Spreading Factor Allocation in LoRa Networks through a Game Theoretic Approach

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***Abstract*—LoRa is a low-power wide-area network solution that is recently gaining popularity in the context of the Internet of Things due to its ability to handle massive number of devices. One of the main challenges faced by LoRa implementations is the allocation of Spreading Factors to the devices. While the assignment of these parameters is virtually simple to execute, scalability and complexity issues hint at its implementation through a game theoretic approach. This would offer the advantage of being readily implementable in vast networks of devices with limited hardware capabilities. Hence, we formulate the SF allocation problem as a Bayesian game, of which we compute the Bayesian Nash equilibria. We also implement the procedure in the ns-3 network simulator and evaluate the resulting performance, showing that our approach is scalable and robust, and also offers room for improvement with respect to existing approaches.**

***Index Terms*—Game theory, LoRa, Internet of Things, Wireless sensor networks, power aware computing.**

I. Introduction

In recent years, the Internet of Things (IoT) paradigm has been gaining momentum, while at the same time showing that traditional connectivity technologies such as WiFi and Bluetooth are not always adequate for massive deployments of multiple devices with low power and reduced computational capabilities. For this reason, research lately turned to Low Power Wide Area Networks (LPWANs), among which LoRa figures as one of the most prominent [1]. In LoRa networks, devices use a proprietary LoRa™ physical layer (PHY) modulation, based on a Chirp Spread Spectrum (CSS) modulation, where packets are differentiated according to their Spreading Factor (SF) [2]. Even though the exact details of the proprietary modulation are not released, the most 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 $\{7, 8, \ldots, 12\}$, which describes its connection to the closest gateway in the area. A higher SF guarantees more reliable reception of the packets, while lower SFs lead to a higher data rate. Moreover, SFs are quasi-orthogonal, i.e., two packets using different numerical values have a very low probability of interfering with each other, so that, for the sake of simplicity, their transmission can be considered to be collision-free.

As a result, the distribution of the SFs in the network ought to be as close as possible to uniform so as to minimize the interference between transmitted packets. However, the procedure to achieve it should be simple and distributed, to enforce scalability and enable the implementation on IoT devices with limited computational power [3]. We believe that the solution to these design needs can be found by adopting a game theoretical standpoint [4]. In particular, we aim to solve a static SF allocation problem on a LoRa network, i.e., a distributed assignment by individual devices acting at the same time based on rational and selfishness principles. This can be seen as an algorithmic implementation of which we offer both a theoretical analysis and also the implementation in the well known ns-3 network simulator [5]. Thus, we are able to evaluate the resulting performance in realistic contexts, and compare it with a reference approach described in [2].

Our study represents a first step in implementing game theory to this kind of problems. For the sake of simplicity, we consider the LoRa network scenario to be static and so are the game theory formulation and the resulting allocation. In a dynamic context, one can think of simply replaying the game periodically; or, more refined results can be obtained with an enhanced analysis that also considers a *dynamic game* formulation to better keep into account overall changes in the network. We focus on a scenario where every device acts in a distributed fashion and only guided by principles of selfishness (i.e., local optimality of its resulting allocation) and rationality, involving the ability to predict direct consequences of its own actions and also assuming that other devices do the same. However, the required computational complexity is fairly limited as every decision-making process revolves around if-then-else choices and lookup tables.

In our contribution, we consider that each device regards itself as a player having the rest of the entire network as its opponent in the game. To characterize different network situations, we resort to *Bayesian* games. In particular, we are able to restrict the relevant part of the competitive interactions among nodes in the network as only those involving adjacent values of the SF. In light of this, each node plays a game against the remaining opponents modeled as a single Bayesian player, whose type follows the SF distribution obtained by using a standard approach [2]. Thanks to this artifice, we are able to compute the Bayesian Nash equilibria of the game and also implement the relative strategies in an algorithmic fashion. This is directly plugged into the discrete-event simulator ns-3 [5], 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 compare the results that we obtained with the performance of the standard approach [2]. The results show that our proposed technique is implementable and even obtains superior performance in some scenarios, although it requires some finetuning in order to properly guide the users to the correct SF allocation beyond a simple selfish choice.

