMPACT OF THE MODEL

As introduced in Section I, accurate path-loss modeling is unarguably needed for precise network planning and simulation. Otherwise, signal strength and interferences at a given distance could not be predicted. Enabling the simulation of IoT networks has the additional benefit of leveraging powerful analyses. For instance, simulations help us anticipate the maximum network delay of IoTs operating in critical industrial environments; deploying just the necessary resources to meet the delay constraints. Similarly, one can forecast the network lifetime in battery-operated IoTs, scheduling maintenance tasks (such as replacing batteries) when strictly necessary; thus, saving in operational expenditures.

To illustrate the impact of a good propagation model in network planning, we have simulated an IoT network controlling

Fig. 10. Mean network delay (MND) and mean network lifetime (MNL) versus number of gateways for different number of gateways.

an SG (specifically, the substation introduced in Section III). The SimPy simulator [40] along with the different path-loss models obtained (i.e., the MicaZ/Iris/Waspote *base models*, the MicaZ/Iris/Waspote *corrected models*, and the ground-truth model) have been used to simulate 50 IoT battery-powered nodes placed randomly in a square area of $30\text{ m} \times 30\text{ m}$ yielding distances similar to those found in the substation presented in previous section. The packet generation rate is exponentially distributed with an average sending interval of 1 s and only LOS conditions are considered. Since, in this type of networks, the number of gateways and their distance to motes is crucial, we have considered five different scenarios in which 1, 3, 5, 7, or 9 gateways are deployed (acting as information sinks and always placed in such a way that distance to nodes is minimized). The mean network delay (MND) and mean network lifetime (MNL) have been studied to determine the impact of path-loss models in time-sensitive and long-lasting critical environment, respectively. MND is computed as the mean time a packet needs to be received by a node's gateway, whereas MNL is calculated as the battery capacity divided by the average node power consumption—we have assumed that IoT nodes are powered by two AA batteries (2200 mAh each). The specifics of the simulation can be found at [22] where the full source code has been uploaded for repeatability of results.

Fig. 10 illustrates the results obtained for the two aforementioned figures of merit and for the seven different propagation models. When the *corrected models* are employed, both, the MND and MNL are remarkably close to those obtained when the ground-truth model is used. On the contrary, discrepancies between results when the *base models* are employed, pose many concerns to accurate network performance estimation. For example, if modelers made use of the inaccurate Iris/MicaZ *base models*, it could be argued that no configuration can provide an MND below 15 ms; thus, rendering the IoT network incapable of controlling critical environments. What is more, when fewer than 3 (conversely 5) gateways are deployed, the Iris (conversely MicaZ) *base model* inaccurately predicts that the network is incapable of delivering any packets (PRR = 0%). However, this

is proven to be false (as it is observed when the VNA-based model is employed); and, even with the simplest (and cheapest) deployment just 1 gateway motes are actually capable of delivering packets to their gateway (and with MND values smaller than 25 ms in any scenario).

A similar analysis can be made if the Waspote *base model* is employed. This very optimistic (and inaccurate) model foresees that the network is insensitive to the number of gateways and can always provide very small delays and large mote lifetime values. However, this is not true, and practitioners would have to find the right tradeoff between cost of deployment and the network figures of merit; ensuring that the critical assets are appropriately monitored (as the *corrected models* anticipate).

Although it is arguably that the specifics of the simulation (distances to gateways, packet generation rate, etc.) have an impact on the results; it is clear that the mathematical tools and procedures proposed in Section II increase the precision of RSSI-derived models which, in turn, have a positive impact on network planning accuracy.

V. CONCLUSION

The RSSI indicator, provided by most IoT mote platforms, offers a powerful and cost-effective mechanism to derive path-loss models, crucial in critical infrastructures for a good network planning. However, in this paper, we have enumerated a series of factors that have nonnegligible negative effects on reported RSSI readings and therefore, on the quality of derived path-loss models. These sources of perturbations are classified as intrinsic (impact of the transceivers, connectors, and antennas) or extrinsic factors (number of acquired measurements, coexisting interfering devices, effect of temperature, length of transmitted packets, battery level of motes, and environmental conditions). To make RSSI-based path-loss models a reasonably good alternative to more expensive and time consuming approaches (such as the use of RF sounding techniques), a set of correction models and methodological procedures have been provided to correct the aforementioned perturbations for three widely-known platforms (MicaZ, Iris, and Waspote). To validate them, we have compared two RSSI derived models (a base model, with no corrections applied to raw RSSI readings, and a corrected model where our proposed tools and procedures are applied and considered) with a ground-truth VNA-based path-loss model of an electrical substation. Results reveal an average reduction in the estimation error of 91.76% for the studied mote platforms. We have shown that this boost in estimation accuracy is directly translated into a remarkable increase in the precision of network simulations. This, in turn, reduces operational expenditures while leading to better performance estimation and network planning in critical industrial environments.

REFERENCES

- [1] S. Güzelgöz, H. Arslan, A. Islam, and A. Domijan, "A Review of wireless and PLC propagation channel characteristics for smart grid environments," *J. Elect. Comput. Eng.*, vol. 2011, no. 7, pp. 1–12, 2011.
- [2] D. Block, N. H. Fliedner, D. Toews, and U. Meier, "Wireless channel measurement data sets for reproducible performance evaluation in industrial environments," in *Proc. 2015 IEEE 20th Conf. Emerg. Technol. Factory Autom.*, Sep. 2015, pp. 1–4.

- [3] R. M. Sandoval, A. J. Garcia-Sanchez, J. M. Molina-Garcia-Pardo, F. Garcia-Sanchez, and J. Garcia-Haro, "Radio-channel characterization of smart grid substations in the 2.4-GHz ISM band," *IEEE Trans. Wireless Commun.*, vol. 16, no. 2, pp. 1294–1307, Feb. 2017.
- [4] R. M. Sandoval, A. J. Garcia-Sanchez, F. Garcia-Sanchez, and J. Garcia-Haro, "Evaluating the more suitable ISM frequency band for IoT-based smart grids: A quantitative study of 915 MHz vs. 2400 MHz," *Sensors*, vol. 17, no. 1, pp. 76–93, 2017.
- [5] T. S. Rappaport, "Characterization of UHF multipath radio channels in factory buildings," *IEEE Trans. Antennas Propag.*, vol. 37, no. 8, pp. 1058–1069, Aug. 1989.
- [6] J. Karedal, S. Wyne, P. Almers, F. Tufvesson, and A. F. Molisch, "A measurement-based statistical model for industrial ultra-wideband channels," *IEEE Trans. Wireless Commun.*, vol. 6, no. 8, pp. 3028–3037, Aug. 2007. [Online]. Available: <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4290044>
- [7] R. A. Alawi, "RSSI based location estimation in wireless sensors networks," in *Proc. 2011 17th IEEE Int. Conf. Netw.*, 2011, pp. 118–122.
- [8] A. Harun *et al.*, "Comparative performance analysis of wireless RSSI in wireless sensor networks motes in tropical mixed-crop precision farm," in *Proc. 2012 3rd Int. Conf. Intell. Syst. Model. Simul.*, Feb. 2012, pp. 606–610.
- [9] G. P. N. Hakim, M. Alaydrus, and R. B. Bahaweres, "Empirical approach of ad hoc path loss propagation model in realistic forest environments," in *Proc. 2016 Int. Conf. Radar, Antenna, Microw., Electron. Telecommun.*, Oct. 2016, pp. 139–143.
- [10] V. C. Gungor, B. Lu, and G. P. Hancke, "Opportunities and challenges of wireless sensor networks in smart grid," *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3557–3564, Oct. 2010.
- [11] C. A. Boano *et al.*, "Hot packets : A systematic evaluation of the effect of temperature on low power wireless transceivers," in *Proc. 5th Extreme Conf. Commun.*, 2013, pp. 7–12.
- [12] D. Capriglione, L. Ferrigno, E. D'Orazio, V. Paciello, and A. Pietrosanto, "Reliability analysis of RSSI for localization in small scale WSNs," in *Proc. 2012 IEEE Int. Instrum. Meas. Technol. Conf.*, May 2012, pp. 935–940.
- [13] C. Won, J.-H. Youn, H. Ali, H. Sharif, and J. Deogun, "Adaptive radio channel allocation for supporting coexistence of 802.15.4 and 802.11b," in *Proc. IEEE 62nd Veh. Technol. Conf. VTC-2005-Fall*, Sep. 2005, vol. 4, pp. 2522–2526.
- [14] F. Barac, M. Gidlund, and T. Zhang, "Ubiquitous, yet deceptive: Hardware-based channel metrics on interfered WSN links," *IEEE Trans. Veh. Technol.*, vol. 64, no. 5, pp. 1766–1778, May 2015.
- [15] M. Bertocco, G. Gamba, A. Sona, and S. Vitturi, "Experimental characterization of wireless sensor networks for industrial applications," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 8, pp. 1537–1546, Aug. 2008.
- [16] K. Benkic, M. Malajner, P. Planinsic, and Z. Cucej, "Using RSSI value for distance estimation in wireless sensor networks based on ZigBee," in *Proc. 2008 15th Int. Conf. Syst., Signals Image Process.*, 2008, pp. 303–306.
- [17] A. Bardella, N. Bui, A. Zanella, and M. Zorzi, "An Experimental Study on IEEE 802.15.4 multichannel transmission to improve RSSI-based service performance," in *Proc. 4th Int. Conf. Real-world Wireless Sensor Netw.*, 2010, pp. 154–161. [Online]. Available: <http://dl.acm.org/citation.cfm?id=1947841.1947860>
- [18] K. Heurtefeux and F. Valois, "Is RSSI a good choice for localization in wireless sensor network?" in *Proc. 2012 IEEE 26th Int. Conf. Adv. Inf. Netw. Appl.*, 2012, pp. 732–739.
- [19] L. Tang, K. C. Wang, Y. Huang, and F. Gu, "Channel characterization and link quality assessment of IEEE 802.15.4-compliant radio for factory environments," *IEEE Trans. Ind. Informat.*, vol. 3, no. 2, pp. 99–110, May 2007.
- [20] F. Barac, S. Caiola, M. Gidlund, E. Sisinni, and T. Zhang, "Channel diagnostics for wireless sensor networks in harsh industrial environments," *IEEE Sensors J.*, vol. 14, no. 11, pp. 3983–3995, Nov. 2014.
- [21] S. Grimaldi, A. Mahmood, and M. Gidlund, "An SVM-based method for classification of external interference in industrial wireless sensor and actuator networks," *J. Sensor Actuator Netw.*, vol. 6, no. 2, pp. 60–85, 2017.
- [22] R. M. Sandoval, "MATLAB Scripts and Data," 2017. [Online]. Available: <http://labit501.upct.es/%7Emartinez/RSSI/>
- [23] Y. Chen and A. Terzis, *On the Mechanisms and Effects of Calibrating RSSI Measurements for 802.15.4 Radios*. Berlin, Germany: Springer, 2010, pp. 256–271.
- [24] D. Konings, N. Faulkner, F. Alam, F. Noble, and E. Lai, "Do RSSI values reliably map to RSS in a localization system?" in *Proc. 2017 2nd Workshop Recent Trends Telecommun. Res.*, Feb. 2017, pp. 1–5.
- [25] G. Lui, T. Gallagher, B. Li, A. G. Dempster, and C. Rizos, "Differences in RSSI readings made by different Wi-Fi chipsets: A limitation of WLAN localization," in *Proc. 2011 Int. Conf. Localization*, 2011, pp. 53–57.
- [26] L. Angrisani, M. D'Arco, and M. Vadursi, "Clustering-based method for detecting and evaluating I/Q impairments in radio-frequency digital transmitters," *IEEE Trans. Instrum. Meas.*, vol. 56, no. 6, pp. 2139–2146, Dec. 2007.
- [27] L. Angrisani, I. Ghidini, and M. Vadursi, "A new method for I/Q impairment evaluation in OFDM transmitters," in *Proc. 2005 IEEE Instrum. Meas. Technol. Conf.*, May 2005, vol. 3, pp. 1842–1847.
- [28] W. Su and M. Alzaghal, "Channel propagation characteristics of wireless MICAZ sensor nodes," *Ad Hoc Netw.*, vol. 7, no. 6, pp. 1183–1193, 2009.
- [29] M. Alzaghal and W. Su, "Channel propagation measurement and simulation of MICAZ mote," *WSEAS Trans. Comput.*, vol. 7, no. 4, pp. 259–264, 2008.
- [30] S. H. Ahmed, S. H. Bouk, N. Javaid, and I. Sasase, "RF propagation analysis of MICAZ Mote's antenna with ground effect," in *Proc. 2012 15th Int. Multiprop. Conf.*, Dec. 2012, pp. 270–274.
- [31] M. Wadhwa, M. Song, V. Rali, and S. Shetty, "The impact of antenna orientation on wireless sensor network performance," in *Proc. 2009 2nd IEEE Int. Conf. Comput. Sci. Inf. Technol.*, 2009, pp. 143–147.
- [32] Digi, "XBee OEM RF module antenna considerations," Tech. Rep., 2012. [Online]. Available: http://www.parallax.com/Portals/0/Downloads/docs/prod/rf/XST-AN019a_XBeeAntennas.pdf%5Cn [Accessed: 8.5.13]
- [33] K. Srinivasan and P. Levis, "RSSI is under appreciated," in *Proc. 3rd Workshop Embedded Netw. Sensors*, vol. 3031, pp. 239–242, 2006.
- [34] P. G. Flikkema and S. G. Johnson, "A comparison of time and frequency-domain wireless channel sounding techniques," in *Proc. Southeastcon. Bringing Together Educ., Sci. Technol., IEEE*, 1996, pp. 488–491.
- [35] Y. Chen and A. Terzis, "On the implications of the log-normal path loss model: An efficient method to deploy and move sensor motes," in *Proc. 9th ACM Conf. Embedded Netw. Sensor Syst.*, 2011, pp. 26–39.
- [36] R. Martinez-Sandoval, A. J. Garcia-Sanchez, F. Garcia-Sanchez, J. Garcia-Haro, and D. Flynn, "A comprehensive WSN-based approach to efficiently manage a smart grid," *Sensors*, vol. 14, no. 10, pp. 18748–18783, Jan. 2014.
- [37] C. Alippi and G. Vanini, "Wireless sensor networks and radio localization: A metrological analysis of the MICA2 received signal strength indicator," in *Proc. 29th Annu. IEEE Int. Conf. Local Comput. Netw.*, Nov. 2004, pp. 579–580.
- [38] S. A. Khan, B. Daachi, and K. Djouani, "Enhanced sensor localization through compensation of battery level decay," in *Proc. 2010 5th Int. Conf. Broadband Biomed. Commun.*, 2010, pp. 1–5.
- [39] A. F. Molisch *et al.*, "IEEE 802.15.4a channel model-final report," *IEEE P802*, vol. 15, no. 04, p. 662, 2004.
- [40] Simpy, "Event discrete simulation for Python." Accessed: Oct. 11, 2017 [Online]. Available: <https://simpy.readthedocs.io>

Ruben M. Sandoval (S'12) received the B.S. degree in telematics engineering in 2011 and the M.S. degree in telecommunication engineering in 2014, both from the Universidad Politécnica de Cartagena (UPCT), Cartagena, Spain, where he is currently working toward the Ph.D. degree. His research interests include efficient wireless sensor networks, IoT, and the applicability of both network paradigms to manage critical environments.

CHAPTER 3. IMPROVING RSSI-BASED PATH-LOSS MODELS
ACCURACY FOR CRITICAL INFRASTRUCTURES: A SMART GRID
SUBSTATION CASE-STUDY

68

2240

IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, VOL. 14, NO. 5, MAY 2018

Antonio-Javier García-Sánchez received the Industrial Engineering degree (M.S. degree) in 2000 from the Technical University of Cartagena (UPCT), Spain. Since 2001, he has joined the Department of Information Technologies and Communications (DTIC), UPCT, obtaining the Ph.D. degree in 2005. Currently, he is an Associate Professor at the UPCT. He is a (co)author of more than 70 conference and journal papers, twenty five of them indexed in the Journal Citation Report (JCR). He has been the main head in several research projects in the field of communication networks and optimization, and he currently is a reviewer of several journals listed in the ISI-JCR. He is also inventor/co-inventor of 10 patents or utility models and he has been a TPC member or Chair in about thirty International Congresses or Workshops. His main research interests are in the areas of wireless sensor networks (WSNs), streaming services, Smart Grid, and IoT.

Since 2001, he has joined the Department of Information Technologies and Communications (DTIC), UPCT. He is a (co)author of more than 50 conference and journal papers, 15 of them indexed in the Journal Citation Report. He has been the main head in several research projects in the field of communication networks and optimization. His main research interests include wireless sensor networks, and Smart Grids.

Joan Garcia-Haro (M'91) received the M.S. and Ph.D. degrees in telecommunication engineering from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 1989 and 1995, respectively. He has been a visiting scholar at Queen's University at Kingston, Canada (1991-1992) and at Cornell University, Ithaca, USA (2010-2011).

He is currently a Professor with the UPCT. He is author or coauthor of more than 80 journal papers mainly in the fields of switching, wireless networking, and performance evaluation.

Dr. Garcia-Haro worked as the Editor-in-Chief for the IEEE GLOBAL COMMUNICATIONS NEWSLETTER, included in the IEEE COMMUNICATIONS MAGAZINE, from April 2002 to December 2004. He has been the Technical Editor of the same magazine from March 2001 to December 2011. He was the recipient of Honorable Mention for the IEEE Communications Society Best Tutorial paper Award (1995).

Chapter 4

Optimal Policy Derivation for Transmission Duty-Cycle Constrained LPWAN

Optimal Policy Derivation for Transmission Duty-Cycle Constrained LPWAN

Ruben M. Sandoval¹, Member, IEEE, Antonio-Javier Garcia-Sanchez, Joan Garcia-Haro, Member, IEEE,
and Thomas M. Chen, Senior Member, IEEE

Abstract—Low-power wide-area network (LPWAN) technologies enable Internet of Things (IoT) devices to efficiently and robustly communicate over long distances, thus making them especially suited for industrial environments. However, the stringent regulations on the usage of certain industrial, scientific, and medical bands in many countries in which LPWAN operate limit the amount of time IoT nodes can occupy the shared bands. This is particularly challenging in industrial scenarios, where not being able to report some detected events might result in the failure of critical assets. To alleviate this, and by mathematically modelling LPWAN-based IoT nodes, we have derived optimal transmission policies that maximize the number of reported events (prioritized by their importance) while still complying with current regulations. The proposed solution has been customized for two widely known LPWAN technologies: 1) LoRa and 2) Sigfox. Analytical results reveal that our solution is feasible and performs remarkably close to the theoretical limit for a wide range of network activity patterns.

Index Terms—Internet of Things (IoT), long-range networks, LoRa, low-power wide-area network (LPWAN), Markov decision process (MDP), Sigfox.

I. INTRODUCTION

THE INTERNET of Things (IoT) is now extensively employed in a wide variety of industrial environments, ranging from agriculture to power grids to manufacturing. The integration of sensing and actuating technologies helps to increase productivity and efficiency, while at the same time, boosting control over the entire production chain. The increasing sophistication of IoT devices now enables robust and long-lasting networks with reduced installation and maintenance costs, which cut back on operational and capital expenditures.

From a technological point of view, industrial IoT deployments have taken over classical wireless sensor networks

(WSNs) by implementing either low-power multihop communication standards (such as IEEE 802.15.4) or opting for cellular communication technologies (such as GSM/3G/4G). The former work in the industrial, scientific, and medical radio bands (ISM), and are therefore license-free. However, due to their limited range, they tend to incur in high initial capital expenditures, since in order to cover medium to long distances, multihop topologies consisting of dozens of nodes are required. This is even more so in the case of many industrial environments where the node density is not particularly high and the areas to be covered tend to be large, making most of these deployed nodes serve merely as relaying nodes in a multihop scheme [1]. On the contrary, IoT networks based on cellular approaches operate in licensed bands which unavoidably leads to higher operational expenditures, and force network operators to rely on Telcos.

However, in the past couple of years, low-power wide area networks (LPWANs) have emerged as alternatives to the aforementioned options, especially for those environments in need of long-range communications, which is the case for many industrial scenarios like power and water grids, agricultural/rural areas or even cities. This type of network is characterized by three main features: 1) long coverage range (up to 30 km [2]); 2) low-power consumption (less than 100 mJ per transmission [3]); and 3) very long-standing deployment (nodes have an expected lifespan of around two years with two AA batteries [3]). LPWAN are deployed following a classic star topology, thus removing the complexity and costs of a multihop infrastructure [1]. Furthermore, since they operate in ISM bands (normally low-frequency bands such as 868/902 MHz for Europe/USA) and offer long-lasting features, maintenance costs are usually much lower compared to cellular alternatives.

Unfortunately, and as a consequence of operating in ISM bands, LPWAN networks are subject to strict legal regulations in many countries. One of the most inconvenient restrictions is the limit established on radio activity device patterns. For instance, in Europe, the ETSI EN 300 220-1 document [4] rules that the transmission duty cycle (TDC) of devices that do not implement listen-before talk mechanisms, as is the case of LPWAN networks, must fall below a certain value (normally expressed as a percentage, e.g., 1%).¹ The duty cycle (DC)

¹Note that throughout the rest of the document, TDC will be used to denote the precise amount (in seconds) of time that nodes can access the medium per hour (e.g., 36 s), whereas DC will represent the percentage of such an hour (e.g., 1%).

Manuscript received December 21, 2017; revised April 16, 2018; accepted May 1, 2018. Date of publication May 4, 2018; date of current version August 9, 2018. This work was supported by the Project AIM under Grant TEC2016-76465-C2-1-R (AEI/FEDER, UE). The work of R. M. Sandoval was supported by the Spanish MEC under FPU FPU14/03424. (Corresponding author: Ruben M. Sandoval.)

R. M. Sandoval, A.-J. Garcia-Sanchez, and J. Garcia-Haro are with the Department of Tecnologías de la Información y Comunicaciones, Universidad Politécnica de Cartagena, 30202 Cartagena, Spain (e-mail: ruben.martinez@upct.es; antoniojavier.garcia@upct.es; joang.haro@upct.es).

T. M. Chen is with the School of Engineering and Mathematical Sciences, City University of London, London EC1V 0HB, U.K. (e-mail: tom.chen.1@city.ac.uk).

Digital Object Identifier 10.1109/JIOT.2018.2833289

is defined as the percentage of time that a given node occupies a particular frequency band (measured over the length of an hour). Hence, a maximum TDC of 1% implies that LPWAN motes have a maximum permitted TDC of 36 s per hour. For example, motes cannot use a specific transmission band more than 36 s an hour, which corresponds to 1% of an hour. This TDC limitation also applies to other geographical zones and bands (e.g., the 779–787 MHz band in China [1], or the 950–956 MHz in Japan [5]) and, although it helps in reducing packet collisions, it potentially jeopardizes the ability of a network to effectively control valuable assets.

It is easy to think of situations in which nodes reporting non-important events (e.g., vibrations detected in a certain asset) may result in depleting the available TDC and thus rendering the mote unable to later give information about critical events (e.g., the global malfunction of such an asset). Therefore, it is crucial to recognize the TDC as one of the main performance-limiting factors in LPWAN-based deployments, and to manage the consumed transmission time as the scarce resource it is (as has been done in many works with the energy left in motes batteries [6]–[8]). Unfortunately, and in contrast to battery management, the academic community still lacks exhaustive analyses that could result in optimal transmission policies in terms of the remaining TDC. Optimal transmission policies would be those that, taking into account the full context of the mote, would determine the action that maximizes the number of total high-importance packets transmitted over the entire node lifespan. The context of a mote could be described by the importance of the event being reported (e.g., low or high), the remaining TDC, propagation conditions, etc. Furthermore, and regarding the derived optimal action, some of the most widespread current LPWAN technologies, such as LoRa [9], allow the use of different configurations when transmitting packets. These configurations can increase the probability of successfully transmitting a packet at the cost of increasing the time-on-air of packets and hence, the consumed TDC. Therefore, an optimal transmission policy would also consider this tradeoff and determine, in case of reporting an event, under which configuration it should be transmitted. It must be noted that, although the TDC-limitation resembles bandwidth restrictions, this is a very different problem. For instance, in the former, present decisions (e.g., transmit a packet) greatly influence future actions (e.g., not being able to transmit further packets) and the applied restrictions operate in time, independently of the number of raw bits transmitted. Conversely, under a bandwidth limitation, one could operate greedily, taking the action that maximizes the current figure of merit by, for example, limiting the amount of transmitted data and/or the speed at which such data is sent.

