

# Strategy theory methods for resource distribution optimizing in internet of things

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**Abstract.** In a Semantic Network where in new and old users coexist, an optimizing resource distribution method represents one of the most important key ideas. This paper provides a new method based on a strategy theory framework to solve Resource Distribution Optimizing in a new way. Formulated as an optimal problem, the resource distribution problem between old users and new users can be modeled and studied with the Strategy Theory, and in particular Blocking Strategy, since they provide useful tools for the definition of multi-factor optimal solution methods in the context of Internet of Things. This paper also provides a performance contrast among the proposed strategy and two other algorithms, frequently used in this context: Ordered state and Steady state.

**Key words.** Internet of Things, Resource Distribution, Strategy Theory, Multi-factor.

## 1. Introduction

In a Semantic Network, two kinds of users can exist: new (non-cognitive) users and old (cognitive) users. new users may be unaware of the presence of old users. Contrary to new users, old users are smart, since they are intelligent and interact with selfish network users, choosing best operating parameters on the base of the sensed spectrum. Due to the natural wireless environment changes, spectrum sharing schemes change frequently, accordingly with the users allocated resource. In this scenario, a strategy theoretic framework allows to study, model and analyze Internet of Things in a distributed way.

Strategy theory have been proposed for Internet of Things in [1], which reports a detailed survey on strategy theoretic method for dynamic spectrum sharing in Internet of Things, by in depth theoretic analysis and an overview of the most recent practical implementations. In [2], the authors investigate the issue about the spec-

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<sup>1</sup>Acknowledgement - This study is supported by the Xi'an Social Science Plan project (16WL12).

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trum sharing between a Resource Distribution network and a new system, comparing a suboptimal distributed strategy theory theoretic resource control algorithm with the optimal solution resource control algorithm and the Strategy Theoretic Analysis proposed in [3]. Besides the above referred papers, in [4] and [5] it is also discussed the Data Stream Methods in spectrum sharing model. In [6,7] authors proposed different strategy-theoretic method to Optimizing Resource Control within wireless networks, making the utility functions being inversely proportional to the transmit resource.

This paper extends the above described results providing a distributed strategy-theoretic method to obtain a quasi-optimal resource distribution method that maximize the resource efficiency of each user, within the coexistence of new and old users. The proposed method takes into account throughput fairness among old users.

## 2. System Model

In this work we consider a Cognitive Wireless context inspired by a tactical/military scenario where a new system (owner of the spectrum rights) coexisting with one or more old systems and sharing the same frequency band. It is to be noted that such kind of context is a suggested scenario by EDA and NATO [8] to provide a better reuse of the frequency resource among several nations (coexistence of networks) and give a great help to accommodate dynamism of the operational deployments. Note that, considering a new system in the network, the proposed scheme includes the possibility to existence of more than one new user.

In the proposed system, each user is characterized by a dedicated sender and receiver, thus each communicating couple consists of a transmitter site and a receiver site. In the most general context, in this work we consider the transmitters and the receiver positions completely independent the ones from the others. Moreover, we use a discrete-time model, based on steps. Indeed, all users act only once and until the next step they can't do anything else. Each user broadcast a pilot signals at the first step of the algorithm in order estimate the channel gain optimizing, that are assumed not changing during the execution of the algorithm.

However, by definition, new users should not undergo a degradation of the required QoS due to the presence of old users. Therefore, we propose the following the solution: the new AP selects and broadcasts periodically on the shared channel a reasonable interference cap on the total interference it willing to tolerate. Together with the interference cap, the value of the total interference received by the new receiver is transmitted. Thanks to this solution, we introduce a sort of "indirect" unaware cooperation among the two kinds of users. The direct result of the introduction of a chosen interference cap is a limitation of the total transmitting resource of the old

users on the shared channel. Thanks to the introduction of the interference cap, for the simplicity of exposition, hereinafter we will consider only one new transmitter-receiver pair, since the proposed scheme can be easily extended to include more than one new user.

Due to the consistent decisions made by new and old users, strategy theory

represents an inbred framework to study, analyze and predict the behavior of this system. For simplicity of exposition, we will consider a fixed new interference cap and therefore a fixed maximum transmission resource for the old users; this assumption can be made without altering the validity of the system, since variations of this value are relatively slow compared with the time of convergence of the algorithm.

