Power Allocation Game for Interference Mitigation in a Real-world Experimental Testbed

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***Abstract*—In this paper we propose a methodology for the experimental evaluation of a simple yet efficient power allocation game on a real-world outdoor experimental testbed. We adapt the existing theoretical framework and the ProActive Power Update (PAPU) algorithm to suit the constraints imposed by the LOG-a-TEC low-cost reconfigurable testbed. The resulting framework is implemented and evaluated in the ISM 2.4 GHz band. We study the effects of the empirical parameter estimation on the best response and players' strategies which represent the Nash equilibra. Our results show that for a certain cost range, the system can reach Nash equilibria. The equilibria and the convergence time are strongly influenced by each player's cost but also by the channel gains.**

I. Introduction

The necessity for more efficient use of radio spectrum is increasing due to the increased number of wireless devices such as smart phones and tablets, and the increasing volume of data transfer generated by apps such as Farmville, Facebook, etc. One solution to the efficient spectrum usage problem is to control the interference. The lack of interference coordination causes low link quality and energy waste thus leading to inefficient use of the radio resources. In order to cater for this, a wide range of methods have been developed. For instance, a plethora of algorithms and protocols for optimizing channel and power allocation such as [1]–[6] have been proposed. These algorithms have in common the use of concepts and tools from two very innovative and fertile fields: Cognitive Radio (CR) and Game Theory (GT).

Cognitive Radio technology is seen as the key enabler for efficient use of radio resources [7]. Future wireless networks will exhibit various degrees of CR behaviour. In a spectrum co-existence scenario, the participating nodes may be configured to have cognitive capabilities. CR devices can observe their operating environment and become aware of their situation, make in situ decisions according to their observations, anticipations and experiences, and then execute intelligent adaptations to maximize their utility subject to constraints [8].

The transmitters are actually decision makers that can freely choose their own resource allocation policies while selfishly maximizing their transmission rates. This resource allocation problem can be modeled as a game in which CR interactions are represented as strategic interactions: each player's payoff depends on the other players' actions. Game Theory (GT) has emerged as an effective framework for CR interaction analysis as shown in several papers such as [9]–[12].

Game theoretic approach in CR has been thus far predominantly used in fully controlled environments of computer simulations to provide the proof of concept. Experimentation facilities play an important role in the transition of technology from concept to prototype. Requirements for an open platform allowing experimentation with cognitive radios have been outlined in [13]. Several large CR testbeds such as CORAL, ORBIT, CORNET and CREW [8] have been deployed in the US and Europe. These are often built using off-the-shelf equipment such as TmoteSky[1], Universal Software Radio Peripheral (USRP)[2], but can also be based on custom made hardware platforms such as CORAL [14], the imec sensing engine[3] and the VErsatile platform for Sensor Network Applications (VESNA)[4]. The majority of experiments performed on these platforms to date focus on spectrum sensing.

While theoretical frameworks and computational simulations abound, the experimental investigation of the behaviour and performance of resource allocation algorithms is scarce. In this paper, we propose a methodology for the experimental evaluation of a simple yet efficient non-cooperative power allocation game on a real-world outdoor experimental testbed. We adopt the theoretical framework and the corresponding algorithm proposed in [15] and then we adapt this framework and algorithm to suite empirical evaluations and also define a power control protocol. The resulting framework is implemented and evaluated on the LOG-a-TEC [16] [17] experimentation facility with the reconfigurable nodes operating in a single channel in the ISM 2.4 GHz band. We study the effects of the empirical parameter estimation on the best response, player's strategies which represent the Nash equilibra.

The rest of the paper is organized as follows: Section II presents the problem formulation and the proposed methodology for experimental evaluation. Section III describes the experimental setup while Section IV presents the adaptations required by the theoretical framework. Section V elaborates on the empirical parameter determination, Section VI discusses

[1]http://www.eecs.harvard.edu/~konrad/projects/shimmer/references/tmote-sky-datasheet.pdf
[2]http://www.ni.com/usrp/
[3]http://www.imec.be/ScientificReport/SR2010/2010/1159118.html
[4]http://sensorlab.ijs.si/hardware.html

the results while Section VII concludes the paper.

