A Bayesian Game Framework for a Semi-Supervised Allocation of the Spreading Factors in LoRa Networks

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***Abstract*—LoRa networks have been gaining ground as a solution for Internet of Things because of their potential ability to handle massive number of devices. One of the most challenging problems of such networks is the need to set the Spreading Factors (SF) used by the terminals as close to a uniform distribution as possible, to guarantee reliable transmission of packets. This can be tackled through stochastic allocations based on centralized strategies, and more recently some contributions proposed fully distributed approaches based on game theory. However, these studies still consider games of complete information, where users have full knowledge on each other payoffs. In reality, it would be more appropriate to extend these approaches to Bayesian games, as we propose to do here. More precisely, we extend the game theoretic formulation to a semi-supervised allocation, where the distributed character of the allocation is retained as the nodes still act independently in choosing their SF, based on what they think it is their best preferred choice. We also utilize the central gateway as a coordinator regulating these proposals and the interaction of the nodes with the coordinator is framed as a Bayesian entry game, where nodes exploit a prior to decide whether to join the proposed allocation or not. Under this framework, nodes reach a satisfactory compromise between the assignment they receive from the network and their desired rate.**

***Index Terms*—Bayesian games, LoRa, Internet of Things, Wireless sensor networks.**

I. Introduction

The paradigm of machine-to-machine (M2M) communication is already taking off to realize novel scenarios for the Internet of Things [1], but in the next few years, it is expected to reach its full potentialities thanks to the widespread adoption of novel technologies for low-power wide area networks (LPWANs), in particular LoRa [2], considered by researchers to be the most promising technological solution to this end.

Indeed, LoRa allows for massive deployments of multiple devices with low power and reduced computational complexity, which makes it extremely attractive as a solution for Internet of Things. LoRa™ is based on a physical layer (PHY) exploiting a Chirp Spread Spectrum (CSS) modulation, where transmitted signals can coexist depending on their Spreading Factor (SF) [3]. Even though most details of the proprietary modulation are not released, the important aspect that we keep into account in the present paper is known, that is, each device must adopt a SF, taking values in the range $\{7, 8, \ldots, 12\}$. There is an inherent trade-off in this choice, since a higher SF leads to a more robust modulation scheme, which means that transmitted data are better protected against noise. On the other hand, the data rate is higher if a lower SF is used instead. Finally, SFs are quasi-orthogonal, i.e., two packets using different numerical values have a very low probability of interfering with each other, so that their transmission can be considered to be almost collision-free.

As a consequence, the first and foremost requirement for a correct deployment of a LoRa network is the choice of the SFs throughout the network approaches a uniform distribution so that the interference between packets is minimized. Only after meeting this requirement, terminals should choose their SF according to their preferred compromise between reliability and data rate. In other words, nodes should prefer differentiating themselves from the neighbors and adopt a locally optimal choice also for their own sake. There are inherent difficulties, however, to force nodes to perform such a choice without a heavy computational burden; also, there are no guarantees whatsoever that the nodes will comply with a centralized choice if they do not see any incentive for themselves in the choice.

Previous contributions [4], [5] argued that game theory is a possible way to achieve a proper distribution of SFs in a simple and distributed fashion, to enforce scalability and also its implementation on IoT devices with limited computational power [6]. For example, [4] considered a matching game played between players representing users and channels, while [5] considered a local game played among pairs of terminals. Both showed that aiming at a local Nash equilibrium leads to a satisfactory allocation of SFs without the need for a centralized coordination, but just relying on rationality and selfishness (i.e., local optimality) of the allocation [7].

However, another crucial detail of LoRa networks is that all the devices in a certain connect to a central gateway, hence it would be possible to expand the aforementioned analysis by exploiting it to coordinate the assignment of the Spreading Factor to each device. Remarkably, we would still avoid using a full-fledged optimization, but for same reasons of scalability, flexibility, and low complexity, we want to keep a game theoretic approach.

