Resource Sharing in the Internet of Things and Selfish Behaviors of the Agents

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***Abstract*—Resource sharing is an issue for different fields of applications, giving rise to the so-called "Tragedy of the commons." This is particularly important in reference to the upcoming Internet of Things, where selfish behaviors from individual users jeopardize system cooperation, on which most network functions rely. We analyze two ways of splitting resources in the context of channel allocation for wireless systems. We describe the outcomes of the different strategies and we identify criteria for the emergence of selfish behaviors in such games.**

***Index Terms*—Resource allocation; Internet of Things; Tragedy of the commons; Game theory.**

I. Introduction

THE CHALLENGE of sharing resources among different users is a topic of growing interest in many fields, also outside engineering. Most of the times, a *tragedy of the commons* is encountered [1]–[3], which happens when independent agents share a resource in a selfish manner. A game theoretic formulation predicts an excessive, and therefore inefficient, usage of the resource, hence the name "tragedy."

The increasing number of interconnected devices in the Internet of Things (IoT) [4], especially in pervasive scenarios such as the Industrial IoT [5] or the Internet of medical things [6], causes this phenomenon to be even more dramatic, as it relates to efficient provision of critical services. A reliable wireless transmission requires a communication free of interference, an objective that conflicts with the desire of multiple device to use the same medium [7]. We consider that the available resource for the communication is a frequency spectrum, for the sake of simplicity divided into disjoint *channels*, i.e., atomic resources where the received signal reaches an acceptable quality of communication [8].

Whatever the procedure used to generate the channels, either frequency, time, or space division, the basic assignment scheme would be a fixed channel allocation (FCA) scheme that permanently assigns channels to users [9]. However, it would be more efficient to perform a dynamic channel allocation (DCA), i.e., place all the channels in a pool and assign them whenever needed [10]. Approaches of *spectrum sharing* [11]–[13] can be also incorporated in such a context. In this paper, we push the DCA approach further by allowing a *game theoretic* choice of the channels [14].

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The use of game theory in wireless networks is strongly motivated by the need for cost-efficient, distributed, and scalable solutions, and the desire to keep into account user selfishness. The fragility of resulting equilibrium can be controlled via pricing in 5G networks [1], whereas the problem is acute in the IoT that is expected to combine different technologies and network ownerships [2], [4]. As a result, game theoretic approaches have received interest in the literature. For example, a game theoretic protocol was designed to perform channel assignment in the context of wireless sensor networks in [15]. The algorithm leverages both network topology and routing information and finds the channel allocation minimizing the interference inside the network through a game among the Parent-Children Sets (PCS) [16].

In [17], a game theoretic scheme for channel allocation is used, where agents know about the payoff values and strategies of each other. The same problem is solved in [18] by matching theory through the Gale-Shapley algorithm. In [7], game theory is employed to improve the throughput while solving the channel allocation problem considering co-channel interference. A non-cooperative game for channel allocation, also based on spectrum clustering is proposed in [19], whereas [20] improves coordination through a Stackelberg game. In [21], models for bandwidth auctions, which can be seen as applications of game theory, are proposed. Other possible related approaches include evolutionary games [22] or bargaining theory [23] applied to channel assignment, which is further extended in [24] to a reference integrative bargaining.

All of these approaches assume that the network parameters are perfectly known to the users (i.e., the players of the game). To better characterize the selfish actions of the users, one must also account for the inherent uncertainty of many network aspects. Generally, this is done in game theory by employing the instrument of Bayesian games [25]; up to our knowledge, this contribution is still missing in the literature of channel allocation. Thus, we consider a Bayesian channel allocation game and we use it to analyze resulting individualistic behavior in resource sharing.

We find out that selfish Nash Equilibria (NEs) are favored by uncertainty, which, if overcomes a certain threshold, encourages the players to stop cooperating and start acting only in their own interests. We also compare the selfish choices of the players with a Pareto optimal solution and calculate the price of anarchy. Finally, we implemented MATLAB simulations to draw some general conclusions. This kind of investigations appears to be promising in light of the proposals for a paradigm shift in resource allocation over next generation networks including distributed intelligence [1], [2], [18], [20].

The rest of this paper is organized as follows. In section II we discuss the system model. Section III reports some numerical results. Finally, IV concludes the paper.