The rest of this paper is organized as follows: Section II reviews the approaches to SF allocation and the use of game theory in LoRa networks in the literature. In Section III, we discuss the game theoretic ingredients for our analysis, including the basic assumptions and a model of one-to-one player interaction that is expanded in Section IV to build our Bayesian game. Section V presents the results including the algorithmic formulation of a possible allocation approach and its evaluation through ns-3. Finally, Section VI concludes the paper.

II. Related work

The literature about LoRa specifications is relatively limited, since the details about specific LPWAN proprietary technical aspects are not released to the research community. In [6], several LPWAN technologies are reviewed, and a technical analysis of LoRa modulation is provided. In particular, a co-channel rejection matrix is developed showing the signal-to-noise ratio and signal-to-interference-plus-noise ratio values required for SF allocation and survival of LoRa signals in the presence of an interferer with a different SF. The authors of [7] performed various experiments to characterize packet losses in the LoRa systems. In their analysis, the model of [6] is basically confirmed, which allows for our analysis that roughly translates in an orthogonality assumption among different SFs.

The lack of implementation details about LoRa PHY layer might explain why the problem of SF allocation, although relatively simple to grasp, has not received many technical proposals. Indeed, [2] 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. For example, cognitive networks are often considered a field of election for game theory, and game theoretic protocol design is reviewed in [4]. Also, spectrum sharing among cellular operators or secure communications are other fields where game theory is often invoked [8]–[12].

However, the literature is not abundant wuth game theoretic investigations applied to the specific scenario of LoRa Networks. The only proposal in this sense is [13], which is however concerned about access technology and the generic context of public safety. The challenge tackled in that contribution revolves around the choice between traditional networks and low power long-range communications. Thus, the problem faced in the present paper, i.e., the SF allocation, has not yet been modeled as a game, which makes our analysis original.

III. Game Theoretical Model

A. Assumptions

Throughout our analysis, we relied on the following assumptions to obtain a simple, yet meaningful, framework.

- There is only one central gateway, and the end devices (EDs) are uniformly distributed around it.
- The SINR of a sent packet depends only on the distance from the gateway (path loss) and on the interference with other packets using the same SF; more refined channel models, also including fading components, can be included by simply altering the nodes positions.
- Each node knows the (aggregate) distribution of the SFs used by the other nodes of the network.

B. Utilities

We consider the pure strategies of the EDs as $(s_1, \dots, s_{12})$, where adopting the strategy s_i means using $SF = i$. We assume the utility $u_i(s_i, s_j)$ of an ED i as a function of its strategy s_i and its opponent's strategy s_j, as

$$u_i(s_i, s_j) = (13 - i)\, \mathbb{1}_{\{s_i \neq s_j\}} \qquad (1)$$

where the numerical choice, which is relevant only in its *ordinal* meaning, is justified by that a node would prefer to use an SF as low as possible; however, the indicator function $\mathbb{1}_{\{s_i \neq s_j\}}$, models the fact that the payoff of a node is set to 0 if it is not able to transmit.

C. Interaction between two nodes

Now, we consider the following building block of our model, i.e., a game theoretic interaction between two nodes. This is modeled as a static game of complete information [8], which is the situation in which only two nodes are present in the entire network and they need to send a packet knowing each other's distance from the gateway. We will use this atomic scenario to infer a more general behavior of the nodes within our Bayesian game in the next section.

For the sake of simplicity, assume that when two packets use the same SF, interference arises and they are automatically lost, and both transmitters are aware of that. So, there are two possible interactions among the nodes, depending on whether: (i) one node is significantly more distant than the other, so that their choice of SF is inherently different, or (ii) the nodes are approximately at the same distance.

Case (i) can be seen by considering the following game in normal form, in which one player can use any $SF \geq j$, while the second one, which is farther away, cannot use $SF = j$, but can use any $SF \geq j + 1$. For the sake of exposition, we consider only the strategies $\{s_j, s_{j+1}, s_{j+2}\}$ since it is immediate to show that all the others are strictly dominated strategies and thus can be neglected.