In particular, we want to preserve rationality and individual best-interest as the guidelines for the assignment, so the decision is made at a single terminal as dictated by rationality and selfishness; hence, in our formulation the proposal made by the central gateway is just a suggestion that the terminal is free to accept or not. This is why the resulting allocation is labeled as "semi-supervised," that is, the end device is free to accept it or not: as it comes from an authoritative source, the terminal has an incentive to believe it - but it is not bound to do so and can even choose a different allocation. Still, as we will show, this mechanism leads to a simple yet efficient solution with good results for both the overall throughput of the network but also for the efficiency of the single devices in terms of power consumptions.

Specifically, we use the model of a Bayesian entry game, which is a common setup of economic game theory (usually modeling the entry of a new outsider agent in a market competition [8], but it is now commonly used also by game theoretic setup applied to wireless communication [9], [10]. The game represents devices entering a network that is coordinated by a central gateway, which aims to reduce interference by assigning a specific Spreading Factor to the new devices. As common in Bayesian games, we consider Nature's move, which in this case is an external intervention to establish whether packets are lost due to interference.

We computed the Bayesian-perfect Nash equilibria of the games and implemented the relative strategies using the discrete-event simulator ns-3 and its extension proposed in [11], studying the evolution of the probability of correct reception of packets, and the probability of interference as the number of nodes in the network increases. We then compared the results that we obtained with the performance of a standard approach, based on a myopic allocation, also described in [11].

The rest of this paper is organized as follows. In Section II we give the background on Bayesian games and review related papers investigating LoRa allocation problems, possibly in conjuction with game theory. Section III presents the game theoretic assumptions and general model for our problem of choice, SF selection. In Section IV we give a characterization as a Bayesian entry game, which is subsequently solved by putting the game in a type-agent representation. Finally, we show numerical results in V and we draw the conclusions in Section VI.

II. Related work

Introduced in [12], Bayesian games are a way to represent games of incomplete information by giving a special characteristic to some players, i.e., to associate them with a set of *types*, which ultimately describe the possible characteristics of that player. While types can be used to differentiate any aspect of the gameplay (including the way by which a dynamic game unfolds), they are most commonly employed to describe possible payoff functions for a player.

It is noteworthy that types are not relevant for the direct player they are assigned to, since the general assumption is that players know their own types, but for their opponents, who have therefore missing information on the behavioral aspects of that player that depend on the type, most specifically the payoff function. Generally, the assignment of types to players is represented as a decision blindly made by the virtual special player *Nature*. This means that types are random variables following a probability distribution. After drawing the types, Nature also reveals the type of a player to that player only, but the other players can exploit the probability distribution as a *common prior*, from which decisions can be inferred by exploiting Bayes' rule.

A typical application of this framework is the so-called *Entry game*, where game theory is used to model the insertion of a new player in a scenario. This can be an economic context, where an outsider enterprise "enters" a market with an incumbent already present. A Bayesian character can be applied to both of these players, since the incumbent can play different strategies to react to the newly coming outsider depending on how strong it believes the outsider to be, and vice versa.

More precisely, in the context of a LoRa network, this situation can be played similarly by considering the SF as an unknown type assigned to end devices. Actually, in the following, we will consider the end device as the entrant in the game, and the gateway as proposing an assignment of SF. Depending on its type, the end device will be also allowed to accept or refuse such a proposal. This is why we refer to the resulting game-theoretic (GT) approach as a semi-supervised allocation. Notably, the role played by the gateway is not that of a centralized authority that controls the assignment of SF without objections, which would require a computationally expensive optimization. Rather, it is considered to be only a suggestion that the end device can ultimately accept or not, and in this way we preserve the distributed character of the game theoretic allocation, where the final call is made by the end device.

It is also worth noting that, while most of the papers applying game theory to LoRa scenarios focus on the applications, we consider the SF assignment from a low-layer technical perspective. This might be motivated by the inherent difficulties of capturing the specifications of the LoRa technology, but on the other hand this is also the exact purpose of applying a Bayesian framework to this end. Indeed, the characteristics of a Bayesian game, requiring a "type" to be assigned to the users, which is not fully disclosed to other players, make it very suitable to the problem at hand.

On the other hand, our paper is aligned with other technical contributions in the field of LoRa taking the stance of analyzing the SF allocation problem. The main difference is that virtually all of these approach either rely on a deterministic approach or a stochastic but with full awareness of the user location distribution within the network. For example, an analysis of a random access network with multiple spreading factors and rates was performed in [13] and used to allocate SFs inside a LoRaWAN cell to minimize the collision probability.

