Application Task Allocation in Cognitive IoT: a Reward-Driven Game Theoretical Approach

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Abstract—In this study we consider the scenario of sensors belonging to different platforms and owned by different owners that join the efforts in an opportunistic way to improve the overall sensing capabilities in a given geographical area by forming clusters of nodes. The considered nodes have cognitive radio and exploit device-to-device communications. A solution is proposed which relies on a Cluster Head (CH) that guides the whole task allocation strategy. The addressed challenges are the following: i) collaborative spectrum sensing for effective communications within the cluster; ii) assignment of each request of sensing tasks to a single node in the cluster. The first challenge is addressed by proposing a collaborative sensing procedure where each node communicates to the CH the received signal energy of licensed users so that the latter makes a decision on the availability of the band by fusing the received information towards a minimisation of the uncertainty in detecting the free spectrum. The second challenge is addressed by proposing a non-cooperative Game theory based approach in which CNs make effort to selfishly increase utility by winning the task. Each node takes part to the competition by considering two elements: the gain that is won for its contribution to sensing and for the execution of the task (in case it wins the competition); the cost in terms of energy to be consumed in case the task is executed. A Nash Equilibrium Point (NEP) is found for the aforementioned game in which each object has no incentive to deviate uni-laterally from the NEP. Extensive simulations are performed to evaluate the impact of probability of false alarm, utility function weighting factors and presence of licensed users on the cumulative system utility.

Index Terms—Task allocation, IoT, Game theory, Spectrum Sensing.

I. Introduction

THE Internet of Things (IoT) is characterized by resource-constrained objects such as sensors, personal electronics and smart vehicles [2]. The way in which resources are used to perform IoT applications severely affects their performance. As a matter of fact, inefficient resource management can lead to an untimely depletion of available resources. For this reason, one of IoT's biggest challenges is the allocation of tasks to available objects so that they share their resources with the objective of collaboratively achieving a common goal, i.e., executing an IoT application [3].

Many IoT applications involve the pervasive aggregation of data from devices in order to manage the physical world. To this end, device-to-device (D2D) communication, which involves direct short-range communication between devices, is expected to play a key role by becoming an intrinsic part of the IoT [4]. In particular, D2D-based proximity services (ProSe) were specifically designed for local data exchange [5], especially in critical situations. In ProSe-enabled applications, devices that are located in vicinity of other devices form a cluster, and require no intervention from the central entity, i.e., the e-NodeB (eNB). D2D operates in two modes defined by the standard [6]: the first mode is D2D-direct, when devices communicate internally; the second mode is D2D-assisted by eNB, when devices communicate externally with the help from eNB. In this work, we focus on scenarios where IoT devices are leveraging D2D-direct, because of closed geographical location, for service provisioning. In order to maintain a hierarchy among the participants in the communication infrastructure, we allow nodes to take the charge of the cluster head (CH). The selection of the CH is done by the other nodes, i.e., the nodes elect the CH on the basis of having Internet connectivity that is required to forward the information to the application server. Indeed, the other nodes select the node as CH who takes responsibilities of performing extra functionalities (extraction of information from data sent by other nodes, Authentication and Authorisation of nodes, etc.). Moreover, we assume that the CH is acting as a gateway between the remote physical nodes and the application server as every request from the application server passes through the CH before reaching the devices. In this regard, allocating the task to a suitable executor among several available providers is a critical issue to address.

The task allocation issue has been extensively addressed in wireless sensor networks (WSNs) [7][8] and IoT [9][10][11], where limited resources represent a critical issue. Considering the specific case of location-based services such as ProSe, objects can coordinate their activities using short-range and D2D communications to share their available resources, and to cooperate to perform the assigned services [12][11]. More recently, cognitive radio techniques have been considered for the realization of ProSe [13][14]. Indeed, D2D terminals are expected to discover their peers, select spectrum, and schedule transmissions, thus enabling the development of distributed resource management mechanisms. Furthermore, the use of cognitive spectrum access in IoT would reduce the burden on the existing network infrastructure.

To the best of our knowledge, the task allocation problem has not been considered yet together with spectrum sensing

in IoT scenarios. Indeed, the potential of cognitive radio is enormous in IoT: we believe cognitive radio in the IoT perspective will add new dimension to the task allocation issue. Accordingly, in this paper we focus on the scenario where sensors (the cognitive nodes, CNs) belonging to different platforms and owned by different owners may join the efforts in an opportunistic way. In this respect, we contribute by designing a procedure that addresses the following two main problems: i) collaborative spectrum sensing for effective task allocation within the cluster of nodes; ii) assignment of each requested task to a single CN in the cluster exploiting the available spectrum for service provisioning. The contribution of the paper is the following:

- A procedure is devised for collaborative sensing to determine whether the spectrum is temporally free to be used by the cluster. To this, each CN communicates to the CH the received signal energy and the latter makes the final decision on the availability of the band by fusing the information shared by the CNs towards the minimisation of the uncertainty in detecting the free spectrum.
- A non-cooperative Game theory is proposed in which CNs make effort to selfishly increase utility by winning the task. This is achieved by making CNs bidding for the assignment following a non-cooperative Game theoretical approach. In the proposed strategy the CN proposing the lowest bid wins the competition. The devised solution ensures that no other CN would have had attained a utility higher than that of the winner for a such a low bid.
- Optimal bid values for individual CN are computed exploiting the Nash Equilibrium Point (NEP) for the aforementioned game, which ensures that each CN has no incentive to deviate uni-laterally from the NEP [15].
- A utility function is proposed, which relies on two elements: the gain that is won by the CN for its contribution to sensing and for the execution of the task (in case it wins the competition); the cost in terms of energy to be consumed by the winner for the task to be executed.
- The performance of our proposed framework is evaluated for IoT scenarios considering proper choice of system parameters involved in devising the solution for the task allocation problem.

The paper is structured as follows: Section II discusses the related works. Section III introduces the scenario considered in this work and describes the overall solution workflow. Section IV provides details about the collaborative spectrum sensing solution, whereas Section V describes the CN bidding solution. Section VI analyzes the computational complexity for the CNs to take part to this algorithm. Section VII provides details about simulation setup and results. Finally, paper conclusions are drawn in Section VIII.

II. PAST WORKS

The task allocation issue has been extensively addressed in WSNs. The author in [7] studied the application of market-based algorithms for energy management, resource allocation and task assignment in WSNs, considering the execution of multiple concurrent tasks at the same time. Multi-objective

optimization problems in WSNs are investigated by [8], where the authors compare a number of approaches focused on finding a trade-off amongst several different criteria, such as network lifetime, coverage and packet loss.

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 requesters/owners can switch off/on their objects (mobile phones, tablets, etc.) depending on their personal needs. Furthermore, objects' mobility affects the network topology, which dynamically changes over time. As a consequence, objects' connectivity becomes unreliable [11]. This requires a strong coordination among IoT objects, which have to dynamically adapt to network changes (i.e., objects leaving or joining) by updating task allocations accordingly. In this regard, [16] and [17] study the resource allocation for IoT applications where the aim is to find and allocate the resources in a way to optimize service execution among the IoT objects. Task allocation for resource usage optimisation in mobile cloud and edge computing is a crucial issue, as confirmed by numerous works, such as [9][18][19]. In particular, the cloud offloading policy is discussed with the aim of determining the cases where it is more convenient to use local resources or cloud resources. In [10], task assignment is performed also taking into account objects' trustworthiness. The proposed approach is based on an auctioning mechanism for multi-objective optimisation of system performance (more specifically mission reliability, utilisation variance and delay to task completion).