		P2		
		s_j	s_{j+1}	s_{j+2}
	s_j	$0, 0$	$13-j, 12-j$	$13-j, 11-j$
P1	s_{j+1}	$12-j, 0$	$0, 0$	$12-j, 11-j$
	s_{j+2}	$11-j, 0$	$11-j, 12-j$	$0, 0$

The only Bayesian Nash equilibrium in this game is (s_j, s_{j+1}), which is coherent with intuition: each player chooses its preferred SF as the lowest possible that avoids interference with its opponent. In case (ii) instead, the two nodes are almost at the same distance, and both can use any $SF \geq j$. Thus, the normal form of the game is

P1 \ P2	s_j	s_{j+1}
s_j	$0, 0$	$13-j, 12-j$
s_{j+1}	$12-j, 13-j$	$0, 0$

This static game has two pure strategies Bayesian Nash equilibria (s_j, s_{j+1}) and (s_{j+1}, s_j); this means that the equilibria are found whenever the players make different choices, which is known in game theory as an anti-coordination game [8].

IV. Selection of the SF as a Bayesian game

A consequence follows from the previous one-to-one scenarios: if a node has j as its preferred SF, only strategies s_j and s_{j+1} are playable by a rational player, i.e., they are the only rationalizable strategies [8]. Based on this, we can extend our model with a Bayesian game to study the behavior of a single player against a Bayesian opponent that represents the entire network. Throughout our analysis we will use the following notations. We will denote with $(p_7, p_8, p_9, p_{10}, p_{11}, p_{12})$ the initial distribution obtained with the standard approach, i.e., every node selects the lowest SF that allows correct reception in the absence of interference, according to its distance from the gateway. Also, if the minimum SF of a player is j, then we say the player is of type j.

Note that the choice of the SF of a node of type j is affected only by nodes of the same type, of type $j-1$, or of type $j+1$. This observation follows directly from the fact that each player has only two rationalizable actions. Thus, in our Bayesian game, player 1 is facing a player 2 comprising all the other nodes in the network whose types are off by 1 at most. Thus, depending on the type j of player 1, we encounter different situations.

If player 1's type is $j = 7$, it considers its adversaries (player 2) to be of type 7 or 8 with probabilities according to:

$$\mathbb{P}[\text{Player 2 of type 7}] = \frac{p_7}{p_7 + p_8} = r$$

$$\mathbb{P}[\text{Player 2 of type 8}] = \frac{p_8}{p_7 + p_8} = 1 - r$$

Therefore, Nature chooses among two possible types of Player 2, type 7 with probability r, which yields the following normal form representation

P1 \ P2	s_7	s_8
s_7	$0, 0$	$6, 5$
s_8	$5, 6$	$0, 0$

and type 8 with probability $1 - r$, which gives

P1 \ P2	s_8	s_9
s_7	$6, 5$	$6, 4$
s_8	$0, 0$	$5, 4$

The normal form representation of this Bayesian game includes 4 type-dependent pure strategies for Player 2 ($s_7\, s_8$, $s_7\, s_9$, $s_8\, s_8$, $s_8\, s_9$). The type-agent representation below shows that if $r < \frac{1}{6}$ then the only pure-strategy Bayesian Nash equilibrium is (s_7, $s_8\, s_7$). If instead r is above that threshold, the game has two pure-strategy Bayesian Nash equilibrium, which are (s_8, $s_7\, s_9$) and (s_7, $s_8\, s_8$).

P1 \ P2	$s_7 s_8$	$s_7 s_9$	$s_8 s_8$	$s_8 s_9$
s_7	$6(1-r)$, $5(1-r)$	$6(1-r)$, $4(1-r)$	6 , 5	6 , $5r + 4(1-r)$
s_8	$6r$, $5r$	5 , $4+2r$	0 , 0	$5(1-r)$, $4(1-r)$

In such a case the game can be reduced in order to study the mixed-strategy Bayesian Nash equilibrium

P1 \ P2	$s_8 s_8$	$s_7 s_9$
s_7	$6, 5$	$6(1-r), 5(1-r)$
s_8	$0, 0$	$5, 4 + 2r$

If q denotes the probability that player 1 chooses SF 7, the mixed-strategy Nash Equilibrium is $q = (4 + 2r)/(6r + 5)$.