In the context of deriving action policies, and especially for WSN/IoT networks, the Markov decision process (MDP) framework stands out for its particularly well-suited form, optimal results and mathematical robustness [10]. The solution of MDP models are known as policies (in this case, transmission policies) and are guaranteed to indicate the best action to take at each moment according to the model of the environment. In the specific domain of decision making frameworks (such as MDP), the best action is conceptually defined as the

optimal response in terms of maximizing the total reward over the entire lifespan of a node. For the problem illustrated here, the total reward of a node is understood as the number of successfully transmitted events prioritized by their respective importance.

Although there are many works in the literature that apply the theory of decision making (and, in particular, MDP) to WSN/IoT networks [11]–[13], to the best of authors' knowledge, none of them has proposed any optimal transmission policy in TDC-limited networks. Hence, with the aim of filling the research gaps, we present the main contribution of this paper: the derivation of an MDP-based transmission policy for TDC-constrained networks.

- 1) Complies with the TDC regulations of each geographical zone (e.g., max DC of 1%) and maximizes the number of successfully reported events.
- 2) Yields the optimal action to be taken when a node is presented with the opportunity of reporting an event. Note that the set of actions might not be limited to transmitting or discarding the information, since several transmission configurations may be possible.
- 3) Considers the importance of the packet when deriving the optimal action. Thus, high-importance packets should be prioritized over low-importance packets when deciding whether to send them or not, and under which available configuration.

The rest of this paper is organized as follows. The related work is presented in Section II. The analytical MDP formulation is first introduced in Section III, where a model of the problem is also characterized. In Section IV, the generic mathematical model is applied to the two currently most popular LPWAN technologies: 1) LoRa [9] and 2) Sigfox [14]. Section V validates the proposed models by comparing the average reward of a simulated industrial IoT network when: 1) our proposed MDP-based approach is used and 2) standard transmission policies are employed. After that, the results obtained from both approaches are compared to the maximum attainable rewards (i.e., the *theoretical limit* of the network) to further highlight the contributions. Finally, Section VI presents the conclusions and outlines future lines of research.

II. RELATED WORK

Long range technologies such as LoRa [9] and Sigfox [14] have started to draw significant attention from the academic and industrial communities. Some of the published works in this field devote their efforts to analyzing the performance of real LPWAN deployments under different conditions: IoT devices monitoring civil infrastructures such as bridges [15], LoRa-based video surveillance systems [16], health monitoring motes [17], etc. On the other hand, some other studies are focused on analyzing the advantages, disadvantages, capabilities, and limits of the current implementations of these technologies from a technological point of view. For example, the real scalability of current LoRa networks [18], [19], the performance of their different configurations [20], and how these types of networks tolerate download traffic [21], amongst other things are being studied. Although they are very

practical and illustrating, none of these works optimizes or analyzes the performance of LPWAN in a generic and theoretic fashion, which would allow their extrapolation to different technologies (LoRa, Sigfox, etc.) or their future implementations, beyond current transceivers. As a notable exception, [22] studied the impact of sub-band selection on LoRa nodes by modeling nodes as an infinite, jockeying M/M/c queue (i.e., c servers, arrivals determined by a Poisson process, and exponentially distributed job services). Although the work is very well detailed, mathematically neat and applicable to future deployments, it does not capture the true, complex nature of real long-range networks, where resources are very scarce (i.e., infinite queues are impossible to implement) and traffic cannot always be assumed to follow a certain distribution.

Regarding the TDC-limitation problem, two works [1], [16] have recently highlighted the importance of TDC-aware networks by illustrating the problem of transmitting real-time video in long-range deployments. Although practical, the solution proposed focuses on deliberately breaking the 36 s/h TDC limitation by complying with it in a network-aggregated fashion (i.e., the average network TDC is kept below 36s/h, not the per-node TDC). In fact, [23] highlighted that the effects of TDC limitations jeopardize the actual capacity of large-scale deployments, and the only de-facto proposal to manage it, a fixed limit on the number of permitted messages per day, fails to provide the network with enough flexibility.

With the interest of contributing to fill the notable gap in research, we propose an approach to derive MDP-based transmission policies that fully comply with the TDC regulations while maximizing the number of high-priority reported events.

III. MATHEMATICAL MODEL

As commented on Section I, the goal of the system is to maximize the expected number of reported events prioritized by their importance, which is defined as the reward. To this end, we have opted for modeling the optimal action-derivation problem as an infinite horizon, discounted reward MDP [24]. First, because of the special ability of this mathematical framework to model the problem as an optimization task over discrete actions [25], which makes it particularly suitable for deriving transmission policies as explored by [8]. And second, because of the remarkable efficiency of current MDP-solving methods, which allows them to be used in very resource-constrained WSN/IoT motes, as [7] and [26] highlighted. The “infinite horizon” property indicates that the optimal policy is derived by considering the entire lifespan of motes. It is usually accepted that this otherwise infinite lifespan of motes may come to an end with certain small probability [6], [10]. This factors in the probability of node breakdown or manual disconnection, and globally represents the idea of maximizing almost immediate rewards instead of distant rewards, i.e., the “discounted reward” attribute of the MDP. For example, a reward of R obtained in the next hour is preferred to a reward of R obtained next year.

The proposed Markovian system operates in a discrete fashion (i.e., discrete time) in which time is subdivided into time

Fig. 1. Timing scale. Awake-asleep cycles of T seconds are divided into T/Q time slots of length Q seconds each. Events can be generated at the beginning of each cycle, when sensor readings are obtained.

slots with a length of Q s. Hence, the j th time slot represents the time within seconds, with $j \in \mathbb{Z}$.

The working cycle of IoT/WSN networks deployed in industrial environments is usually ruled by the awake-asleep mote cycles. These motes usually remain in a dormant state to save energy, then wake up, sense some parameters and report them to a gateway, if needed, before going back to sleep. The periodicity with which nodes wake up and enter into the dormant state (i.e., the length of the awake-asleep cycle) equals T seconds or, similarly, T/Q time slots. Depending on how critical the controlled assets are, T should vary accordingly to allow for finer monitoring. Therefore, at the beginning of each k th awake-asleep cycle, there might be a requirement to transmit an event e , i.e., sensor readings, (see Fig. 1). Each event of the arbitrary type i is generated with a probability λ_i . The set of the probabilities of generating any event conforms vector $\Lambda = (\lambda_0, \lambda_1, \dots, \lambda_P)$, with λ_0 being the probability of not generating any event and equal to $\lambda_0 = 1 - \sum_{i=1}^P \lambda_i$. Note that $0 \leq \lambda_i \leq 1$ and $\sum_{i=0}^P \lambda_i = 1$. Moreover, each packet reports an event of a different importance, which is represented by the priority of such an event $\mathbf{G} = (0, G_1, G_2, \dots, G_P)$. The first item in the vector indicates the priority of reporting a nongenerated event.

As introduced in Section I, over any given period of 1 h, a node can occupy the transmission band up to $3600 * DC$ seconds or, equivalently, $[(3600 * DC)/Q]$ time slots. The specific TDC consumption is determined by the transmission action, as some configurations lead to greater over-the-air times. Hence, when a given action a_i is taken, $C(a_i)$ time slots of TDC are expended. Considering up to $N + 1$ different actions, the vector $\mathbf{C}$ models the time slot consumption of each action $\mathbf{C} = (0, C(a_1), C(a_2), \dots, C(a_N))$, with the first action being not reporting the given event (or not having anything to report). Continuing with the dynamics of the TDC, at the beginning of each awake-asleep cycle, $Q_r = [(T * DC)/Q]$ time slots of TDC are obtained. This is derived from the fact that some time (T seconds) has passed and accordingly, some TDC has been “recharged.” Note, that since it is particularly illustrating, we employ a terminology similar to the one found in energy consumption modeling. This defines a scheme in which the TDC is regarded as a commodity that can be consumed with transmissions and is recharged/regained (and stored) at the beginning of each cycle. Note that the maximum storable amount of TDC is equal to $Q_{MAX} = [(3600 * DC)/Q]$. Some similarities can be observed between the proposed scheme and the classic Token Bucket algorithm [6]. A token is added to the bucket every $1/Q_r$ seconds, the bucket can hold at the

most Q_{MAX} tokens, and events can be sent if there are enough tokens in the bucket to process their virtual length (defined by the vector $\mathbf{C}$). However, it is “time slots” and not packets (or bytes of packets) which are being stored. In fact, under the proposed system, packets will never be buffered or stored. Thus, they will be discarded if, at the time of being generated, they are not sent (either because there are not enough tokens/time slots or it is not in the interest of the future rewards).

As indicated in Section I, the generation and consumption of TDC work in a per-band fashion. That is, when different bands are available to motes, they must choose in which band each event will be transmitted. It is in such a band where the TDC will be consumed. However, since gateways (which are the core of the LPWANs) cannot be actively listening to different bands simultaneously, we will regard different bands as different networks. Hence, the model here introduced, which represents a specific network, shall be simply replicated if motes can operate in different networks (bands).

Then, the state s of any given mote can be fully described by the tuple (q_k, G_k) where q_k indicates the remaining TDC, in terms of time slots, at the beginning of the awake-asleep cycle k , and G_k denotes the priority of the event generated in the k th cycle (including 0 if no event has been generated). Note that this process exhibits the Markov property, i.e., the state of the system is fully described by the current state and no past information is needed.

We can now represent the state space of the system as a 2-D Markovian model (see Fig. 2). The first dimension (horizontal axis) represents the accumulated TDC, whereas the second dimension (vertical axis) exemplifies the generation of an event. Horizontally, we move a deterministic number of time slots to the right every cycle: Q_r (the TDC recharge rate). Similarly, we move to the left when we transmit an event. The number of time slots we move in that direction depends on the action (specifically, on the TDC consumption of such an action defined by $\mathbf{C}$). Vertically, we move randomly following the event generation probability. At the beginning of each cycle, we move to a new event-generation position based on $\mathbf{A}$. Fig. 2 illustrates this.

At any given state s , a certain set of actions, $\mathbf{A}$, are at the disposal of motes based on their remaining TDC, q_k , and the priority of the generated event G_k (that is, the state of such motes). Motes will act according to a transmission policy (defined by π) which should be regarded as a simple mapping between states and actions ($\pi : \mathbf{S} \rightarrow \mathbf{A}$). This policy determines what is called the value function $V(s, \pi)$, formally described as the expected total reward obtained when such a policy is followed given a starting state s

$$V(s, \pi) = \mathbb{E}_s^\pi \left(\sum_{k=0}^{\infty} \gamma^k \cdot r(s_k, a_k) \right), s \in \mathbf{S} \quad (1)$$

where k is the awake-asleep cycle index, a_k and s_k are the action taken and the state at that cycle, respectively. $1 - \gamma$ is the independent and identically distributed (i.i.d) probability of a node terminating its lifespan, again, due to a breakdown or a simple disconnection. Note that $\gamma \in [0, 1)$. $\mathbb{E}_s^\pi$ represents

Fig. 2. State space of the proposed system. Transitions between states are depicted with arrows. Horizontal and vertical transitions are depicted independently for the sake of clarity.

the expectation of the total reward under such policy. On the other hand, $r(s_k, a_k)$ denotes the reward obtained when action a_k is performed being at state s_k . This reward has been modeled to reflect the final goal: to successfully report events to the gateway (especially high-importance events). To appropriately consider this “success rate” in reporting events, it should be noted that, as indicated in Section I, some transmission configurations increase the probability of reception. Hence, the expected reward should increase accordingly. Thus, the reward is formally defined as follows:

$$r(s_k, a_k) = G_k \cdot \text{PRR}(a_k) \quad (2)$$

that is, the reward obtained when reporting a generated event is defined as the product of the priority of such event and the packet reception rate (PRR) under the employed configuration (i.e., the action). The function $\text{PRR}(a_k)$ depends on the particular technology and specific examples for different technologies will be given in Section IV.

The aim of the MDP is then to find the optimal policy π^* that maximizes the value function given an initial state

$$\pi^* = \arg \max_{\pi} V(s, \pi). \quad (3)$$

This optimal policy π^* effectively maximizes the expected number of reported events (prioritized by their respective importance) over the entire mote lifespan, while complying with the TDC regulations at the same time.

Since the states, transitions, actions, and rewards structures of the system can be fully described, we have opted for tackling the optimal policy-derivation problem via model-based approaches (for which these four elements are needed). On the other hand, reinforcement learning (RL) alternatives depend on feedback signals to derive such policies. These feedback signals are typically modeled via ACKs in wireless networks. However, LPWAN gateways (in charge of acknowledging packets) are also TDC-limited. This poses a very strict limit on the number of ACKs that may be sent and thus, renders RL

alternatives unfeasible. Unfortunately, traditional model-based approaches, like policy iteration or value iteration [25], require tabular representations of the system and thus, can only be applied if the number of states and actions is small. Therefore, to enable the application of such algorithms, Section IV elaborates on a set of simplifications that can be applied to the proposed model of Fig. 2, without any loss of precision, in real long-range networks.

A. Modeling the Generation Probability

As indicated above, to solve a model-based decision-making problem, the transition matrix of the MDP (i.e., how states evolve when actions are performed) must be known. Although the horizontal transitions in the 2-D MDP model represented in Fig. 2 are deterministically defined by the actions taken and the TDC obtained in each cycle (Q_r), the vertical transitions depend on the Λ vector (the event-generation probabilities). For the generic scenario in which events are being generated based on the sensor readings, the event-generation probabilities are unknown. Note that if events are generated periodically, the sensing rate must simply be adjusted to balance the consumption-generation of TDC. However, these probabilities can be effectively estimated by looking at the generation history of each mote. By considering the number (and type) of generated events over a given number of sensing cycles, we can estimate the probability of packet generation. It is worth remarking that we only need an estimation of how likely is that an event is generated, not an estimation of when it will be generated. Nevertheless, large imprecisions in the estimation of Λ may translate, under some circumstances, in a slight degradation of the performance of the derived policy (see Section V-C for further analysis on this degradation). Since, at the beginning of a mote's life, this knowledge (the history of generated events) might be very scarce (especially for very rare events) we may incorporate some prior knowledge of the environment in order to start off with appropriate accuracy. For example, other motes deployed in the same scenario might provide valuable information regarding the probability of generating an event. Considering that events are independent to each other, the occurrence of a given type of event i can be regarded as a realization of a Bernoulli process with probability λ_i , which models how likely that event is to occur. To estimate λ_i , we can compute how likely the history of events ($e_1, e_2, \dots, e_n$) is under each value of $\lambda_i \in [0, 1]$ and weight it by our prior knowledge. Then, we can derive the value of λ_i that maximizes (λ_i^*) that product and thus, define the vector Λ^* . Formally,

$$P(\lambda_i \vee e_1, e_2, \dots, e_n) \propto P(e_1, e_2, \dots, e_n \vee \lambda_i) \cdot P(\lambda_i) \quad (4)$$

$$\lambda_i^* = \arg \max_{\lambda_i} P(e_1, e_2, \dots, e_n \vee \lambda_i) \cdot P(\lambda_i). \quad (5)$$

$P(\lambda_i)$ characterizes our prior belief about the distribution of a specific event generation probability. For instance, it seems reasonable to consider that high-importance events would tend to occur less frequently than low-importance events in well-functioning industrial environments.

Additionally, if Λ is known to change over time, that is, there is a seasonality component, a moving average can be used to let our knowledge about the event-generation process change over time. Furthermore, if events are known to be correlated, we can let $\lambda_{i,j}$ represent the probability of generating an event of type i after having generated an event of type j . Then, to estimate $\lambda_{i,j}$, we would only consider this type of sequence when analyzing the event history.

IV. PARTICULARIZATION OF THE MODEL

To assess the performance and benefits of the proposed solution, the MDP-based system model has been applied to the two most popular technologies in the current LPWAN networks arena: 1) Sigfox and 2) LoRa. The generic modeling (depicted in Fig. 2) is particularized to the specifics of Sigfox and LoRa technologies in Sections IV-A and IV-B, respectively. Furthermore, it is shown how the inherent properties of both technologies reduce the complexity of the MDP models (i.e., the size of the state and action space) and thus, allow them to be solved directly on actual IoT/WSN motes. In Section V, these models are used to simulate Sigfox/LoRa motes under a wide range of conditions. The rewards obtained with our proposal are compared with those obtained under different habitual policies.

Throughout the following sections, the European 868–868.6 MHz ISM sub-band [4], with its 1% DC limitation, is used. However, results can be directly applied to other bands without any loss of generality.

A. Sigfox

Sigfox operates both as an LPWAN technology (with a proprietary communication solution) and as a service provider (with its own LPWAN network, installed in 17 countries) [2]. Technology-wise, it employs ultranarrow band (UNB) signals along with BPSK modulation to attain communication distances longer than 50 km. Like most LPWAN technologies, it works in sub-GHz ISM bands, and provides a rather modest bitrate of 100 bps [27].

For the evaluation of the transmission policies, an IoT/WSN network deployment in an industrial environment is assumed. In such a scenario, it is usual that following the awake-asleep mote cycle, events are generated based on the preprocessed sensor readings. These readings reflect the value of certain assets (e.g., industrial machinery, soil moisture, rotor vibration, etc.) and thus, are reasonably supposed to all be equal in length. Since Sigfox only allows payloads of up to 12 bytes, this payload length is considered in this and following sections. The entire packet length, once the headers have been added, is 26 bytes (208 bits) in length, which at 100 bps, takes 2 s to be sent. However, to increase the PRR, Sigfox transmits, by default, three times the same packet (one after another), thus occupying the working band for 6 s ($T_{TX} = 6$).

Note that Sigfox provides a single transmission configuration. Hence, reducing the action space to either transmit or do not transmit (a_1 and a_0 , respectively). The time is divided into time slots of $Q = 0.05$ s. Thus, each 6-s transmission consumes 120 time slots of TDC. The length of the awake-asleep

TABLE I
VARIABLES OF THE SIGFOX'S MODEL

Parameter	Formula	Value
Q	N/A	0.05 seconds
T	N/A	5 seconds
T_{TX}	N/A	6 seconds
DC	N/A	1%
C	T_{TX}/Q	120 time slots (note that the TDC consumption for not sending any packet is 0)
Q_r	$T \cdot \frac{DC}{Q}$	1 time slot
Q_{MAX}	$3600 \cdot \frac{DC}{Q}$	720 time slots

cycle is chosen to be $T = 5$ s. This value is consistent with the sensing rate of IoT/WSN motes deployed in industrial scenarios that do not require real-time monitoring (which is not attainable with current LPWAN solutions [23]) and yields a recharge rate of 1 time slot ($Q_r = 1$) per cycle. Similarly, the 1% DC implies a maximum storable TDC of 36 s or $Q_{MAX} = 720$ time slots. Table I specifies the variables of the model along with the formulas when applicable.

Concerning the event generation, two types of events, based on their priorities, have been considered as an example: 1) low-importance and 2) high-importance events. Note that this does not entail any loss of generality and the models presented in this paper can be easily generalized to any number of different priorities. Thus, we define the Λ vector as follows: $\Lambda = (\lambda_0, \lambda_1, \lambda_2)$. This reflects a scenario in which low-importance events can be regarded as readings lying within acceptable values (i.e., controlled assets are operating normally), whereas high-importance events would model reports on anomalies in the controlled assets. As explained in Section III, the rewards obtained by motes depend on both the importance of the transmitted event (1 or 2 for the low- and high-importance events, respectively) and the PRR. Unfortunately, the exact curves for deriving the PRR from the signal-to-noise ratio (SNR) are not currently available for Sigfox motes. Therefore, the sensitivity of Sigfox gateways (-147 dBm [28]) is rightfully employed to compute the PRR. That is, if the received power is over the sensitivity threshold, the PRR will be 1, and 0 otherwise.

The parameters in Table I configure the Sigfox system model depicted in Fig. 3. This system shows states with 721 different TDC values (from $TDC = 0$ to $TDC = Q_{MAX} = 720$) and 3 different G values (the type of the generated event). Hence, configuring a joint state-space of 2163 (721×3) different states. Conversely, and as indicated above, the action-space is limited to two different actions: report (a_1) and do not report (a_0) an event.

B. LoRa

LoRa is unarguably the main actor in the current LPWAN scene. It has the support of many worldwide technology leaders (Cisco, Microchip, IBM, HP, etc.) [29], and unlike Sigfox, it enables the deployment of private networks. From a technological point of view, LoRa offers a proprietary chirp spread spectrum modulation to achieve communication distances greater than 15 km in sub-GHz bands [30]. Moreover,

Fig. 3. State space of the Sigfox Markovian model. Transitions between states are depicted with arrows. Horizontal and vertical transitions are depicted independently for the sake of clarity.

LoRa allows us to modify several transmission properties: the bandwidth and central frequency of the communication, the coding rate (CR), which is the ratio between the length of the packet and the length of the error-correction code, the transmission power, and the spreading factor (SF). This last parameter, the SF, is defined as the ratio between the symbol rate and chip rate. Higher SFs can increase the sensitivity and range of communication at the expense of increasing the over-the-air time of the packets. Thus, this parameter is fundamental in the derivation of the optimal transmission policy and leads to a tradeoff which is worth studying. Higher SF factors increase the PRR and hence, the expected immediate reward, but consume more TDC, reducing the potential future rewards. Similarly, the CR also affects both the TDC consumption, as decreasing it increases the effective length of the packet, and the expected reward, since with higher values, the PRR increases as the communication gets more resistant to errors. The relation between the SF/CR configurations and the bit-error-rate and therefore, the PRR, has been modeled in [31] and is illustrated in the following expression:

$$BER = 10^{\alpha e^{\beta SNR}} \quad (6)$$

where alpha and beta depend on the specific configuration of the SF and CR, covered in Table II. In turn, the PRR, used to model the rewards as per (2), can be computed as follows:

$$PRR = (1 - BER)^L \quad (7)$$

where L is the length of the packet. As indicated above, the specific configuration of SF/CR also affects the transmission rate of packets. For a bandwidth of 125 KHz, which is the most common configuration, the effective transmission rates (TXR) are included in Table II for all the six configurations of SF available, and the two different values of CR studied (the two CR configurations for which the α and β parameters were available).

If the time slot length (Q) is set to 0.051 s, and again, 26-byte packets are considered (208 bits), the time slot consumption of each action can be easily computed as follows (note that the SF/CR configurations define the action set):

$$C(a_i) = \frac{T_{TX}}{Q} = \frac{208/TXR_{a_i}}{Q} \quad (8)$$

Similarly, for an awake-asleep cycle of 5 s, the time slot recharge rate equals 1 time slot ($Q_r = 1$) and the maximum

TABLE II
 α , β , AND TXR PARAMETERS FOR DIFFERENT VALUES OF CR AND SF

CR	SF	a_i	α	β	TXR
4/5	7	a_1	-30.2580	0.2857	3410 bps
	8	a_2	-77.1002	0.2993	1841 bps
	9	a_3	-244.6424	0.3223	1015 bps
	10	a_4	-725.9556	0.3340	507 bps
	11	a_5	-2109.8064	0.3407	253 bps
	12	a_6	-4452.3653	0.3317	127 bps
4/7	7	a_7	-105.1966	0.3746	2663 bps
	8	a_8	-289.8133	0.3756	1466 bps
	9	a_9	-1114.3312	0.3969	816 bps
	10	a_{10}	-4285.4440	0.4116	408 bps
	11	a_{11}	-20771.6945	0.4332	204 bps
	12	a_{12}	-98658.1166	0.4485	102 bps

TABLE III
VARIABLES OF THE LoRa's MODEL

Parameter	Formula	Value
Q	N/A	0.051 seconds
T	N/A	5 seconds
TXR	N/A	(3410, 1841, 1015, 507, 253, 127, 2663, 1466, 816, 408, 204, 102) bps
DC	N/A	1%
C	$C(a_i) = \frac{208/TXRA_i}{Q}$	(1, 2, 4, 8, 16, 32, 2, 3, 5, 10, 20, 40) time slots (note that the TDC consumption for not sending any packet is 0)
Q_r	$T \cdot \frac{DC}{Q}$	5 time slots
Q_{MAX}	$3600 \cdot \frac{DC}{Q}$	706 time slots

storable TDC 706 time slots ($Q_{MAX} = 706$). Table III summarizes the variables of the model along with the formulas when applicable.

