Task Allocation in Clusters of Cognitive Nodes: a Remuneration-aided Approach

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***Abstract*—In this work, we propose a remuneration-aided Game theoretical solution for task allocation in cognitive radio (CR) enabled Internet of things (IoT) scenarios, where cognitive nodes (CNs) in close proximity and with similar sensing capabilities are clustered around a cluster head (CH). We consider a framework in which task allocation in the system is driven by CNs with spectrum sensing capabilities. In the proposed approach, the CH assigns a remuneration to CNs for their contribution in spectrum sensing prior to initiating the task allocation procedure. Such remunerations can be used by CNs in proposing the bids to win the task in the Game. Hence a non-cooperative Game approach modelled as an auction process is proposed. We show that the proposed framework is able to exploit cognitive behaviour efficiently in conditions suitable for cognitive radios (low spectrum occupancy), and under the same conditions the overall system utility increases by 29% *w.r.t* the case when licensed users (LUs) occupy the band 70% of the time. Additionally, the framework allows the system to reap benefits of energy efficiency while experimenting cognitivity.**

***Index Terms*—IoT, Game theory, Cognitive Radio**

I. Introduction

The Internet of things (IoT) consists of objects that are characterised by limited resources such as sensors, personal electronics and smart vehicles. Hence, the performance of IoT objects is severely affected by the utilisation of resources. Inefficient resource management can cause undue depletion of available resources. This puts emphasis on a feasible solution of task allocation to available objects in IoT scenarios, so that resources can be shared in a collaborative manner to achieve a common objective, i.e., executing an IoT application [1].

In this regard, objects of similar capabilities can collaborate by forming clusters to provide services or improve data accuracy. Each cluster has a cluster head (CH) that acts as a gateway between the remote entities (e.g e-NodeB, eNB) and the local objects. When objects are located in vicinity of each other, they can establish device-to-device (D2D) communications to provide Proximity Services (ProSe), which can be managed by CH and require no intervention from eNB.

It is of great concern for spectrum regulatory authorities that IoT traffic is rapidly increasing, therefore it is necessary to regulate technologies like cognitive radio (CR), in order to ensure timely service delivery without leaving any radio footprints. It is estimated that, by 2020, more than 21 billion IoT objects will be in public-use, thus, demanding access to spectrum through existing network infrastructure [2]. CR is expected to reduce the spectrum congestion issues with licensed users (LUs) significantly by exploiting the spectrum white spaces in licensed spectrum.

In this work we consider a scenario where CR-enabled objects opportunistically take part in clusters and coordinate with other objects within the cluster for the provisioning of services to applications running on top of IoT. The CR technology helps the objects to locate spectrum white spaces in order to establish D2D links with the CH. The paper provides the following contributions:

- We propose a remuneration-aided Game theoretical framework to find the suitable executor of tasks;
- We show that the remuneration factor computed by CH for every CN can be used to win tasks by computing bid values as a result of Nash Equilibrium;
- We evaluate the performance of our proposed system in terms of energy consumption.

The paper is structured as follows: Section II discusses the related work. In section III we define the considered scenario. Section IV provides details about system modelling and proposed strategy, whereas section V presents the remunerations and Nash Equilibrium derivation. Section VI provides details about simulation setup and results. Finally, paper conclusion is drawn in section VII.

II. Related Work

Allocating the task to a suitable executor among several available executors is a critical issue that has been addressed extensively in Wireless Sensor Networks (WSN). The author in [3] studied resource allocation in WSN in order to prolong battery lifetime. A centralised algorithm for task allocation is proposed in [4], where a single/central node maintains a report on the devices' status in the network with the aim to reduce overall energy consumption in heterogeneous WSN.