II. Problem statement and methodology

In [18], the authors propose a theoretical framework for a non-cooperative game-theoretic power control scheme for wireless and ad-hoc networks. In [15], the authors reformulate the problem by also considering energy efficiency alongside with interference and propose the ProActive Power Update (PAPU) algorithm. Simulation results showed that PAPU can utilize energy more efficiently by sacrificing a small amount of network utility compared to the Asynchronous Distributed Pricing (ADP) protocol proposed in [18].

The power allocation game proposed in [15] and adopted in this paper is formulated as follows. Given a wireless network of N transmit-receive pairs (Tx_i-Rx_i), where a "pair" is referred to as a "player", the objective is to find stable points of power allocation for each player such that the players' global utility is maximum while the cumulated power levels are kept to a minimum.

More formally, given a set of N players, $N = \{1, 2, ..., N\}$, and their corresponding power allocation profile $P = \{p_1, p_2, ..., p_N\}$, the utility function of each player is given by:

$$u_i = log(1 + \frac{h_{ii}p_i}{n_0 + \frac{1}{B}\sum_{j \neq i} h_{ji}p_j}) - c_ip_i \qquad (1)$$

where p_i, p_j are the transmit powers of players i and j, h_{ii} is the direct gain, h_{ji} is the channel gain between transmitter j and receiver i, B is the total channel bandwidth and n_0 is the noise power. For simplicity and in accordance to [15], we consider B=1. Now, the objective is to maximize the global utility function (2a), while minimizing the globally allocated power (2b) where $p_i \in [0, P_i^{max}]$.

$$max \sum_i u_i \qquad (2a)$$

$$min \sum_i p_i \qquad (2b)$$

Note that the considered theoretical framework is designed for non-cooperative power allocation games, meaning that the decisions are taken autonomously by the CRs (i.e. no coalition is made for decision making purposes). Yet, non-cooperative does not mean non-collaborative; a certain amount of signalling/communication among the devices is assumed in this case (there are games for which this may not be necessary). From the GT perspective, in a non-cooperative game [19] what the players know is the game (i.e. the players, payoff function, the set of available strategies, the payoff values at each iteration), but they do not know in advance what actions the other players will take.

In the evaluations performed in a simulation environment [15], the values for the direct gain, the cross gains, the transmitted power and noise were chosen conveniently to provide the proof of concept. Communication and reconfiguration delay were not taken into account. In order to provide more insights into how such a game would perform in a more realistic environment and to provide empirical validation for the theoretical framework, we adopt the theoretical framework and the PAPU algorithm proposed in [15] and propose a methodology that enables studying the effects of the empirical parameter estimation on the best response and player's strategies.

Validation of theoretical models in real-world set-ups poses several constraints that are most often testbed specific. The methodology employed for investigating the feasibility of experimenting with interference mitigation based on the power allocation game consisted of:

- Identification of the experimental set-up and the constraints.
- Adaptation of the theoretical framework for the use in a testbed rather than in a simulation scenario.
- Empirical determination of the values of parameters such as channel gain.
- Implementation and experimental evaluation.

III. Experimental set-up

The cognitive radio experimentation facilities of the LOG-a-TEC[5] testbed [20] consist of 50 VESNA devices divided into two clusters of 25 nodes, one located in the Logatec city center and the other located in the Logatec industrial zone. The testbed consists of three types of nodes, i.e. UHF receivers operating at 470 - 862 MHz and transceivers operating at 868 MHz and 2.4 GHz ISM bands [16] [21].