Technically, LoRa only defines the physical layer of the wireless communication, whereas LoRaWAN standardizes the upper layers. Within these layers, the medium access control (MAC) sublayer ensures compliance with TDC regulations in a very specific fashion. Instead of simply enforcing the maximum TDC of, for example, 1% per hour (i.e., 36 s), it forces the motes to undergo a silent period after each packet transmission. Therefore, the TDC regulation is not only met "per hour," but also between any two transmitted packets. This silent period (T_{off}) depends on how long the radio was ON to transmit the last packet (T_{TX}) and it is formally defined as

$$T_{off} = \frac{T_{TX}}{DC} - T_{TX}. \quad (9)$$

Although this helps in reducing the number of packet collisions, it has the undesirable effect of preventing LoRa motes from being able to transmit packets in bursts. Furthermore, this alters the way in which the model (Fig. 2) makes a transition. Instead of progressively "accumulating" TDC each cycle, a mote would lie at the end of the TDC chain (at the right-hand side of it, where Q_{MAX} is in Fig. 2) and every time it generates a packet, it moves the number of time slots defined by C to the left (see Fig. 4). Only then, would the mote start to progressively move to the end of the chain again (Q_r time slots each cycle). And when it finally reaches the end of the chain, another packet can be sent again (i.e., when the mote is not at the end of the chain, it is considered to be in its T_{off} period and hence, cannot send any further packets). This behavior results in the leftmost side of the chain

Fig. 4. State space of the LoRa Markovian model. Only when motes reach the end of the chain (at the right-hand side of the model) can new packets be. Therefore, states with fewer than 666 time slots will never be visited.

never being visited. In particular, the states to the left of the value $Q_{MAX} - C_{MAX} = 666$ time slots (see Fig. 4) will not be reached. Note that $C_{MAX} = 40$ time slots and corresponds to $C(a_{12})$. Therefore, these states can be omitted to speed up the computation of the MDP solution.

Thus, the state-space of the LoRa model is simplified to only account for TDC values ranging from 666 to 706 (41 different values) and event generation from 0 to 2 (three different values). Hence, the entire system model contains 123 different states (41×3) and 13 different actions (not sending a packet plus the 12 different combinations of SF and CR). Note that LoRa motes operating in the 868–868.6 MHz sub-band can select one of the three different channels to transmit a packet. However, since they belong to the same sub-band, the TDC consumption is aggregated among them, and the system dynamics are not altered at all. Therefore, TDC-wise motes are assumed to select a channel randomly when facing a new transmission, which is the current by-default behavior of LoRaWAN motes as per the standard.

V. PERFORMANCE ANALYSIS OF THE TRANSMISSION POLICIES

To analyze and judge the performance obtained when the proposed MDP-based transmission policy is implemented in LPWAN motes, two metrics are employed: 1) a measure of how well motes could possibly do [i.e., the maximum attainable reward, defined by (11)] and 2) a measure of how well motes do with other policies [the reward obtained by following other transmission policies, defined by (10)]. The former represents the highest performance a node can attain if it knew beforehand all the events that would be generated over a fixed time period of K sensing cycles. Mathematically, it represents a *theoretical limit* on the attainable rewards, and can be computed as the maximization of the sum of discounted rewards over the set of available actions for the K cycles (11). Although knowing what events will be generated beforehand is not realistic, it offers us a clear insight into the *regret* of using a certain transmission policy. This figure of merit (the *regret*) is formally defined as the difference between the maximum attainable reward (R^{MAX}) and the reward obtained with a given transmission policy $[R, (10)]$, which is a particularization

of the (1) for a fixed time period and a given event history]

$$R = \sum_{k=0}^K \gamma^k r(s_k, a_k), \text{ with } a_k = \pi(s_k) \quad (10)$$

$$R^{\text{MAX}} = \max_{a_k} R, \text{ subject to} \quad (11)$$

$$\text{TDC}_{k+1} = \min(Q_{\text{MAX}}, \text{TDC}_k + Q_r - C(a_k)) \geq 0. \quad (12)$$

Furthermore, in order to have a good idea of the true performance of the MDP-based transmission policy under different scenarios, our proposal is compared to two different intuitive policies.

- 1) *Always Transmit (AT)*: Every generated event is transmitted if enough TDC is available. This is the by-default policy in scenarios where the priorities of events are disregarded, as is the case in the majority of current LPWAN deployments. Every generated event is treated the same way and transmitted if possible.
- 2) *Transmit High-Importance Events Only (THIEO)*: Only high-importance events will be transmitted (if enough TDC is available). In very TDC-restricted networks (like networks with 1% of DC) it is tempting to save such TDC for the dispatching of high-importance events. This policy is aimed at guaranteeing the transmission of high-importance events by allocating all the available TDC to them.

Since the rewards obtained depend on the history of generated events, all the policies will be tested for different values of Λ . Let $\theta = (\lambda_1/\lambda_2)$ be the relation between λ_1 and λ_2 (the probabilities with which low and high-importance events are generated, respectively). By varying θ , different types of networks can be characterized. For instance, $\theta = 2$ represents a network in which low-importance events, events containing readings that lie within normal/expected values, are generated twice as often as high-importance events (reports on anomalies or unexpected values). Furthermore, let $\phi = \lambda_1 + \lambda_2 \in [0, 1]$ be the probability of which an event of any type is generated during every sensing cycle. This parameter adjusts the *activity* of the network. For instance, $\phi = 0.6$ indicates that with a 60% probability, an event is generated at any given cycle. These two parameters (ϕ and θ) define the activity patterns of the network and particularize λ_1 and λ_2 (e.g., for $\theta = 2$, $\phi = 0.6$, the following values are derived: $\lambda_1 = 0.4$ and $\lambda_2 = 0.2$).

For the evaluation of the different policies, ϕ has taken values from 0 to 1 in steps of 0.05 (20 different values that cover a wide range of networks between very quiet to very active ones). On the other hand, θ has been set to the following discrete values: 0.5, 1, 2, and 4 to analyze four different LPWAN networks according to the relation between both types of events. For each of these 80 combinations (20 different values of ϕ and 4 different values of θ), 1000 sensing/awake-asleep cycles of 5 s each have been simulated with 20 different seeds to compute the average discounted reward [ADR, the average of (10) over 20 different randomly generated event-histories]. For the MDP-based transmission policy, the estimated generation rates (Λ^*) are updated with past experiences every 50 sensing cycles, following the procedure described in Section III-A. It should be mentioned

that the Python code employed to run the simulations has been made publicly available to support the research in this area [32].

A. Sigfox

The difference in the ADR (i.e., *regret*) between the maximum attainable reward (i.e., the *theoretical limit*) and the proposed solution (denoted as MDP-based) is remarkably low for the entire space of ϕ and θ (see Fig. 5). In fact, the greatest difference found is 0.186 for $\phi = 0.71$ and $\theta = 4$ (this means ADR values of, in the worst case, just 3.12% smaller than the *theoretical limit*). However, these differences increase up to 1.23 for the AT policy and 2.24 for the THIEO policy ($\phi = 1.0$, $\theta = 1$ and $\phi = 0.24$, $\theta = 4$, respectively), yielding ADR values 14.09% and 58.96% smaller than the *theoretical limit*, respectively. Such increments in the *regret*, reflect the fact that only with the MDP-based proposed transmission policy, can motes effectively adapt to the changing conditions of a realistic network, swiftly finding a suitable event-reporting policy that boosts their performance. Ultimately, this translates into a higher number of events being reported, always in a way in which their respective priorities are considered.

When motes generate very few events (that is, for low values of ϕ), the AT policy gets very close to the *theoretical limit*. In these situations, the TDC is accumulated faster than it is consumed, and thus, every event can (and should) be transmitted. This is precisely what AT policy does. On the other hand, when the network is very active (high values of ϕ), the rewards obtained under the THIEO policy (which only reports high-importance events) also tend to reach the *theoretical limit* (especially for $\theta = 0.5$, when more high-importance packets are generated). The intersection between AT and THIEO rewards occurs at different points of ϕ based on the exact value of θ . For instance, high values of θ entail a higher proportion of low-importance events and thus, make the THIEO policy tend to drop too many events by discarding low-importance ones. Moreover, and as a secondary effect, when more high-importance events are generated (i.e., when θ grows), the global ADR tends to increase. This is reflected by the fact that ADR values are generally greater for $\theta = 0.5$ than for $\theta = 4$.

Nevertheless, for the Sigfox technology, neither AT nor THIEO policies can effectively adapt to the ever-changing conditions of industrial LPWAN networks, and thus, they would perform very poorly in dynamic scenarios, which are the most common type of industrial environment. Conversely, the proposed, MDP-based policy efficiently controls the behavior of LPWAN motes to adapt their transmission patterns to fluctuating conditions of the environment, attaining near-optimal performance for a wide range of situations.

B. LoRa

Since in LoRa, packets can be sent under different configurations, for the AT and THIEO policies, the SF is adjusted with the adaptive data rate algorithm [33]. This algorithm is part of the LoRaWAN recommendations and it is basically in

Fig. 5. ADR values obtained with Sigfox motes for (a) $\theta = 0.5$, (b) $\theta = 1.0$, (c) $\theta = 2.0$, and (d) $\theta = 4.0$.

charge of finding the most suitable SF for the given conditions (specifically, the perceived SNR). With respect to the CR, the two configurations (4/5 and 4/7) have been exhaustively evaluated. On the other hand, the bandwidth and the transmission

Fig. 6. ADR values obtained with LoRa motes for (a) $\theta = 0.5$, (b) $\theta = 1.0$, (c) $\theta = 2.0$, and (d) $\theta = 4.0$.

power, which do not affect the TDC consumption, have been set to their default values: 125 kHz and 30 dBm, respectively.

The first notable fact in Fig. 6 is the large difference between the ADR obtained under the MDP-based policy and the ADR

achieved under the AT and THIEO intuitive policies. The maximum *regret* yielded by the AT policy is 5.1 for $CR = 4/5$, and 4.01 for $CR = 4/7$ (both for $\phi = \theta = 1.0$). ADR values are 68.58% and 55.14% smaller than the *theoretical limit*, respectively. In turn, the maximum *regret* obtained under the THIEO policy is 4.7 for $CR = 4/5$ and 3.43 for $CR = 4/7$ (both for $\phi = 1$ and $\theta = 0.5$). ADR values are 60.05% and 50.07% smaller than the *theoretical limit*, respectively. These rather large differences reveal the importance of reckoning with a policy that adapts to environmental conditions, especially when the set of possible actions is fairly large. In LoRa, 13 different actions are considered. THIEO and AT policies, limited to employing a fixed set of two actions, either not transmitting or transmitting under a fixed configuration determined by the adaptive data rate algorithm, cannot regulate mote behavior to meet the network conditions. As in the Sigfox case, THIEO tends to perform better than AT for high values of ϕ and especially for low values of θ . In other words, when either a large proportion of events are high-importance events, or a large number of them are generated in absolute terms, it is advisable to employ the TDC only for sending high-importance events.

In contrast, the proposed MDP-based solution seems to perform relatively well under any circumstances, with the maximum *regret* being 1.18 for $\phi = 0.85$ and $\theta = 2$. This means that ADR values are, in the worst case, 18.21% smaller than the *theoretical limit*. The ability of the proposed solution to choose the best SF and CR configurations in each scenario results in a higher capacity to adapt to different situations, hence, being able to effectively report a larger number of prioritized events.

It is worth noting that the differences appreciated between Sigfox and LoRa (in terms of ADR), stem from the fact that LoRa enforces a silent period T_{off} after every transmission. This makes that a larger portion of packets get sent later in time. With a discount rate γ strictly smaller than 1—the common practice—postponing transmissions entails a penalization in the obtained reward (precisely, the reward is scaled by γ). In fact, it can be shown how, if γ approaches one, the obtained ADR values under LoRa surpasses those obtained under Sigfox—the average nondiscounted rewards are generally larger for LoRa than for Sigfox.

Regarding the complexity of the proposed transmission policy for both, LoRa and Sigfox motes, it should be noted that traditional MDP-solving methods, such as value iteration, have been formally proven to run in polynomial time with respect to the number of states and actions for a fixed discount rate γ [34]. Moreover, the memory requirement has been shown to be linear with the number of states [25]. These two properties make the proposed MDP-based solution very well-suited for running in resource-constrained devices, such as IoT motes and in time-critical scenarios, such as industrial environments. Furthermore, the obtained transmission policies can be easily stored in 1-D arrays in motes. These are extremely efficient and fast memory structures. In fact, for the worst-case scenario (LoRa), the complete policy could be stored in less than 62 bytes (123 different states multiplied by 4 bits per state).

TABLE IV
DEGRADATION OF ADR VERSUS σ OF THE PERTURBATION

σ of noise	LoRa degradation of ADR	Sigfox degradation of ADR
0.02	0.00%	0.19%
0.08	0.10%	0.33%
0.2	2.56%	1.37%
0.4	5.54%	3.73%
0.8	9.76%	4.34%
1.6	18.56%	6.75%

C. Impact of the Estimation of Λ on the ADR

For the proposed MDP-based approach, the event-generation rate, Λ , need to be estimated. When the estimated Λ largely diverges from the true underlying event-generation rate, the derive transmission policies might be suboptimal. We have analyzed this by purposely introducing perturbations in the estimated Λ , and then analyzing the obtained performance degradation. This degradation has been computed as a difference between the ADR obtained with the true Λ and the ADR obtained with the perturbed Λ . In turn, the perturbed Λ has been generated by adding zero-mean Gaussian noise (and varying standard deviation σ) to the true Λ .

Table IV shows the results of the analysis for Sigfox and LoRa motes. Once enough noise is added (which depends on the specific technology), a quasi-linear dependency between σ and ADR degradation can be appreciated. Moreover, it should be noted that, even in the presence of large perturbations (large values of σ), the ADR degradation is kept within reasonable limits (about 18.5% and 6.7% for LoRa and Sigfox, respectively). Note that, since Λ ranges between 0 and 1, the magnitude of perturbing noise values generated with $N(0, \sigma = 1.6)$ can be considered large enough. This demonstrates the resilience of the proposed approach to errors in the estimation of Λ and its applicability to scenarios where traffic generation patterns are hard to estimate.

VI. CONCLUSION

Long-range IoT networks have started to draw the attention of the academic and industrial communities as very promising alternatives to other classic IoT technologies. This is mainly due to their longer communication ranges, robustness, simplicity, and convenient use of the license-free ISM bands. However, the limitations imposed on ISM bands in many countries hinder the ability of long-range IoT motes to make free use of the shared medium. In particular, the restriction to the amount of time motes can occupy the ISM bands (normally less than 36 s an hour) might jeopardize the ability of these kinds of networks to operate in industrial scenarios, where sensed data must flow in a timely fashion.

To alleviate this situation, an optimal transmission policy based on the analytical framework of MDP, has been derived with two objectives: 1) to maximize the number of reported events, prioritized by their importance and 2) to comply with the ISM regulations. This has been accomplished in two steps. First, a general model of long-range IoT motes has been proposed and, second this model has been tuned for two widely known technologies: 1) LoRa and 2) Sigfox.

CHAPTER 4. OPTIMAL POLICY DERIVATION FOR TRANSMISSION DUTY-CYCLE CONSTRAINED LPWAN

3124

IEEE INTERNET OF THINGS JOURNAL, VOL. 5, NO. 4, AUGUST 2018

Motes of both technologies have been simulated under different network conditions. Unlike other traditional policies tested, whose performance is strongly coupled with network conditions, our obtained results reveal that the proposed solution performs very close to the maximum theoretical limit under almost any condition. Furthermore, the proposed solution is computationally fitted for resource-constrained motes and for time-critical scenarios, thus making it a good solution for IoT motes deployed in industrial scenarios.

REFERENCES

- [1] C. Pham, "QoS for long-range wireless sensors under duty-cycle regulations with shared activity time usage," *ACM Trans. Sensor Netw.*, vol. 12, no. 4, pp. 1–31, Nov. 2016. [Online]. Available: <http://doi.acm.org/10.1145/2979678>
- [2] J. Petäjäjärvi, K. Mikhaylov, A. Roivainen, T. Hanninen, and M. Petäjäjärvi, "On the coverage of LPWANs: Range evaluation and channel attenuation model for LoRa technology," in *Proc. 14th Int. Conf. ITS Telecommun. (ITST)*, Dec. 2015, pp. 55–59.
- [3] M. Bor, J. Vidler, and U. Roedig, "LoRa for the Internet of Things," in *Proc. Int. Conf. Embedded Wireless Syst. Netw.*, 2016, pp. 361–366. [Online]. Available: <http://dl.acm.org/citation.cfm?id=2893711.2893802>
- [4] "Final draft ETSI EN 300 220-1 V2.4.1 (2012-01)," ETSI, Sophia Antipolis, France, Rep. RENV-ERM-TG28-434, 2012. [Online]. Available: http://www.etsi.org/deliver/etsi_en/300200_300299/30022001/02_04_01_40/en_30022001v020401o.pdf
- [5] S. Aust, R. V. Prasad, and I. G. M. M. Niemegeers, "IEEE 802.11ah: Advantages in standards and further challenges for sub 1 GHz Wi-Fi," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Ottawa, ON, Canada, Jun. 2012, pp. 6885–6889.
- [6] W. Zhu, P. Xu, M. Zheng, G. Wu, and H. Wang, "Transmission policies for energy harvesting sensors based on Markov chain energy supply," in *Proc. 10th EAI Int. Conf. Body Area Netw.*, 2015, pp. 228–232, doi: 10.4108/eai.28-9-2015.2261406.
- [7] P. Blasco, D. Gunduz, and M. Dohler, "A learning theoretic approach to energy harvesting communication system optimization," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1872–1882, Apr. 2013.
- [8] N. Michelusi, K. Stamatiou, and M. Zorzi, "Transmission policies for energy harvesting sensors with time-correlated energy supply," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2988–3001, Jul. 2013.
- [9] (2017). *LoRa*. [Online]. Available: <https://www.lora-alliance.org/>
- [10] M. A. Alsheikh, D. T. Hoang, D. Niyato, H.-P. Tan, and S. Lin, "Markov decision processes with applications in wireless sensor networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 3, pp. 1239–1267, 3rd Quart., 2015.
- [11] Z. Ye, A. A. Abouzeid, and J. Ai, "Optimal stochastic policies for distributed data aggregation in wireless sensor networks," *IEEE/ACM Trans. Netw.*, vol. 17, no. 5, pp. 1494–1507, Oct. 2009.
- [12] X. Fei, A. Boukerche, and R. Yu, "An efficient Markov decision process based mobile data gathering protocol for wireless sensor networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Mar. 2011, pp. 1032–1037.
- [13] S.-T. Cheng and T.-Y. Chang, "An adaptive learning scheme for load balancing with zone partition in multi-sink wireless sensor network," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 9427–9434, 2012. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S095741741200382X>
- [14] (2017). *Sigfox*. [Online]. Available: <http://www.sigfox.com>
- [15] F. Orfei, C. B. Mezzetti, and F. Cottone, "Vibrations powered LoRa sensor: An electromechanical energy harvester working on a real bridge," in *Proc. IEEE SENSORS*, Orlando, FL, USA, Oct. 2016, pp. 1–3.
- [16] C. Pham, "Deploying a pool of long-range wireless image sensor with shared activity time," in *Proc. IEEE 11th Int. Conf. Wireless Mobile Comput. Netw. Commun. (WiMob)*, Oct. 2015, pp. 667–674.
- [17] J. Petäjäjärvi, K. Mikhaylov, M. Hämmäläinen, and J. Iinatti, "Evaluation of LoRa LPWAN technology for remote health and wellbeing monitoring," in *Proc. 10th Int. Symp. Med. Inf. Commun. Technol. (ISMICT)*, Worcester, MA, USA, Mar. 2016, pp. 1–5.
- [18] M. C. Bor, U. Roedig, T. Voigt, and J. M. Alonso, "Do LoRa low-power wide-area networks scale?" in *Proc. 19th ACM Int. Conf. Model. Anal. Simulat. Wireless Mobile Syst.*, 2016, pp. 59–67. [Online]. Available: <http://doi.acm.org/10.1145/2988287.2989163>
- [19] O. Georgiou and U. Raza, "Low power wide area network analysis: Can LoRa scale?" *IEEE Wireless Commun. Lett.*, vol. 6, no. 2, pp. 162–165, Apr. 2017.
- [20] M. Bor and U. Roedig, "LoRa transmission parameter selection," in *Proc. 13th IEEE Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, Ottawa, ON, Canada, 2017, pp. 27–34.
- [21] A.-I. Pop, U. Raza, P. Kulkarni, and M. Sooriyabandara, "Does bidirectional traffic do more harm than good in LoRaWAN based LPWA networks?" *CoRR*, vol. abs/1704.0, pp. 1–6, Dec. 2017. [Online]. Available: <http://arxiv.org/abs/1704.04174>
- [22] R. B. Sørensen, D. M. Kim, J. J. Nielsen, and P. Popovski, "Analysis of latency and MAC-layer performance for class A LoRaWAN," *IEEE Wireless Commun. Lett.*, vol. 6, no. 5, pp. 566–569, Oct. 2017.
- [23] F. Adelantado et al., "Understanding the limits of LoRaWAN," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 34–40, Jan. 2017.
- [24] M. Wiering and M. Van Otterlo, "Reinforcement learning," in *Adaptation, Learning, and Optimization*, vol. 12. Heidelberg, Germany: Springer, 2012.
- [25] A. Geramifard et al., "A tutorial on linear function approximators for dynamic programming and reinforcement learning," *Found. Trends Mach. Learn.*, vol. 6, no. 4, pp. 375–451, 2013.
- [26] K. Shah and M. Kumar, "Distributed Independent reinforcement learning (DIRL) approach to resource management in wireless sensor networks," in *Proc. IEEE Int. Conf. Mobile Adhoc Sensor Syst.*, Oct. 2007, pp. 1–9.
- [27] A. Augustin, J. Yi, T. Clausen, and W. M. Townsley, "A study of LoRa: Long range & low power networks for the Internet of Things," *Sensors*, vol. 16, no. 9, Sep. 2016, Art. no. E1466.
- [28] W. Yang et al., "Narrowband wireless access for low-power massive Internet of Things: A bandwidth perspective," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 138–145, Jun. 2017.
- [29] *Member Directory of LoRa Alliance*, LoRa-Alliance.org, 2018. [Online]. Available: <https://lora-alliance.org/member-directory>
- [30] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 855–873, 2nd Quart., 2017.
- [31] F. V. D. Abele, J. Haxhibeqiri, I. Moerman, and J. Hoebeke, "Scalability analysis of large-scale LoRaWAN networks in ns-3," *CoRR*, vol. 4, no. 6, pp. 2186–2198, 2017. [Online]. Available: <http://arxiv.org/abs/1705.05899>
- [32] R. M. Sandoval, A.-J. Garcia-Sanchez, J. Garcia-Haro, and T. M. Chen, *Python Scripts*. Accessed: May 15, 2018. [Online]. Available: <http://labit501.upct.es/~rmartinez/policies/>
- [33] "A technical overview of LoRa and LoRaWAN," LoRa-Alliance, Beaverton, OR, USA, Rep. 1, 2015. [Online]. Available: https://www.tuv.com/media/corporate/products_1/electronic_components_and_lasers/TUeV_Rheinland_Overview_LoRa_and_LoRaWANmp.pdf
- [34] M. L. Littman, T. L. Dean, and L. P. Kaelbling, "On the complexity of solving Markov decision problems," in *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence, Ser. UAI'95*, San Francisco, CA, USA: Morgan Kaufmann, 1995, pp. 394–402. [Online]. Available: <http://dl.acm.org/citation.cfm?id=2074158.2074203>

Ruben M. Sandoval (M'12) received the B.S. degree in telematics engineering and M.S. degree in telecommunication engineering from the Universidad Politécnica de Cartagena, Cartagena, Spain, in 2011 and 2014, respectively, where he is currently pursuing the Ph.D. degree.

His current research interests include efficient wireless sensor networks, IoT, and the applicability of both network paradigms to manage critical environments.

Antonio-Javier Garcia-Sanchez received the M.S. and Ph.D. degrees from the Universidad Politecnica de Cartagena, Cartagena, Spain, in 2000 and 2005, respectively.

Since 2001, he has been with the Department of Information Technologies and Communications, UPCT. He has co-authored over 50 conference and journal papers, 15 of them indexed in the *Journal Citation Report*. He has been the main head in several research projects in the field of communication networks and optimization. His current research interests include wireless sensor networks and smart grids.