II. System Model

We start from a static game of complete information that will serve as a reference result. Consider a two-player game, where two channels are available. Both players, denoted as "Pl 1" and "Pl 2" can choose whether they want to transmit on channel 1 or 2 ("ch 1" or "ch 2," respectively), therefore they both have two possible actions. If channel 1 provides a better gain to both players, they both achieve a higher payoff (10) if they transmit on such a channel. But if they both transmit on the same channel, they cause interference to each other and both get payoff 0. The game can be represented by the normal form shown in Table I. We remark that these choices of utility functions are relatively arbitrary as they just represent the preferences of the players as an ordinal ranking [7], [20].

Table I
Static game of complete info, 2 channels

Pl 1 \ Pl 2	ch 1	ch 2
ch 1	0,0	10,1
ch 2	1,10	0,0

This game presents two pure NEs, (ch1, ch2) and (ch2, ch1). In both of them, the two players prefer to choose a worse channel rather than colliding and the result is that they transmit on two different channels. Therefore, all the available resources are used. If we consider the same game, but with different preferences for the two players, the payoffs are:
– player 1 has a better gain on channel 1, therefore his payoff is 10 when transmitting alone on channel 1
– player 2 has a better gain on channel 2, therefore his payoff is 10 when transmitting alone on channel 2

This game can be represented in normal form, see Table II.

Table II
Static game of complete info, 2 channels

Pl 1 \ Pl 2	ch 1	ch 2
ch 1	0,0	10,10
ch 2	1,1	0,0

In this case, the situation is very similar to the one in Table I. The game presents the same two NEs, (ch1, ch2) and (ch2, ch1). However, in this case the one of the two NEs, (ch1, ch2), represents the social optimum. Therefore, the available resource is still completely used and collisions are prevented.

We now consider a game with a similar setup, but with a higher number of channels. We considered the case in which two players have to choose two channels to transmit upon, out of 4 possible channels. The payoffs when transmitting on the four different channels are distributed as follows:
– channel 1 has the highest gain for both players, therefore when transmitting alone on this channel they both achieve a payoff of 100
– channels 2 and 3 have a worse gain than channel 1, but better than channel 4, the payoff for the two players when transmitting alone on those channels is 50
– channel 4 has the worst channel gain, their payoffs when transmitting alone on this channel is 10
– as before, if they transmit on the same channel, they cause interference to each other, thereby achieving zero payoff.

The final payoff for the two players is the sum of the payoffs that they achieve in the two channels they decide to transmit on. This can be represented by the matrix in Table III.

Table III
Static game of complete info, 4 channels

	ch 12	ch 13	ch 14	ch 23	ch 24	ch 34
ch 12	0,0	50,50	50,10	100,50	100,10	150,60
ch 13	50,50	0,0	50,10	100,50	150,60	100,10
ch 14	10,50	10,50	0,0	110,100	100,50	100,50
ch 23	50,100	50,100	100,110	0,0	50,10	50,10
ch 24	10,100	60,150	50,100	10,50	0,0	50,50
ch 34	60,150	10,100	50,100	10,50	50,50	0,0

We see that there are 6 pure NEs: (ch 12, ch 34), (ch 13, ch 24), (ch 14, ch 23), (ch 34, ch 12), (ch 24, ch 13), (ch 23, ch 14). The NEs represent all the possible ways in which the two players can divide the two channels. Both players prefer to transmit on worse channels than colliding in one or more channels. Our conclusion reprises classical contributions in the field [8], [15], and tells that, when the players are completely informed on the game setup, they are induced to cooperate in order to use all the available resource.

However, these conclusions change considerably if we consider a Bayesian setup for this game, to take uncertainty of the channel evaluations into account [25]. We analyzed the same game proposed in Table I and II in a Bayesian setup. We considered the case in which both players can have two different types:
– type A players have a higher channel gain (and therefore a higher payoff) when transmitting on channel 1
– type B players have a higher channel gain when transmitting on channel 2

In this setup, there are 4 different possible payoff tables, where the situation becomes equivalent to either Table I or Table II. Since the players have 2 types and 2 possible actions, there are 4 possible strategies for each player: each player needs to choose what action to play depending on its type being A or B.