This implies a coordinated scheme that must be followed by all the terminals, while our approach is unique in using game theory (and more specifically Bayesian games) to drive the players to act independently without any coordination.

Indeed, [3] described a practical solution in this sense, but based on a deterministic approach. In our opinion, the problem shows all the requirements pointing towards a game theoretic solution, namely, a simple analytical characterization and the need for a distributed and scalable solution. Indeed, game theory has been successfully applied with such a motivation to many other problems of wireless communications in the literature.

One important reference is [14], which gives a modulation analysis of LoRa, proposing a co-channel rejection matrix which determines the signal-to-interference-plus-noise ratio (SINR) values required for SF allocation and persistence of LoRa signals in the presence of an interferer with a different SF. The tables we are going to use in our Bayesian game are partly inspired by this technical contribution. Another analytical framework to consider the problem of SF allocation in a LoRa network via matching theory where both the effects of co-SF and inter-SF interferences are integrated is [15].

However, all of these approaches require a centralized coordination. As hinted by [4], game theory would instead allow to delegate this allocation to individual choices of the LoRa end terminals seen as selfish players. However, both [4] and also our previous contribution [5] rely on games of complete information, which still would require a certain confidence for the end terminals to know all the parameters involved; note that complete information would not only require that a player is certain on its own payoff (in this case, a user terminal being aware of its own physical layer conditions) but also of all the others, and, on top of that, it is also aware that every other player knows this, and so on ad libitum. Thus, we might want to relax the notion of complete information by considering the approach of Bayesian games, which involves incomplete information - each player being characterized with a type.

In particular, in this paper we consider a Bayesian entry game, played by the gateway as a coordinator and each individual node. Despite such a model being actually standard in game theory [16], as previously argued, we notice that nobody has used it to characterize a problem similar to ours. Already existing mentions of the Entry Game in similar technological scenarios seem all to be related to different problems, more specifically described as follows. In [8], the most natural choice of application to the entry game to cognitive networks is used. This is actually the same as the economic market between an incumbent and an outsider, often also called a primary and a secondary. In this case, the secondary may be undecided on whether to entry or not, depending on the reactions he expects from the primary.

In [9], instead, a different entry game is considered (more related to minority games or distributed coordination games) and there is no Bayesian character. The objective here is to have a limited access of sensors to preserve their energy. Finally, we studied a security problem based on an entry game in [10], i.e., related to friendly jamming of a malicious node, which then considers whether to entry or not, so once again the focus is entirely different.

III. Game Theoretical Model

A. Assumptions

Our analysis makes the following assumptions in order to derive our game-theoretic framework.

- The LoRa terminals, called end devices (EDs), are uniformly distributed around a single central gateway.
- The SINR of a packet is ultimately dependent only on the distance between the ED and the gateway (that is, the path loss) and the interference with other packets using the same SF. For the sake of simplicity, we neglect the contributions of shadowing and multi-path fading, even though they could be added without compromising the same game theoretic structure that we utilize, only with more complex mathematical formalizations.
- Each ED is aware of the distribution of the SFs used by the other EDs, and can use this as an available information (a prior) in the Bayesian game.

B. Utilities

The pure strategies of any ED are denoted as as $(s_7, \ldots, s_{12})$, where adopting the strategy s_i means using $SF = i$. The utility of an ED is given by the following expression

$$v(s_i, s_j) = g_{\succeq}(s_i) \mathbb{1}_{\{\Lambda_{i,j}^{\mathrm{dB}} > T_{i,j}\}} \tag{1}$$

where $g_{\succeq} : \{7, \ldots, 12\} \to \{1, \ldots, 6\}$ is a bijection that maps SFs into values in the range 1-6 according to the node's preferences. In particular, assuming each node prefers to use a SF as low as possible we define the utility function as $v(s_i, s_j) = (13 - i)\mathbb{1}_{\{\Lambda_{i,j}^{\mathrm{dB}} > T_{i,j}\}}$. The indicator function $\mathbb{1}_{\{\Lambda_{i,j}^{\mathrm{dB}} > T_{i,j}\}}$, instead, models the fact that the payoff of a node is set to 0 if it is not able to transmit because the SINR $\Lambda_{i,j}^{\mathrm{dB}}$ is lower than the threshold $T_{i,j}$, which is given by [14]