On the other hand, IoT is based on WSN but the IoT scenario is different from most of WSN scenarios. This is mainly due to the fact that in IoT the requester/owner has complete control over objects, for instance the requester/owner can switch off/on the objects (e.g. mobile phones, iPads) depending on their personal needs. Also objects can be mobile, which causes frequent network variations and unreliable connections. For this reason, objects should be intelligent enough to adapt to changes in network composition. In this regard, [5] studies resource allocation for IoT applications where the aim is to find and allocate the resources to optimise service execution among objects. Nevertheless, there are only handful of works in literature that address the problem of finding the optimal resource allocation independently of the application assigned to the network. For instance, Pilloni *et al.* in [6] propose an IoT_Prose framework for IoT applications in D2D scenarios. A Game theoretical solution is derived around the utility function that allows individual objects to maximise their utility. The authors in [6] considered energy cost for repeated tasks where devices perform tasks repeatedly while waiting for the next task assignment from CH.

More recently, the CR technique has been considered for the realisation of IoT services. In this regard, [7] comprehensively studied the concept of CR technology in the perspective of Machine to Machine (M2M) IoT. Moreover, the authors conclude that cognitive M2M operations require an energy-efficient, reliable, and internet-enabled protocol stack with enabled intelligence from the physical layer to the transport layer. In [2] the authors emphasised the fact that IoT objects can be able to exploit spectrum resources effectively in a spectrum constrained world. Without cognitivity the IoT traffic will increase the load on the existing network infrastructure.

III. Considered Scenario

In this section, we first describe the considered scenario of opportunistic task allocation in the IoT. We then provide an overview of the adopted spectrum sensing technologies.

A. Opportunistic Task Allocation

The scenario considered in this paper is that of IoT objects that collaborate opportunistically in the execution of *sensing tasks*, to perform applications that rely on measured data, independently from the IoT platform they belong to [8]. Such an opportunistic behaviour among the objects allows their sensors to perform tasks for someone else (the application used by someone else) and report sensor data to remote databases on a best-effort basis, whenever conditions are suitable. In such a way, sensors functionalities can be hired by any application if it is keen on collaborating with other IoT infrastructures; with this approach there will be a direct welfare benefit for the overall community. Accordingly, the different IoT platforms, which may have a direct control of a varying number of physical and virtual objects, may share the knowledge about the physical world and allow the objects to share services with other groups of external collaborative objects.

Within this setting, we consider a scenario where CNs (either fixed or mobile) are sensor objects located in a geographical region; one of them is selected to act as CH because of extra functionalities (i.e. internet connectivity and computational resources) it possesses, as shown in Fig.1.

B. Usage of Spectrum Sensing

In the proposed system, cognitive radio is employed for the exploitation of the spectrum white spaces in licensed band for intra-cluster communication. Indeed, D2D operates in two modes defined by the standard: the D2D-direct, where devices communicate internally, and the eNB-assisted D2D, where

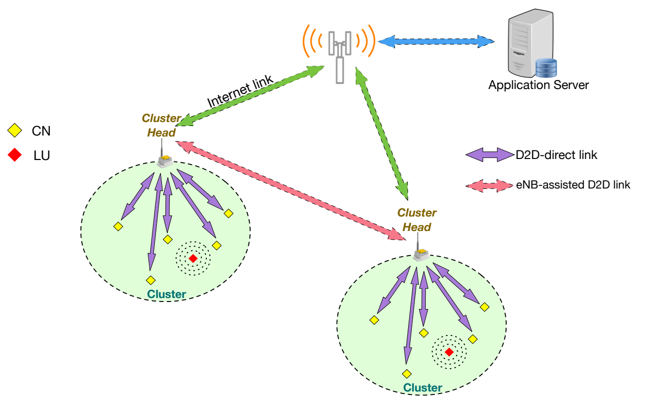

Fig. 1. Considered scenario of opportunistic CN collaboration, where the CH is the only object connected to external entities and coordinates the assignment of tasks to all the CNs

devices communicate externally with the help of the eNB [9]. In our scenario, we assume that intra-cluster communication (objects-CH) is D2D-direct, whereas inter-cluster communication (CH-CH) is eNB-assisted D2D. If LU activity is detected in the band, the CN delays the scheduling process or looks for other opportunities in other bands.