The constraints imposed by the testbed are as follows:

- **Topological** - The topology of the testbed is determined by the alignment of the public light poles on which the sensor nodes are mounted. The theoretical framework behind PAPU assumes that the cross gains are significantly smaller than the direct gains. If this constraint is not satisfied then the game might not converge. This constraint and the topology of the testbed narrows down the choice for the location of the players.
- **Transmission capability** - The testbed is able to transmit on one channel at a time, therefore limiting the type of games that can be supported to single channel ones.
- **Power levels** - The nodes' CC2500 transceivers support discrete power levels. Unlike in the theoretical framework, where continuous power levels are considered, the empirical game has to be adjusted to one of the associated power levels specified by the radio chip. This clearly affects players' strategies.
- **Sensing** - The nodes of the testbed use energy detection for spectrum sensing. This simple method cannot distinguish between different types of detected signals (i.e. it can not accurately detect spread spectrum signals). As a result, the accuracy of the measurements is lower, therefore the best responses of the users are misguided by the errors.
- **Delay** - The delay for setting up a transmission or a sensing vary depending on the nodes, since the management

[5] http://log-a-tec.eu/cr.html

network through which this setup is conducted is wireless. Typical values for this setting are from 1 to 3 seconds. The delay affects the speed of the game, thus the time required to converge.

- **Synchronization** - The nodes of the testbed do not use a clock synchronization protocol, therefore the lack of synchronization has to be taken into account when designing and implementing the game.
- **Calibration** - The low cost nodes are not calibrated, therefore a setting of -0 dBm transmission power might result in a slight shift of the level of the actual transmitted power. This affects the final strategies of the players.

Considering the theoretical framework behind PAPU and the constraints imposed by the LOG-a-TEC testbed we define the interference-aware power control game between two players operating at 2.4 GHz, in the industrial zone cluster. The power levels set for the VESNA nodes in LOG-a-TEC follows: [0, -2, -4, -6, -8, -10, -12, -14, -16, -18, -20, -22, -24, -26, -28, -30] dBm. The two players are transmit-receive pairs coexisting in the same area, as depicted in Fig. 1. Player 1 is formed by the Tx-Rx pair Node25-Node2 whereas player 2 is formed by Node16-Node17. The distances between the nodes are: $d(TX_1, RX_1) \approx$ 50m, $d(TX_2, RX_2) \approx$ 65m, $d(TX_2, RX_1) \approx$ 230m, $d(TX_1, RX_2) \approx$ 150m.

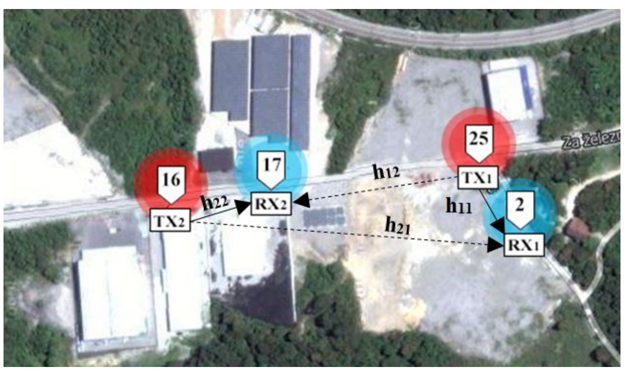


Fig. 1. Inter-network interference between wireless systems where h_{ij} is the channel gain between transmitter i and receiver j. Arrows point to sensor node location. Numbers in arrows are location identifiers.

IV. The Adaptation of the Theoretical Framework

The best response of any of the players involved in the game is given by [15]:

$$b_i(p_{-i}) = \frac{1}{c_i} - \frac{\sum_{j \neq i} h_{ji} p_j + n_0}{h_{ii}} = \frac{1}{c_i} - \frac{I + n_0}{h_{ii}} \quad (3)$$

where $b_i(p_{-i})$ represents the best response of player i given the current state of the game (the power profile for all other players is denoted by p_{-i}), c_i represents player i's energy cost, I represents the interference at the receiver, h_{ij} are the channel gains, p_j is the transmitted power for all the other players and n_0 is the noise. In typical controlled evaluation setups, such as simulators, the values for h_{ji} and p_j are chosen conveniently. A testbed allows the study of the game when these parameters are constrained by the environment and acquired in a realistic environment. As a result, the following adapted expressions are used in the experimental evaluation:

$$\begin{aligned} b_i(p_{-i}) &= \frac{1}{c_i} - \frac{\sum_{j \neq i} h_{ji} p_j + n_0}{h'_{ii}} \\ &= \frac{1}{c_i} - \frac{Pr_{measured}i - P_{useful}}{h'_{ii}} \end{aligned} \quad (4)$$