### 3. The Proposed Strategy

#### 3.1. Strategy Description

The strategy theory proposed in this paper can be modeled as strategy with  $N$  old users, namely the players of the strategy, operating on one wireless resource. This strategy can be easily extended considering  $M$  wireless resources (i.e. subcarriers of the same multi-carrier channel or different channels) following the method proposed in [8], where subcarrier distribution is based on the normalized channel gain. Formally, the proposed strategy theory can be modeled as follows:

Set of Players:  $N = \{1, 2, 3, \dots, N\}$  where  $i \in N$  is the  $i$ -th old user.

Set of Strategies:  $S = \{P_{\min}, \dots, P_{\max}\}$ .

Utility function:  $u_i(P)$  where  $i \in N$  is the  $i$ -th old user.

Following the method proposed by [8], we take into account the resource efficiency problem at the physical layer, considering a utility function expressed in bit/Joule as performance measure of the model. Each player tries to maximize the following utility function:

$$u_i(p(t), p(t-1)) = W \frac{R_i f(\gamma_i)}{p_i(t)} - \Omega(p(t-1)) p_i(t) \quad (1)$$

where  $p$  is the complete set of strategies of all old users,  $W$  is the ratio between the number of information bits per packet and the number of bits per packet,  $R_i$  is the transmission rate of the  $i$ -th user in bits/sec,  $f(\gamma_i)$  is the efficiency function, that represents a stochastic modeling of the number of bits that are successfully received for each unit of resource drained from the battery for the transmission.

Thanks to the efficiency function, the utility function each user tries to maximize is related to its instantaneous signal to noise plus interference ratio (SINR), defined as:

$$\gamma_{i,c}(t) = 10 \log \left( \frac{g_{i,i} p_i(t)}{I_i^r(p_{-i}(t-1), p)} \right) \quad (2)$$

where with the notation we refer to all components of  $p$  not belonging to user  $i$ ,  $p_{-i}$  is the resource allocated from the old transmitter  $i(TX_i)$   $g_{j,i}$  is the path gain from  $TX_j$  to  $RX_i$ ,  $g_{12,i}$  is the interference channel from the new to the old receiver  $RX_i$ ,  $p_i$  is the new transmitted resource, while  $\sigma^2$  is the AWGN component at  $RX_i$ .  $I_i^r(p_{-i}(t-1), P)$  represents the total interference received by the  $i$ -th user and it can be written as:

$$I_i^r(p_{-i}(t-1), P) = \sum_{k \neq i} g_{k,i} p_k(t-1) + \sigma^2 + g_{12,i} P \quad (3)$$

The path gain can be written as:

$$g_{i,j} = \frac{K}{\left[ (x_i - x_j)^2 + (y_i - y_j)^2 \right]^d} \quad (4)$$

Where  $K=0.097$  and  $d=4$ .

The adopted channel model is composed by a small scale fading and a path-loss component. In particular, the path-loss model is the Okomura-Hata model, while the small scale fading is modeled as a Rayleigh process.

Since the above defined utility function depends on the path gains, each old user need to know it. In order to solve this problem that could have a strong impact on the signaling process, we assume that each receiver periodically send out a beacon, thanks to which transmitters can measure path gains.

In order to make the NE of the strategy as optimizing as possible (moving it to the Pareto Optimum), we consider the adaptive pricing function that generates pricing values basing on the interference generated by network users. Thus, users that cause high interference transmitting at high resource will obtain high value of pricing, due to the fact that  $\Omega(p)$  is strictly increasing with  $p$ . The pricing function  $\Omega_i(p_{i,-i})$  is written as follows:

$$\Omega_i(p(t-1)) = \beta - \delta \exp \left( -\mu \frac{p_i(t-1) \sum_{i=1, k \neq i}^N g_{k,i}}{I_i^r(p_{-i}(t-1), P)} \right) \quad (5)$$

Where:

$\beta > 1$  is the maximum pricing value,

$\delta > 1$  is the price weight of the generated interference,

$\mu > 1$  is the sensitivity of the users to interference.

These three parameters are very useful to adapt the pricing function to the considered wireless network requirements; i.e. we can make the algorithm converge faster decreasing the value of or force all old users to transmit at lower resource levels increasing their sensitivity..