In this work, we consider the spectrum sensing based on energy detection because of its low complexity and simple implementation as it requires no prior information about LU signals [10]. In the following we provide mathematical formulation of the local probabilities of detection and false alarm as needed for the successful collaborative task allocation.

Every i-th CN is able to receive signal $y_i(n)$ as

$$y_i(n) = s_i(n) + w_i(n), \qquad n = 1, 2, \cdots, N \tag{1}$$

where $s_i(n)$ is the LU signal at the i-th CN with variance $\sigma^2_{s,i}$, $w_i(n)$ is the additive white Gaussian noise (AWGN) with zero-mean and $\sigma^2_{n,i}$ variance, and N is the time-bandwidth component. We assume that all CNs in a cluster collect N samples in order to perform spectrum sensing. Therefore, the sensing signal-to-noise ratio (SNR) γ_i at i-th CN, in AWGN-only environment, is $\gamma_i = \sigma^2_{s,i}/\sigma^2_{n,i}$. The energy detector calculates the metric ξ_i, a soft information, by accumulating N samples,

$$\xi_i = \textstyle\sum_{n=1}^{N} |y_i(n)|^2 \tag{2}$$

The CNs then communicate this soft information to CH that evaluates the performance of each of the CNs by computing the local probabilities of detection (P_d) and false alarm (P_{fa}) in the operating channel environment (AWGN or fading channel) [10]. The P_d is about making a correct assumption about occupied spectrum band. For the improvement of the overall system, the aim of every CN is to detect the band activity with increased P_d while minimizing P_{fa} that is considered as liability in spectrum sensing topics. After estimating the noise variance $\sigma_{n,i}$ under AWGN channel conditions, the CH calculates the probabilities for the i-th CN as [11]

$$P_d^i = (\xi_i \geq \zeta_i | \Lambda_1) = Q\left(\frac{\zeta_i - N\sigma^2_{n,i}\left(\gamma_i + 1\right)}{\sqrt{N}\sigma^2_{n,i}\left(\gamma_i + 1\right)}\right), \tag{3}$$

and

$$P_{fa}^i = (\xi_i \geq \zeta_i | \Lambda_0) = Q\left(\frac{\zeta_i - N\sigma_{n,i}^2}{\sqrt{N}\sigma_{n,i}^2}\right) \quad (4)$$

where Λ_1 and Λ_0 refer respectively to the presence and absence of a LU in the spectrum band, $Q(\cdot)$ is the Q-function [11] and ζ_i is the threshold set by the spectrum sensing. We can clearly see in (3) and (4) that the performance of energy detector on correct detection of LU is highly influenced by sensing SNR γ_i. Because CNs are dispersed over geographical locations, it is highly likely that each CN is experiencing different sensing SNR values. With this assumption, the CH is able to differentiate individual performance, and remunerations are distributed.

One can deduce that at high γ_i the CN increases the chance of detecting the LU activity with high P_d^i while keeping the threshold ζ_i fixed. The threshold ζ_i can be computed by fixing the P_{fa} in (4) as

$$\zeta_i = N\sigma_{n,i}^2\left(\frac{Q^{-1}\left(P_{fa}^i\right)}{\sqrt{N}} + 1\right) \quad (5)$$

The CH decides about the band, after collecting all the information from CNs, with the help of AND/OR/Majority rule, and computes global probability of detection P_D and false alarm rate P_F.