In a recent work [11], the IoT_Prose framework is proposed in order to exploit D2D communications among the nodes to implement IoT applications. A Game theoretical solution is proposed by defining a utility function that allows objects to maximise the utility of individual nodes. The authors in [11] considered a repeated task allocation problem where nodes are executing the "*won*" tasks repetitively together with the bidding for new ones, if the request comes in. In this case, it is obvious that nodes would deplete their energy bank quickly causing cutbacks in network lifetime. Moreover, a static spectrum allocation is considered by the authors. With respect to [11], our work can be regarded as step-ahead because of the following considerations:

- in this paper, a framework for cognitive-IoT systems is conceived, where task allocation is complemented with spectrum sensing;
- in contrast to the framework in [11], we consider non-repeated tasks in our framework, and hence energy consumption cost is re-formulated accordingly;
- a novel utility function for CNs is devised where reward is weighted with the remuneration factor ς_i for each CN i (related to SS), and cost is defined as the inverse of the residual energy.

Cognitive radio together with D2D is able to utilise resources efficiently and minimise the interference between D2D and cellular users when D2D users are operating in in-band mode [13]. In another work, [20] proposes a system architecture that makes use of cognitive radio capabilities in

order to enhance energy and spectral efficiency together with the provisioning of QoS (Quality of Service) to applications via software defined network (SDN) flows.

More recently, cognitive radio techniques are considered for the realisation of IoT services. In this regard, [14] comprehensively studied the concept of cognitive radio technology in the perspective of machine-to-machine (M2M) IoT. Moreover, the authors conclude that cognitive M2M operation requires an energy-efficient, reliable, and Internet-enabled protocol stack with enabled intelligence from physical layer to transport layer. In [21] the authors emphasise on the fact that IoT objects can be able to exploit spectrum resources effectively in spectrum constrained world.

III. REWARD-BASED STRATEGY FOR TASK ALLOCATION

In this section, firstly we describe the scenario of opportunistic task allocation in the IoT and the research problem addressed; secondly, we present the adopted system model and the proposed strategy.

A. Considered Scenario: Opportunistic Task Allocation

The IoT deployments can reach the highest societal impact only if the different platforms, services and devices can interoperate and share the available resources. In this case, the running applications can rely on the data sensed by any sensor whatever the platform it belongs to and can exploit services provided by any other deployed infrastructure. This interoperability can happen at different layers, from the application to the sensor level passing through the service and virtualisation layers. Herein, the scenario we consider is the one of opportunistic collaborative execution of *sensing tasks* at the sensors level with direct D2D communications [22]. Such an opportunistic behaviour among the nodes allows their sensors to perform tasks for someone else (the application used by someone else) and report sensor data to a remote database on a best-effort basis, whenever conditions are suitable. In such a way, sensors' functionalities can be hired by any application provided that different IoT infrastructures are keen on collaborating; 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 devices, 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 mobile sensor objects (*aka* nodes) are located (a fraction of them may be fixed) in a geographical region, out of which one node is acting as CH because of extra functionalities it possesses, as shown in Fig.1. In Fig.1, nodes of particular sensing capability are clustered under the same CH. The CH is unique with respect to the other nodes due to reliable direct Internet connection to the application server, and due to its role of distributing tasks among the nodes in the cluster. An exemplary case is the one of temperature sensing in a specific area, where the nodes with relevant capabilities are grouped and form a task cluster. Since each node of the task cluster
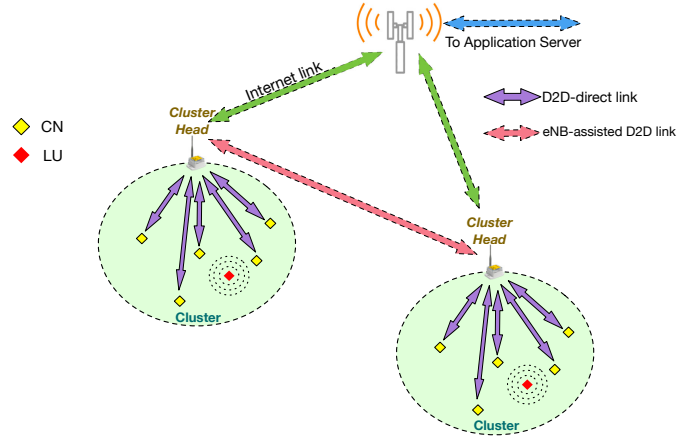

Fig. 1. Considered scenario of opportunistic nodes collaboration, where the CH is the only device connected to the Application Server via an internet link and coordinates the assignment of tasks to all the nodes

performs similar and replaceable tasks, one can regard the group of nodes as a stand-alone entity whose services can be hired by the application servers upon request sent to the CH. Usually, the CH is located in the vicinity of other nodes and easily accessible from the nodes that are located at short distances.

Moreover, we consider that nodes are equipped with cognitive radio functionalities, allowing them to sense the spectrum for possible exploitation of spectrum holes for transmission in licensed spectrum. The motivation behind the use of cognitive radios is arisen by the fact that in the future IoT traffic will skyrocket, and allotted spectrum together with ISM (Industrial, Scientific, Medical) bands might not be sufficient to accommodate the traffic while maintaining an adequate level of quality in device communications. Thus, a node with cognitive radio capabilities, namely a cognitive node (CN), is capable of using the spectrum without harming the licensed user (LU) transmissions with interference.

Whenever the CH receives the service request (which corresponds to a task to be executed by the cluster) from the application server, the CH sends a relevant control signal to the clustered CNs over a broadcast control channel to initiate the sensing of the spectrum. Upon successfully detecting the "*free*" spectrum space within the cluster, the CH triggers the distributed task allocation algorithm in the cluster to decide which CN should be selected to perform the task. For the sake of clarity, we list all the notations and acronyms used in this paper in Tab. I and Tab. II, respectively.

B. Research Problem

Within the scenario depicted above, we aim at designing a procedure that addresses the following two main problems:

- Collaborative spectrum sensing for effective task allocation within the cluster of CNs;
- Assignment of each requested task to a single CN in the cluster exploiting the available spectrum for service provisioning.

As to the first objective, the CNs observe on-going activities, if any, in the spectrum band to estimate whether it is tem-

TABLE I
TABLE OF NOTATIONS

Symbols	Description
σ_s^2	Variance of LU signal
σ_n^2	Variance of noise component
γ_i	Sensing signal to noise ratio at CN i
ξ_i	Energy calculated at CN i
ζ_i	Spectrum sensing threshold
$b_{k,i}$	Bid proposed to win task k by CN i
$\Psi(b_{k,i})$	Probability of winning the competition if $b_{k,i}$ is proposed by CN i for task k
ς_i	Remuneration obtained by CN i for sensing the spectrum
$\chi_{k,i}$	Residual energy as a result of winning task k by CN i
α	Residual energy cost weight
N_c	Number of CNs
N	Number of Samples to be sensed for spectrum sensing
y_i	Received signal at CN i
s	Noise-less LU signal
w	Noise component
P_{fa}^i	Probability of false alarm for CN i
P_d^i	Probability of detection for CN i
P_F	Global probability of false alarm
P_D	Global probability of detection
P_e	Probability of detecting the spectrum erroneously
E_β^i	Initial battery level
E_{nf}^i	Energy required to transmit a single packet in AWGN
h_i	Channel gain between CN i and the CH.