Joan Garcia-Haro (M'91) received the M.S. and Ph.D. degrees in telecommunication engineering from the Universitat Politecnica de Catalunya, Barcelona, Spain, in 1989 and 1995, respectively.

He is currently a Professor with the Universidad Politecnica de Cartagena, Cartagena, Spain. He has been a Visiting Scholar with Queen's University, Kingston, ON, Canada, from 1991 to 1992, and with Cornell University, Ithaca, NY, USA, from 2010 to 2011. He has authored or co-authored over 80 journal papers mainly in the fields of switching, wireless networking, and performance evaluation.

Dr. Garcia-Haro was a recipient of the Honorable Mention of the IEEE Communications Society Best Tutorial Paper Award in 1995. He served as the Editor-in-Chief for the *IEEE Global Communications Newsletter*, included in the *IEEE Communications Magazine*, from 2002 to 2004, and the Technical Editor from 2001 to 2011.

Thomas M. Chen (M'89-SM'08) received the B.S. and M.S. degrees in electrical engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, and the Ph.D. degree from the University of California at Berkeley, Berkeley, CA, USA.

He is a Professor of cyber security with the City, University of London, London, U.K. He was a Senior Member of Staff with GTE Laboratories (currently, Verizon), Waltham, MA, USA. He joined Southern Methodist University, Dallas, TX, USA, as an Associate Professor, and then Swansea University, Wales, U.K., as a Professor of networks. He has co-authored or co-edited seven books. He holds two U.S. patents. His current research interests include network security, privacy, and cyber terrorism.

Dr. Chen served as the Editor-in-Chief of *IEEE Communications Magazine*, *IEEE Network*, and IEEE COMMUNICATIONS SURVEYS & TUTORIALS.

Chapter 5

Smart Usage of Multiple RAT in IoT-oriented 5G Networks: A Reinforcement Learning Approach

SMART USAGE OF MULTIPLE RAT IN IOT-ORIENTED 5G NETWORKS: A
REINFORCEMENT LEARNING APPROACH

Ruben M. Sandoval, Sebastian Canovas-Carrasco, Antonio-Javier Garcia-Sanchez, and Joan Garcia-Haro
Department of Information and Communication Technologies, Technical University of Cartagena, Cartagena, Spain.
Emails: {ruben.martinez, sebas.canovas, antoniojavier.garcia, joang.haro}@upct.es

ABSTRACT

Smart Cities and Smart Industries are the flagships of the future IoT due to their potential to revolutionize the way in which people live and produce in advanced societies. In these two scenarios, a robust and ubiquitous communication infrastructure is needed to accommodate the traffic generated by the 10 billion devices that are expected by the year 2020. Due to its future world-wide presence, 5G is called to be this enabling technology. However, 5G is not a perfect solution, thus providing IoT nodes with different Radio Access Technologies (RATs) would allow them to exploit the various benefits offered by each RAT (such as lower power consumption or reduced operational costs). By making use of the mathematical framework of Reinforcement Learning, we have formulated the problem of deciding which RAT should an IoT node employ when reporting events. These so-called transmission policies maximize a predefined reward closely related to classical throughput while keeping power consumption and operational costs below a certain limit. A set of simulations are performed for IoT nodes provided with two RATs: LoRa and 5G. The results obtained are compared to those achieved under other intuitive policies to further highlight the benefits of our proposal.

Keywords 5G, IoT, Reinforcement Learning, Multi-RAT, LPWAN, Machine Learning

1. INTRODUCTION

The growing demand for automatization mechanisms in all quotidian areas has led to the Internet of Things (IoT) paradigm. This technological revolution has enabled the interconnection of all sorts of devices, known as *things*, by equipping them with a communication module and a basic sensor, memory, and computing unit. It is now extensively demonstrated that endowing things with some intelligence has a positive impact on the entire society, leading to a better management of critical resources such as water [1], energy [2] and city assets in general [3], [4].

The progressive integration of different automation systems in urban environments is leading to the so-called *Smart City*.

In these Smart Cities ubiquitous machine-to-machine (M2M) and machine-to-human (M2H) communications enable cleaner, sustainable and more cost-efficient urban spaces, ultimately improving citizens' quality of life. A

similar concept emerges in the manufacturing and productive sector, where the term *Smart Industry* (SI) has been coined and received increasing attention in past years. In this particular communication environment, most of generated data is derived from M2M interactions, either from monitoring, actuation, or a combination of both -which gives rise to modern autonomous systems (e.g. control and actuation on industrial plants)-. This computerization entails a significant reduction in both cost and safety risks, since a real-time monitoring of critical facilities can be performed without the requirement of additional human resources.

This increase in the number of control, monitoring and actuation communication tasks in both cities and industries lead to a prominent rise in data generated. Since most IoT devices communicate via wireless communications, several efforts are being devoted to the development of new Radio Access Technologies (RATs) to alleviate the expected network congestion. Among these RATs, 5G excels as a promising solution to enable power and cost-efficient wireless network infrastructures. Long Term Evolution (LTE), that can be considered to have laid the foundations for the 5G revolution, has already had a measurable positive impact on the performance of cellular networks (one of the most popular RATs for IoT). However, the number of IoT devices is expected to reach 10 billion by the year 2020 [5]. This sheer increment in data transmitted along with the particularities of IoT-generated traffic, as discussed below, have posed serious doubts about the sustainability of the current and future cellular networks as an effective RAT for the IoT [6], [7].

It is worth mentioning that the traffic generated by the IoT is nothing like traditional phone-generated data, for which cellular networks are very well suited for. This traffic is mainly characterized by the transmission of sporadic small bursts of data that, in most cases, should reach the destination without an excessive delay. The large volume of aggregated traffic (considering the expected 10 billion of devices) and the sporadic nature and on-demand usage of the network, implies a heavy signaling overhead that can potentially hinder the performance of both, cellular network infrastructure and IoT devices [6], [8], [9].

This work has been supported by the project AIM, ref. TEC2016-76465-C2-1-R (AEI/FEDER, UE). Ruben M. Sandoval and Sebastian Canovas Carrasco also thank the Spanish MEC for an FPU (refs. FPU14/03424 and FPU16/03530) pre doctoral fellowship.

Conversely, cellular-oriented communication protocols, like LTE and the much-anticipated 5G, are geared towards faster, more stable transmissions of information that, indeed, can be of interest to certain situations -e.g. to transmit a daily report of an important asset, or in general, to deliver large packets-. For all other situations, and with the aim of maximizing network and cost efficiency, a promising suite of solutions that make use of the unlicensed ISM (Industrial, Scientific and Medical) bands is being extensively used as a RAT for the IoT. As one of the main key features of Smart Cities/Industries is the large areas to be covered, low-power wide area networks (LPWAN) technologies are called to be the de-facto mean of communication for those small and sporadic transferences of information. The distinguishing feature of LPWAN is the long-range radio links forming a star network topology, in which end devices (nodes) are directly connected to a collector device (gateway) that provides access to the IP network. These networks are designed to notably improve the battery life of nodes and support on-demand bursty traffic by reducing the signaling overhead to a minimum.

However, the main drawback of LPWAN technologies is its low bitrate. Depending on the technology and configuration, it fluctuates from one hundred bits per second to a few thousands of bits per second, potentially being insufficient for handling all the traffic generated by an IoT device. Such low bitrate is due to the modulation techniques employed in most LPWAN, that focus on being as much robust as possible against interferences and increasing the receiver sensitivity (depending on the specific technology, up to -150 dBm) to achieve large link distances. Therefore, a trade-off between data rate and sensitivity arises. For instance, in LoRa [10], one of the most popular LPWAN technologies, this trade-off can be tuned by the so-called Spreading Factor (SF) parameter, which controls the spreading of the signal. For larger values of SF, the sensitivity increases (achieving longer transmission distances) whereas the data rate decreases.

Furthermore, with the aim of reducing cost, most of these LPWAN work in ISM bands. Unfortunately, in many countries, these bands are subject to strong regional regulations. For example, in Europe, China and Japan, communication devices that do not provide Listen-Before-Talk techniques cannot exceed a certain transmission Duty Cycle (DC) limit [11]. This value is defined as the percentage of time that a given device can transmit in a particular frequency band, usually measured over an hour. In Europe, the maximum DC for some bands is limited to 1%, that is, a node cannot occupy the channel for more than 36 seconds per hour [12]. To accomplish this restriction, after each transmission, LoRa nodes remain silent during a time period known as off-period (t_{off}). The duration of such t_{off} follows the expression: $t_{off} = \frac{t_{on}}{DC} - t_{on}$, where t_{on} stands for the duration of the transmission.

As can be seen, there are at least, two competing RATs that cannot, on their own, successfully support the traffic generated by the IoT, either due to a lack of specialization in

sporadic traffic and very low energy consumption (cellular technologies) or to a low offered bitrate (LPWAN). Therefore, there is an increasing trend toward the use of multiple RATs in the IoT to minimize this problem. However, although many works look into employing heterogeneous RATs in wireless networks (as will be commented in the Related Work section), to the best of our knowledge, very few studies tackled this problem from a mathematical point of view -that is, how nodes optimally decide which RAT should be used at any given time-. With the interest of filling this gap, and by making use of the mathematical framework of Reinforcement Learning (RL), a subfield of Machine Learning (ML), we propose a mechanism to derive transmission policies that optimally determine the RAT to be employed for each transmission. These transmission policies consider the global state of the node and are oriented to maximize some predefined performance metric while being computable in very hardware-constrained devices.

Therefore, the contribution of this work is threefold: (i) a methodological and thorough justification for the need of multiple RATs in IoT-oriented 5G networks; (ii) a mathematical formulation that models performance of IoT nodes as an RL problem that truly embraces the nature of these devices; and (iii) the proposal of a state-of-the-art ML technique to solve such an RL problem and its analysis, via simulation, to highlight the importance of ML-oriented transmission policies in 5G deployments.

The rest of the paper is organized as follows. In Section 2, a review of the related work is presented. Next, in Section 3 we describe the positive impact of ML techniques to the problem under consideration and its importance to the future 5G standard. The mathematical framework is discussed in Section 4, where a generic RL-based model of nodes is formulated for an arbitrary number of RAT. Furthermore, in this section, a popular ML genetic algorithm is also proposed for deriving the optimal transmission policy. This generic model is particularized for IoT nodes endowed with multiple RATs in Section 5. Next, in Section 6, the proposed model is used to simulate IoT nodes fitted with two RATs: 5G and LPWAN. The ML-derived policy is compared to three other intuitive policies to further highlight the scope of application and benefits of our proposal. Finally, Section 7 concludes.

2. RELATED WORK

Nowadays, the wide variety of RATs available on the market (cellular networks, LPWAN, Bluetooth, WiFi, ZigBee, etc.) makes the idea of adopting a unique and normalized solution for IoT, a priori, an unfeasible approach. This is why, in the related literature, we can find different reviews and surveys comparing RATs, each with advantages and disadvantages. In [6], a complete survey about the enabling RATs for the IoT is conducted, paying special attention to the different LPWAN technologies available for long-range communications (LoRa, Sigfox, and Ingenu). Following a similar approach, in [13], an analysis of the potential RATs for IoT in a 5G ecosystem is performed. Short-range

transmission technologies (ZigBee, Bluetooth, and Low-Power WiFi), LPWAN, and cellular networks from 2G to 5G are considered. The wide diversity of RATs available on the market is remarked, as well as the necessity for finding a way to combine them.

On the other hand, preliminary works about multi-RAT support for 5G can be found in the literature. Authors in [14] bring to light the need of heterogeneous Radio Access Networks (RAN) to alleviate the congestion and overload of the cellular infrastructure. The mixture of cellular networks with RATs working on ISM frequency bands, such as WLAN technologies, is proposed for the forthcoming 5G. This concept is also remarked in [15], where authors claim that the intelligent integration of WiFi and cellular networks can duplicate or even triplicate the quality of service and network performance.

In this framework, very few papers apply ML techniques to smartly optimize the access to the medium in 4G/5G for M2M communication. Authors in [16] proposed an RL-based algorithm for cellular networks that enables Machine Type Communication devices to cooperatively communicate to minimize the network congestion. This is accomplished by the intelligent selection of the base station to transmit from the device-side. The use of ML techniques is also exploited in [17], where authors introduced an ant-colony heuristic algorithm to smartly decide which RAT should be used by users. These decisions were made to maximize system utility and better balance resource utilization. The RATs considered were LTE, WiMAX, and WiFi and the results obtained showed a performance improvement between 20% and 70% with respect to other RAT usage strategies. However, none of these ML works consider the nature of IoT devices (low-power consumption and limited hardware resources) or the use of LPWAN technologies (which are known to be well-suited for IoT devices).

3. IMPORTANCE OF THE PROPOSED SOLUTION TO THE 5G STANDARDIZATION PROCESS

As shown in previous sections, the use of cellular networks is gathering momentum as an enabler for the IoT due to the need for global coverage in most user and industrial applications. This requirement can be met by employing the infrastructure of the Mobile Network Operators (MNO), which already offers an almost-global coverage. This solution also reduces the installation cost of IoT systems by avoiding the acquisition of specific equipment to connect IoT devices to the Internet. In this context, several efforts are devoted to make cellular networks more suitable for the IoT, leading to the emergence of the 5th Generation of mobile networks (5G). 5G is envisaged to adapt the advantages of cellular networks to the characteristics of the IoT, that is, massive number of devices, enabling lower end-to-end latency and energy consumption, and global coverage [7].

However, there are still some shortcomings that may delay the ubiquitous use of 5G in IoT. The first stems from the cost of using licensed frequency bands. Using such private parts

of the spectrum entails a cost that may turn unaffordable as the number of deployed IoT devices grows; either due to the expenses derived from renting the infrastructure to the MNO or due to the direct cost of licensing the bands from the competent authorities. Even if data transmissions are sporadic, the total aggregated traffic of the network may render cellular-based IoT deployments hard to maintain in terms of operational costs. On the other hand, and although 5G is envisioned to reduce power consumption, cellular-based nodes are intrinsically dependent on signaling. This overhead in the communications unavoidably lead to an increase in power consumption of IoT devices [18].

Under these circumstances, the use of multiple RATs is one of the key tools of 5G deployments to benefit from the advantages of each wireless technology. However, the scientific community has focused on a set of supporting technologies (WiFi/WiMAX/mm-wave/etc.) potentially ill-suited to IoT devices [19], [20]. First, due to the large power consumption of such technologies (in particular when compared to LPWAN alternatives), and second due to the cost increase of their respective radio transceiver (especially for WiMAX/mm-wave and, again, when compared to LPWAN technologies such as LoRa). Furthermore, previous studies in this field have solely focused on alleviating network congestion, neglecting the intrinsic requirements of IoT deployments, that is, their low-cost and low-power nature.

As 5G ultimately aims to encompass a wide variety of traffic-generating devices, the authors believe that the future 5G standard releases should devote further efforts to acknowledge the limitations of IoT networks. In this paper we have made a step forward in this direction, by not only maximizing throughput of IoT nodes, but also considering potential restrictions in the usage of the different RATs (such as battery limitation, daily transference quota, etc.) In this sense, we believe, and have demonstrated in this work, that Machine Learning techniques can play an essential role in deriving optimal transmission policies for the future 5G. Therefore, we envisage that 5G could potentially benefit from this subfield of the Artificial Intelligence area and hence, should be paid more attention by the standardization bodies.

4. MATHEMATICAL FRAMEWORK

As discussed above, the objective of the policy-derivation algorithm is to determine which RAT should be used by an IoT device in any given situation. This can be translated into the RL jargon as determining the optimal action a to take (out of a set of $\mathbf{A}$ allowed actions, being $a \in \mathbf{A}$) given a state s (a description of the internal/external state of the IoT node, with $s \in \mathbf{S}$). Having performed action a in the state s , some *reward* is obtained -this feedback signal helps nodes understand what actions are better to take than others-. This reward can, for instance, measure how much information has been reported, how important such information was, etc. The function $\mathcal{R}$ mathematically defines such a reward as a

mapping between state-action pairs and real numbers, that is, $\mathcal{R}: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$.

After receiving some reward, that can be positive or negative, IoT nodes shift from one state to another, again, depending on the previous state-action pair. These transitions can be stochastic to allow RL entities to probabilistically transition from one state to another. Formally, $\mathcal{P}$ models the transition from one state to another by mapping a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{S})$ to a real number representing the probability of transitioning from state s to state s' after taken action $\mathbf{n}$. That is, $\mathcal{P}: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$.

The goal of RL algorithms is to find an optimal action policy (π^*) that maximizes the expected total reward obtained over some finite or infinite horizon (such accumulated reward is denoted as γ). In the former case, the reward is aggregated for T units of time -e.g. T seconds- whereas in the latter, it is the average reward per unit of time what it is maximized. Therefore, the objective of π^* is to, being the IoT node in a certain state s , propose an action $\mathbf{n}$ to take such as the total expected attained reward γ is maximized. Following the above formulation, an action policy π can be mathematically represented as a mapping between states and actions, that is, $\pi: \mathcal{S} \rightarrow \mathcal{A}$. This optimal policy can be implemented either as a tabular solution (i.e. for each state, a table stores the optimal action to take) or approximated by a function (i.e. there is a function that takes states as inputs and returns actions as outputs). When the process under optimization is relatively complex, the number of potential different states (the space of $\mathcal{S}$) is too large to be tabulated. Being function approximators the only feasible alternative, and due to the recent successes of Artificial Neural Networks (ANN) in approximating functions, a plethora of ANN-based algorithms have recently emerged in the RL field. The basic idea is to have an ANN that, when fed with the current state of the RL entity (the IoT node in our case), it returns the most promising action to follow.

Among all ANN-based alternatives, Evolution Strategies (ES) [21] has recently demonstrated to be one of the best-suited alternatives to derive optimal policies; especially when the effects of the actions are long-lasting (that is, taking the action $\mathbf{n}$ at a given instant t has a measurable non-negligible effect at time t' , with $t' \gg t$). ES is a type of Genetic Algorithm [22], a black-box optimization meta-heuristic loosely inspired in natural selection. By iteratively tweaking the parameters of the ANN via *natural selection*, the modeled policy π tends to improve in proposing actions to take.

5. APPLICATION TO THE PROBLEM

Let an IoT network monitor a set of critical assets with some parameters of interest. Such a network is, in turn, composed of IoT nodes provided with different RATs that can be used to report certain detected events. Thus, having detected an event, an IoT node must decide whether to report it or not. If it chooses to report it, it also has to determine which RAT to use. Thus, the set of all allowed actions $\mathcal{A}$ is composed of

$\{a_0, a_1, \dots, a_N\}$, where N is the number of allowed RATs to use, and a_0 models the action of not reporting but dropping the event. Each of these generated events can have a different priority (G). For instance, if a malfunction in a life-supporting device is detected, a top-priority event must be sent. Contrary, if a regular event is detected (such as mild vibrations in an engine), a low-priority event could be generated. Priorities are let to vary in a range from 0 to 1 to illustrate different event priorities where 1 means top priority.

To model the nature of wireless communications, each RAT may have a limit on its usage. This can be due to two different reasons: (i) a limit in the total expenditure allowed, e.g. per day, derived from using such technology for example, IoT nodes may not be allowed to spend more than 1\$ a day when using 5G transmissions. Or (ii) a limit on the traffic generated by any given technology, this can be expressed in bytes (e.g. per day) or in packets for example, Sigfox nodes cannot generate more than 140 packets a day [23], or nodes making use of cellular technologies may not generate more than 1Mb of traffic a day. Therefore, when action a_i (with $i \neq 0$) is taken, the state s of the IoT mote changes since the usage of the technology i , denoted as u_i , is also updated. When the usage of technology i reaches its limit, u_i^{MAX} , such a technology is no longer available that day. Without any loss of generality, periods of 24 hours (1 day) are considered in limiting the usage of RAT.

Furthermore, each action/RAT entails a different energy consumption (denoted as c_i for action i). Since a single battery per node is assumed, if battery level (denoted as b) drops to zero, no further events can be reported. To complete the definition of the node state, the length (L) of the generated packet (created as a response to an arising event) must be considered. It should be noted that the event-generation process is modeled as a Poisson distribution with an average rate of λ events per second.

As commented in the Introduction, some LPWAN technologies, depending on the country, must undergo an enforced off-period (t_{off}) after every transmission. To model this and, at the same time, packet buffering capabilities, individual infinite queues are assumed to exist for each RAT (that is, there exist N different queues in each node). Therefore, the transmission time of a packet does not only depend on the length of such a packet (L) but also on the occupation of the queues (denoted as o_i for the i -th RAT). If an off-period of t_{off} seconds is enforced in an IoT node as a result of a packet transmission, the LPWAN queue of that node is not only filled with such a packet, but also artificially extended with another fictitious packet that would take t_{off} seconds to be transmitted. Note that this artificially generated packet has no impact on the obtained reward. Using this trick, we force nodes not to use the LPWAN RAT for, at least, t_{off} seconds -and thus, to comply with regional regulations-.

Finally, from the mathematical point of view, the state s of a node is the vector conformed by

$(L, G, b, t, u_1, u_2, \dots, u_N, o_1, o_2, \dots, o_N)$. That is, the state is defined by the length of the generated packet, the priority of such a packet, the remaining battery of the node, the time of the day (t), the usage level of each RAT, and the occupation of their corresponding queues. When the above vector is fed into the ANN-based policy, an action that maximizes the expected total reward is obtained. In turn, we have mathematically modeled the reward obtained for each action as follows:

$$R(s, a_i) = G \frac{L}{\text{delay}(a_i)}$$

The reward is modeled as the priority multiplied by the length of the transmitted packet (in bits), divided by the delay in the transmission. This way, nodes are encouraged to report events as fast as possible, while prioritizing their importance. The units of this reward are bits per second, which match the units of a throughput metric. Hence, what the reward function maximizes is the *prioritized* throughput of an IoT node. Note that the *delay* of the action a_i is not only related to the bitrate of the i -th RAT but also to the occupation of the queue of such a RAT. Also, since battery depletion prevents nodes from reporting more events (and hence, 0 reward is obtained from that point onwards), π^* naturally optimizes energy consumption as well.

6. SIMULATIONS AND RESULTS

To evaluate the mathematical framework and its solution via RL, we have simulated an IoT network in which nodes support two RATs (that is, $N = 2$): a cellular-based connection (this might represent future 5G cellular links) and a LoRa transceiver. Thus, a_1 and a_2 indicate the actions of using 5G and LoRa respectively. It is very common, and will be even more popular in 5G deployments, that parts of the licensed spectrum are sub-rented or even get offered in an auction-based fashion to third parties (this is the cornerstone of, e.g., cognitive spectrum applications in 4G/5G networks [24], [25]). These third parties may be, for example, operators of IoT networks or governments that need a wireless infrastructure for their Smart City initiatives. We have modeled this spectrum renting scheme and assumed that a sub-band of a wider licensed band is at the disposal of

the IoT nodes, offering a transmission speed of 100kbps. For the LoRa connection, we assume that devices transmit with SF 7, and thus, have a throughput of 2.43kbps. Regarding band usage limitations, we limit to 1Mb per day the use of 5G networks ($u_1^{MAX} = 1 \text{ Mb/day}$) to reduce operational costs. We do not set any daily restrictions on LoRa ($u_2^{MAX} = \infty$). To illustrate the impact of the off-period policies (imposed in most European countries) on the performance of IoT networks, we simulate two environments, one with such a policy enforced and one without it. Energy consumption of both RATs is taken from [26] and [27] for cellular and LoRa-based RAT respectively as determining it is out of the scope of this work. We assume that IoT nodes are powered by two AA batteries designed to last, at least, for three years (i.e. the maximum allowed energy consumption for a day is $\frac{1}{1095}$ the total energy stored in such batteries, where 1095 is the number of days in three years). The average event-generation rate is varied between 1 packet every 30 seconds ($\lambda = \frac{1}{30}$) and 1 packet every 10 minutes ($\lambda = \frac{1}{600}$) to assess the influence of this figure on the total attained reward. These values are in-line with typical wireless monitoring networks [28] [30]. Furthermore, packets of varying sizes are assumed to be generated; specifically, lengths are randomly generated with uniform distribution between 30 and 200 bytes (being, again, in accordance with typical IoT deployments [11]). Similarly, priorities of packets are also uniformly distributed between 0 and 1. Finally, Table 1 specifies all considered parameters.