IV. Remuneration-aided Task Allocation

In the considered scenario N_c is the number of CNs that operate under a CH connected to the application server via Internet, as illustrated in Fig 1. As can be seen in Fig 1, the CH has multiple roles: firstly, it is an interface between the CNs and the application server; and secondly, as a head of cluster for distribution of the tasks among the CNs and providing rewards against every service provided by the CNs. The CNs perform spectrum sensing operations, and report them to the CH via low-rate lossless dedicated control channels. We consider that the CH takes the final decision about the band with the help of AND-rule. After successfully detecting the white space in spectrum, the CH initiates the task allocation among the CNs taking into account their initial battery life of E_β before the k-th task. We consider a D2D communication between CNs and the CH as there is no central entity responsible for scheduling the radio resources. After successful task execution, the CNs go back to idle mode where we assume that energy consumption is negligible.

A. Proposed Strategy

Based on the system model described above, we assume that an update-request, coming from an application server, is to be considered as a separate task that a CN would have to compete for to have it assigned.

The two main operations involved in the proposed framework are spectrum sensing and task allocation. Moreover, the CNs can increase their utility function by getting a:

- *Remuneration factor* ς_k, as a result of sensing the spectrum with high certainty before competing for task k,
- *Reward* b_k, as a result of performing task k, which is assigned to a CN in the cluster.

Because spectrum sensing is performed before every k-th task allocation, the remunerations obtained as a result of spectrum sensing plays an important role in setting up the bid values for every CN. For that reason, we call the proposed strategy a remunerations-aided strategy. The remuneration is a function of the performance of spectrum sensing. During spectrum sensing, after collecting the reports (information) from the CNs, the CH decides (free or occupied) about the spectrum through information fusion using AND-rule.

A bidding process among the CNs is followed to identify the winner of assignment of the task advertised by the CH. A rational bid value b_k by each of the CNs to win the k-th task are computed considering the amount of energy each CN would need to perform the task and the remuneration ς_k earned in the spectrum sensing. The CN with the lowest bid value wins the competition, and gets the reward after performing the task. According to the reward and energy consumed, the winner CN calculates its utility value. We formulate the CN's utility function based on the aforementioned considerations

$$H(b_{k,i}) = \Psi(b_{k,i})\left(\varsigma_{k,i}b_{k,i} - \alpha\frac{1}{\chi_{k,i}}\right) \quad (6)$$

where $\Psi(b_{k,i})$ is the probability that CN i wins the competition for task k by proposing bid $b_{k,i}$, $\varsigma_{k,i}$ is the remuneration factor for CN i as a result of sensing the spectrum prior to task k, α is the weighing factor associated with the residual energy cost and $1/\chi_{k,i}$ is the cost associated with the residual energy level if CN i wins to perform task k. More explicitly, the cost $1/\chi_{k,i}$ is minimum for the CN with maximum residual energy after executing task k. From (6) it can be learnt that, on average, CN i is able to win task k if it proposes bid value $b_{k,i}$ having obtained spectrum sensing remuneration $\varsigma_{k,i}$, provided that the residual energy is $\chi_{k,i}$.

The reliability of the CNs can be judged based on the their performance in spectrum sensing, which eventually decides the overall reward for the winning CN. For this reason, the final reward, $\varsigma_{k,i} \cdot b_{k,i}$, to be given to CN i is considered in (6). The process of computing the remuneration factor for the CNs in spectrum sensing depends on how efficient the CNs are at sensing the spectrum (increasing the reliability) [12].

The residual energy level $\chi_{k,i}$ is given as,

$$\chi_{k,i} = E_\beta^i - (1 - P_e)E_{tx}^i \quad (7)$$

where E_{tx}^i is the energy required by the i-th CN to deliver the service to the CH. The formulation of E_{tx}^i is inspired by a water-filling approach studied in [13] where the energy dissipated in circuitry E_c, and the energy required to cancel out the fading attenuation are considered as $E_{tx}^i = E_c + E_{nf}/h_i$, where h_i is the exponentially distributed channel gain between CN i and the CH, and E_{nf} is the energy required by the CN to transmit a single packet under no-fading condition. P_e is the probability of detecting the spectrum erroneously in (7). P_e can be computed as [14]