TABLE II
TABLE OF ACRONYMS

Acronyms	Meaning
CN	Cognitive Node
CH	Cluster Head
D2D	Device-to-Device
ProSe	Proximity Services
IoT	Internet of Things
LU	Licensed User
AS	Application Server
WSN	Wireless Sensor Network
SS	Spectrum Sensing

porarily free and can be used for the cluster task assignment operations. We generalise our approach w.r.t the band, which means that the proposed approach can be applied to any band that allows cognitive radio operations. To this, each CN in the cluster observes the band to estimate the received signal energy, if exists, and sends the information to the cluster head. The latter then makes the final decision on the availability of the band by fusing the information shared by the CNs towards the minimisation of the uncertainty in detecting the free spectrum.

The second objective is achieved through a non-cooperative Game theory in which CNs make effort to selfishly increase the utility by winning the task. The non-cooperative Game theoretical approach ensures that an optimal CN wins the task, at a given time, by proposing the lowest bid value in such a way that no other CN would have had attained a utility higher than that of the winner .

C. System Model

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. The CNs communicate with the CH through a wireless channel that is characterised by Rayleigh fading, for which the channel gain h follows an exponential distribution [23]. A CN can be termed as an entity capable of performing spectrum sensing as well as delivering the IoT-related services requested by the application server. As can be seen in Fig. 1, the CH has multiple roles: firstly, as an interface between the CNs and the application server; and secondly, as a head of a cluster for the distribution of the tasks among the CNs and providing rewards to them for every service provided. The tasks that are requested to the cluster are indexed with k.

We further assume that every CN, before joining the cluster, has an initial energy budget E_β^i that it is able to utilise to execute tasks. The communication between CNs and CH can be regarded as D2D communication as there is no central entity responsible for scheduling the radio resources. After successful task execution, the CN transmits the information regarding the performed service in the form of packets over the wireless channel at the expense of energy consumed; afterwards, the CNs go back in idle mode where we assume that energy consumption is negligible.

D. Proposed Strategy

In this subsection we describe the steps of the proposed strategy for task allocation in cognitive IoT environments. Because remunerations and rewards are involved in our system, we term the proposed strategy a reward-based strategy.

Based on the system model defined above, we assume that an update-request, coming from the application server, is sent to the CH to be assigned to one of the CNs of the reference cluster. The CH then signals to the CNs to perform spectrum sensing in the spectrum band chosen by the CH, which is the first phase depicted in Fig. 4 showing the messages that are exchanged between CH and CNs. These control signals are characterised as loss-less and low-rate signals with negligible implementation overhead on the system. This spectrum sensing operation is performed by CN i and the result is sent to the CH that then decides whether the spectrum has to be considered free or not. The details of this procedure are provided in the Section IV.

If the spectrum is considered free, the CH communicates this to the CN with some other parameters and this starts the bidding process. Each CN uses the information received to compute the bids and tries to win the competition for the assignment of the task advertised by the CH. Indeed, as already mentioned, in order for a CN to have this task assigned, it has to take part in a competition with the other CNs, by communicating a bid $b_{k,i}$ to the CH. The one with the lowest bid wins the competition, as the CH (and the overall system it represents) has the objective to keep the rewards to be given for each task allocation low. In our proposal, each CN takes a decision on the bid on the basis of a utility, which we have defined on the basis of the following two elements: the cost in terms of energy to be consumed by the winner for the task to be executed; the gain that is won by the CN for its contribution to sensing and for the execution of the task (in case it wins the competition). More details about the bidding process are provided in Section V.

IV. SPECTRUM SENSING PROCESS

In the proposed system, cognitive radios are employed for the exploitation of the spectrum white spaces in licensed bands for intra-cluster communication. If any LU activity is detected in the band, CNs delay the scheduling process or look for other opportunities in other bands.

Moreover, spectrum sensing based on energy detection is considered in this work because of its low complexity and simple implementation as it requires no prior information about LU signals [24]. In the following we provide a 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

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

where $s_i(n)$ is the LU signal at the i-th CN with variance $\sigma_{s,i}^2$, $w_i(n)$ is the additive white Gaussian noise (AWGN) with zero-mean and variance $\sigma_{n,i}^2$, and N is the time-frequency 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

$$\gamma_i = \frac{\sigma_{s,i}^2}{\sigma_{n,i}^2} \qquad (2)$$

It can be seen in (2) that each of the CNs is experiencing different γ_i that indicates the dispersed positions of CNs inside a cluster. The energy detector calculates the metric ξ_i, a soft information, by accumulating N samples,

$$\xi_i = \sum_{n=1}^{N} |y_i(n)|^2 \qquad (3)$$

The CNs then communicate this soft information to the CH that evaluates the performance of each CN i by computing the local probabilities of detection (P_d^i) and false alarm (P_{fa}^i) in the operating channel environment (AWGN or fading channel) [24]. As the P_d^i is about making a correct assumption about occupied spectrum band by LU, the aim of every CN is to detect the band activity with increased P_d^i while minimising P_{fa}^i that is considered as liability in spectrum sensing. After estimating the noise variance $\sigma_{n,i}^2$ under AWGN channel conditions, the CH calculates the probabilities for the i-th CN as [25]

$$P_d^i = (\xi_i \geq \zeta_i | \Lambda_1) = Q\left(\frac{\zeta_i - N\sigma_{n,i}^2 (\gamma_i + 1)}{\sqrt{N}\sigma_{n,i}^2 (\gamma_i + 1)} \right) \qquad (4)$$

and

$$P_{fa}^i = (\xi_i \geq \zeta_i | \Lambda_0) = Q\left(\frac{\zeta_i - N\sigma_{n,i}^2}{\sqrt{N}\sigma_{n,i}^2} \right) \qquad (5)$$

where

Λ_1 : LU is present in the spectrum band, $\sigma_{s,i}^2 > 0$,

Λ_0 : LU is absent, $\sigma_{s,i}^2 \approx 0$,

and $Q(\cdot)$ is the Q-function. We can clearly see in (4) and (5) that the performance of energy detector on correct detection of LUs is highly influenced by γ_i given in (2). One can deduce that at high γ_i the sensing node 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}^i in (5) as

$$Q^{-1}\left(P_{fa}^i\right) = \left(\frac{\zeta_i - N\sigma_{n,i}^2}{\sqrt{N}\sigma_{n,i}^2} \right) \qquad (6)$$

The CH then computes the global probabilities of detection and false alarm, respectively P_D and P_F, using a pre-defined fusion AND-rule by incorporating all the CNs' information. Accordingly, $P_D = \prod_{i=1}^{N_c} \left(P_d^i \right)$ and $P_F = \prod_{i=1}^{N_c} \left(P_{fa}^i \right)$. This information is used by the CH to evaluate the probability P_e of detecting the spectrum erroneously. Specifically, P_e is computed as

$$P_e = P_0 \cdot P_F + P_1 \cdot (1 - P_D) \qquad (7)$$

where P_0 is the a-priori probability that a LU is not present in the spectrum band, otherwise $P_1 = 1 - P_0$. The CH learns about P_0 from the past appearances of the LU in the band.

V. CLUSTER NODES BIDDING PROCESS

The previous Section described the overall system strategy. This Section defines and discusses the rationale for the CN bidding process. First, they key parameters that affect the choice on the bid value are defined in Subsection V-A. Accordingly, Subsection V-B introduces the CN utility function. Then, Subsection V-C explains how to find the optimal solution to maximise the overall system utility when selecting the CN to which task is assigned; this analysis justifies the adoption of a distributed approach, which is then explained in Subsection V-D.