Evolution Strategies algorithm has been allowed to run for 1000 iterations to iteratively tune the ANN-defined policy. This ANN is, in turn, composed of two hidden layers of 45 and 5 neurons with *tanh* as an activation function [31]. Figure 1 shows the training phase of the ANN-based policy. In this process the expected total reward obtained for a whole day (that is, γ) increases as the policy π improves by iteratively applying the ES algorithm. This illustrates that the obtained policy is being more and more refined to make IoT nodes act wiser. Note that transmission policies are trained off-line in more powerful computers while the practical use

Table 1 Parameters of the simulation

Parameter	Value
5G rate	100kbps
LoRa rate	2.43kbps
LoRa T_{off} (if applies)	$\frac{T_{on}}{DC} - T_{on}$ with $DC = 0.01$
5G usage limitation (u_1^{MAX})	1Mb/day
LoRa usage limitation (u_2^{MAX})	∞
5G power consumption (c_1)	2.15W
LoRa power consumption (c_2)	0.1353W
Battery of nodes (b)	2AA batteries (30780 joules in total, 28.1 joules/day)
Average events per second (λ)	Varied from $\frac{1}{30}$ to $\frac{1}{600}$
Packet length (L)	$U(30, 200)$ bytes
Packet priority (G)	$U(0, 1)$

Figure 1 Evolution of γ as ES algorithm iterates (first 250 iterations are shown). Obtained for $\lambda = 1/90$ and off-period not enforced. Note that γ ultimately indicates the average number of prioritized bits transmitted in a day.

Figure 2 Total reward (γ) as a function of the event-generation rate. Off-period not enforced. Error bars represent the standard deviation around the mean value.

of such policies is a light-weight process that simply entails a *forward pass* of the ANN (a task computationally viable even for very hardware-constrained IoT devices).

In order to further show the benefits of the proposed solution, the γ obtained under the proposed solution is compared to the γ obtained when three other policies are employed:

- (i) randomly chose a RAT (5G/LoRa) denoted as *random* policy, (ii) start with 5G until its exhaustion and then use LoRa if necessary denoted as *5G-first* policy, and (iii) consider important events those with $G > 0.5$ and thus, only employ 5G for those critical transmissions (and employ LoRa when $G \leq 0.5$ or when 5G has been exhausted) denoted as *priority-based* policy.

Figure 2 depicts the obtained results for different values of λ . It is worth mentioning that, γ values obtained when an off-period is enforced after every transmission are remarkably close to those obtained when such limitation is not considered (differences are, in average, less than 0.047%). Therefore, due to space limitations, we have only included the results obtained when an off-period is not enforced. These small differences indicate that, for typical IoT event-generation rates (i.e. those evaluated in this simulation),

forcing nodes endowed with multiple RATs to undergo an off-period in their LPWAN transceivers, does not have a measurable effect on their performance. We argue that, if event-generation rate were dramatically increased (thus, forcing nodes to transmit a larger number of packets), this forced off-periods may have a non-negligible effect. However, we also acknowledge that IoT nodes are not conceived, nor enabled to transmit at such excessive data rates (mainly due to their limited hardware and energy resources).

Regarding the results presented in Figure 2, it is worth noting how the ANN-based proposed policy clearly outperforms the rest of them when the event-generation rates are larger than $\frac{1}{120}$. Specifically, when the proposed policy is preferred over the second-best policy (*5G-first*), γ increases 75.6%, 59.0%, 43.1%, and 17.1% for the four highest event generation rates respectively. If λ is smaller or equal to $\frac{1}{120}$, the relatively low event-generation rates make the *5G-first* policy perform similarly to our proposal. For these small values of λ , employing the 5G RAT for all transmissions is always the best option, since neither the 5G daily quota nor the battery allowance exhaust; thus, both policies attain similar values of γ . As can be noted, ANN-based policy is properly adapted to different event-generation rates, always achieving an optimal performance. Unarguably, these results are subject to change when the 5G daily quota or the battery capacity changes; however, we believe that the main idea is adequately pinpointed: as nodes transmit more and more data, long-lasting technologies such as LoRa (both in terms of extending lifespans of the nodes and in their usage limitation) should be progressively embraced. Another interesting fact should be highlighted: if non-adaptive policies (such as *5G-first*, *priority-based*, or *random*) are applied, and the event-generation rates are relatively high ($\frac{1}{30}$ to $\frac{1}{60}$), it is the battery capacity the limiting factor in attaining larger values of γ . These rates make batteries deplete half-way through the 24-hour simulation, and thus, larger values of λ do not lead to larger values of γ for the three aforementioned policies. This reveals that, when designing transmission policies for hardware-constrained IoT devices with multiple RAT, it is the battery consumption, and not the bitrate of their

Figure 3 RAT usage for the two best policies: the proposed one (left) and the *5G-first* (right) for 1000 packet transmissions. Obtained for $\lambda = \frac{1}{30}$ and off-period not enforced.

transceivers, the main limiting factor in increasing network performance. By carefully discarding non-critical events in more demanding scenarios (i.e. where larger values of λ are present), our proposed policy can get the most out of the allocated resources (battery and 5G daily quota) to maximize obtained rewards. Figure 3 corroborates this statement by analyzing the typical usage of each RAT made by our proposed policy and the *5G-first* policy. 5G transmissions are depicted in blue stars, LoRa transmissions in red circles, and discarded packets in black crosses. Two variables are analyzed: packet length and packet priority (the rest of variables are not shown for the sake of clarity, although they still play an important role in deciding on the RAT). Note how the proposed policy (left picture) tends to discard large non-important packets (shown in the bottom right side of the picture) while high-importance packets are normally transmitted via 5G-cellular links. LoRa is employed when either the packet priority is not high, the packet is relatively large or the 5G daily quota has been exhausted (this variable is not shown in Figure 3). Conversely, the *5G-first* policy disregards packet properties and makes an excessive early use of 5G transmission (note that there are far more blue stars than red circles) until 5G daily quota is exhausted and LoRa comes into play. Discarded packets are not prioritized by their importance and thus, there is a homogenous distribution of black dots.

The reason why the *priority-based* policy performs worse than the *5G-first* policy lies in the usage of the 5G RAT. The former tends to systematically underuse 5G, whose daily quota is not met even for the lowest values of λ (in such scenarios, it is the battery and not the 5G daily quota the limiting factor). Finally, the *random* policy makes the same mistakes as the *priority-based* policy while also disregarding event priorities; hence the lower attained γ .

7. CONCLUSION

5G has proved itself to be a future revolution in the way in which, not only users, but also machines could communicate with their peers. It is precisely in this type of communications (machine-to-machine) in which the IoT paradigm will play a major role. However, cellular networks may not be fully geared towards the very sporadic and bursty nature of IoT data transfers, and many authors have argued that IoT devices could potentially benefit from having multiple Radio Access Technologies (RAT). These RATs would be used intelligently and on-demand to access the wireless shared medium.

To evidence this, we have presented a mathematical model that lies the foundations for improving the performance of IoT devices fitted with multiple RAT. To optimize such a figure of merit, we have resorted to a set of analytical tools popularized by the Machine Learning (ML) research field. In particular, a Genetic Algorithm known as Evolution Strategies has been used to derive optimal transmission policies. These policies are shown to outperform other intuitive approaches in different simulated scenarios while still being computationally light-weight enough to run in

hardware-constrained IoT devices. The solution based on an Artificial Neural Network (ANN) optimizes the use of the available RATs (5G and LoRa), leading to an improvement in the attained rewards of up to 75.6% when compared to other policies. Although the precise presented results depend on the parameters of the simulated network (and, deeply studying other scenarios is left as a future work), we truly believe that this work has served its purpose: to raise awareness about the potential use of ML techniques in deriving transmission policies that could make the future 5G standard feasible for the IoT revolution.

Furthermore, there are plans to extend the presented work with traffic traces generated from IoT devices so that the derived ANN-based transmission policy can learn from real data. Nevertheless, authors believe that the traffic generation patterns are in-line with actual IoT deployments (as indicated in the Simulation Section).

8. REFERENCES

- [1] P. Kulkarni and T. Farnham, "Smart City Wireless Connectivity Considerations and Cost Analysis: Lessons Learnt From Smart Water Case Studies," *IEEE Access*, vol. 4, pp. 660–672, 2016.
- [2] R. Martinez-Sandoval, A. J. Garcia-Sanchez, F. Garcia-Sanchez, J. Garcia-Haro, and D. Flynn, "A comprehensive WSN-based approach to efficiently manage a smart grid," *Sensors*, vol. 14, no. 10, pp. 18748–18783, Jan. 2014.
- [3] F. Orfei, C. Benedetta Mezzetti, and F. Cottone, "Vibrations powered LoRa sensor: An electromechanical energy harvester working on a real bridge," in *2016 IEEE SENSORS*, 2016, pp. 1–3.
- [4] J. G. James and S. Nair, "Efficient, real-time tracking of public transport, using LoRaWAN and RF transceivers," in *TENCON 2017 - 2017 IEEE Region 10 Conference*, 2017, vol. 2017 Decem, pp. 2258–2261.
- [5] A. Orsino, G. Araniti, L. Militano, J. Alonso-Zarate, A. Molinaro, and A. Iera, "Energy Efficient IoT Data Collection in Smart Cities Exploiting D2D Communications," *Sensors*, vol. 16, no. 6, p. 836, Jun. 2016.
- [6] M. Centenaro, L. Vangelista, A. Zanella, and M. Zorzi, "Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios," *IEEE Wirel. Commun.*, vol. 23, no. 5, pp. 60–67, Oct. 2016.
- [7] M. Agiwal, A. Roy, and N. Saxena, "Next Generation 5G Wireless Networks: A Comprehensive Survey," *IEEE Commun. Surv. Tutorials*, vol. 18, no. 3, pp. 1617–1655, 2016.

- [8] A. Biral, M. Centenaro, A. Zanella, L. Vangelista, and M. Zorzi, "The challenges of M2M massive access in wireless cellular networks," *Digit. Commun. Networks*, vol. 1, no. 1, pp. 1–19, 2015.
- [9] T. Wild, F. Schaich, and Y. Chen, "5G air interface design based on Universal Filtered (UF)-OFDM," in *2014 19th International Conference on Digital Signal Processing*, 2014, pp. 699–704.
- [10] LoRa-Alliance, "LoRa," 2017. [Online]. Available: <https://www.lora-alliance.org/>. [Accessed: 22-Feb-2018].
- [11] R. M. Sandoval, A.-J. Garcia-Sanchez, J. Garcia-Haro, and T. M. Chen, "Optimal policy derivation for Transmission Duty-Cycle constrained LPWAN," *IEEE Internet Things J.*, pp. 1–11, 2018.
- [12] ETSI, "Final draft ETSI EN 300 220-1 V2.4.1 (2012-01)," 2012.
- [13] M. R. Palattella *et al.*, "Internet of Things in the 5G Era: Enablers, Architecture, and Business Models," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 3, pp. 510–527, 2016.
- [14] W. H. Chin, Z. Fan, and R. Haines, "Emerging technologies and research challenges for 5G wireless networks," *IEEE Wirel. Commun.*, vol. 21, no. 2, pp. 106–112, 2014.
- [15] N. Himayat *et al.*, "Multi-radio heterogeneous networks: Architectures and performance," *2014 Int. Conf. Comput. Netw. Commun. ICNC 2014*, pp. 252–258, 2014.
- [16] M. Hasan, E. Hossain, and D. Niyato, "Random access for machine-to-machine communication in LTE-advanced networks: Issues and approaches," *IEEE Commun. Mag.*, vol. 51, no. 6, pp. 86–93, 2013.
- [17] J. Li, X. Zhang, S. Wang, and W. Wang, "Context-oriented multi-RAT user association and resource allocation with triple decision in 5G heterogeneous networks," *China Commun.*, vol. 15, no. 4, pp. 72–85, Apr. 2018.
- [18] P. Andres-Maldonado, P. Ameigeiras, J. Prados-Garzon, J. Navarro-Ortiz, and J. M. Lopez-Soler, "Narrowband IoT Data Transmission Procedures for Massive Machine-Type Communications," *IEEE Netw.*, vol. 31, no. 6, pp. 8–15, Nov. 2017.
- [19] M. R. Palattella *et al.*, "Internet of Things in the 5G Era: Enablers, Architecture, and Business Models," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 3, pp. 510–527, 2016.
- [20] J. Navarro-Ortiz, S. Sendra, P. Ameigeiras, and J. M. Lopez-Soler, "Integration of LoRaWAN and 4G/5G for the Industrial Internet of Things," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 60–67, 2018.
- [21] T. Salimans, J. Ho, X. Chen, S. Sidor, and I. Sutskever, "Evolution Strategies as a Scalable Alternative to Reinforcement Learning," *ArXiv e-prints*, Mar. 2017.
- [22] D. Whitley, "A genetic algorithm tutorial," *Stat. Comput.*, vol. 4, no. 2, pp. 65–85, 1994.
- [23] R. Sanchez-Iborra, J. Sanchez-Gomez, J. Ballesta-Viñas, M.-D. Cano, and A. F. Skarmeta, "Performance Evaluation of LoRa Considering Scenario Conditions," *Sensors*, vol. 18, no. 3, 2018.
- [24] X. Wang, Z. Li, P. Xu, Y. Xu, X. Gao, and H. H. Chen, "Spectrum Sharing in Cognitive Radio Networks #x2014;An Auction-Based Approach," *IEEE Trans. Syst. Man, Cybern. Part B*, vol. 40, no. 3, pp. 587–596, 2010.
- [25] D. C. Parkes, L. H. Ungar, and D. P. Foster, "Accounting for Cognitive Costs in On-line Auction Design," in *Agent Mediated Electronic Commerce*, 1999, pp. 25–40.
- [26] B. Dusza, C. Ide, L. Cheng, and C. Wietfeld, "An accurate measurement-based power consumption model for LTE uplink transmissions," in *2013 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2013, pp. 49–50.
- [27] L. Casals, B. Mir, R. Vidal, and C. Gomez, "Modeling the Energy Performance of LoRaWAN," *Sensors*, vol. 17, no. 10, 2017.
- [28] D. Bankov, E. Khorov, and A. Lyakhov, "Mathematical model of LoRaWAN channel access," in *18th IEEE International Symposium on A World of Wireless, Mobile and Multimedia Networks, WoWMoM 2017 - Conference*, 2017, no. 15, pp. 1–3.
- [29] D. Bankov, E. Khorov, and A. Lyakhov, "Mathematical model of LoRaWAN channel access with capture effect," in *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2017, vol. 2017 Octob, no. 14, pp. 1–5.
- [30] B. Afzal, S. A. Alvi, G. A. Shah, and W. Mahmood, "Energy efficient context aware traffic scheduling for IoT applications," *Ad Hoc Networks*, vol. 62, pp. 101–115, Jul. 2017.
- [31] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, 2010, pp. 249–256.

Part III

Summary of Articles

Chapter 1

Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids

1.1 Brief summary

By the beginning of the year 2016, the IoT started to become a widespread solution across many environments. Although the general public was mostly familiarized with the concept of IoT in the Smart Home/City context, truth is, the positive impact of this new paradigm (the IoT) could extend to other environments such as industries and critical infrastructures. Among these rather unexplored environments we focused on the Smart Grid (SG); mainly because electrical grids bring power to the rest of critical infrastructures and industries, and a failure in any SG has the potential to disrupt the functioning of any other electrically-dependent environment. Thus, and increase in the prevention of any failures in these scenarios may entail a tremendous benefit for current societies.

The introduction of communication capabilities to the SG was anticipated to have a positive impact on its performance and efficiency. However, to make IoT networks cost-effective, most deployments used unlicensed Industrial, Scientific and Medical (ISM) radio bands. Particularly, the 2400MHz band was normally employed due to the (belief of) smaller delays and larger bandwidths. Also, one should not forget that the IoT began as a continuation/extension of the very-well known and extensively employed Wireless Sensor Networks (WSNs) and Mobile Ad-Hoc Networks (MANETs). These two types of networks were also making extensive use of the 2400MHz ISM band; thus being latter inherited by the IoT. Like many other Information and Communication Technologies (ICT), the IoT makes an extensive use of the wireless medium as its main communication means. Therefore, it becomes apparent that having a deep insight into this form of transmission is essential to improve the performance of the IoT and ultimately the efficiency of the Smart Grid.

Therefore, in our work, we questioned whether this default frequency band was appropriate for SG environments, in particular, when compared to other license-free ISM bands such as the 868MHz or 915MHz bands. Although further commented in the Methodology Section, what we did was a comprehensive quantitative comparison and analysis of the available bands, evaluating three main Key Performance Indicators (KPIs): the associated power consumption per packet, the average network delay, and the Packet Reception Rate (PRR). To facilitate the systematic analysis, a dual-band SG-oriented propagation model was derived, tested, and implemented in the well-known TOSSIM network simulator. This way, we could run many simulations (in different controlled environments), to determine the true performance of each communication band.

After extensive simulations, we concluded that the 915MHz band performs better than the 2400MHz in most scenarios. The typically by-default 2400MHz band, was only superior in absence of other interfering electronic devices (such as WiFi or Bluetooth) and for shorter distances. Otherwise, the 915MHz band showed smaller network delays, higher reception rates, and a much reduced power consumption (which lead to extended node lifetimes).

1.2 Methodology and tools

Bearing in mind that the main objective of the article was to determine which frequency band was best suited for the IoT-based Smart Grid, we followed the methodology represented in Figure 1.1

Figure 1.1: Methodology employed in this article

The **first step** was to determine the KPIs that would help us evaluate the performance of each band. After that, we defined what would be the *base network*, a reference IoT network against which we would vary some conditions (variables) to explore different environments. The *base network* was an IoT network deployed in an Iberdrola's substation composed of 8 nodes with different radio visibility conditions (see Figure 2 of the associated paper for more information).

The **second step** implied acquiring real propagation data from the aforementioned Iberdrola's substation. To do so, we employed the Agilent Technolo-

gies E5071B Vector Network Analyzer (VNA). Thanks to this VNA, we could characterize a typical Smart Grid substation from a propagation perspective.

After acquiring the data, the **third step** was to analyze and evaluate different well-known propagation models. We chose to employ the log-normal shadowing path-loss (LNSPL) model due to its mathematical simplicity (which makes it a good option for network simulators) and precision in replicating the behavior of lossy, dispersive propagation environments (like the SG or any other environment full of metallic structures). For more information about this model, see Equation 1 and 2 of the paper. We then fit the acquired data to the chosen model via Gradient Descent (a regression algorithm typically employed in modeling propagation environments).

The **fourth step** was to implement the derived propagation model into the TOSSIM simulator. It is worth mentioning that, in line with the “scientific reproducibility commitment” of this work, all the acquired data and programmed scripts were made publicly available to foster reproducibility of results and to help future practitioners in extending our work.

In the **fifth step**, we simulate a wide range of different networks derived from modifying the variables defined in the first step of the methodology. Thanks to having implemented the propagation model, we could have an in-depth knowledge of the effects of each band on the IoT-based Smart Grid and analyze how subtle differences in network topology impact on IoT performance.

The last step (the **sixth step**), consisted of extracting the KPIs and presenting the results.

1.3 Results and Contributions

The results can be roughly divided into two groups: main results and derived results. Regarding the main results, we highlight the in-depth analysis of how the frequency band affects communications in an IoT-oriented SG. Results indicate that, only in the absence of other 2400MHz interfering devices (i.e. no other co-existing devices like WiFi or Bluetooth devices were present) and for rather small networks (average distance between nodes of 7.7m), can the 2400MHz band outperform its 915MHz counterpart. In any other context, the large propagation losses found in Smart Grids makes the 915MHz lead to smaller network delays, power consumption values, and larger Packet Reception Rates (PRR).

Although the 2400MHz band is thought to provide larger bandwidths (when compared to other lower-band alternatives), the appreciable increase in path losses ultimately causes more packets being lost and a general reduction in the overall throughput. However, one should not forget that frequency is not the only element at play. Transceivers that work in the 915MHz band utilize different modulation schemes. In particular, the studied radio transceiver (the Texas Instruments CC1000) employs the FSK modulation, known for its resilience in terms of noise and phase variation. On the contrary, its 2400MHz counterpart, the Texas Instruments CC2420 transceiver, uses the OQPSK mod-

ulation which tends to provide faster but weaker links. By implementing both modulations in the TOSSIM simulator, we could replicate the effects that each modulation scheme had on the communication channel.

From the performed simulations we could also comment the rather limited effect that packet-length has on the KPIs. Although we did find that larger packets led to a decrease in the PRR (as expected), quadrupling the packet size only lead to a moderate decrease of 5% in the PRR. On the other hand, the radio visibility conditions studied (i.e. line-of-sight –LOS–, obstructed line-of-sight –OLOS– and non-line-of-sight –NLOS–) were proven to have a dramatic impact on all the studied KPIs (for further information see Figure 3 of the paper).

Regarding the main contributions of the article under discussion, they can be summarized in the following 4 points:

- We proved that the by-default 2400MHz band is not the right option for most IoT-oriented Smart Grids. The typical average size of a sensing network deployed in a Smart Grid (either in a substation, or in the Transport and Distribution segment) exceeds the 7.7m and usually co-exists with other 2400MHz interfering devices. Therefore, we find that a general recommendation should be to first try 915MHz-based IoT networks.
- We concluded that visibility conditions has a far larger impact than packet length or even distance. As a general recommendation, it is more advisable to deploy an IoT node twice as far from the Gateway but having direct line-of-sight than placing it half as far but with a complete blocked line-of-sight.
- We provided a dual-band propagation model focused on IoTs operating in Smart Grids.
- This model is implemented into an broadly used network simulator, also extending it to support different visibility conditions (LOS/OLOS/NLOS) and modulation schemes (FSK/OQPSK).

I would also like to highlight how the academic community benefited from the above contributions. Thanks to the marked orientation for replicability of our work, many scientific papers chose to incorporate the knowledge presented above.

Just to name a few, Singh *et al.* [69] considered the fact that 2400MHz deployments are only of interest in small-sized noise-free networks when planning their IoT network geared towards sensing and monitoring underground mines. Similarly, Berkvens *et al.* [70] used the power consumption analysis presented in our work to justify their use of lower frequency bands, discarding the classical choice of 2400MHz ISM bands. Finally, it is worth indicating that we also made use of the data obtained for this work to elaborate on a subsequent work (presented in this Thesis report as well). In particular, we reused the mathematical model of the channel and the noise measurements taken.

1.4 Conclusions

In this work we presented a comprehensive analysis of the impact of the working frequency band on IoT networks deployed in Smart Grids. To accomplish this, we implemented a dual-band propagation model in a well-known network simulator (TOSSIM). Such a propagation model was (i) based on the Log-normal shadowing path-loss model and (ii) derived from measurements taken in a Smart Grid substation with a Vector Network Analyzer. In the mathematical derivation of this model, we considered not only the effect of distance but also visibility conditions, distinguishing between LOS/OLOS/NLOS. More importantly, due to our commitment to fostering replicability in science, we released all the captured data and programmed scripts and models –and precisely, thanks to that, we have shown how several publications adopted and used the results presented in our paper–.

The definition of three precise Key Performance Indicator (KPI) allowed us to quantify the performance attained by IoTs deployed in Smart Grid environments. More specifically, we could pinpoint the effect of the frequency band on such kind of networks. Results indicated that when in presence of other interfering 2400MHz devices, the 915MHz band should be the new by-default option for all deployments. Conversely, when both bands are under the influence of similar noise level, 2400MHz band is the preferred option for small size networks, whereas for large size networks the 915MHz band is the best choice.

Although the exact values of when to use one or another band will depend on the specific environment and network layout, the models and figures presented here seek to raise awareness and set ground rules for when to consider the proper standardized ISM band in SG environments as the best option.

Chapter 2

Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band

2.1 Brief summary

The Smart Grid can be briefly defined as the modernization of current power grids that arises as a result of the inclusion of Information and Communication Technologies (ICTs). This modernization process will transform current grids into more cooperative, intelligent, and economical infrastructures [71]. Along with this innovation, the following advantages are shown to be associated with the SG: a true shift from fossil sources to renewable ones, a steep reduction in greenhouse gas emissions and energy prices as well as an increase in energy efficiency.

Within the range of ICTs that are being introduced into the Smart Grids, Wireless Sensor Networks and their successors, IoT networks, are two key technologies that play a mayor role in enabling seamless and real-time communications. However Smart Grids are typically harsh environments full of metallic structures, electromagnetic noise and obstructed propagation paths. Therefore, IoT networks that aim to monitor or manage any segment of a Smart Grid must ensure that are ready to cope with such a harsh environment. Ultimately, this can only be guaranteed if an in-depth propagation analysis has been carried out. Once we have an electromagnetic characterization of the SG, one could not only forecast the performance of the IoT but also optimize and tune (via simulations) its different parameters.