$$P_e = P_0 P_F + P_1(1 - P_D) \quad (8)$$

where P_F and P_D are the global probability of false alarm and detection respectively, computed by the CH after fusing the spectrum sensing information shared by the CNs. The CH then authorizes the winning CN by allowing it to carry out task execution utilizing the detected spectrum white space with probabilities P_F and P_D. The timeline of the process is shown in Fig. 2. P_0 is the probability that a LU is not present in the spectrum band otherwise $P_1 = 1 - P_0$. The second term in (7) explains the fact that if CNs are unable to detect the spectrum correctly (i.e., $P_e = 1$), the CH would raise the red flag by communicating the P_e with CNs, thus denying CN from transmitting. In the upcoming section, we derive the Nash Equilibrium Point (NEP) using (6) for our proposed scenario.

V. Cognitive Node (CN) Remuneration and the Nash Equilibrium Point

In this section, we describe the methodology for computing the remuneration factor for spectrum sensing activity. We, then, derive the Nash Equilibrium Point in the non-cooperative game in the context of proposed scenario.

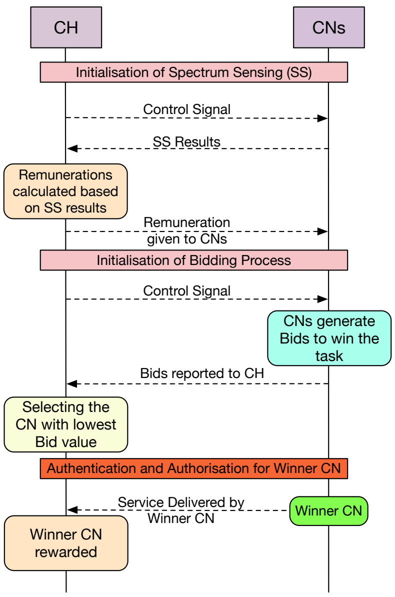

Fig. 2. The timeline of messages exchanged between CH and CNs for the considered scenario

A. Cognitive Node (CN) Remuneration

At first, the CH signals the CNs over control signalling channel in the cluster to perform spectrum sensing in the spectrum band chosen by CH prior to bidding for task. CNs start the spectrum sensing operation using energy detection and send the soft information ξ about the band to CH after every spectrum sensing operation. CH computes the P_d^i for every reporting CN, and combines the information coming from CNs with the help of adopted AND-rule fusion. Once CH takes the decision about spectrum band, it then calculates the global P_D and P_F, and gives the remunerations to CNs together with P_D and P_F, as shown in Fig. 2. Similar to [12], we define a metric based on reduction of uncertainty about LU by sensing the spectrum band. The information about the uncertainty of LU activity in spectrum band can be modelled with the help of binary entropy function. The remuneration factor ς_i as a function of local P_d of i-th CN can be obtained as before any task,

$$\varsigma_i = 1 - \left[-P_d^i \log_2\left(P_d^i\right) - \left(1 - P_d^i\right)\log_2\left(1 - P_d^i\right)\right] \quad (9)$$

Using (9) we obtain the plot depicted in Fig. 3 where we define two regions: when LU is present, and when LU is not present. Each of these regions can be hypothesized after CH combines the information from CNs. If the final decision rules in the favour of presence of LU in the band, the CH communicates with CNs about the final decision and allows them to sense other spectrum bands. Furthermore, the CNs are getting remunerations if they detect the activity with high $P_d > 0.5$. On the other hand, CNs get remunerations for detecting the white spaces with P_d lower than 0.5 provided that LU is legitimately absent in the band. It is worth noticing in Fig. 3 that if CNs are observing the spectrum with P_d = 0.5, the remunerations will be zero. This is because, the uncertainty caused by the spectrum sensing is high at P_d = 0.5, thus making it almost impossible for CH to decide (free or occupied) about the spectrum.