If the type distribution is uniform for both players, the normal form of the game is shown in Table IV.

Table IV
Bayesian game, 2 channels

Pl 1 \ Pl 2	11	12	21	22
11	0,0	$\frac{1}{4}$(11,10)	$\frac{1}{4}$(11,2)	$\frac{1}{4}$(22,22)
12	$\frac{1}{4}$(20,11)	$\frac{1}{4}$(20,20)	$\frac{1}{4}$(20,2)	$\frac{1}{4}$(20,12)
21	$\frac{1}{4}$(2,11)	$\frac{1}{4}$(2,20)	$\frac{1}{4}$(2,2)	$\frac{1}{4}$(2,12)
22	$\frac{1}{4}$(22,22)	$\frac{1}{4}$(11,20)	$\frac{1}{4}$(11,2)	(0,0)

The payoffs are obtained taking the expected value over all the possible outcomes for the two considered strategies considering all the type distribution for the two players. For example, player 1's payoff for $(12, 11)$ is $20/4 = 5$, as he gets payoff 0 in two cases out of 4, and 10 in the other two cases.

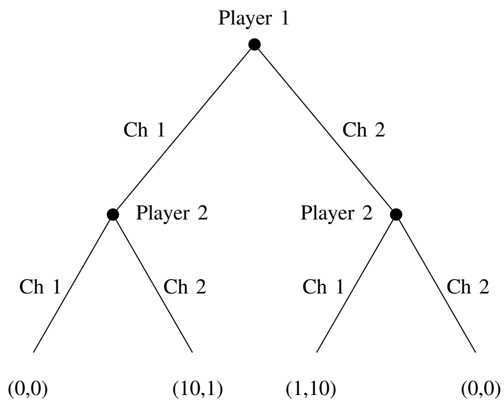

Figure 1. Stackelberg formulation for game in Tab I

In this formulation, there are 3 Bayesian NE (BNEs):
– (11,22) and (22,11) are the equivalent of the previous games NEs. The players agree of transmitting on one channel and they cooperate to use all the achievable resource, even if this means that the allocation is not the most favorable one (still, players prefer to avoid collisions)
– (12,12) a selfish BNE. Since there is uncertainty in the game, the two players are induced to transmit on their preferred channel, no matter what the other player does

We implemented the Bayesian game described above using MATLAB and analyzed what happens with different type distributions and a higher number of channels. Then, we calculate the price of anarchy (PoA) in this game, considering the selfish BNE as the worst case scenario. For the social optimum scenario, instead, we consider a Stackelberg formulation, where players move in order: the one moving first always picks its best channel, the player moving second will choose the best channel among the remaining ones. For example, for the Stackelberg formulation of game in Table I (Fig. 1), the only *subgame-perfect* NE of the game is (ch1, ch2). For the Bayesian game described in Table IV, if player 1 is always first to choose, he will get a payoff equal to 10, no matter what type is player 2. Player 2, instead, will get a payoff of 10 when his type is different from player 1's type and a payoff of 1 when their preferred channel is the same one. The average outcome of the game is $\frac{1}{4}(40, 22)$ and therefore

$$\text{PoA} = \frac{\text{total payoff social optimum}}{\text{total payoff worst case NE}} = \frac{40+22}{20+20} = 1.55 \quad (1)$$

III. Results

Consider the case with two players contending two channels. Here, each player has a preferred choice, which gives a better payoff. Each player can also be of two different types, specifying what is the preferred kind of channel. We introduced two parameters to evaluate the outcomes of our simulations, what we call *Type distribution parameter* (*TDP*), i.e., the ratio between the probabilities of being of the first versus the second type. This means that for $TDP = 1$, the players have probability 0.5 to be of type 1. We let this parameter vary in the interval $[1, 11]$.