A. Key Parameters for the Proposed Strategy

1) Residual Energy After Performing a Task: The cost of CN i to perform task k in case it wins the competition is in inverse proportion with its residual energy, once that it executes the task and transmits the result to the CH: the lower the residual energy after task k's execution, the higher the cost for CN i. Accordingly, the residual energy $\chi_{k,i}$ is given as

$$\chi_{k,i} = E_\beta^i - (1 - P_e) \cdot E_{tx}^{k,i} \qquad (8)$$

where $E_{tx}^{k,i}$ is the energy required by the i-th CN to deliver task k to the CH, and P_e is the probability of detecting the spectrum erroneously. The second term in Eq. (8) is the average transmission energy of the i-th CN when the spectrum is correctly detected with probability $1 - P_e$. The formulation of $E_{tx}^{k,i}$ is inspired by the water-filling approach studied in [23], where energy dissipated in circuitry E_c^i and energy required to cancel out the fading attenuation E_{nf}^i are considered as

$$E_{tx}^{k,i} = E_c^i + \frac{E_{nf}^i}{h_i} \qquad (9)$$

where h_i is the exponentially distributed channel gain between the i-th CN and the CH, and E_{nf}^i is the energy required by the CN to transmit a single packet under non-fading condition.

2) Remuneration Factor: As far as the remuneration factor ς_i is concerned, we rely on an approach similar to the one in [26] and we define a metric based on reduction of uncertainty about LU activity by sensing the spectrum band that can be modelled with the help of binary entropy function. The remuneration ς_i as a function of local P_d^i of i-th CN can be obtained as

$$\varsigma_i = 1 - \left[-P_d^i \log_2\left(P_d^i\right) - \left(1 - P_d^i\right) \log_2\left(1 - P_d^i\right) \right] \quad (10)$$

Using Eq. (10) we obtain the plot depicted in Fig. 2 where we define two regions: when an LU is present, and when LUs are not present. In case an LU is present in the reference band, the CNs get remunerations if they detect the activity with high $P_d^i > 0.5$. Furthermore, the CH communicates to the CNs to sense different spectrum bands in order to find the spectrum white spaces, and start the task allocation process. CNs get remunerations for detecting the white spaces with P_d^i lower than 0.5 provided that the LU is legitimately absent in the band. It is worth noticing in Fig. 2 that if the CNs are observing the spectrum with $P_d^i = 0.5$, the remuneration will be zero. This is because the uncertainty caused by the spectrum sensing is maximum at $P_d^i = 0.5$, thus making it almost impossible for the CH to decide (free or occupied) about the spectrum.

Example: In the following, we discuss an exemplary case where the CNs derive the probability of detection. Let's assume that N_c CNs are equipped with cognitive capabilities and the CH requests to them to perform spectrum sensing. For each CN, the SNR γ_i is assumed to be uniformly distributed between -30dB and 0dB. Because IoT transmissions are narrowband and only require small bandwidth portions to transmit, the energy detection based spectrum sensing operation suffices as it has low computational complexity and, is non-coherent. Moreover, it is well-suited for narrowband systems where noise estimation is possible. Fig. 3 evaluates the performance of the considered spectrum sensing technique for different P_{fa}^i values. Note that the value of P_{fa}^i to be considered by all the CNs (the same for all) is set and communicated by the CH.

After every CN in a cluster calculates the ξ_i and informs the CH, the CH then takes the decision by calculating P_d^i for every CN with the help of Fig 3. The computation of P_d^i follows Eq. (4) and needs only the knowledge of the SNR γ_i value. As defined by Eq. (3), the CNs accumulate N samples at a sampling rate of 125 kbps for a sensing time of 0.24 msec. The remuneration factor ς_i is then evaluated for every contributing CN based on their P_d^i values with the help of Eq. (10). Upon detecting the spectrum white spaces, the CH proceeds with the task allocation procedure, in which a Game theory based bidding process is considered. The CN utility function to be maximised by the bidding process is explained in the following subsection.

B. The Cluster Node Utility Function

Based on the strategy proposed in Section III-D and on the key parameters introduced in Section V-A, each CN evaluates the bid $b_{k,i}$ that maximises its own utility function. Indeed, the utility function $H_i(b_{k,i})$ expresses the trade-off for CN i
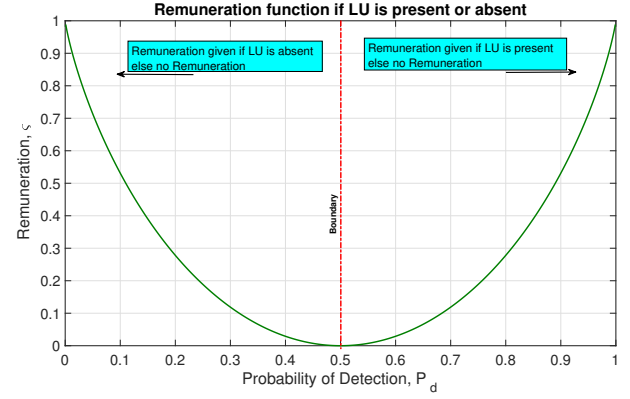

Fig. 2. Remunerations given as a function of local probability of detection P_d^i. A boundary is drawn that separates two cases: if an LU is present, and if LUs are absent
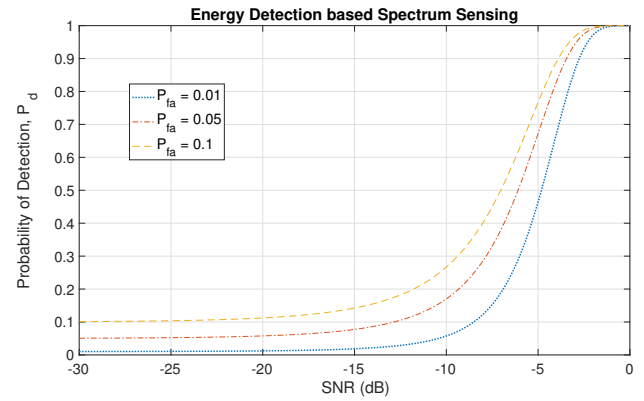

Fig. 3. Node-specific SNR values are translated to probability of detection for fixed probability of false alarm values. The data sampling rate is 125 kbps and the sensing time is 0.24 msec

between the cost of executing task k and the benefit of having a reward in return, while also taking into account that the higher the proposed bid the lower the probability to win the competition with the other CNs, since the winning CN is the one that proposes the lowest bid. Accordingly, the CN's utility function is defined as

$$H_i(b_{k,i}) = \Psi(b_{k,i}) \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right) \quad (11)$$

where $\Psi(b_{k,i})$ is the probability of winning the competition by the i-th CN for the k-th task by proposing the bid $b_{k,i}$, ς_i is the remuneration factor evaluated according to Eq. (10) as a result of sensing the spectrum, α is the weighing factor associated with residual energy cost and $1/\chi_{k,i}$ is the cost associated with the residual energy level, computed using Eq. (8), if the i-th CN wins to perform the k-th task. More explicitly, the cost $1/\chi_{k,i}$ is minimum for the CN with the maximum residual energy after executing the k-th task. The probability of winning the competition is included as it may drive the CN to increase the bid a bit (and gain more) if its probability to win still remains high.