After each CN calculates the energy ξ using (2), the CNs send soft information regarding the band to CH. With the help of estimated noise, the CH calculates the γ_i for each of the CNs followed by the calculations of P_d for every CN with the help of Fig. 4. The CH takes the final decision by calculating global P_D and P_F, and based on that decision remunerations are given to CNs, as shown in Fig. 3.

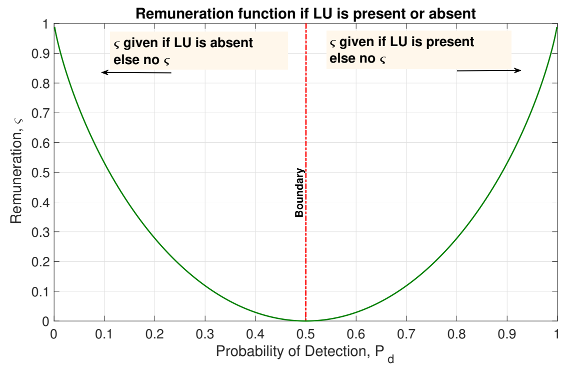

Fig. 3. Remunerations given as a function of local probability of detection P_d. A boundary is drawn to separate the cases of present and absent LU

In case of successful detection of spectrum white space, CH then proceeds with task allocation, in which a Game theory approach is considered. Since the objective of every CN is to maximize its own utility function, a Nash equilibrium point (NEP) exists that we derived for every CN in the system considering remuneration factor obtained in spectrum sensing.

B. The Nash Equilibrium Point

Before initializing the Game, each CN waits for the CH to initiate the task allocation process. Recall that in this regard,

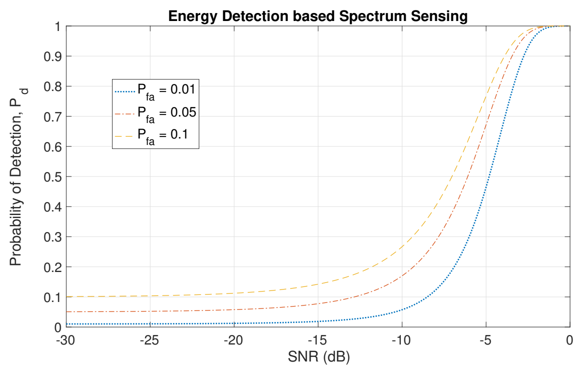

Fig. 4. CN-specific SNR values are translated to probability of detection for fixed probability of false alarm values

every CN in the cluster generates a bid whenever a competition is initiated by the CH for each task k. Since each CN behaves as any other, we assume that the bids are all distributed according to pdf $f(\cdot)$ and cdf $F(\cdot)$. Hence the probability for CN i to win the Game for task k is given by:

$$\Psi(b_{k,i}) = (1 - F(b_{k,i}))^{N-1} \quad (10)$$

To compute its utility function and generate the bid, each CN needs to know the value of this probability. Accordingly, each CN estimates $f(\cdot)$ dynamically, by computing the average μ and variance σ from past observations. In this paper we define the CN utility function for non-repeated task execution in a *cognitive* IoT scenario. More precisely, the considered approach is applicable to the energy-saving scenario where a winner CN goes back to idle mode (low power mode) to save energy after delivering the update to the application server. To win the Game, each CN i tries to propose the lowest bid $b_{k,i}$

$$b_{k,i} = min\left\{b_{k,1}, b_{k,2}, \cdots, b_{k,N}\right\} \quad (11)$$

The aim of proposed strategy is to find a rational bid value for each CN so that the overall system utility is maximized. Such a Game can be regarded as non-cooperative, where every CN is interested to maximize its own utility function, and can be modelled using a Nash Game [15]. The formulation of $\Psi(b_{k,i})$ in (6) can be characterized as

$$\Psi(b_{k,i}) = P(b_{k,j} > b_{k,i}), \forall j \neq i \quad (12)$$

Because every CN is calculating bids independently and in a non-cooperative fashion, $\Psi(b_{k,i})$ can be written as

$$\Psi(b_{k,i}) = P(b_{k,1} > b_{k,i}) \times \cdots \times P(b_{k,N} > b_{k,i}) \quad (13)$$