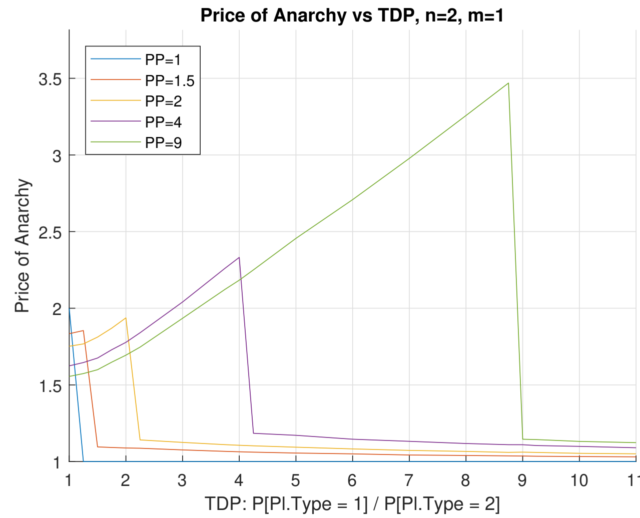

Figure 2. Price of anarchy vs. Type distribution parameter

$$TDP = \frac{P[\text{Pl.}_{\text{type}} = 1]}{P[\text{Pl.}_{\text{type}} = 2]} \in [1, 11] \quad (2)$$

The second parameter is the *Payoff parameter* (*PP*) defined as the ratio between the payoff obtained by players when they transmit alone in their preferred channel and the payoff when they transmit alone on the worse channel. We used the same range of values for this parameter and the *TDP*.

$$PP = \frac{\text{Payoff}_{\text{Better}}}{\text{Payoff}_{\text{Worse}}} \in [1, 11] \quad (3)$$

In Fig. 2 we show the behavior of the PoA as a function of the *TDP* parameter. All the curves grow almost linearly in the first part of the graph, then there is a vertical drop in the PoA value, after which the value remains almost equal to 1. The first part of the curve is explained with the fact that if the type probability grows and both players transmit on their preferred channel, more collisions occur. Therefore, when the *TDP* parameter grows, the social optimum solution becomes more and more convenient. The reason for this drop in the PoA can be found in the fact that the selfish BNE is no longer a solution for the game. If the probabilities are too high, there is not enough uncertainty left in the game and the players prefer to cooperate, like in the static game. For higher values of *TDP*, the only two BNEs are the ones in which the two players agree on transmitting on two different channels; therefore, the total payoff is equal to the social optimum and the PoA is 1.

A larger PoA is reached if the payoff on the preferred channel is much higher than the other (high *PP*). Hence, we calculated the PoA as a function of the *PP* parameter, see Fig. 3. In this plot, the curves remain almost equal to 1 for low values of the *PP* parameter, then they increase vertically and finally, for higher values of *PP* they stay constant. This behavior is again motivated by the fact that for very low values of the *PP* parameter, the selfish BNE is not a solution of the game. When the selfish BNE becomes available, the price of anarchy grows and then stabilizes to a fixed value. A higher