In the upcoming subsections, we explain the solution we propose to be adopted by each CN to compute the fitting bid value.
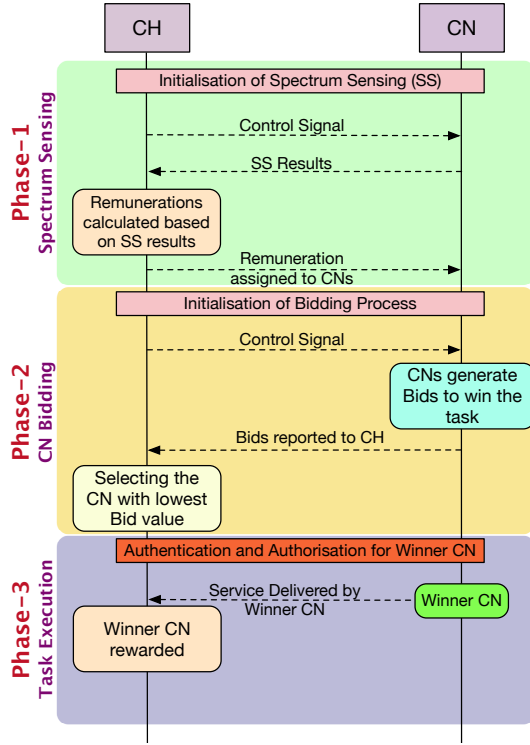
Fig. 4. Workflow and timeline of messages for the proposed reward-based strategy. Several control signals are necessary between CH and CNs for better coordination and execution of services. Such control signals are characterised as lossless and low-rate signals. Multiple shades are used in order to differentiate different phases of the strategy for optimal task allocation. Please refer to Tab. II for acronyms

It is worth mentioning at this point, that additional elements could be taken into account in the task assignment process as important for some application scenarios. The task execution duration is probably one of the most important, as the system (and the CH) should reward the CN also taking into account QoS parameters, such as: latency, reliability, accuracy of the sensing task. These could be introduced as additional elements in the decision process of the CH, so that the winner is selected by taking into account the bid and an additional term that includes the QoS related factors. To this, the CH should be able to evaluate the quality level of the services provided by the different CNs from the history of tasks executed in the past; alternatively, there should be a collaboration among the CNs towards the evaluation of the services each CN is capable to provide. The introduction of this extension in the proposed work would require to devise the system for the evaluation service level provided by each peer, but won't change the overall strategy and the non-cooperative game among the CNs.

C. Maximisation of the Expected System Utility

The aim of the proposed approach is to find the CN that maximises the system utility function for the lowest reward value. In other words, the overall system utility can only be maximised when the selected CN attains its own highest utility, as defined in Eq. (11), requiring a reward that is lower than the other CNs in the cluster. Therefore, the expected system utility for each task k can be defined as

$$E[\mathcal{U}_k] = \sum_{i=1}^{N_c} H_i(b_{k,i}) \cdot x_{k,i} \qquad (12)$$

where $x_{k,i}$ represents the state of the i-th CN with respect to the assignment of task k, i.e. $x_{k,i} = 1$ if the i-th CN is selected as the CN that has to execute task k, $x_{k,i} = 0$ otherwise.

Considering that task k is assigned to the i-th CN when

$$b_{k,i} = b^{min} = min\{b_{k,1}, b_{k,2}, \cdots, b_{k,N_c}\} \qquad (13)$$

the optimisation problem for task k can be defined as

$$\max_{\mathbf{X}} \quad \sum_{i=1}^{N_c} H_i(b) \cdot x_{k,i} \qquad (14)$$

$$\text{s.t.} \quad \sum_i x_{k,i} = 1 \qquad (14a)$$

$$H_i(b_{k,i}) \geq H_i(b) \quad \forall i \qquad (14b)$$

$$b^{min} = \sum_i b_{k,i} \cdot x_{k,i} \qquad (14c)$$

$$b_{k,i} \geq b^{min} \quad \forall i \qquad (14d)$$

where $\mathbf{X} = [[x_{k,i}]^{N_c}, b, [b_{k,i}]^{N_c}, b^{min}]$ is the array of the considered variables. Equations (14a)-(14d) ensure that the following conditions are satisfied: task k is assigned to exactly one CN (Eq. (14a)); the highest value of the expected utility function $H_i(b)$ corresponds to a bid equal to $b_{k,i}$, i.e. the optimal bid (Eq. (14b)); the value of the winning bid b^{min} is equal to the value of the optimal bid of the winning CN (Eq. (14c)); all the optimal bids are equal to or greater than the winning bid b^{min} (Eq. (14d)).

The problem described in Eq. (14) is an NP-hard problem in which the complexity grows exponentially with the number of variables (i.e. $2N_c + 2$). This means that its convergence might not be possible at an affordable computational complexity. Nevertheless, a more straightforward equivalent distributed solution to this problem can be found by maximising the CN expected utility functions independently and then selecting the CN corresponding to the lowest optimal bid. This approach corresponds to a first-price sealed-bid auction [15]. The computation of the optimal bid values and the complexity of the proposed auction will be discussed in detail in the following subsections.

D. Computation of the Bids Generated by the CNs

In this subsection we describe the procedure that each CN follows to compute its bid, which is then communicated to the CH. Such a bid is computed by maximising the CN utility function expressed by (11). Recall that the analysed scenario is modelled as a non-cooperative game among the CNs; accordingly, by proving that such a maximisation brings to the NEP, we assure that each object has no incentive to deviate uni-laterally from it [15]. Note that to maximise Eq. (11), we still need to estimate the probability for CN i to win the competition for task k (i.e., $\Psi(b_{k,i})$), which represents the major objective of the following discussion and mathematical treatment.

Firstly, we observe that, since every CN behaves as any other, we assume that the bids are all distributed according to a probability distribution function, pdf $f(\cdot)$, and its corresponding cumulative distribution function, cdf $F(\cdot)$. Hence, the probability for CN i to win the competition for task k is given by

$$\Psi(b_{k,i}) = (1 - F(b_{k,i}))^{N_c-1} \tag{15}$$

Every CN estimates $f(\cdot)$ dynamically after computing the average μ and variance σ from past observations. Unlike previous works where CN utility function is defined for repeated task execution, in this paper we define it for non-repeated task execution in a *cognitive* IoT scenario. Moreover, 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 k-th task, each CN should try to propose rationally the lowest bid $b_{k,i}$. In this regard, the aim of the proposed strategy is to find a rational bid value for each CN so that the overall system utility is maximised. Such a game can be regarded as non-cooperative where every CN is interested to maximise its own utility function. Such a game can be modelled using Nash game [27]. To win task k, the formulation of $\Psi(b_{k,i})$ in Eq. (11) is necessary for each of the CNs.

We characterise the winning probability $\Psi(b_{k,i})$ for the i-th CN when competing for task k as

$$\Psi(b_{k,i}) = P(b_{k,j} > b_{k,i}), \forall j \neq i \tag{16}$$

Because every CN calculates its bid independently and non-cooperatively, we can write Eq. (16) as

$$\Psi(b_{k,i}) = P(b_{k,1} > b_{k,i}) \times P(b_{k,2} > b_{k,i}) \times \cdots \times P(b_{k,N_c} > b_{k,i}) \tag{17}$$

which can be also written as

$$\Psi(b_{k,i}) = (1 - P(b_{k,1} \leq b_{k,i})) \times (1 - P(b_{k,2} \leq b_{k,i})) \times \cdots \times (1 - P(b_{k,N_c} \leq b_{k,i})) \tag{18}$$

This proves that Eq. (18) is equivalent to Eq. (15). Substituting Eq. (15) in Eq. (11), we have

$$H_i(b_{k,i}) = \left[(1 - F(b_{k,i}))^{N_c-1} \right] \left[\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right] \tag{19}$$