$$\begin{aligned} b_i(p_{-i}) &= \frac{1}{c_i} - \frac{\sum_{j \neq i} h_{ji} p_j + n_0}{h'_{ii}} \\ &= \frac{1}{c_i} - \frac{Pr_{measured|p_i=0}}{h'_{ii}} \end{aligned} \quad (5)$$

where h'_{ii} stands for the measured or the measurement-based estimation of the direct gain, $Pr_{measured}i$ stands for the received power measured by player i when player i is also transmitting ($p_i \neq 0$), P_{useful} stands for the estimated useful power received by Rx_i when Tx_i is transmitting, and $Pr_{measured|p_i=0}$ stands for the received power measured by player i when player i's transmitter is silent ($p_i = 0$).

For the entire system to be stable, the PAPU algorithm must converge to a Nash equilibrium. The convergence issue studied in [15] gives the following condition for the convergence and stability of PAPU:

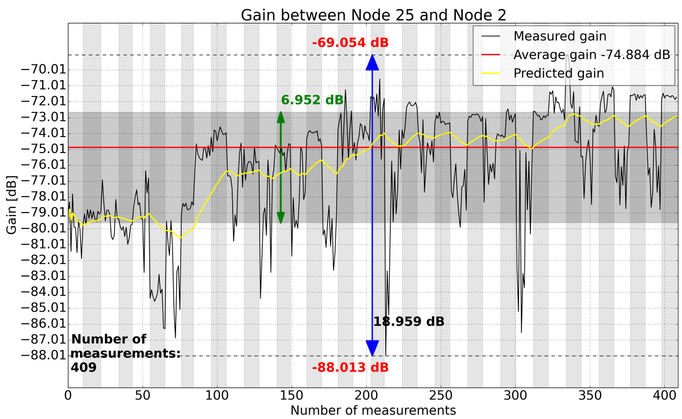
$$|\frac{h_{ji}}{h_{ii}}| < \frac{1}{N}, i = 1, ..., N \quad (6)$$

Eq. (6) is a decisive factor when choosing the topology on which the power allocation game is implemented. If Eq. (6) is not fulfilled for all players, there will be no strategy profile that will satisfy the players.

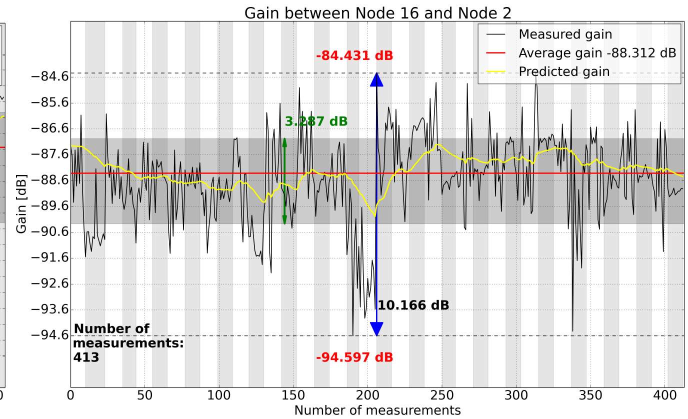
In the theoretical case, considering Eq. (3), an equilibrium is reached in the game when $p_i(t-1) = p_i(t)$ for all players at once. However, in practice, where p_i can take only discrete values, and, in a real environment is very unlikely to have two best responses equal to each other, therefore a more robust stopping criterion is needed in order to determine the equilibrium. In this study, the criterion is given by the following condition: $|b_{i-k}(p_{-i}) - b_i(p_{-i})| < P_{th}$, where $k = 0, 1, 2, 3, 4$ and P_{th} stands for the threshold power used to compensate for the environment dynamics. Usually, after reaching the NE, the best responses do not change. In other words, we use a queue of the last four best responses, and, if the absolute value of the difference between the most recent best response and the ones in the queue is less that a threshold, we consider that the system has reached the equilibrium. The selected size of the queue is a trade-off between accuracy and convergence speed. Having a queue of a larger size, would lead to a higher convergence time, while with a shorter queue, we make sure that the system is actually stable (i.e. it's not a coincidence that the values are similar).