$$\mathbf{T} = \begin{bmatrix} 6 & -16 & -18 & -19 & -20 & -20 \\ -24 & 6 & -20 & -22 & -22 & -22 \\ -27 & -27 & 6 & -23 & -25 & -25 \\ -30 & -30 & -30 & 6 & -26 & -28 \\ -33 & -33 & -33 & -33 & 6 & -29 \\ -36 & -36 & -36 & -36 & -36 & 6 \end{bmatrix}. \tag{2}$$

The element $T_{i,j}$ is the SINR margin that a packet with $SF = i$ must have in order to be correctly decoded if there is an interfering packet with $SF = j$.

C. Interaction between nodes

Our previous contribution [5] defines a game theoretic interaction between two nodes, modeled as a static game of complete information [17]. Then, this is expanded into a

Bayesian game where nodes only have an imperfect knowledge on their SF based on a prior (the distribution in the network), which is common knowledge among all nodes. The added contribution to this interaction that we make in this paper is that the gateway is also allowed to signal a recommended SF that end devices can decide to accept or not, in a semi-supervised fashion. If they accept, the game immediately ends with the proposed allocation being factual.

In our formulation, if the end device decides not to comply with the gateway suggestion, it is left with determining what SF to set. Note that it would be possible to combine the two models and let the node play another Bayesian game then, akin to the one played in [5] to better determine the SF of individual choice. In the present paper, for simplicity reasons, we assume that this is already determined instead. This is actually not a limitation, since we assume that end devices are behaving as rational users and therefore are always able to anticipate the result of their choice of SF. The end device can consider that the semi-supervised decision made by the network is generally aiming at maximizing the global welfare, and not its own specific benefit, so it may be willing to deviate from that proposal. On the other hand, the end device is also fully aware that the proposal made by the network is made with the intent of limiting mutual interference from neighboring nodes using the same SF, so it might be a good idea to follow the recommendation.

Indeed, we assume that when two nodes use the same SF, they interfere with each other arises and therefore they lose the packet; also this information is available to the users as part of the common knowledge setup. However, in our Bayesian formulation, the individual users do not know whether their choice of SF being different from the semi-supervised suggestion would result in interference or not. This information is available to the gateway, while the end devices only have a prior probability distribution available.

IV. The Bayesian Entry Game and its Solution

We now formalize the problem as an entry game and we solve it through the application of game theory methods.

A. Entry of a node in the network

In this scenario, we studied the entry of an end device in a network in which a gateway receives the packets and acts as a central coordinator. The device's preference is to use always the lowest Spreading Factor allowed by its distance from the gateway, while the gateway's objective is achieving the highest possible throughput, that requires the nodes to use different Spreading Factors. To achieve this goal, the gateway proposes a semi-supervised allocation. The end device is free to accept it or not, but in this latter case, a punishment is possible in the form of augmented interference for the terminal.

The problem of choosing the Spreading Factor can be modeled as a dynamic game in which:

1) the gateway assigns a SF to the end device;
2) the end device (E), which is the first to play, can either use the SF assigned by the gateway (A) or its favourite one (R);
3) if the end device does not follow the gateway's directives, the gateway (G) can either punish it (h) or take no action (ℓ), depending on how the violation affects the probability of interference.

We assumed that the end device makes its choice according to its beliefs on the probability of interference $P_{\text{interference}}$, which comes from its knowledge of the SF distribution of the network.

We focused on a typical case in which a gateway, that is able to cover up to 7500 meters, is located on a strategic position hence nodes tend to be clustered nearby: N end devices are dynamically disposed around the gateway within a circular area radius of $R = 2500$ meters. In this model, all the nodes prefer to set their Spreading Factor to 7 and the probability of interference has been estimated: the value has been taken from the plot of the probability of interference in [14] as $P_{\text{interference}}$. We considered the gateway's proposal being always the Spreading Factor 8: the case in which Spreading Factor 7 is proposed does not result in a game since A and R are the same action.