The NEP for this game is the point where rational bid values for CNs can be computed such that lowest bid value corresponds to the maximum individual utility of the winner CN at a given time.
In this regard, we have to solve Eq. (19) to derive the NEP for this game. Therefore, we compute the derivative of Eq. (19) and equate to zero as

$$\frac{\partial H_i(b_{k,i})}{\partial b_{k,i}} = 0 \tag{20}$$

Substituting Eq. (19) in Eq. (20), we get what follows

$$\left[(1 - F(b_{k,i}))^{N_c-2} \right] (1 - N_c) F'(b_{k,i}) \times \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right) + (1 - F(b_{k,i}))^{N_c-1} = 0 \tag{21}$$

Eq. (21) is solvable with two possible solutions given as

$$F(b_{k,i}) = 1 \tag{22}$$

$$(N_c - 1) F'(b_{k,i}) \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right) + F(b_{k,i}) = 1 \tag{23}$$

We will proceed with solution Eq. (23), which is more general and incorporates also Eq. (22). We can see that Eq. (23) is a first order linear differential equation that can be manipulated. Hence, the NEP exists and the result of Eq. (23) is the following

$$F(b_{k,i}) = 1 + \mathbb{C} \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right)^{\frac{-1}{N_c-1}} \tag{24}$$

where $\mathbb{C} \in \mathbb{R}$. With the existence of a NEP in the game, it can now be justified that there exists a CN at any given time that can attain a utility function higher than any other CN in the cluster by proposing a bid value that is the lowest amongst all the CNs in the cluster for a task request.

To compute the bid values for a cluster, we assume that CNs generate their bid values $b_{k,i}$ according to an exponential distribution with parameter λ. We can write

$$F(b_{k,i}) = 1 - e^{-\lambda b_{k,i}} \tag{25}$$

Substituting Eq. (25) in Eq. (21), we obtain the following relation

$$(1 - N_c) \frac{\partial \left(1 - e^{-\lambda b_{k,i}} \right)}{\partial b_{k,i}} \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right) + \left(1 - \left(1 - e^{-\lambda b_{k,i}} \right) \right) = 0 \tag{26}$$

To further simplify Eq. (26) we get

$$(1 - N_c) \left(\lambda e^{-\lambda b_{k,i}} \right) \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right) + \left(e^{-\lambda b_{k,i}} \right) = 0 \tag{27}$$

Solving Eq. (27) we find the rational bid values for every CN such that their expected utility, as expressed in Eq. (11), is maximised.

Accordingly, the comprehensive utility of the system, defined as the utility that the system achieves when k tasks are assigned to the optimal CNs and appropriate rewards are provided in return, can be then computed as

$$\mathcal{U} = \sum_{i=1}^{N_c} \sum_{k=1}^{K} \left(\varsigma_i b_{k,i} - \alpha \frac{1}{\chi_{k,i}} \right) \cdot x_{k,i} \tag{28}$$

Fig. 5 shows the impact of the remuneration factor on the utility function. As it is evident, the higher the remuneration, the lower the bid that the CNs compute (the one that maximises the utility function) and then the higher the probability to win the game for the k-th task.

It is worth mentioning that the proposed framework can still be used when the same task is assigned to more than one object at the same time, such as in the case of collaborative sensing. Indeed, the problem would still be formulated as a non-cooperative game where each object selfishly maximises its own utility, as expressed by Eq. (11), without forming coalitions or making agreements with each other. Nevertheless, in this case the resulting auction would have multiple
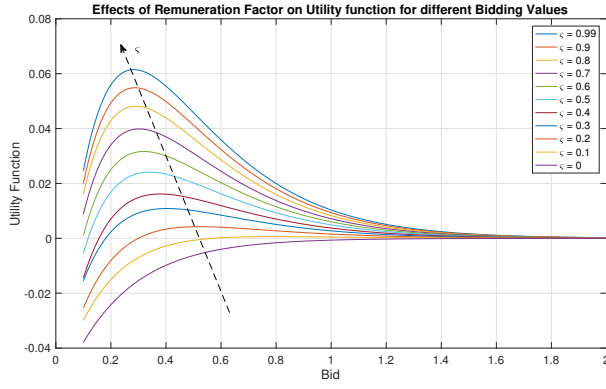
Fig. 5. Utility as a function of the bid at varying remuneration factors, with the following setting: $\alpha = 5$, $P_1 = 0.3$, $P_D = 0.9$ and $P_F = 0.01$

winners. Consequently, Eq. (13) would change based on the number of expected winners and on the type of auction considered (e.g. Discriminatory, Uniform Price, Vickrey Multi-Unit [28]). Therefore, results would be affected by the changes of Eq. (16)–(27), but the whole process depicted by Fig. 4 would remain unchanged.

VI. CLUSTER NODES COMPUTATIONAL COMPLEXITY

For each task allocation, each CN has to sense the spectrum and estimate the powers of the signals in the bands under observation. The result is then sent to the CH. Afterwards, the CN receives the remunerations that are then used to compute the solution to Eq. (27). The complexity of this operation is quite low as it arises from the following considerations. Indeed, the solution can be found numerically by defining a vector **b** that defines the range where the CN looks for the solution. Note that this range can be easily found by considering the overall system settings; for instance, for the settings considered in the previous subsection, the appropriate search range would be $[0, 1]$, as can be seen from Fig. 5. This vector also defines the search resolution: the higher the number of elements the higher the resolution. As the number of operations to be performed per candidate bid is quite limited, we can selected a very high resolution so that the bid can be analysed with a step of 0.001, which corresponds to a vector **b** of $n = 1000$ elements. In Eq. (27) we can identify three vectors that do not change from one bid process to another and then remain constant (so these are computed only once): $(1 - N_c) \left(\lambda e^{-\lambda b_{k,i}}\right) b_{k,i}$, $(1 - N_c) \left(\lambda e^{-\lambda b_{k,i}}\right) \lambda$, and $\left(e^{-\lambda b_{k,i}}\right)$. During each bid process, the first vector has to be multiplied by the remuneration ς_i communicated by the CH and the second vector by $1/\chi_{k,i}$. The three resulting vectors are then added, and afterwards the maximum value is found. The complexity is then equal to two scalar products among two vectors, the sum of three vectors and the search for the maximum value which has complexity $O(n)$. Therefore, the overall complexity is linear with respect to the search vector length.

VII. SIMULATION RESULTS

Extensive simulations have been performed in a MATLAB environment. Tab. III lists all the parameters that are considered in the simulations [23] [29]. We consider communications with packet size of 125 bytes at 125 kbps, that are typical of IoT objects, such as the ALTA IoT devices by Monnit [30]. This means that packets are typically transmitted in 8 msec. Using this type of objects, the sensing hardware at transmission mode draws 22.6 mA when operating at 3 Volts DC. Therefore, the energy consumed by the circuit to transmit a packet in 8 msec would roughly be around 5 mJ, as mentioned in Tab III. Furthermore, the energy required to sense the spectrum is considered negligible as compared to the energy consumed in the circuit and transmission, which are E_c^i and $E_{tx}^{k,i}$, respectively [31]. Because of the unpredictable position of CNs w.r.t. the CH, CNs are considered to experience fading that is modelled with a channel gain exponentially distributed. Because some parameters are initialised randomly, we consider averaging the results obtained from running 1000 scenarios in order to clear the randomness out of the system.