In this line, the paper presents an exhaustive characterization of a typical Smart Grid. More precisely, we studied two representative scenarios, both in the Transport and Distribution segment (T&D): a main power room, and a 400kV outdoor substation. The electromagnetic characterization has been carried out in the 2.4GHz ISM band, in which most IoT technologies operate. We examined large/small-scale fading, coherence bandwidth (CBW), root-mean-

square (RMS) delay, as well as electromagnetic interference. These phenomena are studied for both SG environments, for three different line of sight conditions, two linear polarization, and for a large-enough band. Aside from pure characterization, we also provided mathematical models by which SG researchers can estimate the above phenomena under different conditions. This way, we not only characterize two specific environments, but also provide the tools for replicating and extending the provided results. In this line, it is also worth mentioning that, following our commitment with open science, we released all captured data (both in raw and processed format), as well as the scripts employed to derive the presented results.

We finish the work by highlighting why an in-depth professional characterization is crucial for WSN/IoT. To do so we simulate an IoT in charge of monitor an SG by employing two different propagation models: a previous well-known model (derived making use of low-cost devices) and the presented model (derived making use of professional, high-end devices). Results indicate how network requirements and power consumption cannot be truly anticipated if non-accurate models are used. Finally, we also show why the low-cost philosophy can lead to imprecise results.

2.2 Methodology and tools

The methodology of this article can be broadly divided into: steps followed to derive PDP-related values (depicted in Fig. 2.1) and steps followed to derive noise-related values (illustrated in Fig. 2.3).

Figure 2.1: Methodology employed in this article to derive PDP-related values

All the PDP-related values are derived from PDP traces taken in the two aforementioned environments (the main power room and the outdoor 400kV substation). For each environment, two different linear polarizations (horizontal and vertical) have been studied and all the available visibility conditions are considered –LOS (where more than 80% of the first Fresnel zone is obstacle-free), OLOS (from 50% to 80%), and NLOS (more than 50% of the first Fresnel zone is occluded). For each scenario and each visibility condition, a 800MHz frequency band (from 2.0GHz to 2.8GHz) has been swept in steps of 1.95MHz (resulting in 410 frequency points) to obtain the Power Delay Profile. Depending on the environment, different distances are evaluated (e.g. 2, 5, 10, 15, 20, 25, and 30 meters for the open air substation). In turn, for each distance, up

to 30 measures are taken in an area of 0.5λ to 3λ (for more information about why this distance is used, see III.C of the article).

Once all PDP traces were acquired, we compute the RMS, CBW, and Path Losses figures for each condition in Matlab. Finally, to encourage re-usability of results, we derive a set of mathematical models that could be used to predict the RMS, CBW, Large-scale fading, and Small-scale fading in other Smart Grids. Thanks to that, researchers can now extrapolate the obtained results to other conditions and environments. Committed as we are with reproducibility and replicability, we published all the raw acquired data and Matlab scripts.

Fig. 2.2 illustrates the different elements involved in acquiring the PDP traces. A high-end Agilent Technologies Vector Network Analyzer (VNA) was used to generate (and receive) a probe signal. Due to the large distances covered, and to increase dynamic range, the signal was transmitted to the transmitting antenna via an optical link (with an amplification pre-stage). Two Biconical Antennas (SBA 9113) were used as the transmitter and receiver and placed 1 meter over the ground to prevent the ground effect from affecting measures.

Figure 2.2: Measurement setup employed in characterizing the Smart Grid

With respect to the background noise levels, we acquire noise traces for the two studied environments and polarizations. Again, the whole 800MHz band was studied and 10 different noise traces acquired for each condition. As with the PDP-related parameters, we obtained various traces (in this case 10).

Figure 2.3: Methodology employed in this article to derive noise-related values

2.3 Results and Contributions

The commented paper elaborates on two main open issues: electromagnetic (EM) characterization of Smart Grids and justification for the need of accurate propagation models.

EM Characterization

With regard to electromagnetic characterization of Smart Grids, our results indicated that Smart Grids are, indeed, very harsh propagation environments – especially for large-bandwidth networks–. The large amount of reflective metallic surfaces give rise to a severe multi-path effect. Although this multi-path effect reduces the effective maximum bandwidth of deployed IoTs, most of these sensing/controlling wireless networks operate under low-bandwidth protocols (such as 802.15.4, ZigBee, etc.) We show that the large symbol duration and small bandwidth of said protocols are a perfect match for this kind of environments. On the other hand, one of the side effects of the multi-path effect is the reduction in the amount of energy lost in propagation. We demonstrate that the path-loss exponent (indicative of how much energy is lost when signal propagates) is smaller than 2. This indicates that transmitted waves are confined within a virtual propagation channel, comprised of the diverse metallic structures present in the SG. As shown in Fig. 8 of the paper (and included below as Fig. 2.4 for completeness), most studied conditions present a path-loss exponent smaller than 2.

Regarding the RMS we found a positive correlation of this figure of merit with distance. This indicates that, as we move the transmitter and the receiver apart from each other, the transmitted power gets more and more (time) spread. An interesting fact is that, due to the overhead cables that run parallel to the floor, horizontal polarization gets more confined and less spread (this can also be seen in Fig. 2.4 where horizontal polarization shows smaller path losses) thus, reducing the RMS –see Fig. 6 of the paper–.

The opposite is true for Coherence Bandwidth in most scenarios. We found a negative correlation of this figure with distance, that is, the further the RX is from the TX, the smaller the CBW gets –see Fig. 7 of the paper–.

The small-scale fading is demonstrated to fit a Weibull Distribution under a comprehensive set of tests: the Generalized Likelihood Ratio Test (GLRT), Kolmogorov-Smirnov Test (KS test), and Mean Squared Error Test (MSE test). Also, the small value of the Normalized Root-Mean-Square Error (NRMSE) shows the good fit of the obtained data to the Weibull Distribution (note that largest obtained NRMSE is 0.2). For more information about the goodness of fit, see Section IV of the paper).

Finally, one of the most interesting results obtained in this paper is the unexpected low value of interferences found for the 2.4GHz band. Due to the regulations imposed for power stations, the 2.4GHz band was unexploited. The only spike in the neighboring bands where found in the 2100MHz band –used by 3G/4G communications– which effectively falls out of the working band of

Figure 2.4: Path loss exponent vs frequency. Different environments, configurations, and polarization are considered.

most 2.4GHz IoT deployments. For all studied environments and polarizations, the background noise levels were found to be around -97dBm.

Justification of accurate propagation models

Section V of the article elaborates on why we really need an accurate propagation model. Whereas previous works employed path-loss models derived from RSSI readings of IoT nodes, we presented a thorough analysis on why such an approach was not recommended. To do so, we derived two path-loss models from two different IoT platforms (making use of the RSSI readings). Results revealed that both models were completely different and, indeed, platform-dependent.

Also, we employed one of the most known RSSI-derived path-loss models as well as our VNA-based path-loss model to simulate an IoT network deployed in an SG. We then derived the Packet Reception Rate (PRR) and Power Consumption of each IoT node in both simulations. Again results highlighted the large differences in terms of model precision. When using the inaccurate RSSI-based model, PRRs dropped (in average) about 15%. Conversely, battery consumption was estimated to be up to 36.8% higher.

Main contributions and overall impact

The main contribution of the presented paper is twofold.

1. A complete characterization of two typical environments of a Smart Grid using a high-end VNA (an outdoor 400kV substation and a main power room). This characterization studied the root-mean-square delay, the coherence bandwidth, the large-scale fading (which encompassed a path-loss modeling), small-scale fading and the background noise. For each of these parameters, mathematical models were provided so researchers could estimate these values in other environments. The final goal of this characterization is to enable more precise simulations of future IoTs deployed in SGs. By increasing the precision of simulations we can plan better networks and ultimately improve network performance.
2. A justification of why the above VNA-based characterization is needed. For this purpose, we derived two path-loss models via RSSI readings (a popular technique widely employed in literature) and demonstrated that they were highly platform-dependent (that is, only valid when the model and the simulations were using the same IoT platform).

The positive impact of this work on the academic community can be confirmed by the fact that high-quality works have chosen to use our results as reference. For instance, our EM characterization of an SG is used in [72]. In such a work, some system design decisions (like which Cost Functions are used) are taken based on the conclusions drawn in our paper. [73] agrees with us in that there are “not enough effective evaluation model and analysis method of the application of the complex electromagnetic environment in the power system”. This, once again, justifies the need for an article like the one presented here. Finally, [74–76] cite our paper as an interesting reference regarding channel characterization of Smart Grids.

2.4 Conclusions

The Smart Grid is an unstoppable modernization process that pertains not only to power engineers but also to telecommunication engineers. This is due to the large percent of processes that depends on transmitting and processing crucial information. Vital data of different substations’ elements is now being transferred wirelessly and on-demand from power stations to processing centers. To improve the performance of such wireless monitoring networks (composed of millions of IoT devices), we need to understand how electromagnetic (EM) propagation behaves in those environments. The best tool that telecommunication engineers have for this purpose is precisely EM characterization.

Reckoning with accurate EM propagation models allow us to simulate and later optimize IoT networks deployed in substations –which, in turn, are responsible for monitoring and controlling crucial aspects of these substations–. Therefore, in this article we have aimed to solve the following problem: the

absolute lack of precise propagation models for IoTs deployed in SGs. Through the different sections we have laid out the mathematical background required to characterize complex environments and later presented the results of such a characterization. We have also thoroughly justified the need for our approach (as opposed to opt for low-cost alternatives that we prove to be highly inaccurate) via extensive simulations.

As demonstrated in the previous subsection, the analyses presented in this paper are embraced by the academic community with good results. Many works have echoed the need for precise characterizations in the SG arena and some others have even used them as a starting point for their own study.

Chapter 3

Improving RSSI-Based Path-Loss Models Accuracy for Critical Infrastructures: A Smart Grid Substation Case-Study

3.1 Brief summary

In the last commented paper we presented an in-depth characterization of a SG substation, highlighting its importance and why we could not rely on RSSI-based models. Furthermore, high-accuracy VNA-based path-loss propagation models demonstrated their superiority to other low-cost alternatives, directly obtaining more precise simulations and better anticipating network performance. However, after such an article, many questions were raised. First: can everyone have access to a high-end VNA? (the tool required to carry out a professional radio characterization). This question is crucial as we proved that radio-electric characterization is a decisive factor for harsh multi-path environments. The second question raised was: is the low-cost RSSI indicator inherently inaccurate? Or, on the contrary, we can do something to improve its precision.

As also shown in the previous paper, most IoT platforms (which operate in the 2.4GHz ISM band) are of a narrow-band nature. This implies that the most crucial parameter in radio characterization is path-loss modeling. Precisely, the factor that RSSI indicator can estimate (with inconveniently low precision). Therefore, the RSSI indicator available in most IoT mote platforms could, if it were accurate and precise enough, offer a powerful and cost-effective mechanism to derive path-loss models –shown to be crucial in critical infrastructures for a good network planning–.

However, in this work, we enumerated a series of factors that have non-negligible negative effects on reported RSSI readings and therefore, on the quality of derived path-loss models. These sources of perturbations are clas-

classified as intrinsic (impact of the transceivers, connectors, and antennas) or extrinsic factors (number of acquired measurements, coexisting interfering devices, effect of temperature, length of transmitted packets, battery level of motes and environmental conditions).

Fortunately, for each and every of these factors that reduce RSSI precision we were able to propose a set of correction models and methodological procedures that limit or compensate their negative effects. These models and procedures have been applied to three widely-known IoT platforms: MicaZ, Iris, and Waspote. This could potentially make RSSI-based path-loss modeling a reasonably good alternative to more expensive, time consuming, and hard VNA-based approaches. To validate the RSSI-correcting proposed method, we compared two RSSI derived models (a base model, with no corrections applied to raw RSSI readings, and a corrected model where our proposed tools and procedures are applied and considered) with the ground-truth VNA-based path-loss model derived in the previous article. Surprisingly, results revealed an average reduction in the estimation error of 91.76% for the studied mote platforms. This increase in precision is also shown to be directly translated to an improvement in IoT simulations, which in turn, will help researchers optimize and plan IoT networks more effectively.

3.2 Methodology and tools

The methodology followed in this article is geared towards deriving a set of tools and correction models that can increase RSSI precision. Therefore, a considerable amount of effort has been devoted to achieve high repeatability of results, large precision in measurements, and intuitive explanations.

Figure 3.1: Methodology employed in this article

Fig. 3.1 summarizes the followed steps. First, we identify and quantify any potential source of perturbations. These perturbations are later grouped into intrinsic and extrinsic sources. The former refers to any element that reduces precision and that is related inherently to the IoT node (e.g. impact of the transceivers, connectors, and antennas) whereas the latter refers to precision-reducing factors related to the environment or the acquisition process itself (such as coexisting interfering devices, effect of temperature, number of obtained measurements, etc.)

By a thorough process, we precisely and numerically quantify the extent of the impact of each factor on RSSI readings. A spectrum analyzer is employed to measure power-related factors (intrinsic ones), the radiation patterns of the three IoT platforms are considered, etc. Once these factors are studied a correction mathematical model or an acquisition methodology are proposed to either eliminate or reduce their negative impact on RSSI precision.

After that, we moved onto the phase of evaluating the impact of the tools and methods proposed. To do so we proposed a three-way process: first, we already reckoned with a VNA-derived path-loss model that will work as a ground-truth for comparison (from the previous article). Second we compute a RAW RSSI-based path-loss model (no corrections applied) from a set of RSSI readings taken (with the three IoT platform) in the SG substation. Finally, we applied the proposed tools to correct such RSSI readings and derived another path-loss model.

In the next step we compared the different path-loss models and we showed that, via the correction tools, the RSSI-based model was much similar to the VNA ground-truth model than the original RAW RSSI-based model.

To prove whether these differences in path-loss models translated to an impact on IoT network simulations, we designed a basic IoT simulator (based on the SimPy Python simulator) that could be tuned to use one of the three computed path-loss models. As expected, results reveal an average reduction in the estimation error of 91.76% for the studied mote platforms when the set of correction tools were applied.

3.3 Results and Contributions

Two set of contributions can be directly taken from the presented paper.

1. First, the set of mathematical tools (models) proposed to correct RSSI readings. These models mainly pertain to the aforementioned intrinsic factors. Specifically, to correct: (i) the derivation between actual received power and sensed RSSI –see Fig. 2 of the paper–, (ii) the derivation between generated power and desired signal power –see Fig. 3 of the paper–, and finally (iii) the effects antennas miss-alignment, i.e. irregular radiation pattern –see Fig. 4 of the paper–.
2. Second, a set of recommendations pertaining to how RSSI values should be acquired. These recommendations have to do with the extrinsic factors and are geared towards reducing the impact of uncontrolled variables on the final derived model. We proposed correction mechanisms for the effects of: the effect of the number of RSSI readings per distance, the effect of co-existing 2.4GHz devices, the effect of temperature, the effect of transceiver sensitivity, the effect of packet length, the effect of variances in nodes of the same platform, the effect of battery charge, and finally, the effect of environmental changes.

112 All the above corrections can be summarized in Fig. 3.2, which shows the correct order to apply them.

Figure 3.2: Methodology employed in this article to correct RSSI readings

When all the intrinsic and extrinsic factors are taken into account, the precision of the RSSI-based path-loss models increases substantially. In Section III, we proved that by deriving a path-loss model with each of the 3 studied IoT platforms (namely, Wasp mote, MicaZ, and Iris). When all the corrections are factored in, the precision of the LOS model increases by 87.89% (for the Iris platform), 95.99% (for the MicaZ platform), and 91.38% for the Wasp mote platform. Conversely, the precision of the NLOS model increases by 91.09%, 93.45%, and 82.46% for the same aforementioned platforms. These results are surprisingly good and indicate that, when the different interfering factors are corrected, the RSSI readings are an accurate way to derive path-loss models. This ultimately paves the way for low-cost modeling of diverse environments, among which we have highlighted for its importance, the Smart Grid.

As indicated above, one of the byproducts of having an accurate path-loss model is the capacity to simulate (and later optimize) IoT networks. One of the most interesting facts presented in this paper is the stark precision of the corrected RSSI-based path-loss model demonstrated in the IoT simulations. Fig. 10 of the paper illustrates this by indicating the predicted Mean Network Delay and Mean Network Lifetime when using each path-loss model. It is surprising how close the values derived from the “VNA-based path-loss model” and the values derived from the “corrected RSSI-based path-loss model” are.

As in the rest of papers that conform this Thesis, both the raw measurements and processed results are published and made publicly available to foster

replicability. This decision has also made possible for several papers to include the results presented here. Below are a few of the papers that cited this work.

[77] used the analyses presented in our paper (regarding the different factors that can affect RSSI readings) to claim that this low-cost indicator should not be used in high-precision applications; and proposed a more precise alternative. Similarly, [78], in its theoretical framework, incorporated our analyses about the RSSI dependence on multiple external factors. This dependency was also used as the underlying reasoning for providing an alternative position method that does not depend on RSSI readings. In the same line, the author of [79] cites our paper as a way to increase RSSI precision when calculating distances between nodes. Finally, [80] highlighted our reflection about the importance of effective and precise IoT networks on monitoring SG substations.

3.4 Conclusions

The takeaway of this study is straightforward: one can accurately and inexpensively compute the path-loss model of a complex environment by employing RSSI readings. However, these readings must be corrected following a two step methodology:

1. Intrinsic factors (impact of the transceivers, connectors, and antennas) that affect RSSI values must be compensated via the proposed mathematical models. This aims to reduce the effects of (mainly) electronics on the acquired values.
2. Extrinsic factors (number of acquired measurements, coexisting interfering devices, effect of temperature, length of transmitted packets, battery level of motes and environmental conditions) should be limited by a carefully planed acquisition campaign. This campaign, aims to reduce the effect of the environment and external elements on acquired values.

We have proven that, by employing the proposed methodology the derived path-loss models improve in average by 91.76%. What is more, we have shown that this boost in estimation accuracy is directly translated into a remarkable increase in the precision of network simulations. This, in turn, can help in reducing operational expenditures while leading to better performance estimation and network planning in critical industrial environments.

Chapter 4

Optimal Policy Derivation for Transmission Duty-Cycle Constrained LPWAN

4.1 Brief summary

One of the most interesting lessons learned from recent IoT deployments is that, in most environments, a large available bandwidth is not required to benefit from all the advantages provided by this new paradigm. What is more, as demonstrated by the second paper presented in this Thesis, using transmission protocols of a narrow-band nature present some advantages, such as allowing an effective communication even in harsh multipath environments.

However, although large bandwidth was simply never needed, it is true that extending node lifetime and communication range have always been a desirable feature in any IoT technology. On the one hand, long node lifetimes guarantee the profitability of newer deployments, minimizing maintenance costs (derived from e.g. replacing batteries) and acquisition costs (e.g. employing batteries instead of solar panels or any other expensive power supplies). On the other hand, extending communication range allows for: (i) removing the need for IoT nodes whose only purpose is acting as intermediate hops in the network, (ii) reducing the number of network sinks (i.e. gateways) as fewer of these devices are needed to cover the same area, and obviously (iii) cover a bigger area with fewer nodes –this is of especial relevance for industrial environments where the node density is not particularly high and the areas to be covered tend to be large–. These three reasons lead to simpler network topologies, as fewer nodes imply a reduced network complexity as well as smaller deployment costs.

From these lessons learned in the past few years (namely, a large bandwidth is not required but low power consumption and long coverage range features are indeed needed), a new set of IoT technologies emerge. Such technologies come under the umbrella of the so-called Low-Power Wide-Area Networks and are definitely called to revolutionize the IoT. Among them, we can highlight two

that are gaining traction in the academic and industrial communities: LoRa –short for Long-Range– and Sigfox. These two technologies are geared towards very low-power transmissions (below 100mJ per transmission [81]) and long coverage ranges (over 30Km [82])

One of the main advantages of LoRa and Sigfox is the use of license-free ISM (Industrial, Scientific and Medical) bands, which allow IoT devices to inexpensively communicate among them. This is in stark contrast to traditional cellular communications (such as 4G/5G), which provide typically shorter communication ranges but larger bandwidths at the expense of having to rent a specific radio-electric sub-band. However, the stringent regulations on the usage of these ISM bands in many countries in which LPWAN operate limit the amount of time IoT motes can occupy the shared bands. When this time is exceeded, LoRa/Sigfox nodes must remain in silence, i.e. they cannot transmit anything, for a variable time –that is normally proportional to the time the node occupied the band in previous transmissions–. This enforced silence time is particularly challenging in industrial scenarios, where not being able to report some detected events might result in the failure of critical assets. For instance, it is easy to think of situations in which nodes reporting non-important events may be forced to remain silent and thus unable to later give information about critical events (e.g. the global malfunction of a given asset).

In the presented article we deal with this limitation in a two-stage approach: first, we mathematically model the behavior of LPWAN-based IoT motes, factoring in their limitation in terms of ISM band usage. Second, we optimize the mathematical model to derive what are known as “optimal transmission policies” that effectively maximize the number of reported events (prioritized by their importance) while still complying with ISM regulations.

Finally, the proposed *generic* mathematical solution is customized to the two LPWAN IoT technologies with greater academic/industrial presence: LoRa and Sigfox. This is carried out to simplify the derivation of such optimal transmission policies, whose (computational) solution may be unfeasible for hardware-constrained devices like IoT nodes. Finally, a set of simulations are performed and analytical results indicate that the proposed solution performs remarkably close to the Theoretical Limit for a wide range of network activity patterns.

4.2 Methodology and tools

Since this article is tackled from a purely “mathematical + simulations” approach, this section is devoted to analyzing the *mathematical* methodology and the *simulation* tools employed within.

First, it is worth clarifying that the precise amount of time (in seconds) nodes can access the shared band is known as Transmission Duty Cycle (TDC). Among other things, in this article we strive to make the scientific community aware of the importance of this value in LPWAN-based network.

Unfortunately, and in contrast to battery management, before publishing this article, the academic community lacked exhaustive analyses that could result in optimal transmission policies in terms of the remaining TDC. Note that this is an interesting problem because not only do IoT nodes must comply with ISM regulations, but also they must smartly manage their TDC to not being unable to report on future critical events. So the general idea behind the methodology explained below is: how can we derive optimal policies for these TDC-limited devices? Before delving into the mathematical formulation, two things must be clarified:

1. First, before explaining what constitutes an optimal policy, the intuitive definition of a policy must be introduced. A policy can be simply understood as an entity that provides answers for your questions. In the context of an IoT node, the questions are: which action should an IoT mote take when facing the opportunity to report an event given a certain *situation*? And answers are: drop the event or report it (and if so, under which configuration). In turn, the word situation refers to the specific state of the mote. Particularly, we represent it with: (i) how much TDC is remaining and, (ii) how important is the event to report?
2. Second, we need to specify in which sense these policies are optimal. For that purpose we define a mathematical figure that captures their goodness. We consider that IoT nodes are awarded *rewards* for each successfully reported event; more important events provide larger rewards (e.g. reporting on a critical failure is more important, and thus provide larger rewards, than reporting on mild vibrations). Therefore, transmission policies can be graded in terms of how much reward accumulate over the lifespan of a node. Policies with larger accumulated rewards are plainly better than those with smaller accumulated rewards.

Simply put, the final goal of the article was to derive those optimal policies that can comply with ISM policies while still maximizing the number of total high-importance packets transmitted over the entire node lifespan. For that purpose, we considered that the working cycle of IoT networks is ruled by the awake-asleep mote cycles. Motes usually remain in a dormant state to save energy, then wake up, sense some parameters and report them to a gateway, if needed, before going back to sleep. Therefore, we could (and did) model the TDC as a commodity; particularly, we employed a terminology similar to the one found in energy consumption modeling. TDC can be consumed with transmissions (events being reported) and is recharged/regained (and stored) at the beginning of each sensing cycle.

Thanks to this mathematical formulation we could leverage the power of Markov Decision Processes (MDP for short) [83]. MDPs are a mathematical tool to optimize the behavior of discrete action-taking agents. Particularly, in this article we posed the optimal policy derivation problem as a two-dimensional, infinite horizon, discounted reward MDP –for more information, please refer to Section III of the mentioned article–.