If player 1's type is instead j with $7 < j < 11$, Player 1 is playing against Player 2 that can be of three different types according to the following probabilities:

$$\mathbb{P}[\text{Player 2 of type } j-1] = \frac{p_{j-1}}{p_{j-1} + p_j + p_{j+1}} = a$$

$$\mathbb{P}[\text{Player 2 of type } j] = \frac{p_j}{p_{j-1} + p_j + p_{j+1}} = b$$

$$\mathbb{P}[\text{Player 2 of type } j+1] = \frac{p_{j+1}}{p_{j-1} + p_j + p_{j+1}} = c$$

In this case, Nature chooses among three different types of Player 2. With probability a Player 2 is of type $j-1$, and the normal form representation of the game is

P1 \ P2	s_{j-1}	s_j
s_j	$13-j, 14-j$	$0, 0$
s_{j+1}	$12-j, 14-j$	$12-j, 13-j$

With probability b Player 2 is of type j, and the normal form representation of the game is

P1 \ P2	s_j	s_{j+1}
s_j	$0, 0$	$13-j, 12-j$
s_{j+1}	$12-j, 13-j$	$0, 0$

Finally, with probability c Player 2 is of type $j+1$, and the normal form representation of the game is

P1 \ P2	s_{j+1}	s_{j+2}
s_j	$13-j, 12-j$	$13-j, 11-j$
s_{j+1}	$0, 0$	$11-j, 12-j$

In the normal form representation of the Bayesian game, Player 2 has 8 type-dependent pure strategies, 6 of which are never a best response, and therefore will not be played by a rational player. The consequently reduced normal form of the game is the following matrix

P2

		$s_{j-1}\, s_j\, s_{j+2}$	$s_{j-1}\, s_{j+1}\, s_{j+1}$
P1	s_j	$a(13-j)+c(13-j)$, $a(14-j)+c(11-j)$	$13-j$, $2a+12-j$
	s_{j+1}	$a(12-j)+b(12-j)+c(11-j)$, $a(14-j)+b(13-j)+c(12-j)$	$a(12-j)$, $a(14-j)$

If $b<(c+1)/(11-j)$ or equivalently $b<(2-a)/(10-j)$ the only pure-strategy Bayesian Nash equilibrium is (s_j, $s_{j-1}s_{j+1}s_{j+1}$). Instead, if b is above such threshold, the game has two pure-strategy Bayesian Nash equilibria (s_j, $s_{j-1}s_{j+1}s_{j+1}$) and (s_{j+1}, $s_{j-1}\ s_j s_{j+2}$). In such a case, if we denote q the probability that Player 1 plays s_j, we have an additional Bayesian Nash equilibrium in mixed strategies when

$$q=\frac{b(13-j)+c(12-j)}{(25-2j)b+(13-j)c}$$

If player 1's type is $j=11$, Player 1 is playing against Player 2 which can be of three different types according to the following probabilities:

$$\mathbb{P}[\text{Player 2 of type 10}]=\frac{p_{10}}{p_{10}+p_{11}+p_{12}}=a$$
$$\mathbb{P}[\text{Player 2 of type 11}]=\frac{p_{11}}{p_{10}+p_{11}+p_{12}}=b$$
$$\mathbb{P}[\text{Player 2 of type 12}]=\frac{p_{12}}{p_{10}+p_{11}+p_{12}}=c$$

However, in contrast with the previous case, Player 2 has only 4 type-dependent pure strategies. If Player 2 is of type 12 it has only one possible action. The normal form representation of the resulting game is

	$s_{10}\, s_{11}\, s_{12}$	$s_{10}\, s_{12}\, s_{12}$	$s_{11}\, s_{11}\, s_{12}$	$s_{11}s_{12}s_{12}$
s_{11}	$2a+2c$, $3a+c$	2 , $3a+b+c$	$2c$, c	$2b+2c$, $b+c$
s_{12}	$a+b$, $3a+2b$	a , $3a$	$a+b$, $2a+2b$	a , $2a$

If $b<(2-a)/3$ the only pure-strategy Bayesian Nash equilibrium is (s_{11}, $s_{10}s_{12}s_{12}$), otherwise the game has two pure-strategy Bayesian Nash equilibria which are represented by (s_{11}, $s_{10}s_{12}s_{12}$) and (s_{12}, $s_{10}s_{11}s_{12}$). In such case, by denoting with q the probability of Player 1 playing 11, we have an additional mixed strategy equilibrium for $q=\frac{2}{3}$.