If E plays A, the payoffs are $13-8 = 5$ for E and 1 for the gateway and the game ends. If E plays R (i.e., chooses SF 7) and G decides to play h, E gets payoff -1 and G gets 0, while if G plays ℓ, E gets payoff $13 - 7 = 5$ and G gets payoff 1 or -1, according to the traffic of the network. The first actor to play is Nature, who decides whether the action "E plays R" causes interference. This happens with probability $p = P_{\text{interference}}$. The value of p is common knowledge and treated by the ED as a known prior.

The extensive form of the game is a tree-like structure, plotted in Fig. 1. The nodes with the same color belong to the same information set. Indeed, while the gateway is aware of whether not following its recommendation results in interference or not (or punishment), the end device cannot possibly know this, so it only estimates the probability p of this happening. This is sensible, as in the end (as we will show in the numerical results) the value of p depends on the number of EDs in the network, and it is legitimate to assume that all EDs have at least a coarse estimate of that.

B. Solution

To solve the Bayesian entry game, one standard procedure is to derive an equivalent normal form of the game with a type-agent representation. In practice, this means that players with a type adopt a strategy that includes the action to pursue for each own of their type. Thus, given the actions ℓ and h of the gateway, the strategies available to player G are a pair xy where both x and y belong to $\{\ell, h\}$, and represent what to do in the case of no interference and interference, respectively. The resulting type-agent representation is drawn in Table I.

This normal form of the type-agent representation implies that if $p < \frac{1}{7}$, the Bayesian-perfect Nash equilibrium is $(R, \ell h)$, meaning that if the probability of interference is

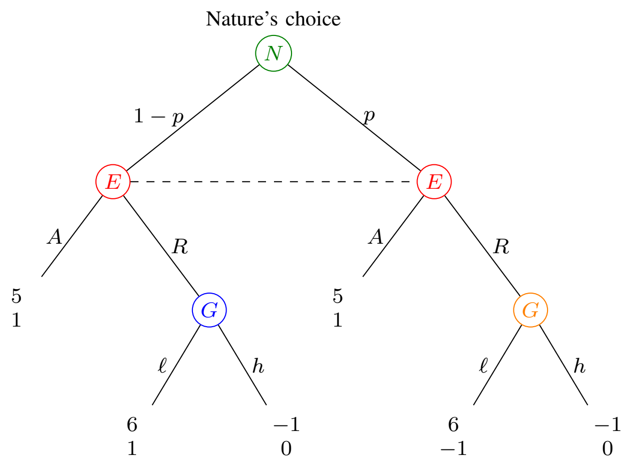

Fig. 1. Extensive form of our proposed Bayesian game

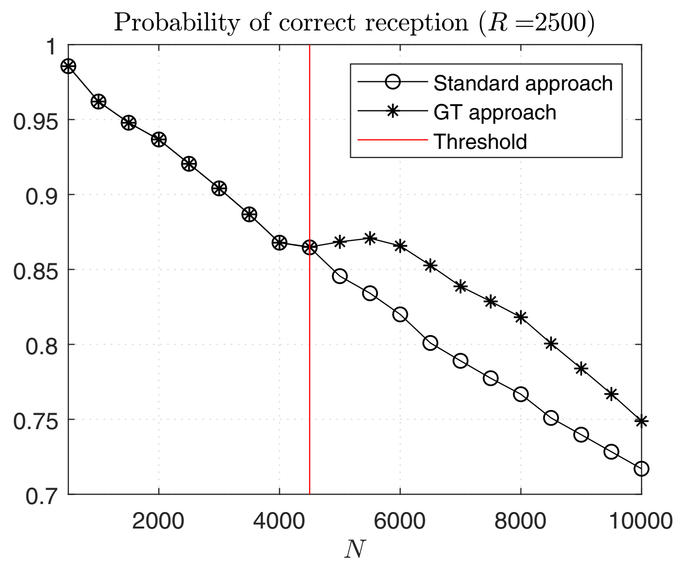

Fig. 2. Probability of correct reception vs. the number of nodes in the area

low, then for the node is more convenient to use its favorite Spreading Factor. If $p > \frac{1}{7}$, the Bayesian-perfect Nash equilibrium moves to $(A, \ell h)$, meaning that the end device should accept the proposal of the gateway.