### 3.2. Existence and uniqueness of ne

A stable outcome can be offered and can be guaranteed to exist, under certain conditions, but does not necessarily mean the best payoff for all the players involved, especially in presence of pricing techniques. In the literature there are lots of mathematical methods to demonstrate the existence and uniqueness of NE, like graphical, quasi-concavity curve and super-modularity [6].

Super-modular Strategy is an interesting class of strategy that exhibits strategic complementation. There are several compelling reasons like existence of pure strategy Nash equilibrium, dominance resolvability, identical bounds on joint strategy

space etc. that make them a strong candidate for resource distribution modeling. Super-modular strategy is based on the concept of “super-modularity”, which is used in the social sciences to analyze how one agent’s decision affects the incentives of others.

S-Strategy is normal form strategy  $\Gamma = \langle N, S, \{f_i\} \rangle$  where  $N$  is the set of users,  $S$  the strategy space,  $f_i$  the set of utility functions and  $\forall i \in N$  these  $S_i$  conditions are satisfied:

- 1) The strategy space of user  $i$  is a complete lattice.  $S$
- 2)  $f_i$  is super-modular in  $s_i$ .
- 3)  $f_i$  presents increasing differences in  $s$ .

The proposed utility function in Equation (1) can be easily demonstrated to be super-modular, since:

- 1) The strategy space  $P$  is a complete lattice;

$$2) \frac{\partial^2 u_i(p)}{\partial p_i \partial p_j} \geq 0 \quad (6)$$

For  $p \in P$  all and  $i \neq j$ .

- 3) The utility function has the increasing difference property.

For the details of proofs we refer to [8], under the proposed conditions. Uniqueness of the NE can be also demonstrated following the same method, since we use a Best Response rule. Even if our proposed pricing function  $\Omega(p(t), p(t-1))$  is more complicated, in  $p(t)$  contrast with the above cited work, the demonstration procedure does not change. Indeed, the pricing function can be considered linear in  $p(t)$ , since the optimizing of  $p(t)$  at time  $t$  is a constant.

#### 4. Resource Optimizing Iterative Water-Filling Algorithm

Steady state is a frequently used algorithm in resource distribution methods. This algorithm is well-known in the literature that resource distribution in parallel uncoupled channels can follow the steady state principle in order to maximize data-rate. A channel can be filled by an amount of resource depending on the existing noise level. A multiuser scenario cannot be modeled as the parallel uncoupled channels case, but it has to be modeled following the method of an interference channels. On the base of these considerations, an iterative steady state procedure can be obtained; each user updates its transmission resource level as follows:

$$P_i^{(t)} = \left( P_{\max}^{(t)} - \frac{\gamma_i(t)}{p_i(t)} \right)^+, \quad i = 1, \dots, N \quad (7)$$

Where  $P_i^{(t)}$  is the resource level assigned at the user in the step  $i$  and  $P_{\max}$  is maximum resource that can be transmitted in the channel (the water level).

Because of  $a^+ = \max\{0, a\}$ , if  $\frac{\gamma_i(t)}{p_i(t)} > P_{\max}$ , then  $P_i^{(t)} = 0$  is assigned to the user  $i$ . Iterative Water-Filling gets excellent performances in presence of low interference environments and/or limited number of users. However for increasing

values of interference, the algorithm get worst; indeed, users experimenting the best channel conditions will transmit at high resource levels, while users experimenting bad channel conditions (i.e. being the receiver close to another transmitter) will receive high interference values and then they will be inactivated. For this reason, EEIWF turns out to be unfair.

For a fixed target data-rate, we can identify a minimum target value for the SINR. In this case, Iterative Water-Filling is resource optimizing, due to the fact that the algorithm tries to maximize the total transmission resource, achieving SINR values that are greater than the target value. For this reason, we propose the following resource optimizing modified version of the algorithm, called Resource Optimizing Iterative Water-Filling (EEIWF). For each step,  $P_{\max}$  is updated as follows:

$$\text{If } \text{SINR}^{(t)} - \text{SINR}^{(t-1)} \geq 0, P_{\max}^{(t)} = \frac{P_{\max}^{(t-1)}}{k}$$

$$\text{If } \text{SINR}^{(t)} - \text{SINR}^{(t-1)} < 0, P_{\max}^{(t)} = P_{\max}^{(t-1)}$$

Where  $k > 1$  represents the reduction factor and it controls the convergence speed of the algorithm. Note that for the algorithm,  $k = 2$  become the bisection method. Such method allows us to maintain the fixed data rate, using the lowest total transmission resource level, taking into account its trend in Figure 1.