P2

		$s_{10}\, s_{11}\, s_{12}$	$s_{10}\, s_{12}\, s_{j+1}$
P1	s_{11}	$2a+2c, 3a+c$	$2, 3a+b+c$
	s_{12}	$a+b, 3a+2b$	$a, 3a$

As a final remark, the case of a type-12 node is trivially not requiring any lengthy analysis, because it is deterministically played. Indeed, if player 1 is such a node, then it is so far from the gateway that it can only use SF 12 for its packet to be successfully received. Thus, this is the only choice of player 1. The relevant cases of player 2 involve it being of type 11, which happens with probability $r=p_{11}/(p_{11}+p_{12})$, or of type 12 too, whose probability is $1-r$. In the former case, player 2 anticipates the move of player 1 and the game ends with payoffs equal to 1 and 2 for player 1 and 2, respectively. Otherwise, the payoff is 0 for both. Thus, the expected payoffs are immediately determined as r and $2r$, respectively.

Data: j =type of the node, the distribution $(p_7,\ldots,p_{12})$ of the SFs
Result: q^*
if $j=7$ **then**
  $r\leftarrow p_7/(p_7+p_8)$;
  if $r<1/16$ **then**
    $q^*\leftarrow 1$;
  else
    $q^*\leftarrow(4+2r)/(6r+5)$;
  end
else if $7<j<11$ **then**
  $\sigma\leftarrow p_{j-1}+p_j+p_{j+1}$;
  $a\leftarrow p_{j-1}/\sigma,\ \ b\leftarrow p_j/\sigma,\ \ c\leftarrow p_{j+1}/\sigma$;
  if $b<(c+1)/(11-j)$ **then**
    $q^*\leftarrow 1$;
  else
    $q^*\leftarrow(b(13-j)+c(12-j))/((25-2j)b+(13-j)c)$;
  end
else if $j=11$ **then**
  $\sigma\leftarrow p_{10}+p_{11}+p_{12}$;
  $a\leftarrow p_{10}/\sigma,\ \ b\leftarrow p_{11}/\sigma,\ \ c\leftarrow p_{12}/\sigma$;
  if $b<(c+1)/(11-j)$ **then**
    $q^*\leftarrow 1$;
  else
    $q^*\leftarrow 2/3$;
  end
else // case $j=1$;
  $q^*\leftarrow 1$;
end

Algorithm 1: Algorithm resulting from the Bayesian game

V. Performance evaluation

The resulting implementation of the Bayesian Nash equilibria found in the game can be outlined according to Algorithm 1. This determines q^* for each node of the network in such a way that there is no incentive for any node to deviate, which offers a robust and scalable implementation of our game theoretic rationale.

To further prove our point and perform evaluations in a realistic context, also including PHY layer details that are left out from the simplifying assumptions of the game theoretic setup, we implemented this game-theory inspired SF allocation strategy in the well known simulator ns-3 [5]. Note that our evaluation just refers to a static game, with the point of showing the superiority of a game-theory approach over a static allocation. A dynamic setup, with the aim of obtaining an even larger diversity of SFs, is a possible extension of these results. Still, the implementation in this simulator (code is available on request) allows us to prove two points. First, the proposed game theoretic procedure is available for practical use at no additional cost than, e.g., the one used as benchmark [2], which is one of the few SF allocation procedures proposed in the literature. In our approach, the LoRa devices set the SF independent of each other by following Algorithm 1, which has extremely limited computational complexity. Second, we are able to evaluate the performance of the resulting game theoretic allocation both qualitatively and quantitatively. For the former, we will be considering whether our procedure leads to a generally good allocation of SF values, and possibly outperform existing approaches, just looking at the character of the SF distribution across the network. For the latter, given that ns3 implements, thanks to the module implemented in [2], a LoRa protocol stack for its simulation and evaluation in a typical urban scenario, we are ultimately able to assess the performance of the resulting SF allocation also including realistic propagation phenomena and interference among terminals.