Based on the PAPU algorithm, we define the following power control protocol:

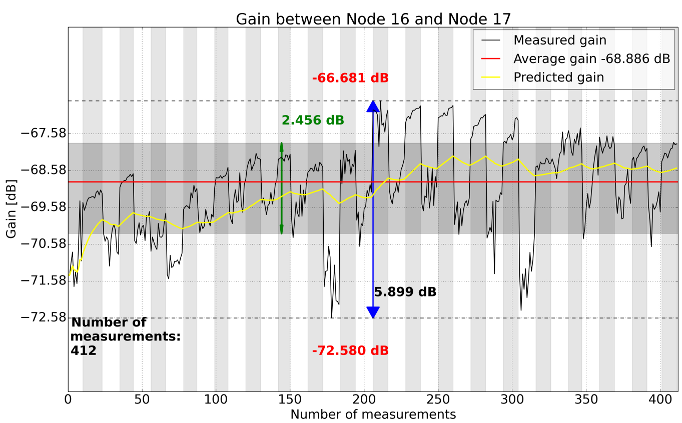
- Step 1: Each player i initializes its power p_i^0, p_{-i}^0.
- Step 2: At time t if player i updates its power, player i will alert the neighbors that a power change has been made.



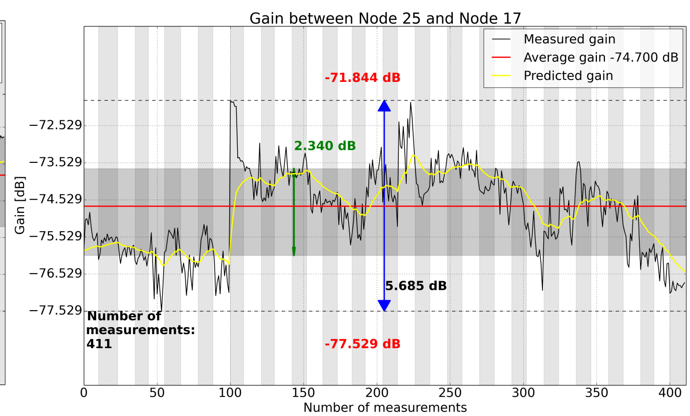
(a) h_{11} representing the direct gain for player 1



(b) h_{21} representing the cross gain for player 1



(c) h_{22} representing the direct gain for player 2



(d) h_{12} representing the cross gain for player 2

Fig. 2. Long term measurements of the channel gains (from August 5th to August 23rd 2013 between 12:30 - 13:30 - white vertical shading and 21:00 - 22:00 gray vertical shading).

- Step 3: If player i detects a change in other players' power, it updates its power according to Eq. (5) and alerts the neighbours of the change.
- Step 4: Player i checks if the Nash equilibrium condition is satisfied
- Step 5: If the Nash equilibrium condition is satisfied, the game is stopped.

V. Empirical parameter determination

For the topology presented in Fig.1, the channel estimation was performed starting from empirical data. The gain between pairs of nodes has been measured and three strategies for deriving their values for the purpose of the PAPU algorithm have been studied: average gain, instantaneous gain and estimated gain using Kalman filter.

The procedure for measuring the channel gain was as follows. First, the receiver Rx_j measured the received power P_{noise} knowing that the transmitter Tx_i was silent. Then, the receiver measured the received power P_{Rx_j} knowing that the transmitter was transmitting with a given power P_{Tx_i}. The gain was then computed according to:

$$h_{ij} = \frac{P_{Rx_j} - P_{noise}}{P_{Tx_i}} \tag{7}$$

Long term channel gain measurements were taken twice a day, in the afternoon (12:30 - 13:30) and late evening (21:00 - 22:00), between August 5th and August 23rd 2013. For channel gain measurements, a signal at 2420MHz with a bandwidth of 400kHz was used at the transmitter side. The measured channel gains are represented in a chronological order in the plots depicted in Fig. 2. The vertical white and grey shadings represent the afternoon period with white and the late evening period with gray, respectively.