Since the probability of interference in reality grows with the number of end devices in the network (N), we expect our approach to behave like the standard one if $N < N_{\text{threshold}}$, where $N_{\text{threshold}}$ is the number of nodes that determine $P_{\text{interference}} = \frac{1}{7}$. When the number of end devices goes beyond $N_{\text{threshold}}$, the nodes start to obey to the gateway and the performance of the network, in terms of probabilities of correct reception and interference, improves.

V. Numerical Results

The proposed approach of the Bayesian entry game has been evaluated with a numerical simulator to assess its performance in a realistic scenario, also including other details that were oversimplified in the analysis (such as interference between packets). We utilized the well known event-based network simulator ns-3 [18] expanded with LoRa modules developed in [11]. We also consider a variable number of EDs in the area, from 1000 to 10000. Notice that our choice of parameters implies to consider all possible scenarios ranging from a scarcely populated area up to a region full with devices, where interference is therefore very likely.

The simulation scenario consists of many nodes uniformly and randomly placed a central gateway, changing the number N of the nodes and keeping the radius R of the area fixed to 2500 m. We compare an "optimal" (but actually myopic) solution centrally computed by the gateway, with the nodes always complying and not playing any game, and the result found as the Nash equilibria of our Bayesian game. It is worth noting that, given that the most important objectives for the ED is not, indeed, to optimize their SF per se but also to avoid using the same SF of neighbor nodes, the "optimal" solution is not necessarily efficient when it indeed optimizes the tradeoff between reliability and data rate but fails to interact with other SFs of the neighbor nodes.

As was expected from the computations discussed above, we see that the standard and the game theoretical approaches perfectly coincide when N is lower than $N_{\text{threshold}}$, which is the value corresponding to $P_{\text{interference}} = 1/7$. For higher N, the game theoretical approach outperforms the standard one both in terms of probability of correct reception and probability of interference, as visible from Figs. 2 and 3. It is worth noting that the probability of interference also implies wasted energy (or the need for retransmissions). Either way, the decreased probability of interference of the proposed methodology makes it more faithful to the original purpose of LoRa, i.e., low power consumption.

TABLE I
Type-agent representation of the Bayesian entry game

		G: $\ell\ell$	G: ℓh	G: $h\ell$	G: hh
E	A	5 1	5 1	5 1	5 1
E	R	6 $1-2p$	$6-7p$ $1-p$	$7p-1$ $p-1$	-1 0

VI. Conclusions and Future Work

We approached the problem of assignment of Spreading Factors in a LoRa network via game theory. We designed a game theoretic algorithm giving a semi-supervised assignment based on a Bayesian entry problem, with the network gateway suggesting a recommended SF but leaving the end device the freedom to accept the suggestion or check other

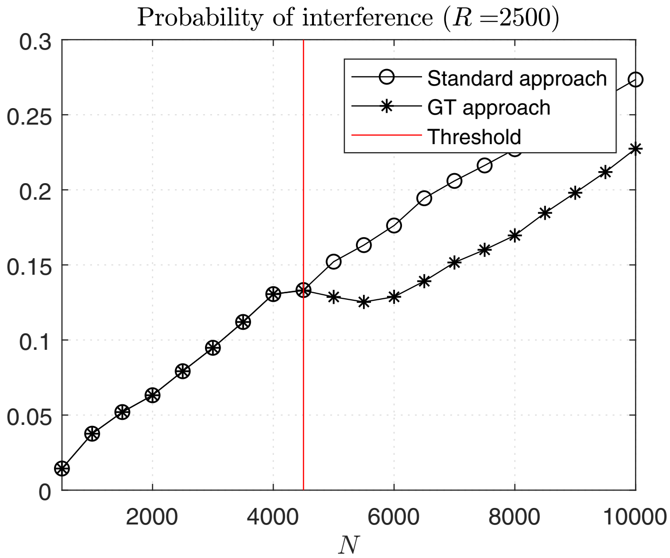

Fig. 3. Probability of interference among packets vs. the number of nodes in the area

ways of setting the SF in local, under a penalty when this causes additional interference.