We considered N nodes deployed with uniform spatial distribution around a single gateway. The parameters of the simulation are N and the radius R of the area covered by the nodes, which allows to consider dense or sparse environments. Our benchmark for comparison is one of the few existing strategies for a static allocation, the one reported in [2], which is referred to as the "Standard approach," and compared with our "Game theory (GT) approach." Differently from our proposal, the Standard allocation requires the imposition to a deterministic SF to all the nodes, which somehow limits its scalability, whereas our GT approach only requires an individual choice of each node and is fully scalable.

In Fig. 1 we show a specific instance of SF allocation for N=4000 users placed in a radius of $R = 2500$ meters. This represents an area densely populated with EDs clustered around a gateway so that they are all in relatively good channel conditions, i.e., theoretically able to use the lowest value of the SF. The standard allocation procedure of [2] exactly ends up in this situation, where all nodes use the same SF equal to 7. This outcome is not ideal since, in spite of good channel conditions, there are losses due to collisions since nodes use the same SF. Our game theoretic approach, instead, leads to a more diverse allocation, where some EDs select an SF equal to 8. This is solely determined by the belief about the opponent's strategy, computed by updating the values of p_7 and p_8. So, in a real evolving scenario, the users selecting a higher SF equal to 8 will not be stuck to it forever, but rather periodically switch between the values of 7 and 8 when they realize that using SF equal to 7 leads to an increased chance of collision.

The proposed game theoretic approach results in a better allocation, at no additional cost, since the choice is ultimately left to the users and their desire to maximize their utility function in a distributed and selfish way. To better show the superior performance of the approach inspired by game theory in smaller network deployment, we show in Fig. 2 the packet error rate resulting from interference between colliding packets. Since the objective of the EDs in the game theoretic setup is to primarily avoid interference from other LoRa devices, the GT approach shows a superior performance. In general, this is due to the fact that some nodes independently increase their SF to reduce interference, as opposed to the standard setup where all devices use a low SF.

However, we show that our proposal still requires some finetuning regarding network scenarios where users are spread over a large area. If we increase the value of R to 7500 meters (three times the previous value), now the EDs are not all able to use the same SF. In particular, the standard allocation already gives a reasonably diverse distribution of SF values, which avoids many collisions. Thus, in this case the reference technique is harder to beat, and actually our proposed GT approach performs slightly worse than it. As visible from Fig. 3 where both approaches are compared for $N = 4000$, in the GT approach some users tend to increase the SF again to avoid collisions, and this leads to a worse overall allocation. Especially, many EDs even use SF 12, which offers worse

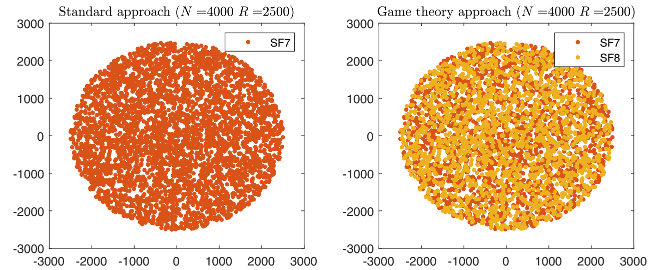

Figure 1: Allocation over a small area scenario (low R): comparison between the standard approach (left) and game theoretic allocation (right).

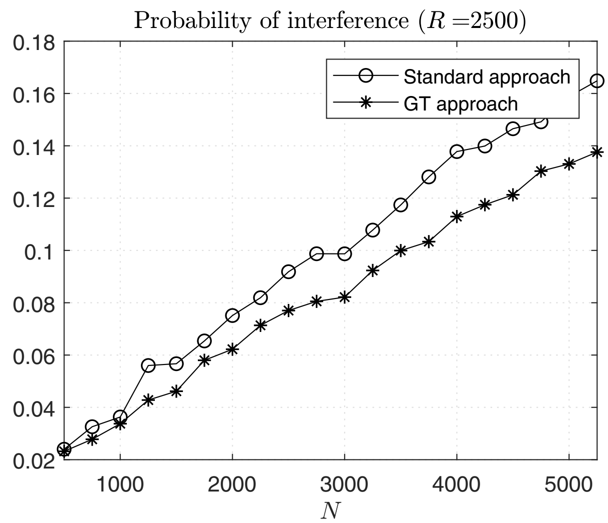

Figure 2: Allocation over a small area scenario (low R): packet error rate vs. number of users.