In the case of number of user, the SINR trend for decreasing values of  $P_{\max}$  is a monotonous decreasing function. Otherwise, When ,  $N \geq 8$ , a reduction of  $P_{\max}$  should also improve SINR final value.

## 5. Simulation Results

In this paragraph we show the results of the simulations that we run in order to verify the behavior of a cognitive network based on our proposed strategy-theoretical framework. In the subsection 5.1 the convergence of the algorithm is shown, while in subsection 5.2 a contrast between proposed strategy and heuristic resource distributions will be presented.

### 5.1. Convergence of the Algorithm

The operating context is a terrain square area of 1 km edge, with a suburban path-loss profile. New transmitter and receiver positions are fixed; while the old receiver positions are placed randomly in a 200 m diameter circle around the respective transmitters. Each old user transmits uniformly with

$p_i \leq p_{\max}$ , here  $p_{\max} = 1$  dBm on the base of a fixed interference cap. Moreover, We consider a noise resource  $\sigma^2 = -10$  dBm, frequency  $f = 1$  Ghz,  $W = 4/5$  , a common rate  $R_i = 10^4$  bit/s,  $\beta = 10^4$ ,  $\delta = 10^4$  and  $\mu = 10^{-2}$ .

Results of a simulation with a new user and  $N = 5$  old users show a fast convergence of the transmitted resource levels and SINR experimented by old users. For increasing numbers of old users in the networks, the algorithm still maintains a very

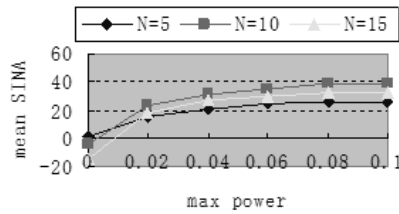


Fig. 1. SINR trends for increasing values of maximum transmission power for different number of users.

short time of convergence, in the particular case of very bad location of old users, a possible growth of the time convergence may be avoided decreasing the value of  $\delta$  parameter.

## 5.2. Performance Contrast

In order to obtain a qualitative evaluation of the proposed strategy, we decide to compare its performance with both EEIWF and an optimal centralized heuristic resource distribution system, like Ordered State (OS). The mean value of the SINR (experimented by old users) has been chosen as the performance index for the three optimal solution methods. We run the simulations for increasing number of old users, while all the other parameters of the system remain the same of the previous shown configuration. The simulation results show clearly that the OS and the proposed strategy have quite the same performance, since the maximum difference between the mean value of the SINR obtained by the OS and the strategy is -3dB. On the other hand, Water-Filling obtains lower mean SINR levels and performance worsens for increasing number of users in the network.

In addition to the SINR, the resource efficiency of the three considered methods is another important key feature that we need to investigate. If the SINR performances are quite the same for the proposed strategy and the OS, on the contrary we can observe a great difference in terms of resource distributions. Indeed, Figure shows that, for a 15-user simulation, OS distribution uses approximately 80% of resource more than strategy distribution. For what concern the EEIWF, while some users are switched off, the others transmit at highest levels, compared with the other two proposed distributions. In the resource distribution of the proposed strategy is shown in purple, in yellow is reported the additional resource allocated by OS (with respect to strategy) and in blue the excess additional resource allocated by EEIWF (with respect to OS).

## 6. Concluding Remarks

In this paper we provide a resource optimizing strategy theoretic framework to solve the resource distribution problem in a cognitive network, wherein new and old

users coexist. The resource distribution problem is solved thanks to the application of Blocking Strategy. Transmission resource of old users is upper bounded by the interference cap, defined as the total interference that new users willing to tolerate, without losing their required QoS. Moreover, old users are discouraged to transmit at high resource levels, since they are charged on the base of the interference they generate, thanks to the introduction of a pricing function inside of the utility function. Tuning utility function parameters, the proposed strategy is able to adapt his performance (in terms of time of convergence) to every kind of network configuration. Indeed, simulation results show a fast convergence of the algorithm for any number of considered users in the cognitive network.

Simulation results show clearly that strategy theory obtains better performance than steady state and the proposed strategy converges to the same SINR values obtained from the heuristic optimal solution method.

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Received November 16, 2016