Figure 4.2: Methodology employed in this article

4.3 Results and Contributions

The discussed paper stands out for three contributions. First, we demonstrated that it is crucial to recognize the TDC as one of the main performance-limiting factors in LPWAN-based deployments. We were among the firsts to try to make scientific community aware about the fact that the TDC should be managed as the scarce resource it is (being even more important than battery or bandwidth). Second, we derive a mathematical framework to derive MDP-based transmission policies for TDC-constrained networks. These policies comply with TDC regulations of each geographical zone while maximizing an optimality criteria (number of prioritized reported events). Finally, we applied and particularized this mathematical framework to the two most popular LPWAN IoT platforms (LoRa and Sigfox), demonstrating that the proposed solution performs remarkably close to the theoretical limit (and far better than other alternative policies).

Particularization of the Sigfox MDP

The particularization for the Sigfox MDP is related to the fact that Sigfox IoT nodes can only report events under a single transmission configuration. Therefore, the set of actions at the disposal of nodes is either drop or transmit a packet. Also, it is worth noting that Sigfox nodes can only transmit up to 140 messages a day.

Particularization of the LoRa MDP

LoRa IoT nodes can adapt the coding rate (the redundancy rate of the error-correction algorithm) and the spreading factor (how much signals are spread over the available bandwidth to increase robustness) of individual packets. Therefore, the set of actions at the disposal of nodes is quite rich. However, The LoRa Alliance [84] imposes a silent period after every single transmission. That is, the 1% duty cycle is guaranteed in a per-packet fashion. This simplifies the markovian state representation –reducing the number of states– and hence, facilitates its computational solution.

Evaluation of the policies

Once the generic MDP model was particularized to the two aforementioned platforms, we performed a thorough evaluation of the performance of the discussed approach. To do so, we proposed three alternative policies:

- Always Transmit (AT) policy: Every generated event is transmitted if enough TDC is available. This is the by-default policy in scenarios where the priorities of events are disregarded, as is the case in the majority of current LPWAN deployments. Every generated event is treated the same way and transmitted if possible.
- Transmit High-Importance Events Only (THIEO): Only high-importance events will be transmitted (if enough TDC is available). In very TDC-restricted networks (like networks with 1% of Duty Cycle) it is tempting to save such TDC for the dispatching of high-importance events. This policy is aimed at guaranteeing the transmission of high-importance events by allocating all the available TDC to them.

We also evaluate an “oracle” policy. This policy can now beforehand which events will be generated to make a decision. Mathematically, it represents a Theoretical Limit on the attainable rewards, and it is obviously an unimplementable policy that simply illustrates an upper bound on the performance.

Results (covered in Fig. 5 and Fig. 6 of the paper and not included here for space considerations) show the very good performance of the proposed MDP-based policies, which adapt to every tested scenario and attain remarkable rewards (MDP results are, in the worst case, just 3.12% worse than the theoretical limit). On the other hand, alternative policies like AT or THIEO can only perform well for a small subset of the conditions evaluated. For instance, for Sigfox, the AT policy works well only when low-importance packets are much more likely than high-importance packets and, in general, very few events are generated. When the traffic increases, this policy wastes the scarce TDC resource. Conversely, the THIEO policy will only perform relatively well when the number of high-importance events exceeds its counterpart (low-importance events) and the traffic is high (many events are generated).

All in all, these results clearly indicated the need for smart policies (like MDP-based ones) that can adapt to different scenarios based on requirements. Traditional approaches that opt for always reporting events are shown to be a bad alternative, and should be discarded in favor of the former.

Overall impact

As with the rest of the commented paper, we committed to make all models, developed tools, and data publicly available. Again, we believe that this could help the scientific community progress and built on previous researchers’ results.

As a result of this policy, several papers opted for using our results and conclusions. Among such articles we would like to highlight the work of Lit *et al.* [85] which elaborates on optimal resource allocation in Wireless Powered IoT networks. Like us, they employed MDPs to formulate the policy derivation problem. In a similar fashion, [86] cite us as success case for the optimization of Sigfox IoT networks for industrial sceanrios. It is worth mentioning that the commented work also served as a starting point for investigating the impact of transmission policies on other fields. For instance, in [5, 19], Canovas *et al.* (and the author of this Thesis himself) employed some of the formulation presented here and the approach of comparing derived policies with alternative intuitive policies.

4.4 Conclusions

LPWAN IoT networks have started to draw the attention of the academic and industrial communities as very promising alternatives to other classic IoT technologies. This is due to four advantages that these technologies present over traditional IoT alternatives: increased robustness over long distances, low-power design, simpler network topologies, and much cheaper deployments. The latter is attained by a mixture of low-complexity electronics and the use of ISM license-free bands. However, the limitations imposed on ISM bands in many countries hinder the ability of Long-Range IoT motes to make free use of the shared medium. In particular, the restriction to the amount of time motes can occupy the ISM bands (normally less than 36 seconds an hour) might jeopardize the ability of these kinds of networks to operate in industrial scenarios.

In this paper we tried to first, put the research focus on the TDC as the main performance-limiting factor in LPWAN networks and second, try to overcome the associated limitations. To this end, an optimal transmission policy based on the analytical framework of Markov Decision Processes (MDP), has been derived with two objectives: (i) to maximize the number of reported events, prioritized by their importance, and (ii) to comply with the ISM regulations. This has been accomplished in two steps. Firstly, a general model of Long-Range IoT motes has been proposed and, secondly this model has been tuned for two widely-known technologies: LoRa and Sigfox. Motes of both technologies have been simulated under different network conditions. Unlike other traditional policies tested, whose performance is strongly coupled with network conditions, our obtained results reveal that the proposed solution performs very close to the maximum Theoretical Limit under almost any condition. Furthermore, the proposed solution is computationally fitted for resource-constrained motes and for time-critical scenarios, thus making it a good solution for IoT motes deployed in industrial scenarios.

Chapter 5

Smart Usage of Multiple RAT in IoT-oriented 5G Networks: A Reinforcement Learning Approach

5.1 Brief summary

As explored in the previous article, the IoT can hugely benefit from new communication protocols like LoRa and Sigfox. This is all the more so in Industrial environments (one of the most relevant spaces of the future IoT), where distances and number of devices may render traditional technologies unfeasible. However, every particular application has its own peculiarities, and we cannot consider LPWANs a silver bullet that works for each and every situation. Furthermore, as commented in the introduction of this Thesis, the IoT must be able to leverage the true potential of various technologies, and only then, the IoT will unleash its true potential. This can be seen for instance in Smart Cities, where low-power, long-range, low-bandwidth technologies like LoRa can be used for low-end applications (like environment monitoring or lighting control systems) whereas more high-bandwidth technologies like 4/5G could be devoted to, e.g., automatic traffic surveillance. Therefore, it seems obvious that the future IoT will be a mixture of networks rather than a one-for-all technology. In this paper we looked into the different problems that arise when nodes are provided with different Radio Access Technologies (RAT). Although this clearly enables devices to reap the benefits offered by each RAT (such as lower power consumption or reduced operational costs), the set of actions at the disposal of the IoT node rapidly increases.

In this paper we made use of the the mathematical framework of Reinforcement Learning (RL) to formulate the problem of deciding which RAT should an IoT node employ when reporting events. By solving this RL problem we obtained optimal transmission policies in the form of Artificial Neural

Networks (ANN). This ANN-based policies are shown to maximize a reward metric closely related to classical throughput while keeping power consumption and operational costs below a certain limit. Finally, an extensive set of simulations are performed for IoT nodes fitted with two different RATs (LoRa and 5G). Once again, the results obtained are compared to those achieved under other intuitive policies to further highlight the benefits of our proposal.

5.2 Methodology and tools

Figure 5.1: Methodology employed in this article

As with the previous article, this paper is tackled from a purely “mathematical + simulations” approach. Therefore, this section is devoted to analyzing the *mathematical* methodology and the *simulation* tools employed within.

Fig. 5.1 outlines the main phases of the presented methodology. The first step in this methodology is to mathematically describe the context of IoT nodes. To do so, we first need to introduce the mathematical framework underlying a Reinforcement Learning problem (first subsection below). Then, the policy derivation task can be fully described in terms of RL parameters (second subsection and second step in the methodology). After it, the policy is trained and it, as well as other alternative policies, are evaluated (last part of the methodology contained here).

RL mathematical model

As discussed above, the objective of the policy-derivation algorithm is to determine which RAT should be used by an IoT device in any given situation. This can be translated into the RL jargon as determining the optimal action a to take (out of a set of $\mathbf{A}$ allowed actions, being $a \in \mathbf{A}$) given a state s (a description of the internal/external state of the IoT node, with $s \in \mathbf{S}$). Having performed action a in the state s , some reward is obtained –this feedback

signal helps nodes understand what actions are better to take than others—. The function $\mathbf{R}$ mathematically defines such a reward as a mapping between state-action pairs and real numbers, that is, $\mathbf{R} : \mathbf{S} \times \mathbf{A} \rightarrow \mathbb{R}$.

After receiving some reward, that can be positive or negative, IoT nodes shift from one state to another, again, depending on the previous state-action pair. These transitions can be stochastic to allow RL entities to probabilistically transition from one state to another. Formally, $\mathbf{P}$ models the transition from one state to another by mapping a tuple $(\mathbf{S}, \mathbf{A}, \mathbf{S})$ to a real number —representing the probability of transitioning from state s to state s' after taken action a —.

The goal of RL algorithms is to find an optimal action policy π^* that maximizes the expected total reward obtained over some finite or infinite horizon (such accumulated reward is denoted as γ). In the former case, the reward is aggregated for T units of time —e.g. T seconds— whereas in the latter, it is the average reward per unit of time what it is maximized. Therefore, the objective of π^* is to, being the IoT node in a certain state s , propose an action a to take such as the total expected attained reward γ is maximized. Following the above formulation, an action policy π can be mathematically represented as a mapping between states and actions, that is, $\pi : \mathbf{S} \rightarrow \mathbf{A}$. In this article we opted for modeling this optimal policy as an Artificial Neural Network (due to the sheer number of different states, that is, the mathematical space of $\mathbf{S}$ was large).

Among all ANN-based alternatives, Evolution Strategies (ES) [87] was recently demonstrated to be one of the best-suited alternatives to derive optimal policies; especially when the effects of the actions are long-lasting (that is, taking the action a at a given instant t has a measurable non-negligible effect at time t' , with $t' \gg t$). ES is a type of Genetic Algorithm [88], a black-box optimization meta-heuristic loosely inspired in natural selection. By iteratively tweaking the parameters of the ANN via natural selection, the modeled policy π tends to improve in proposing actions to take.

Application to the problem

We considered that IoT nodes were monitoring/controlling some parameters of interest of particular assets. Once a worth-reporting event was detected, the node had to decide whether to drop the event (action a_0) or reporting it using one of the 2 available RATs (LoRa —action a_1 — or 5G —action a_2 —). To embrace the heterogeneity of the IoT, each of these generated events could have their own priority G . For instance, if a malfunction in a life-supporting device is detected, a top-priority event must be sent. Contrary, if a regular event is detected (such as mild vibrations in an engine), a low-priority event could be generated. Priorities are let to vary in a range from 0 to 1 to illustrate different event priorities —where 1 means top priority—.

To model the nature of wireless communications, we let each RAT have a limit on its usage. We believe this is a realistic scenario as large-scale IoT networks making use of pay-per-use technologies (like 5G) may render the

deployment unaffordable. Therefore, we limit the usage of 5G to 1Mb a day. On the other hand, as LoRa makes use of license-free bands, we did not set any upper limit on its usage. This way, every time an event is sent through 5G, the usage of such an RAT is updated. When the 1Mb is exhausted, this precise node will not be able to transmit under 5G for the rest of that day. Without any loss of generality, periods of 24 hours (1 day) were considered in limiting the usage of RATs.

As commented in the previous article, LoRa devices, depending on the country, must undergo an enforced off-period (t_{off}) after every transmission. To model this, as well as packet queuing capabilities, we assumed that individual infinite queues exist for each RAT (in our case, 2 queues). Therefore, if at the time of transmitting, there is another packet being transmitted using the same RAT, the second packet is queued. Once the packet being transmitted is completed, the enqueued one is finally sent. This way, the transmission time of a packet does not only depend on its length (L), but also on the occupation of its associated queue (denoted as o_i for RAT i). To model de TDC dynamics of LoRa, if an off-period of t_{off} seconds is enforced in a mote, as a result of transmitting a packet, the queue of LoRa (o_1) is not only filled with such a packet, but also artificially extended with another fictitious packet that would take t_{off} seconds to be transmitted. Note that this artificially generated packet has no impact on the obtained reward. Using this trick, we force nodes not to use the LPWAN RAT for, at least, t_{off} seconds –and thus, to comply with regional regulations–.

Also, each action/RAT entails a different energy consumption (denoted as c_i for action i). Since a single battery per node is assumed, if battery level (denoted as b) drops to zero, no further events can be reported. It should be noted that the event-generation process is modeled as a Poisson distribution with an average rate of λ events per second.

To sum up the mathematical application of the RL model, note that the state of the mote s is therefore composed of: L (the length of the packet associated to the event), G (the priority of the generated event), b (the remaining battery of the node), t (the time of the day, important to know how much long will it take to reset usage quotas), u (the usage of 5G during this day, measured in transmitted bits), and o_1 and o_2 (the occupation of the queues for LoRa and 5G respectively).

Finally, the reward (the feedback signal used in any RL problem to teach the action-taking agent) was modeled as $\mathbf{R}(s_i, a_i) = G \cdot \frac{L}{\text{delay}(a_i)}$. The reward is modeled as the priority multiplied by the length of the transmitted packet (in bits), divided by the delay in the transmission. This way, nodes were encouraged to report events as fast as possible, while prioritizing their importance. The units of this reward are bits per second, which match the units of a throughput metric. Hence, what the reward function maximized was the prioritized throughput of an IoT node. Note that the delay of the action a_i is not only related to the bitrate of the i -th RAT but also to the occupation of the queue of such an RAT. Also, since battery depletion prevents nodes

Figure 5.2: Evolution of γ as ES algorithm iterates (first 250 iterations are shown)

from reporting more events (and hence, 0 reward is obtained from that point onwards), π^* naturally optimizes energy consumption as well.

Methodology of the learning and simulation phases

To train the ANN-based transmission policy, we simulate a real IoT network deployed in a Smart City with the help of Python. When IoT nodes reported an event with LoRa, we assumed they did so using the fastest Spreading Factor, the seventh, which provides an effective data rate of 2.43kbps (read more about Spreading Factors in the previous chapter of this Thesis or in the main document of this article). Conversely, for the 5G RAT, we modeled a sub-renting scheme (very common in IoT deployments seeking low maintenance costs) in which only a small fraction of the whole 5G band is at the disposal of nodes. This way, 5G provided an effective data rate of 100kbps. Events were assumed to be generated with a varying λ between $\lambda = \frac{1}{600}$ and $\lambda = \frac{1}{30}$.

With regard to the Evolution Strategies (ES) algorithm –integral part of the training phase– it was allowed to run for 1000 iterations to iteratively tune the ANN-defined policy. This ANN is, in turn, composed of two hidden layers of 45 and 5 neurons with tanh as an activation function [89]. Fig. 5.2 shows the training phase of the ANN-based policy. In this process the expected total reward obtained for a whole day (that is, γ) increases as the policy π improves by iteratively applying the ES algorithm. This illustrates that the obtained policy is being more and more refined to make IoT nodes act wiser.

Once the ANN was trained and an optimal transmission policy (π^*) was obtained, we moved on to the evaluation of such a policy via simulations. The environment to simulate these policies was the same as for the training phase. Again, we proposed different alternative policies to which we could compared

the ANN-based policy: (i) randomly chose an RAT (5G/LoRa) –denoted as random policy–, (ii) start with 5G until its exhaustion and then use LoRa if necessary –denoted as 5G-first policy–, and (iii) consider important events those with $G \geq 0.5$ and thus, only employ 5G for those critical transmissions (and employ LoRa when $G < 0.5$ or when 5G has been exhausted) –denoted as priority-based policy–.

5.3 Results and Contributions

As with the previous articles, in this paper we presented two set of results.

1. First, we proposed a mathematical framework to model multi-RAT IoT devices. This framework is generic-enough to be applicable to many other environments (whether it be wireless IoT networks, wired IoT networks or a mixture of them, such as PLC-powered devices). We believe this framework –on its own– is a very valuable contribution as it allows future researchers to derive powerful smart policies that can automatically learn the best way to proceed when fitted with multiple RAT.
2. Second, we later applied this generic model to a particular Smart City context where nodes are fitted with LoRa and 5G RATs. This is also of special interest as we believe that such a combination will become very popular in future IoT deployments. Along with this particularization, we provided a set of simulations that demonstrate that our approach is not only viable but desirable (as it can swiftly adapt to many conditions). The results of this are covered below.

After the training phase, the ANN-based transmission policy is capable of determining which RAT should be used at any given time. Furthermore, the RL-oriented approach guarantees that these derived policies maximized the accumulation of rewards, and by doing so, the prioritized throughput of the network. To validate this, we have compared the performance obtained under the suggested approach to the performance attained with other alternative policies (commented above). Fig. 5.3 shows the performance metric (γ , that is, the accumulated reward) for the different traffic-generation conditions commented in Subsection 5.2.

It is worth noting how the ANN-based proposed policy clearly outperforms the rest of them when the event-generation rates are larger than $\frac{1}{120}$. Specifically, when the proposed policy is preferred over the second-best policy (5G-first), γ increases 75.6%, 59.0%, 43.1%, and 17.1% for the four highest event generation rates respectively. If γ is smaller or equal to $\frac{1}{120}$, the relatively low event-generation rates make the 5G-first policy perform similarly to our proposal. For these small values of γ , employing the 5G RAT for all transmissions is always the best option, since neither the 5G daily quota nor the battery allowance exhaust; thus, both policies attain similar values of γ . As can be noted, ANN-based policy is properly adapted to different event-generation

Figure 5.3: Total reward (γ) as a function of the event-generation rate. Error bars represent the standard deviation around the mean value

rates, always achieving an optimal performance. For a deeper insight into the results, please see Section VI of the commented paper.

Although in this paper we followed the same reproducibility commitment and data and scripts were made publicly available, due to the short time span that such an article has been published (it was released a few months before writing this thesis), it has not yet attracted the attention of the academic community.

5.4 Conclusions

The IoT has proved itself to be a future revolution in the way in which machines could collaboratively communicate and interact with their peers. It is precisely within Smart Industries and Cities where the IoT paradigm will play a major role in automating daily processes. However, although LPWAN networks have facilitate the interconnection of distant nodes at very low costs, they, on their own, may not be capable of routing the whole IoT traffic. To solve this, we have argued that fitting IoT nodes with multiple Radio Access Technologies (RATs) may give these nodes an extra layer of flexibility that help them unleash their true potential. These RATs would be used intelligently and on-demand to access the wireless shared medium.

To justify this statement, we provided a generic mathematical model that lies the foundations for improving the performance of IoT devices fitted with multiple RAT. Under this model, nodes are expected to maximize the prioritized throughput by employing a set of analytical tools popularized by the Machine Learning (ML) research field. In particular, a Generic Algorithm known as Evolution Strategies has been used to derive optimal transmission

policies. These policies are shown to outperform other intuitive approaches in different simulated scenarios while still being computationally lightweight enough to run in hardware-constrained IoT devices.

The solution based on an Artificial Neural Network (ANN) optimizes the use of the available RATs (5G and LoRa), leading to an improvement in the attained rewards of up to 75.6% when compared to other policies.

Part IV

Conclusions and Future Lines

Chapter 1

Conclusions

The IoT is a revolutionizing process that encompasses a wide range of innovative technologies: from the design of nano-scale microcontrollers to the development of complex communication algorithms. The miniaturization of electronics, denser and more efficient batteries and recent advances in modulation schemes have paved the way for what we now perceive as a truly ubiquity Internet of Things.

Being the IoT a very vast and open research field, multiple and varied approaches can be followed to improve the IoT in some meaningful way. Since this is a Thesis in Telecommunication Engineering, we have focused our efforts on contributing to the communication plane –crucial to attain a smart, responsive IoT–. Particularly, this aim has been pursued from four different angles: (i) easing the complex process of integrating multiple resources and technologies into the IoT, (ii) improving the performance of these networks, and intelligently managing (iii) the scarce resources, and (iv) produced data.

In the previous sections, we have presented five different articles in which the above four angles have been pursued, yielding valuable contributions to the IoT field (as thoroughly discussed in each article). These five articles, which represent the result of four years of research in the IoT arena, have drawn their own conclusions and have contributed in their own way to the ample research field of the IoT. As a summary, the following paragraphs synthesize such conclusions so readers can have a clear view of the topics addressed in this Thesis and their outcomes:

- When operating IoT networks, there existed a common belief that the 2.4GHz frequency band was the best suited choice among the available options. However, as extensively proved in this Thesis, in presence of other interfering devices (a pretty common situation), the by-default working band should be the 915MHz one. This recommendation is based on the evaluation of three key performance indicators (network delay, packet reception rate, and power consumption) in different environments. Results indicate that, if the 915MHz frequency band is used, IoT nodes can ben-

efit from a lower power consumption, larger packet reception rates and, unexpectedly, higher transmission rates.

- In complex environments like Smart Grids, there is a pressing need for having accurate propagation model. These models are shown to have a dramatic impact on the performance estimation of IoT networks deployed in complex environments. For instance, when inaccurate propagation models are employed, the life expectancy of IoT nodes cannot be appropriately anticipated –as well as other KPIs like packet reception rate and/or power consumption–.
- We have also shown that, contrary to what one could expect, the low-complexity nature of most IoT communication standards is beneficial when used under harsh conditions. For instance, the low rate (translated to a large symbol duration) and narrow-band modulation schemes are especially suited for harsh environments where the multi-path effect is the predominant detrimental propagation phenomenon. This provides solid arguments for the impressive performance of LoRa and other Long-Range technologies in a wide range of environments (like cities, industries and smart grids).
- Another interesting conclusion derived from this Thesis is the capability of a low-cost, low-complexity indicator like the RSSI for deriving accurate path-loss models. However, this only holds true if certain corrections are applied to the raw measures returned by the RSSI. We showed that there is a plethora of factors (both intrinsic and extrinsic) that must be considered, but when they are accounted for, the precision of RSSI-derived models improve by 91.76% –becoming an ideal tool for deriving path-loss models–.
- As indicated above, the derivation of accurate propagation models ultimately aims at improving IoT simulation fidelity. It is a well-known fact that simulations let researchers rapidly test their new ideas and approaches in a controlled and studied environment which can eventually, increase network efficiency and performance. In the same line (i.e. improving IoT efficiency), we proved that current European regulations could potentially hinder the performance of many IoT networks. Specifically, we showed that some long-range technologies (like LoRa or Sigfox) operating in license-free ISM bands, are subject to stringent regulations (in terms of how much time the radio spectrum can be occupied) that can become the performance limiting factor.
- As a way to reduce the negative impact of these regulations on IoT performance, we demonstrated that mathematically modeling IoT nodes as Markov Decision Processes (for a later optimization) is an effective approach. Particularly, the application of this mathematical tool was shown to bring performance indicators remarkably close to Theoretical Maximum values, translating to a general increase of the network throughput.

- The mathematical tool of Markov Decision Processes and its extension, known as Reinforcement Learning, are shown in the last presented article to also be excellent tools in the mitigation of radio spectrum congestion. Via Neural Networks we derived smart transmission policies that could effectively incorporate multiple Radio Access Technologies (e.g. 5G and Long-Range protocols). This multi-RAT approach is shown to lead efficient utilization of radio resources. Increasing, among other Key Performance Indicators, aggregated throughput and node battery lifetime.

All in all, the above conclusions highlight the few areas this Thesis has been focused on. Contributions have been geared towards making the IoT a more resilient, effective, and real concept; closing the gap between potentiality and reality.

Chapter 2

Future Lines

At the time of writing this thesis, there are three articles being under review in three relevant journals. Clearly, our intent is to finish the reviewing process and contribute to the IoT arena with these three novel works. The commented works look into:

1. Better managing the Transmission Duty Cycle of both nodes and gateways in LoRa-based IoT networks. In this work we apply Machine Learning techniques (specifically, Reinforcement Learning and Evolutionary Algorithms) to maximize the performance of the IoT.
2. We extended and improved the mechanism in charge of managing multiple RATs. By applying a wide range of Machine Learning Techniques, hardware-constrained IoT nodes can further benefit from being fitted with multiple radio transceivers. Ultimately, this impact on a better management of scarce resources (radio spectrum, battery, CPU, etc.) and also in a global network performance.
3. We optimize the operating characteristics of LoRa IoT nodes so they can more easily integrate into large networks, thus facilitating the process of scaling IoT networks. By proposing a mathematical model for IoT nodes, we derive a set of optimal transmission policies that balance both performance and resource (i.e. battery) consumption.