Looking at Fig. 2a, it can be seen that the average gain for the pair of nodes representing Player 1 is -74.8 dB with a standard deviation of 6.952 dB and a dynamic range of 18.9 dB for the 19-day period considered. Even in short term measurement periods, such as an afternoon or an evening session, gain variations of over 5 dB can be found. Similar observations can be made on Figs. 2d–2c for other pairs of nodes. The gain is highly dynamic and thus using the average as a means of approximation does not reflect the actual state of the channel. Therefore the best-response strategy of the power allocation game will yield unrealistic values. This method would be suitable if the gain variation were not considerable (e.g. < 3 dB), which happens only occasionally.

Alternatively, the instantaneous channel gain could be considered as input to the best-response strategy. However this approach can prove expensive in terms of delay and power. Measuring the channel gain before each step in the game is time consuming (for the particular case of the LOG-a-TEC testbed one such measurement takes 5-6 s). It would constitute a viable choice if the number of required measurements was small, however this cannot be guaranteed in a power allocation game. Additionally, the instantaneous channel gain measurements are prone to measurement errors.

The third approach is to use a simple channel estimation technique such as the Kalman filter [22]. This method consists of two steps: the first step is estimating the next measured gain and the second step represents the correction of the estimated gain by performing a new gain measurement. The resulting predicted gain is then computed. The values of the Kalman predictor for long term measurements are depicted in Fig. 2 in yellow.

For a short history, it approximates well the channel gain (see first 3-5 measurements in each subfigure) as the dynamic range of the values fed into the filter is lower, the standard deviation is small, therefore the Kalman filter performs a more precise estimation. This is not the case for longer histories as the wireless channel is known to have high variations over longer periods. Additionally, in wireless communication, taking into account old measurements into such decisions as considered here, is not so useful due to the dynamicity of the channel.

By analyzing the long-term measurements, three important conclusions reflecting the implementation of the game have been drawn. First, the channel gain Kalman predictor approach is more suitable for the power allocation game because it compensates for the measurement errors to which the instantaneous gain is prone, while also relying on measurement history. Second, the Kalman filter based estimations of the gain are more accurate than the average. This is supported by the smaller values of the mean square error between the Kalman estimations and the instantaneous value (K–inst) than the values of the mean square error between average and instantaneous values (avg–inst) as listed in Table I. Third, we noticed that using a shorter history for the Kalman predictor yields better results while also having some practical advantages as far as implementation is concerned. At the beginning of each experiment, the Kalman predictor is used with a history of 9 most recent measurements.

TABLE I
MEAN SQUARED ERROR FOR THE AVERAGE AND PREDICTED GAIN WITH RESPECT TO INSTANTANEOUS GAIN

MSE	Average gain (avg–inst)	Predicted gain (K–inst)
h_{11}	4.65×10^{-16}	2.14×10^{-16}
h_{12}	7.9×10^{-17}	1.59×10^{-17}
h_{21}	2.8×10^{-19}	2.55×10^{-19}
h_{22}	1.26×10^{-15}	8.11×10^{-16}

VI. Experimental results

A. On how the cost affects the best response of the players

The best response formula used for the empirical evaluation of the game is given in Eq. 3. The first term of the formula is the cost c_i whose role is to penalize the players for transmitting with high power. Fig.3a and Fig.3b depict the variation of the best response as a function of cost for average gains and different $I + n_0$. It can be seen that the value of the best response for both players decreases as the cost increases.

The feasible values of the cost also have to take into account the power levels supported by the testbed. In the case of LOG-a-TEC, the best response has to respect the lower boundary of -55 dBm and the upper boundary of 0 dBm. This constraint excludes a large set of low values of the cost. Additionally, the experiments have shown that a very high cost value prevents the game to converge to an equilibrium making the communication system unstable. This observation has led to putting a higher boundary on the cost value. In the worst case scenario observed during the experiments, when the $I + n_0$ is -84 dBm for the first player and -72 dBm for the second player, the feasible values for c_i lie in the $[1000; 4000]$ interval.