A. Effects of False Alarm Rate

We assume that conditions are conducive for cognitive radios; for this reason we consider that the LUs are occupying the spectrum 30% of the time. Low false alarm rates help CNs to detect the activities in the spectrum band with greater precision, as seen in Fig. 3. This results in high remuneration factor ς_i assigned to the CNs by the CH. We can see in Fig. 6 that spectrum sensing inefficiency (high P_{fa}^i) impacts the CNs' bidding process significantly. An increase of approximately 120% in CNs' bids (prices) can be observed when P_{fa}^i increases from 0.01 to 0.1. Moreover, an increasing trend can be observed in the computed bids due to the decreasing residual energy of CNs over time (increasing the cost of the system utility function). In Fig. 6, it is worth noticing that with high P_{fa}^i values, the bids of competing CNs are highly fluctuating, indicating the uncertainty in the system that affects the overall system utility; this effect can be observed in Fig. 7. On the other hand, a tight competition can be seen among the CNs at lower P_{fa}^i, which introduces an improvement in the overall system utility, as can be seen in Fig. 7. The energy consumption in the system is shown in Fig. 8, where the residual energy in the overall system slowly decays because only a single CN performs the task at a given time. Moreover, the system evidently shows better energy consumption performance that eventually increases the overall network lifetime when spectrum sensing is efficient. The rational behind the improved energy consumption in case of $P_{fa}^i = 0.01$ is that with high remunerations assigned, competition is steady among CNs. Furthermore, the energy consumption gap widens, as more and more tasks are performed, between the cases with $P_{fa}^i = 0.01$ and $P_{fa}^i = 0.1$. Therefore, the proposed Game theoretical approach strikes a balance between profit and cost according to Eq. (11), in such a way that the overall system utility function is maximised at $P_{fa}^i = 0.01$.

Parameters	Values
N_c	10
Number of Scenarios	1000
Tasks	100
P_{fa}^i	0.01, 0.05, 0.1
P_1	0.3 & 0.7
α	1, 5, 10
λ	0.5
Channel Gain, h	exponentially distributed r.v.
γ_i, dB	[-30, 0]
E_β^i, mJ	[95, 100]
E_c^i, mJ	5
E_{nf}^i, mJ	1

Fig. 8. Average residual energy *w.r.t* task number at different P_{fa}^i, fixed α = 5 and spectrum occupancy by LUs is 30% of the time. Lowest false alarm rate enables energy efficiency in the system

Fig. 6. Average bid values w.r.t task number at different P_{fa}^i, with $\alpha = 5$ and spectrum occupancy by LUs for 30% of the time. It is assumed that at any given time, only a single task is advertised by the CH. The winning CN proposing the lowest bid for the considered task is represented by marked bold line

Fig. 9. Average bid values *w.r.t* task number with varying α and fixed false alarm rate to 0.05. The *marked* bold lines represent the winning CN with lowest bid for the given task

B. Effects of Cost Weight Factor

Increasing the value of α, which increases the weight of the residual energy component in Eq. (11), the system is expected to improve the energy consumption. In this subsection, we try to evaluate the performance of the proposed system as a function of α while keeping $P_1 = 0.3$ and $P_{fa}^i = 0.05$. It is shown in Fig. 9 that increasing α, the game allows CNs to increase the bids to balance out the high cost. It is worth noticing that high weight-age makes the overall system a CN-selective in a way that it is more likely that the winner CN is the one that is consuming less energy to execute the task. Hence, the energy consumption is reduced when $\alpha = 10$, as seen in Fig. 11.

Moreover, we see that by giving less weight to the energy component in Eq. (11), the overall system utility increases significantly as the profit is maximised at lower costs. The system utility function is depicted in Fig. 10 where lower values of α can be seen outperforming the system with cost weight factor greater than 1.

C. Effects of Spectrum Occupancy by LUs

Because the proposed system is relying on cognitive radio technologies that help CNs to utilise licensed spectrum without

Fig. 7. Cumulative system utility *w.r.t* task number at different P_{fa}^i, α= 5 and spectrum occupancy by LUs for 30% of the time. A rising trend in the system overall utility can be seen when less uncertainty is observed in spectrum sensing
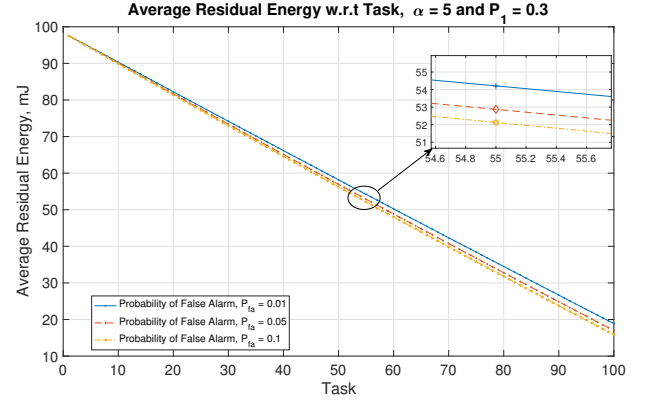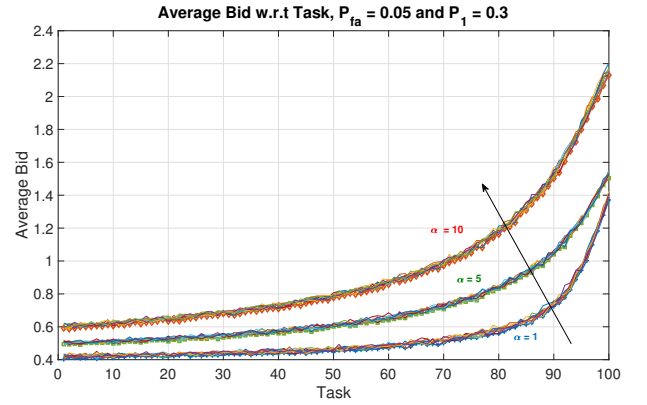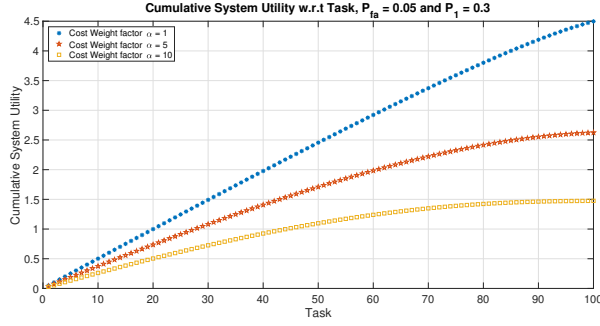
Fig. 10. Cumulative system utility *w.r.t* task number with varying α, $P_{fa}^i =$ 0.05, and $P_1 = 0.3$

Fig. 11. Average residual energy w.r.t task number with varying α, $P_{fa}^i =$ 0.05, and $P_1 = 0.3$
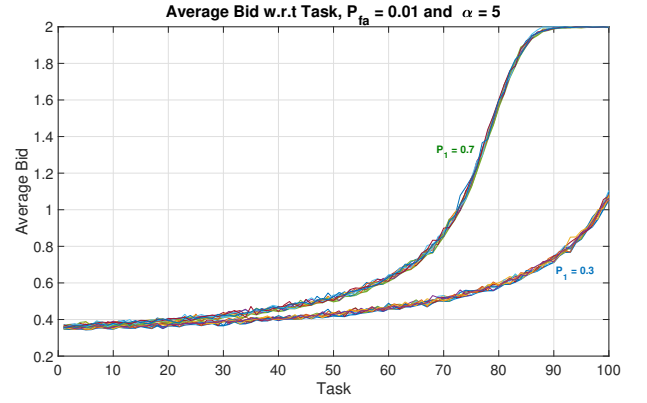

Fig. 12. Average bid values w.r.t task number at $P_{fa}^i = 0.01$ and $\alpha = 5$, for different spectrum occupancy by LUs. The bold lines represent the winning CN proposing the lowest bid for the given task
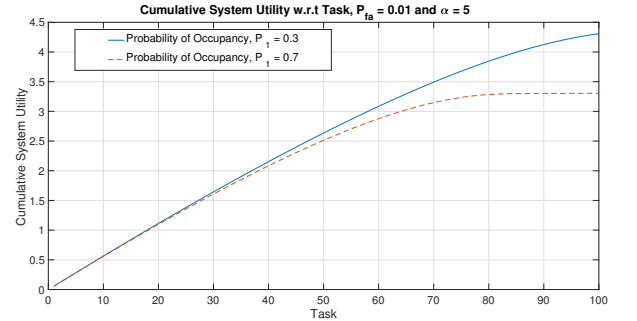

Fig. 13. Cumulative system utility w.r.t task number at $P_{fa}^i = 0.01$ and fixed $\alpha = 5$, for different spectrum occupancy by LUs

causing harmful interference to LUs, we evaluate the performance of our proposed system for two different scenarios. We consider a spectrum occupancy of 30% and 70%As shown in Fig. 12, when the spectrum band is free most of the time ($P_1 = 0.3$), a stiff contest in the game can be seen among the CNs, since each CN is proposing low bid values (low price) to win the task.