Moreover,

$$\Psi(b_{k,i}) = (1 - P(b_{k,1} \leq b_{k,i})) \times \cdots \times (1 - P(b_{k,N} \leq b_{k,i})) \quad (14)$$

It is evident now that (14) is equivalent to (10). Substituting (10) in (6) and we have

$$H(b_{k,i}) = [(1 - F(b_{k,i}))^{N-1}] \left[\varsigma_{k,i} b_{k,i} - \alpha \frac{1}{\chi_{k,i}}\right] \quad (15)$$

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
N_c	10	# of scenarios	1000
Tasks	100	P_{fa}	0.01
P_1	0.3 & 0.7	Fusion Rule	AND-rule
α	5	λ	0.5
E_{nf}, *Joules*	1	γ, *dB*	[-30, 0]
E_β, *Joules*	[95, 100]	E_c, *Joules*	5
Channel Gain, h	exponentially distributed r.v.		

After some mathematical manipulation, (15) can be solved and final result can be given as

$$(1 - N)\frac{\partial\left(1 - e^{-\lambda b_{k,i}}\right)}{\partial b_{k,i}}\left(\varsigma_{k,i} b_{k,i} - \alpha\frac{1}{\chi_{k,i}}\right) + \left(1 - \left(1 - e^{-\lambda b_{k,i}}\right)\right) = 0 \quad (16)$$

To further simplify (16) we get

$$(1 - N)\left(\lambda e^{-\lambda b_{k,i}}\right)\left(\varsigma_{k,i} b_{k,i} - \alpha\frac{1}{\chi_{k,i}}\right) + e^{-\lambda b_{k,i}} = 0 \quad (17)$$

Solving (17) we find the rational bid values for every CN in such a way that NEP can be obtained in the game where no CN can unilaterally deviate to maximize its own incentive.

VI. SIMULATION RESULTS

Extensive simulations have been performed in MATLAB. Table I lists all the parameters that are considered in the simulations. The energy parameters E_c and E_{nf} are normalized w.r.t E_β [13]. We also consider that CH calculates P_D and P_F using pre-defined fusion rule after collecting all the information from CNs. Because some parameters are initialized randomly, we averaged 1000 scenarios in order to clear the randomness out of the system.

Since the system relies on cognitive radio, which helps CNs to exploit licensed spectrum without causing harmful interference to LU, we evaluate the performance in terms of spectrum occupancy. We can see in Fig. 5 that when spectrum band is free most of the time ($P_1 = 0.3$), a stiff contest in Game can be seen among the CNs by proposing low bid values (low price) to win the task. Such a stiff contest increases the overall system utility, justifiably shown in Fig. 6 where the system utility is superior for spectrum band that is less occupied by the LU. Moreover, energy cost is high when the spectrum is highly occupied, i.e. $P_1 = 0.7$, and hence, CNs seek high rewards for the task with time as seen in Fig. 5 where bid value reaches the maximum bid value of 2 for all the CNs before the 100th task.