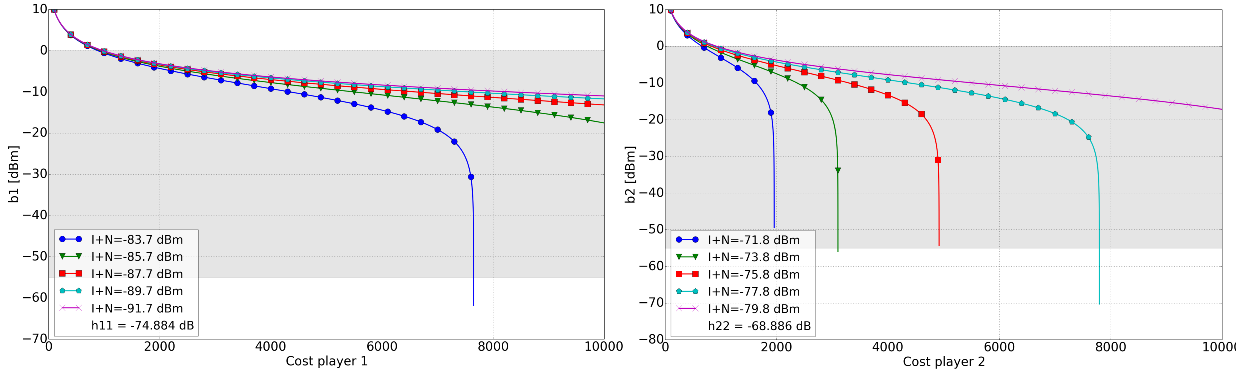
B. On how the gain affects the best response of the players

The gain is another of the parameters of the best response formula from Eq. 3 and the logarithmic representation of the dependency of $b_i(p_{-i})$ to h_{ii} is depicted in Fig.4a and Fig.4b. For a fixed cost of $c_i = 1000$ for both players and the worst case scenario where the values of $I + n_0$ are -88dBm for player 1 and -72dBm for player 2, it can be seen that the best response has high variations for small gains and negligible variations for high ones.

C. On the Nash Equilibrium

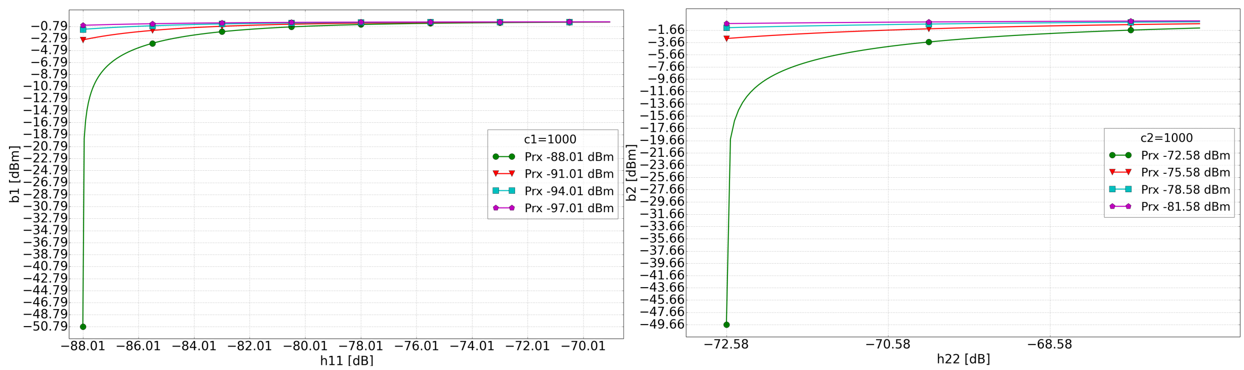
The existence of a Nash equilibrium for the PAPU algorithm has been proven in [15]. The simulated value of the Nash equilibrium for PAPU considering $c_i = 1000$ and average value of the gain is (-0.24, -1.25) represented as a green bullet in Fig.5a. By introducing more realistic gains based on the Kalman estimator, the simulated Nash equilibrium slightly varies around (-0.14, -1.1), as depicted with red triangles in Fig.5a. In this case the influence of the predicted gains to the player's final strategies is evident.