A stiff contest among the CNs attributed to the maximisation of the utility function can be observed in Fig. 13, where the system utility is superior when the spectrum band is less occupied by LUs. Moreover, the energy cost will be high when the spectrum is highly occupied (i.e., $P_1 = 0.7$), and hence CNs seek high rewards (proposing high bids) as seen in Fig. 12. Hence the average bid value reaches the maximum bid value of 2 for all the CNs. We can notice from Fig. 14 that with higher spectrum occupancy probability (i.e., $P_1 = 0.7$), the network dies out quickly. This is mainly because when the spectrum is often occupied by an LU, the CN has to sense the spectrum frequently before proceeding to task allocation process. Until the CNs have not finished the task, they would not go back to idle mode. In this regard, a saturation point occurs in the system utility as can be seen from Fig. 13 for $P_1 = 0.7$. Hence the system is able to perform better when the probability of an LU occupying the spectrum is low because the spectrum band is easily available for transmission and false decision probability is low as shown in Eq. (7).

D. Comparison with a centralised approach

In this subsection, simulation results of a comparison between the proposed de-centralised approach and a centralised greedy strategy are presented. The objective of the centralised strategy is to maximise the residual lifetime. Accordingly, for each task assignment, the considered greedy algorithm selects the CN with the highest residual energy and provides it with
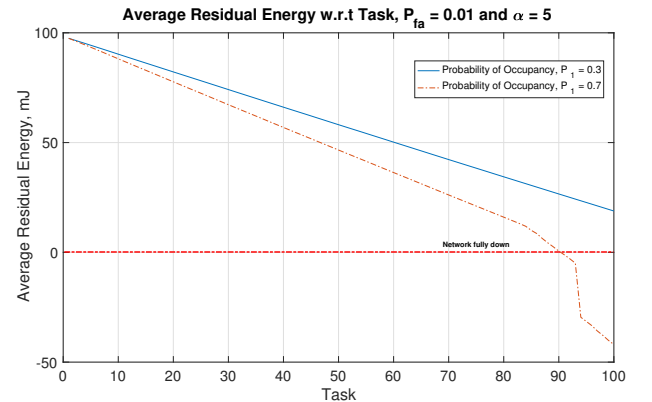

Fig. 14. Average residual energy w.r.t task number at $P_{fa}^i = 0.01$ and fixed $\alpha = 5$, for different spectrum occupancy by LUs

a constant reward that is computed statically as

$$b_{k,i}^{centr} = \frac{\alpha}{E_\varrho}$$

where E_ϱ is considered to be 10 mJ, i.e., about 10% of the maximum residual energy E_β^i available at the beginning of the competition. This value has been chosen considering that lower values resulted in negative utility values as the number of computed tasks grew, i.e., the reward was not enough for the CN to be convenient to perform the task, which means that in real scenarios the CN would likely not accept the assignment.
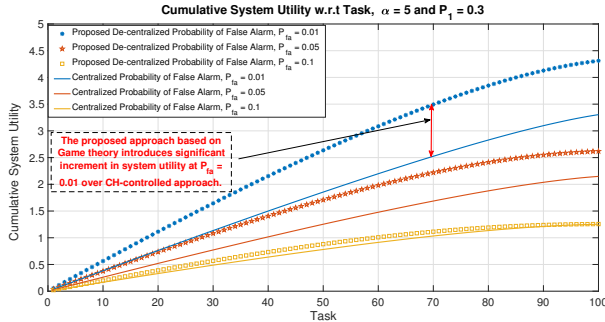

Fig. 15. Cumulative system utility comparison between the proposed distributed approach and a centralised approach. The distributed approach based on Game theory yields a performance gain over the centralised approach

The performance comparison is presented in Figs. 15 and 16. As it is evident in Fig. 15, the proposed de-centralised approach outperforms the centralised one in terms of overall system utility. Nevertheless, as the P_{fa}^i increases, the gain attained by the de-centralised approach diminishes until $P_{fa}^i = 0.1$ when both the approaches, centralised and de-centralised, have similar system performance. This is mainly due to the fact that the high false alarm rate has overwhelming effect on the approaches, and thus making it impossible to outperform each other.

It is interesting to evaluate the performance also in terms of energy consumption as the centralised approach is oriented to increase the network lifetime. Because the CH is controlling the selection of CNs for task allocation, a significant increase in network lifetime can be noticed in Fig. 16. As a final remark, we can conclude that the centralised approach is not
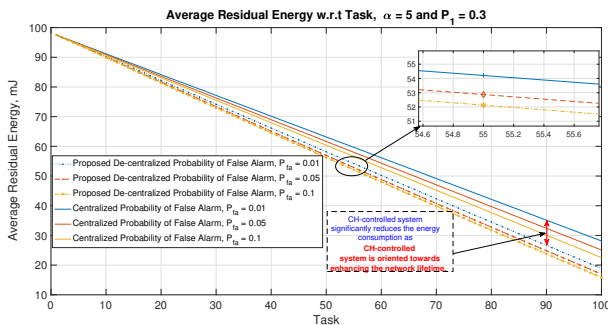

Fig. 16. Average residual energy comparison between the proposed distributed approach and a centralised approach. As the centralised approach is oriented towards maximising the network lifetime, we observe minimum energy consumption w.r.t the proposed approach

able to strike a flexible trade-off between cumulative system utility and residual energy.

VIII. CONCLUSION AND FUTURE WORKS

Task allocation is a critical issue in IoT applications. Moreover, IoT is gaining popularity as more and more applications are being deployed. In order to accommodate IoT traffic in the spectrum, cognitive radio technology is being conceived for IoT to avoid spectrum congestion in the future. In this regard, we propose a Game theoretical framework for task allocation in cognitive-IoT applications. We derived a utility function for the framework on the basis of remunerations obtained by CNs during spectrum sensing. Increasing the uncertainty (P_{fa}^i) results in increasing the price, which severely degrades the performance of task allocation. Moreover, overall system utility decreases as P_{fa}^i increases in the system. We also show that giving more weight to the energy consumption in the system utility brings to higher rewards paid to the CNs. Additionally, with more occurrences of LUs in the spectrum band, the system performance decreases and the energy consumption increases significantly.

Future works will be oriented towards the study of cooperative execution of the same task by more than one node, i.e., the same task that is executed by multiple nodes at the same time. Furthermore, new constraints will be incorporated to include quality related parameters (e.g. Quality of Service, Quality of Information). Finally, the proposed approach will be tested by means of experiments performed using real devices.

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