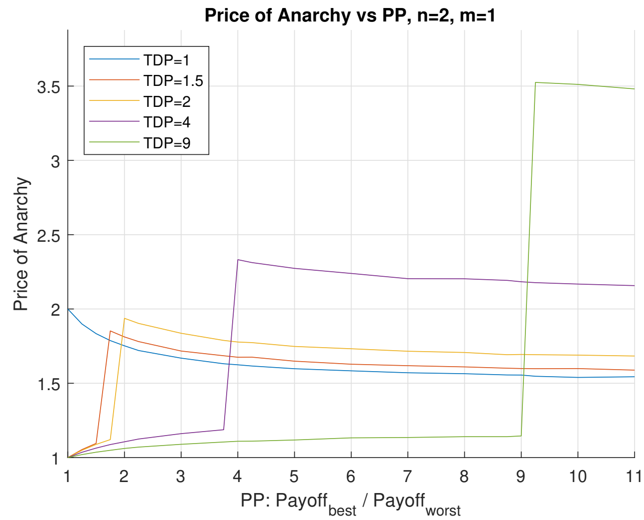

Figure 3. Price of anarchy vs. Payoff parameter

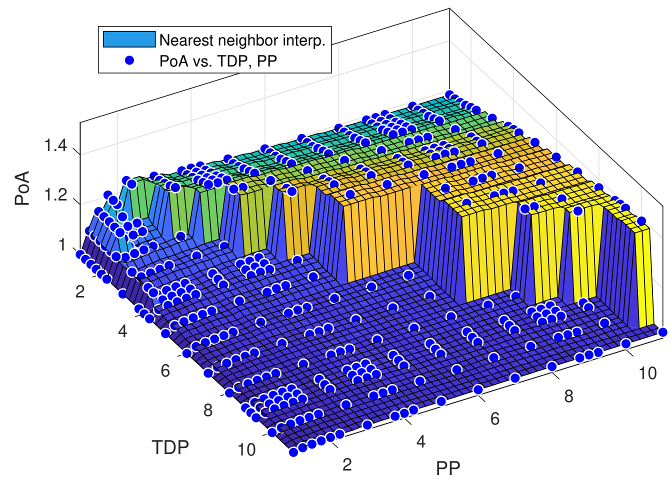

Figure 5. Price of anarchy vs TDP and PP with $n = 6, m = 2$

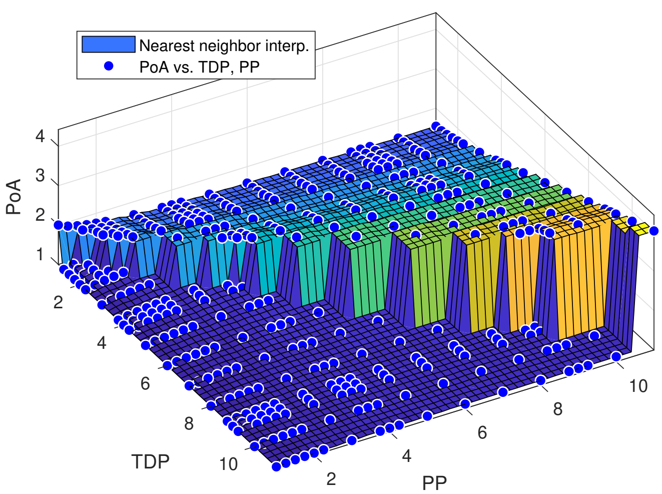

Figure 4. Price of anarchy vs TDP and PP with $n = 2, m = 2$

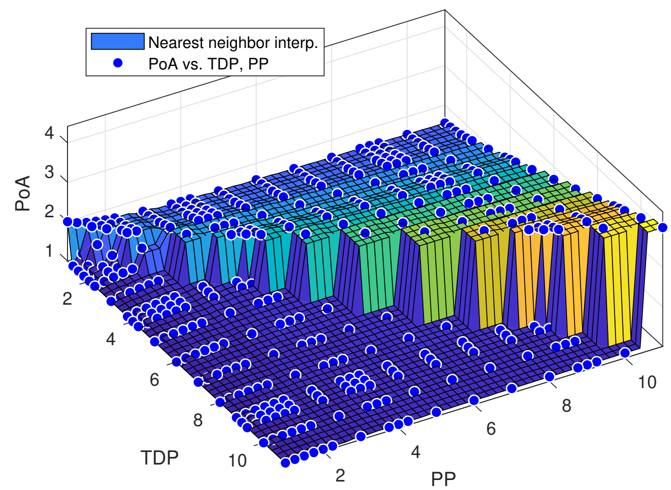

Figure 6. Price of anarchy vs TDP and PP with $n = 6, m = 3$

PoA value is reached when the *TDP* parameter is higher, but in this cases the selfish BNE arises only for higher values of the *PP* parameter. This can be explained with the fact that if the uncertainty in the game is low, only a large payoff advantage encourages the player to play selfishly.

We noticed that there is a threshold value for the selfish BNE to become a solution for the game, this threshold is reached when the *PP* parameter value is almost equal to the *TDP* one:

$$\text{PP}_{\text{threshold}} \approx \text{TDP} \tag{4}$$

It is possible to notice this threshold behavior in the 3D plot showing the PoA behavior as a funcition both of the *TDP* parameter and the *PP* parameter (Fig. 4).

We also investigate the system behavior when the number of the available channels and/or the users is increased. Specifically, in Figs. 5 and 6, we consider a scenario with $n = 6$, $m = 2$ (just increasing the number of available channels) and a case with $n = 6$, $m = 3$ where the whole system is scaled proportionally, respectively. The respective PoA is also displayed in 2D graphs in Figs. 7 and 8.