Especially, we modeled the entry of a new device in a network in a steady-state regime, focusing on the case in which the devices are situated near the gateway. Simulations showed improvements in throughput, especially as the number of devices increases.

Possible extensions of this model could involve the relaxation of some of the assumptions described above. In particular, we expect the game theoretical model to lead to improvements when the devices are not uniformly distributed around the gateway. In a similar spirit, the probability of causing interference to the neighbors can also be non-uniform and therefore follow a more complicated prior. The investigation of such scenarios is a possible subject for future research.

References

[1] R. Lu, X. Li, X. Liang, X. Shen, and X. Lin, "GRS: The green, reliability, and security of emerging machine to machine communications," *IEEE Commun. Mag.*, vol. 49, no. 4, pp. 28-35, 2011.

[2] A. Augustin, J. Yi, T. Clausen, and W. Townsley, "A study of LoRa: Long range & low power networks for the internet of things," *Sensors*, vol. 16, no. 9, pp. 1466, 2016.

[3] D. Magrin, M. Centenaro, and L. Vangelista, "Performance evaluation of LoRa networks in a smart city scenario," *Proc. IEEE ICC*, 2017.

[4] Z. Qin and J. A. McCann, "Resource efficiency in low-power wide-area networks for IoT applications," *Proc. IEEE GLOBECOM*, pp. 1-7, 2017.

[5] A. Tolio, D. Boem, T. Marchioro, and L. Badia, "Spreading factor allocation in LoRa networks through a game theoretic approach," *Proc. IEEE ICC*, 2020.

[6] O. Georgiou and U. Raza, "Low power wide area network analysis: Can LoRa scale?," *IEEE Wirel. Comm. Lett.*, vol. 6, no. 2, pp. 162-165, 2017.

[7] D/ Niyato and E. Hossain, "Competitive spectrum sharing in cognitive radio networks: a dynamic game approach," *IEEE Trans. Wirel. Comm.*, vol. 7, no. 7, pp. 2651-2660, 2008.

[8] L. Guijarro, V. Pla, and B. Tuffin, "Entry game under opportunistic access in cognitive radio networks: A priority queue model," *in Proc. IEEE IFIP Wireless Days*, pp. 1-6, 2013.

[9] S. M. AlTabbakh, E. M. Elshahed, R. A. Ramadan, and H. M. Elzahed, "Energy management of wireless sensor network based on modeling by game theory approaches," *in Proc. IEEE Eur. Mod. Symp.*, 2015.

[10] L. Badia and F. Gringoli, "A game of one/two strategic friendly jammers versus a malicious strategic node.," *IEEE Networking Letters*, vol. 1, no. 1, pp. 6-9, 2019.

[11] D. Magrin, *Network level performances of a LoRa system*. Master Thesis in Telecommunication Engineering, University of Padova, 2016

[12] J.C. Harsanyi, "Games with incomplete information played by "Bayesian" players," (part I) *Management science*, vol. 14, no. 3, pp. 159-182, 1967.

[13] B. Reynders, W. Meert, and S. Pollin, "Power and spreading factor control in low power wide area networks," *Proc. IEEE ICC*, 2017.

[14] C. Goursaud and J.-M. Gorce, "Dedicated networks for IoT: PHY/MAC state of the art and challenges," *Trans. Int. of Things*, vol. 1, no. 1, 2015.

[15] L. Amichi, M. Kaneko, E. H. Fukuda, N. Rachkidy and A. Guitton, "Joint allocation strategies of power and spreading factors with imperfect orthogonality in LoRa networks," *IEEE Trans. Commun.*, 2020.

[16] A. V. Guglielmi and L. Badia, "Bayesian game analysis of a queueing system with multiple candidate servers," *Proc. IEEE CAMAD*, pp. 85-90, 2015.

[17] S. Tadelis, *Game Theory: An Introduction*, Princeton, 2013

[18] Ns-3 reference manual [online], available at: https://www.nsnam.org/docs/release/3.9/manual.pdf