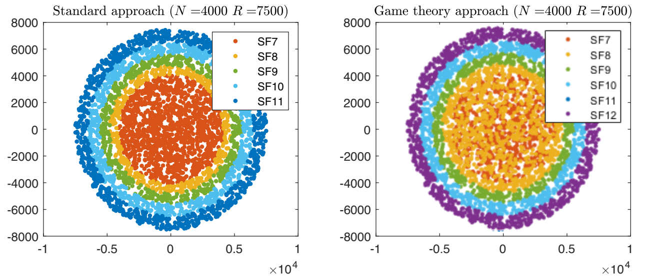

Figure 3: Allocation over a large area scenario (high R): comparison between the standard approach (left) and game theoretic allocation (right).

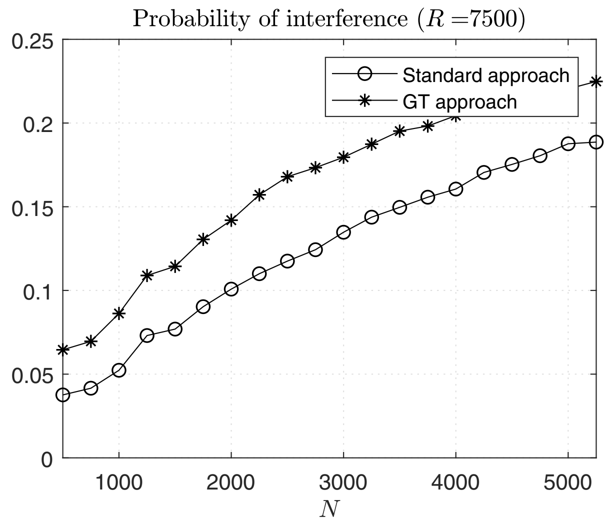

Figure 4: Allocation over a large area scenario (high R): packet error rate vs. number of users.

performance, even though it was possible to avoid using it entirely. They do so to avoid collisions, but since there are other EDs choosing it, they still interfere with each other.

The poorer performance of this allocation is confirmed from a quantitative standpoint by considering Fig. 4 where we evaluate the packet error rate versus the number of users. Despite the individual effort of the users to avoid collisions, the SF allocation that results from the GT approach actually leads to an increased interference among the users. Differently from the previous scenario, where increasing the SF was always beneficial, in this case it just changes the EDs that are involved in the collision because of their identical SF values. Clearly, a more reactive game theoretic design is required in this sense. Yet, it is worth noticing that the situation in which nodes are placed in a smaller area (as in Figs. 1 and 2) is a relevant case for many applications since it is expected that most LoRa nodes operate around gateways placed in strategic positions.

In any event, since this paper aims at giving an initial contribution in the field of game theory applied to LoRa operations, it is proven that the proposed technique is practical and effective, and the improvement of its performance in larger area networks can be considered as an open point for improvement of the game theoretic approach.

VI. Conclusions and Future Work

In this paper, we developed a game theoretical model to tackle the problem of assignment of Spreading Factors in a LoRa network. We designed a distributed algorithm for static allocation, which was proven to be effective and implementable. Our proposed approach turned out to be successful, and even better than existing allocation policies, when the nodes are clustered around a central gateway. On the other hand, it obtained worse performance for networks spread over a larger area. It is imperative to explore further ways to avoid myopic deviations triggered by selfish behaviors but leading to unchanged, or even worse, packet error rates.

This is a criticality of the approach that we adopted. Indeed, a static allocation – which is the result of a static game – certainly suffers from this kind of deviation that are made once and for all by the users. A dynamic game theoretic setup would probably avoid these problems, but also requires a carefully planned analysis to determine stability conditions and a correct dimensioning of the required complexity to plan the entire strategy ahead of time. Thus, its development is clearly out of the scope of the present contribution, but it is certainly worth considering as an extension for future work.

Also, other extensions can be envisioned in a more practical perspective, such as enabling game theoretic deviations only in smaller scale scenarios (e.g., allowing for them only between the lower SF values), where they are offering superior performance at no cost.

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