Overall, these results show that the system behavior maintains similar trends, therefore suggesting that the proposed analysis scales well. Clearly, further extensions can be devoted to scenarios where the number of channels and users is increased to much larger sizes, as typical of IoT scenarios [4], and this can be subject of future work. But the results presently available seem to be encouraging in this sense.

More specifically, Fig. 6 shows that the PoA stays basically the same when expanding the system from $n = 4$ channels and $m = 2$ users to $n = 6$, $m = 3$, thereby maintaining the same ratio of available resources. For the case with $n = 6$, $m = 2$, which is reported in Fig. 5, the qualitative behavior of the plots is similar, but the values reached for the PoA are lower (the maximum value reached is less than 2). Indeed, more channels are available and 2 channels remain free, therefore it is more difficult for the transmissions to collide. This is also better visible by comparing the 2D graphs of Figs. 7 and 8. While for $m = 6$, $n = 3$ the trend is substantially preserved, when $m = 6$ and $n = 2$ the growth of the PoA is no longer linear, but shows a sub-linear increase, implying that the lower PoA is also less sensitive to unbalances in the payoffs.

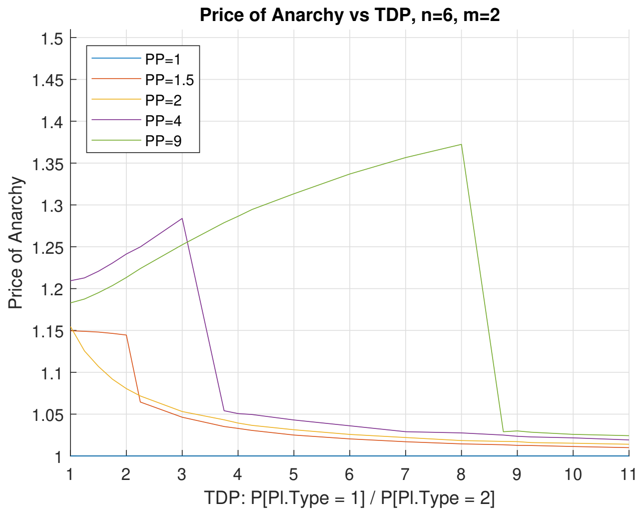

Figure 7. Price of anarchy vs TDP with $n = 6, m = 2$

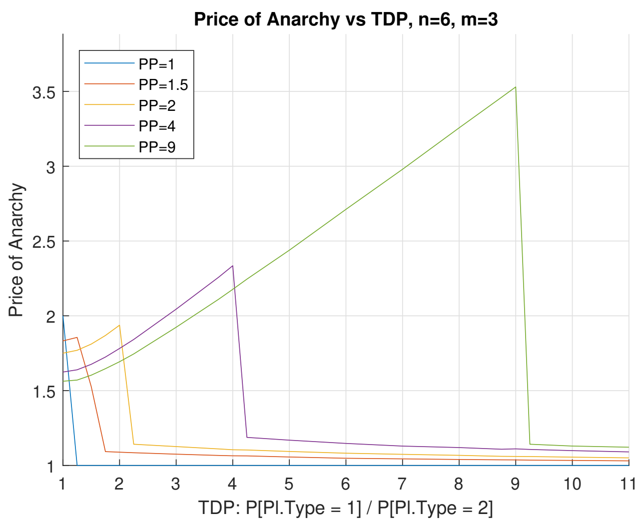

Figure 8. Price of anarchy vs TDP with $n = 6, m = 3$

IV. Conclusions

We proposed a game theoretic analysis to characterize wireless communications over multiple channels in the IoT. We designed a Bayesian game to keep into account the uncertain estimates of the resource quality from the perspective of other users, and we seek cases where the players are encouraged to play selfishly, depending on their perceived information.

The results show that player behaviors depend on the uncertainty in the game. A selfish BNE arises when there is sufficient uncertainty about the preferences of the other players, and the ratio between the payoffs on the preferred vs. the not preferred channels is high enough.

These conclusions are quite general, and the proposed evaluated criteria also enable guidelines for the use in practical IoT contexts [5], [6]. Future work may explore larger setups as typical of IoT scenarios with significantly higher number of nodes, also employing stochastic tools, and the extension of the Bayesian games in a dynamic setup, to see whether cooperation can be established over time [8], [17].

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