We can notice from Fig. 7 that with more spectrum occupancy $P_1 = 0.7$ the network dies out quickly. This is mainly because when spectrum is occupied often by LU, the CN have to sense the spectrum frequently before proceeding to task allocation process. Until CNs have not finished the task, they would not go back to idle mode. As network dies out completely, system utility fails to increase any more from that

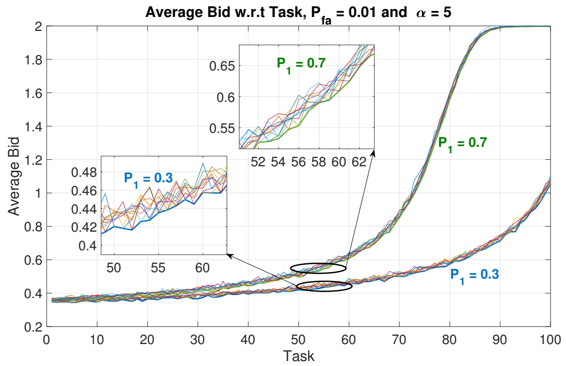

Fig. 5. Average Bid values w.r.t task at $P_{fa} = 0.01$ and α = 5, for different spectrum occupancy by LU. The bold lines represent the winning CN

point, as can be seen in Fig. 6 for $P_1 = 0.7$. Hence the system is able to perform better when the probability of LU occupying the spectrum is low because spectrum band is easily available for transmission and false decision probability is low as in (8).

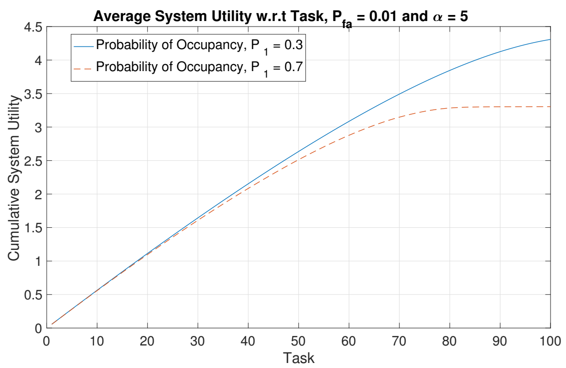

Fig. 6. Cumulative System Utility w.r.t task at $P_{fa} = 0.01$ and fixed α = 5, for different spectrum occupancy by LU

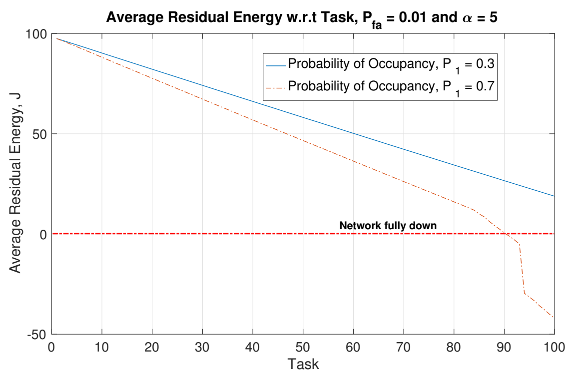

Fig. 7. Average Residual Energy w.r.t task at $P_{fa} = 0.01$ and fixed α = 5, for different spectrum occupancy by LU

VII. Conclusion

In this paper, we propose a framework for task allocation in cognitive IoT scenarios. We consider spectrum sensing to be performed prior to task allocation, for which remuneration factors are computed for every CN contributing in spectrum sensing. Cooperative spectrum sensing is implemented for such a scenario, whereas a non-cooperative Game is conceived for task allocation. We show that Nash equilibrium exists and CNs are able to optimize their system utility. Moreover, the propose framework is able to exploit cognitive behaviour under conditions that are conducive for cognitive radios (low spectrum occupancy). We observe a stiff contest between CNs for any given task-request from application server when LU is occupying the spectrum 30% of the time. This allows the increase in system utility by winning the rewards for execution of task, and makes the system more energy efficient as compared to the case when spectrum is 70% of the time occupied by LU.

Acknowledgment

This work was partially supported by the INSIEME MiSE project, H2020, PON 2014/2020 POS. 395, by the MIUR within the Smart Cities framework (Project CagliariPort2020, ID: SCN_00281) and by Fondazione di Sardegna (Project ODIS, CUP: F72F16003170002).

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