By running the game on the real–world testbed, the Nash equilibria are much more spread as shown with blue squares in Fig.5a, mostly due to interference and noise. It can be seen that the variation of the best response is relatively small with 0.3 dBm for Player 1 and 0.5 dBm for Player 2. In the first two cases where simulation was used, the Nash equilibrium results in a (0, -2) value. For the case of LOG-a-TEC, in the experimental setup, the multitude of Nash equilibria obtained in different runs, after being rounded to the discrete values



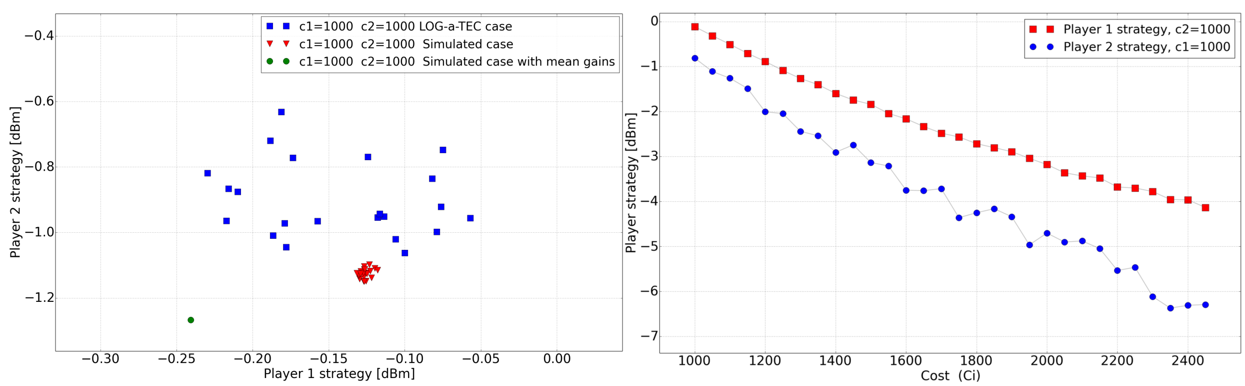
(a) $b_1(p_{-1})$ versus c_1 and $I + n_0$ (b) $b_2(p_{-2})$ versus c_2 and $I + n_0$

Fig. 3. The best response of Player 1 and Player 2 as function of each player's cost and of the interference plus noise level.



(a) $b_1(p_{-1})$ versus h_{11} and $I + n_0$ (b) $b_2(p_{-2})$ versus h_{22} and $I + n_0$

Fig. 4. The influence of the channel gains on the players' best responses.



(a) Experimental Nash equilibrium compared to simulated one for two players.

(b) Players' best response as function of players' costs.

Fig. 5. On the Nash equilibria and their values as according to different costs.

of the transmission power supported in LOG-a-TEC, are (0,0) and (0,-2).

Fig.5b depicts player strategies for different cost schemes. It can be seen that with the increase of the cost c_i, there is a decrease of the allocated powers as discussed in subsection VI-A. All the experiments were performed as following: the channel gains h_{ii} were computed at the beginning of each experiment by predicting the gain, interference and noise power levels. $I + n_0$, were measured and updated at each iteration, $k = \overline{0,4}$ and $P_{th} = 0.8$dBm. For Fig.5b, all the experiments were repeated 20 times and the Nash equilibrium are given as averaged values.

VII. Conclusion

In this paper we proposed a methodology for the experimental evaluation of a game theoretical framework for interference mitigation, particularly the ProActive Power Update algorithm, on the LOG-a-TEC low cost outdoor cognitive radio testbed. The theoretical framework was adapted considering the constraints of the testbed and the resulting framework was then implemented to run on the testbed and the experiments have been performed in the 2.4 GHz ISM band. This enabled the study the effects of the empirical parameter estimation on the best response and players' strategies which represent the Nash Equilibra. The results showed that for a certain cost range, the system can reach Nash equilibria. The equilibria and the convergence time are strongly influenced by the cost but also by the channel gains.

This work also shows that the implementation of a decentralized game theoretic power allocation algorithm on a low-cost testbed is possible and, most importantly, convergence to Nash equilibrium in a real world environment is achievable. Our experimental results may prove useful in developing new protocols in decentralized CR networks. Additionally, the current framework and implementation (openly available at https://github.com/sensorlab/logatec-games) can be used for future work such as evaluating the framework under dynamic cost conditions.

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