We also plan to further investigate on how some of the presented algorithms (mainly evaluated in simulations) behave in real scenarios. To this end, we took some measurements in a real test-bed in the Department of Engineering of Cambridge University that are to be analyzed and published.

Part V

Appendices

Índice de impacto de las publicaciones

(Fuente JCR Science Edition)

Publicación 1

Título: “Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz”

Revista y Editorial: Sensors, MDPI

Fecha de aceptación: 28 de diciembre de 2016

Factor de Impacto: 2.677

Cuartil: Q1 (Instrument & Instrumentation)

Publicación 2

Título: “Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band”

Revista y Editorial: Transactions on Wireless Communications, IEEE

Fecha de aceptación: 19 de diciembre de 2016

Factor de Impacto: 4.951

Cuartil: Q1 (Telecommunications)

Publicación 3

Título: “Improving RSSI-based path-loss models accuracy for critical infrastructures: A smart grid substation case-study”

Revista y Editorial: Transactions on Industrial Informatics, IEEE

Fecha de aceptación: 14 de noviembre de 2017

Factor de Impacto: 5.430

Cuartil: Q1 (Engineering Industrial) y Q1 (Computer Science, Interdisciplinary Applications)

Publicación 4

Título: “Optimal policy derivation for Transmission Duty-Cycle constrained LPWAN”

Revista y Editorial: Internet of Things Journal, IEEE

Fecha de aceptación: 1 de mayo de 2018

Factor de Impacto: 9.515

Cuartil: Q1 (Telecommunications) y Q1 (Computer Science, Information Systems)

Part VI

References

Bibliography

- [1] R. M. Sandoval, A.-J. J. Garcia-Sanchez, F. Garcia-Sanchez, and J. Garcia-Haro, "Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz," *Sensors*, vol. 17, no. 1, p. 76, dec 2017. [Online]. Available: <http://www.mdpi.com/1424-8220/17/1/76>
- [2] R. M. Sandoval, A.-J. J. Garcia-Sanchez, J.-M. M. Molina-Garcia-Pardo, F. Garcia-Sanchez, and J. Garcia-Haro, "Radio-Channel Characterization of Smart Grid Substations in the 2.4-GHz ISM Band," *IEEE Transactions on Wireless Communications*, vol. 16, no. 2, pp. 1294–1307, feb 2017. [Online]. Available: <http://ieeexplore.ieee.org/document/7797244/>
- [3] R. M. Sandoval, A. J. Garcia-Sanchez, and J. Garcia-Haro, "Improving RSSI-based path-loss models accuracy for critical infrastructures: A smart grid substation case-study," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 5, pp. 2230–2240, 2018. [Online]. Available: <http://ieeexplore.ieee.org/document/8114199/>
- [4] R. M. Sandoval, A.-J. Garcia-Sanchez, J. Garcia-Haro, and T. M. Chen, "Optimal policy derivation for Transmission Duty-Cycle constrained LPWAN," *IEEE Internet of Things Journal*, vol. 5, no. 4, pp. 1–1, aug 2018. [Online]. Available: <https://ieeexplore.ieee.org/document/8354856/>
- [5] R. M. Sandoval, S. Canovas-Carrasco, A. Garcia-Sanchez, and J. Garcia-Haro, "Smart Usage of Multiple RAT in IoT-oriented 5G Networks: A Reinforcement Learning Approach," in *2018 ITU Kaleidoscope: Machine Learning for a 5G Future (ITU K)*, nov 2018, pp. 1–8.
- [6] Deloitte, "Data is the new gold - The future of real estate service providers," Deloitte, Tech. Rep., 2018. [Online]. Available: <https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Public-Sector/gx-real-estate-data-new-gold.pdf>
- [7] Gartner, "Hype Cycle for Emerging Technologies 2018," 2018. [Online]. Available: <https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018/>

- [8] IEEE, “IEEE Xplore,” 2019. [Online]. Available: <http://ieeexplore.ieee.org>
- [9] S. Poslad, S. E. Middleton, F. Chaves, R. Tao, O. Necmioglu, and U. Bügel, “A semantic IoT early warning system for natural environment crisis management,” *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 2, pp. 246–257, 2015.
- [10] S. Ramnath, A. Javali, B. Narang, P. Mishra, and S. K. Routray, “IoT based localization and tracking,” in *2017 International Conference on IoT and Application (ICIOT)*, may 2017, pp. 1–4.
- [11] S. Yuvaraj and M. Sangeetha, “Smart supply chain management using internet of things (IoT) and low power wireless communication systems,” in *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*. IEEE, 2016, pp. 555–558.
- [12] T. Robles, R. Alcarria, D. M. de Andrés, M. N. de la Cruz, R. Calero, S. Iglesias, and M. López, “An IoT based reference architecture for smart water management processes.” *JoWUA*, vol. 6, no. 1, pp. 4–23, 2015.
- [13] H. Ghayvat, S. Mukhopadhyay, X. Gui, and N. Suryadevara, “WSN-and IOT-based smart homes and their extension to smart buildings,” *Sensors*, vol. 15, no. 5, pp. 10 350–10 379, 2015.
- [14] P. Rajalakshmi and S. D. Mahalakshmi, “IOT based crop-field monitoring and irrigation automation,” in *2016 10th International Conference on Intelligent Systems and Control (ISCO)*. IEEE, 2016, pp. 1–6.
- [15] K. Ashton, “That ‘Internet of Things’ Thing,” 2009. [Online]. Available: <https://www.rfidjournal.com/articles/view?4986>
- [16] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, “Fog Computing and Its Role in the Internet of Things,” in *Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing*, ser. MCC ’12. Helsinki, Finland, 17 August 2012: ACM, 2012, pp. 13–16. [Online]. Available: <http://doi.acm.org/10.1145/2342509.2342513>
- [17] IBM, “IBM Research Alliance Builds New Transistor for 5nm Technology,” 2017. [Online]. Available: <https://www-03.ibm.com/press/us/en/pressrelease/52531.wss>
- [18] C. Fuentes, M. Porcheron, J. E. Fischer, E. Costanza, N. Verdezoto, V. Herskovic, O. Zuckerman, and L. Takayama, “New Directions for the IoT: Automate, Share, Build, and Care,” in *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, ser. CHI EA ’19. New York, NY, USA: ACM, 2019, pp. W35:1—W35:8. [Online]. Available: <http://doi.acm.org/10.1145/3290607.3299000>

- [19] S. Canovas-Carrasco, R. M. Sandoval, A.-J. Garcia-Sanchez, and J. Garcia-Haro, "Optimal Transmission Policy Derivation for IoNT Flow-Guided Nano-Sensor Networks," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2288–2298, 2019.
- [20] S. Canovas-Carrasco, A.-J. Garcia-Sanchez, and J. Garcia-Haro, "A nanoscale communication network scheme and energy model for a human hand scenario," *Nano communication networks*, vol. 15, pp. 17–27, 2018.
- [21] C. Perera, A. Zaslavsky, P. Christen, and D. Georgakopoulos, "Context Aware Computing for The Internet of Things: A Survey," *Communications Surveys Tutorials, IEEE*, vol. 16, no. 1, pp. 414–454, 2014.
- [22] S. Bandyopadhyay, P. Balamuralidhar, and A. Pal, "Interoperation among IoT standards," *Journal of ICT Standardization*, vol. 1, no. 2, pp. 253–270, 2013.
- [23] M. R. Palattella, M. Dohler, A. Grieco, G. Rizzo, J. Torsner, T. Engel, and L. Ladid, "Internet of Things in the 5G Era: Enablers, Architecture, and Business Models," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 3, pp. 510–527, 2016.
- [24] R. S. Sinha, Y. Wei, and S.-H. H. Hwang, "A survey on LPWA technology: LoRa and NB-IoT," *Ict Express*, vol. 3, no. 1, pp. 14–21, 2017. [Online]. Available: <http://dx.doi.org/10.1016/j.ict.2017.03.004>
- [25] M. Siekkinen, M. Hienkari, J. K. Nurminen, and J. Nieminen, "How low energy is bluetooth low energy? comparative measurements with zigbee/802.15. 4," in *2012 IEEE wireless communications and networking conference workshops (WCNCW)*. IEEE, 2012, pp. 232–237.
- [26] P. Lopez-Iturri, E. Aguirre, L. Azpilicueta, J. J. Astrain, J. Villadangos, and F. Falcone, "Implementation and Analysis of ISM 2.4 GHz Wireless Sensor Network Systems in Judo Training Venues," *Sensors*, vol. 16, no. 8, p. 1247, 2016. [Online]. Available: <http://www.mdpi.com/1424-8220/16/8/1247>
- [27] I. C. L. Ng and S. Y. L. Wakenshaw, "The Internet-of-Things: Review and research directions," *International Journal of Research in Marketing*, vol. 34, no. 1, pp. 3–21, 2017.
- [28] R. Hassan and G. Radman, "Survey on Smart Grid," in *Proceedings of the IEEE SoutheastCon 2010 (SoutheastCon)*, mar 2010, pp. 210–213.
- [29] R. Deng, Z. Yang, M. Chow, and J. Chen, "A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 3, pp. 570–582, jun 2015.

- [30] P. Siano, "Demand response and smart grids—A survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, feb 2014. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1364032113007211>
- [31] UN, "Department of Economic and Social Affairs - United Nations," 2018. [Online]. Available: <https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html>
- [32] Union for the co-ordination of transmission of electricity, "Final Report on the Disturbances of 4 November 2006," UCT, Tech. Rep., 2007. [Online]. Available: [https://www.entsoe.eu/fileadmin/user_{-}upload/{-}library/publications/ce/otherreports/Final-Report-20070130.pdf](https://www.entsoe.eu/fileadmin/user/_upload/{-}library/publications/ce/otherreports/Final-Report-20070130.pdf)
- [33] K. Yamashita and J. Li, "Analysis and control of major blackout events," in *Power Systems Conference and Exposition, 2009. PSCE '09. IEEE/PES*, 2009, pp. 1–4. [Online]. Available: [http://ieeexplore.ieee.org/xpls/abs_{-}all.jsp?arnumber=4840091](http://ieeexplore.ieee.org/xpls/abs/_all.jsp?arnumber=4840091)
- [34] M. Yigit, V. C. Gungor, and S. Baktir, "Cloud Computing for Smart Grid applications," *Computer Networks*, vol. 70, pp. 312–329, sep 2014. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1389128614002382>
- [35] K. G. Boroojeni, M. H. Amini, S. S. Iyengar, M. Rahmani, and P. M. Pardalos, "An economic dispatch algorithm for congestion management of smart power networks," *Energy Systems*, vol. 8, no. 3, pp. 643–667, 2017.
- [36] R. Ullah, Y. Faheem, and B.-S. Kim, "Energy and congestion-aware routing metric for smart grid AMI networks in smart city," *IEEE access*, vol. 5, pp. 13 799–13 810, 2017.
- [37] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *2010 First IEEE International Conference on Smart Grid Communications*. IEEE, 2010, pp. 415–420.
- [38] Q. Memon and N. Cetinkaya, "Short-Term Power Production Forecasting in Smart Grid Based on Solar Power Plants," *International Journal of Engineering and Applied Sciences*, vol. 4, no. 12, 2018.
- [39] J. Hao, R. J. Piechocki, D. Kaleshi, W. H. Ching, and Z. Fan, "Smart grid health monitoring via dynamic compressive sensing," in *IEEE PES ISGT Europe 2013*. IEEE, 2013, pp. 1–5.
- [40] S. Güzelgöz, H. Arslan, A. Islam, and A. Domijan, "A Review of Wireless and PLC Propagation Channel Characteristics for Smart Grid Environments," *Journal of Electrical and Computer Engineering*, vol. 2011, no. 7, pp. 1–12, 2011. [Online]. Available: <http://www.hindawi.com/journals/jece/2011/154040/>

- [41] V. C. Gungor, B. Lu, and G. P. Hancke, "Opportunities and Challenges of Wireless Sensor Networks in Smart Grid," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 10, pp. 3557–3564, 2010.
- [42] S. Guzelgoz, "Characterizing Wireless and Powerline Communication Channels with Applications to Smart Grid Networks," Ph.D. dissertation, University of Florida, 2011. [Online]. Available: <http://scholarcommons.usf.edu/etd/3138>
- [43] H. Tsuchiya, "Characterization of the radio propagation channel in residential environment for smart meter communications," in *Asia-Pacific Microwave Conference 2011*. IEEE, 2011, pp. 713–716.
- [44] A. Saha, M. Kuzlu, and M. Pipattanasomporn, "Demonstration of a home energy management system with smart thermostat control," in *2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*. IEEE, 2013, pp. 1–6.
- [45] J. W. S. Liu, C.-S. Shih, and E. T.-H. Chu, "Cyberphysical elements of disaster-prepared smart environments," *Computer*, vol. 46, no. 2, pp. 69–75, 2012.
- [46] P. Network, "How Smart Parking Technology will Reduce Pollution in the City," p. 1, 2018. [Online]. Available: <http://www.parking-net.com/parking-industry-blog/get-my-parking/how-smart-parking-technology-will-reduce-pollution-in-the-city>
- [47] A. Khanna and R. Anand, "IoT based smart parking system," in *2016 International Conference on Internet of Things and Applications (IOTA)*, jan 2016, pp. 266–270.
- [48] M. Hassanaliereagh, A. Page, T. Soyata, G. Sharma, M. Aktas, G. Mateos, B. Kantarci, and S. Andreescu, "Health monitoring and management using Internet-of-Things (IoT) sensing with cloud-based processing: Opportunities and challenges," in *2015 IEEE International Conference on Services Computing*. IEEE, 2015, pp. 285–292.
- [49] S. Tripathy, J. Mathew, and Others, "Design and evaluation of an IoT enabled secure multi-service Ambulance Tracking System," in *2016 IEEE Region 10 Conference (TENCON)*. IEEE, 2016, pp. 2209–2214.
- [50] I. Chandra, N. Sivakumar, C. B. Gokulnath, and P. Parthasarathy, "IoT based fall detection and ambient assisted system for the elderly," *Cluster Computing*, pp. 1–9, 2018.
- [51] B. Hammi, R. Khatoun, S. Zeadally, A. Fayad, and L. Khoukhi, "IoT technologies for smart cities," *IET Networks*, vol. 7, no. 1, pp. 1–13, 2017.

- [52] S. Chen, H. Xu, D. Liu, B. Hu, and H. Wang, "A vision of IoT: Applications, challenges, and opportunities with china perspective," *IEEE Internet of Things journal*, vol. 1, no. 4, pp. 349–359, 2014.
- [53] N. E. KLEPEIS, W. C. NELSON, W. R. OTT, J. P. ROBINSON, A. M. TSANG, P. SWITZER, J. V. BEHAR, S. C. HERN, and W. H. ENGELMANN, "The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants," *Journal of Exposure Science & Environmental Epidemiology*, vol. 11, no. 3, pp. 231–252, 2001. [Online]. Available: <https://doi.org/10.1038/sj.jea.7500165>
- [54] L. Favre, T. M. Schafer, J.-L. Robyr, and E.-L. Niederhäuser, "Intelligent algorithm for energy, both thermal and electrical, economic and ecological optimization for a smart building," in *2018 IEEE International Energy Conference (ENERGYCON)*. IEEE, 2018, pp. 1–5.
- [55] Z. Wang, L. Wang, A. I. Dounis, and R. Yang, "Multi-agent control system with information fusion based comfort model for smart buildings," *Applied Energy*, vol. 99, pp. 247–254, 2012.
- [56] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, and M. Hoffmann, "Industry 4.0," *Business & information systems engineering*, vol. 6, no. 4, pp. 239–242, 2014.
- [57] D. Kwon, M. R. Hodkiewicz, J. Fan, T. Shibutani, and M. G. Pecht, "IoT-based prognostics and systems health management for industrial applications," *IEEE Access*, vol. 4, pp. 3659–3670, 2016.
- [58] World Economic Forum, "Industrial Internet of Things: Unleashing the Potential of Connected Products and Services," WEF, Tech. Rep., 2015. [Online]. Available: <http://reports.weforum.org/industrial-internet-of-things/>
- [59] T. Stock and G. Seliger, "Opportunities of sustainable manufacturing in industry 4.0," *Procedia Cirp*, vol. 40, pp. 536–541, 2016.
- [60] M. Centenaro, L. Vangelista, A. Zanella, and M. Zorzi, "Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios," *IEEE Wireless Communications*, vol. 23, no. 5, pp. 60–67, oct 2016. [Online]. Available: <http://ieeexplore.ieee.org/document/7721743/>
- [61] F. Adelantado, X. Vilajosana, P. Tuset-Peiro, B. Martinez, J. Melia-Segui, and T. Watteyne, "Understanding the Limits of LoRaWAN," *IEEE Communications Magazine*, vol. 55, no. 9, pp. 34–40, 2017.
- [62] C. Pham, "QoS for Long-Range Wireless Sensors Under Duty-Cycle Regulations with Shared Activity Time Usage," *ACM Trans. Sen.*

- Netw.*, vol. 12, no. 4, pp. 33:1—33:31, sep 2016. [Online]. Available: <http://doi.acm.org/10.1145/2979678>
- [63] C. Phan, “Deploying a pool of long-range wireless image sensor with shared activity time,” in *2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE, oct 2015, pp. 667–674. [Online]. Available: <http://ieeexplore.ieee.org/document/7348026/>
- [64] Cisco, “Cisco Visual Networking Index: Forecast and Trends 2017-2022,” Deloitte, Tech. Rep., 2017. [Online]. Available: <https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white-paper-c11-741490.pdf>
- [65] M. Jo, T. Maksymyuk, B. Strykhalyuk, and C.-H. Cho, “Device-to-device-based heterogeneous radio access network architecture for mobile cloud computing,” *IEEE Wireless Communications*, vol. 22, no. 3, pp. 50–58, 2015.
- [66] J. A. Ayala-Romero, J. J. Alcaraz, and J. Vales-Alonso, “Energy Saving and Interference Coordination in HetNets Using Dynamic Programming and CEC,” *IEEE Access*, vol. 6, pp. 71 110–71 121, 2018.
- [67] W. Ejaz and M. Ibnkahla, “Multiband spectrum sensing and resource allocation for IoT in cognitive 5G networks,” *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 150–163, 2017.
- [68] O. Galinina, A. Pyattaev, S. Andreev, M. Dohler, and Y. Koucheryavy, “5G multi-RAT LTE-WiFi ultra-dense small cells: Performance dynamics, architecture, and trends,” *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 6, pp. 1224–1240, 2015.
- [69] A. Singh, U. K. Singh, and D. Kumar, “IoT in mining for sensing, monitoring and prediction of underground mines roof support,” in *2018 4th International Conference on Recent Advances in Information Technology (RAIT)*, mar 2018, pp. 1–5.
- [70] R. Berkvens, B. Bellekens, and M. Weyn, “Signal strength indoor localization using a single DASH7 message,” in *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2017, pp. 1–7.
- [71] N. Kayastha, D. Niyato, E. Hossain, and Z. Han, “Smart grid sensor data collection, communication, and networking: a tutorial,” *Wireless Communications and Mobile Computing*, vol. 14, no. 11, pp. 1055–1087, aug 2014. [Online]. Available: <http://doi.wiley.com/10.1002/wcm.2258>
- [72] V. K. Daragh, “A Heterogeneous Communications Network for Smart Grid by Using the Cost Functions,” Ph.D. dissertation, alma, 2017. [Online]. Available: <http://amsdottorato.unibo.it/7837/>

- [73] Q. Li, H. Zhang, T. Zheng, X. Wang, and Y. Lv, "Maximum inner product method for extracting the path-loss parameters in primary transformer substations," *China Communications*, vol. 16, no. 4, pp. 120–129, apr 2019.
- [74] A. Z. UD DIN, Y. AYAZ, M. I. A. AHMAD, S. MASAUD, M. HASAN, and N. MUHAMMAD, "Cost-effective telemetry for energy network of an electricity distribution company: part I," *TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES*, vol. 1, no. 2, pp. 889–902, mar 2019. [Online]. Available: <http://online.journals.tubitak.gov.tr/openDoiPdf.htm?mKodu=elk-1804-8>
- [75] I. T. Almalkawi, M. Guerrero Zapata, J. N. Al-Karaki, J. Morillo-Pozo, and F. Directions, "Wireless Multimedia Sensor Networks: Current Trends and Future Directions," *Sensors*, vol. 10, no. 7, pp. 6662–6717, jan 2010. [Online]. Available: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3231118&tool=pmcentrez&rendertype=abstract>
- [76] R. He, B. Ai, G. L. Stüber, and Z. Zhong, "Geometrical-Based Statistical Modeling for Polarized MIMO Mobile-to-Mobile Channels," *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 8, pp. 4213–4227, aug 2018.
- [77] N. Keerativoranan, A. Haniz, K. Saito, and J.-i. Takada, "Mitigation of CSI Temporal Phase Rotation with B2B Calibration Method for Fine-Grained Motion Detection Analysis on Commodity Wi-Fi Devices," *Sensors*, vol. 18, no. 11, 2018. [Online]. Available: <https://www.mdpi.com/1424-8220/18/11/3795>
- [78] Y. Yu, R. Chen, L. Chen, G. Guo, F. Ye, and Z. Liu, "A Robust Dead Reckoning Algorithm Based on Wi-Fi FTM and Multiple Sensors," *Remote Sensing*, vol. 11, no. 5, 2019. [Online]. Available: <https://www.mdpi.com/2072-4292/11/5/504>
- [79] C. Mingzong, "Antenna Design Research Applied to Zigbee Indoor Positioning System," Ph.D. dissertation, National University of Kaohsiung, 2018. [Online]. Available: <https://ir.nuk.edu.tw/handle/310360000Q/17943>
- [80] C. Li, W. Chao, S. Lin, J. Guo, W. Hu, and Z. Tang, "Research on Software Simulation Technology of New Generation Smart Substation Secondary System," in *2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, oct 2018, pp. 2510–2513.
- [81] M. Bor, J. Vidler, and U. Roedig, "LoRa for the Internet of Things," in *Proceedings of the 2016 International Conference on Embedded Wireless Systems and Networks*, ser. EWSN '16. USA: Junction Publishing, 2016, pp. 361–366. [Online]. Available: <http://dl.acm.org/citation.cfm?id=2893711.2893802>

- [82] J. Petajajarvi, K. Mikhaylov, A. Roivainen, T. Hanninen, and M. Pet-tissalo, "On the coverage of LPWANs: range evaluation and channel at-tenuation model for LoRa technology," in *2015 14th International Con-ference on ITS Telecommunications (ITST)*, dec 2015, pp. 55–59.
- [83] M. Wiering and M. Van Otterlo, *Reinforcement Learning*, ser. Adaptation, Learning, and Optimization, M. Wiering and M. van Otterlo, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, vol. 12. [Online]. Available: <http://link.springer.com/10.1007/978-3-642-27645-3https://books.google.es/books?id=YPjNuvrJR0MC>
- [84] LoRa-Alliance.org, "LoRa Alliance," 2018. [Online]. Available: <https://loro-alliance.org>
- [85] X. Liu, Z. Qin, Y. Gao, and J. A. McCann, "Resource Allocation in in wireless powered IoT networks," *CoRR*, vol. abs/1810.0, 2018. [Online]. Available: <http://arxiv.org/abs/1810.05891>
- [86] H. Sabti, "IoT REVOLUTION IN OIL, GAS AND MINING INDUSTRIES: A REVIEW," in *Internet of Things and Data Analytics Handbook*. John Wiley and Sons, Ltd, 2018, pp. 513–520. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119173601.ch31>
- [87] T. Salimans, J. Ho, X. Chen, S. Sidor, and I. Sutskever, "Evolution Strategies as a Scalable Alternative to Reinforcement Learning," *ArXiv e-prints*, mar 2017.
- [88] D. Whitley, "A genetic algorithm tutorial," *Statistics and computing*, vol. 4, no. 2, pp. 65–85, 1994.
- [89] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the thirteenth interna-tional conference on artificial intelligence and statistics*, 2010, pp. 249–256.