Kolkata Paise Restaurant Game for Resource Allocation in the Internet of Things

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***Abstract*—The Internet of Things (IoT) is a promising networking technology that will realize many innovative smart city applications. It is anticipated that the number of connected IoT devices will greatly outweigh the available communication resources, and, thus, a key challenge is to optimize the allocation of wireless resources among the IoT devices, which are often limited in their functionality. In this paper, a distributed approach is proposed for enabling IoT devices with incomplete information and multiple objectives to effectively utilize the limited communication resources. In particular, a massive IoT consisting of IoT devices with imperfect knowledge competing over limited communication resources is formulated using a novel Kolkata paise restaurant game. For the formulated game, it is shown that the socially optimal solution coincides with the Nash equilibrium. Furthermore, a learning framework is developed to enable the IoT devices to autonomously learn their equilibrium strategies to optimize their transmission. The effectiveness of the proposed scheme in increasing the number of successful transmissions as a function of the amount of available information, device density, and transmission probability is analyzed. Simulation results show that the proposed learning framework can significantly increase the percentage of communication resources used to successfully transmit by up to threefold, compared to a baseline random allocation scheme. The results also show that the proposed learning framework with imperfect knowledge is more effective in an IoT with higher device density.**

I. Introduction

The Internet of Things (IoT) is anticipated to realize omnipresent, interconnected devices delivering innovative applications [1]. In an IoT, a massive number of devices, such as wearables, sensors, smartphones, drones, and other machine type devices, will enable a myriad of services that include smart city [2], smart grid [3], drone-based systems [4], [5], and industrial monitoring [6], [7]. However, such IoT applications require extensive and reliable wireless connectivity among IoT devices. Given the limited nature of the wireless resources that must be shared among a large number of IoT devices, the problem of resource management has emerged as a major challenge for the IoT [8]–[13]. In particular, resource allocation schemes for the IoT and its devices must consider unique properties of IoT [1], such as limited device capabilities, high quality-of-service (QoS) requirements, and massive scale.

To develop resource allocation schemes suitable for the IoT, the transmission properties of the IoT devices must be carefully considered. The transmissions from the IoT devices will typically be short packets [10], and they are often infrequent due to limited communication resources and energy constraints. Moreover, resource allocation mechanisms for the IoT should be distributed as it is impractical to assume that a base station (BS) can manage a large number of IoT devices. Furthermore, the IoT devices may have imperfect knowledge on other IoT devices due to limited device capabilities. Therefore, it is important to develop a practical resource allocation scheme for the IoT devices considering both realistic transmission properties and key constraints of the IoT.

There are many works on designing and analyzing different resource allocation schemes for the IoT devices based on various approaches, such as optimization [8] and learning [11]. Other works, such as in [9], [10], and [12], design and evaluate protocols to improve reliability, latency, and energy efficiency under various IoT scenarios. Under different multiple access schemes, a framework to optimize the transmission power of IoT devices is proposed in [8]. In [11], a learning method to reduce the delay of urgent messages, while maximizing the throughput of periodic messages, is designed. Moreover, in [9], a resource allocation scheme based on resource pooling to improve reliability is analyzed while in [12], the authors study resource allocation in a network based on cloud random access to optimize the power efficiency. The work in [10] considers different short packet transmission scenarios and discusses the optimal ways to transmit metadata. However, none of these works take advantage of the properties of short packet transmission, such as relative payload size and design of metadata, when addressing the problem of resource allocation in the IoT. Further, most of the prior art requires a central entity to allocate the scarce communication resources [9], [12] or a perfect knowledge of transmissions from the IoT devices [9]. Such assumptions do not typically hold for the IoT devices with limited resources and capabilities.

To develop a distributed resource allocation scheme for the IoT devices, a game-theoretic approach can be used to enable them to allocate the scarce communication resources in a self-organizing manner. In particular, the *Kolkata paise restaurant (KPR) game* is a suitable framework for allocating multiple resources to multiple users with individual preferences on the resources. The authors in [14] introduce and discuss the basics of a KPR game. Such a game typically studies decision-making scenarios in which there are customers with common preference ranking of restaurants, and the goal of the customers is to go to a more preferred restaurant, while avoiding to choose the same restaurant as other customers. The work in [14] shows that the socially optimal solution of a KPR game is a Nash equilibrium (NE) and investigates different learning methods that converge to the socially optimal NE. Moreover, the learning methods introduced in [14] do not require a complete knowledge of other players and can converge to the NE only with partial knowledge, which is suitable for the IoT devices. However, the game design and the learning methods of [14] are tailored towards social applications, and, thus, they are not directly applicable to the IoT. In particular, the existing KPR model in [14] does not consider different preference ranking for different players, varying number of players, and zero utility for overlapping resource usage.

The main contribution of this paper is to study and analyze the IoT resource allocation problem using a KPR game that is tailored toward the unique features of the IoT. In particular, we consider a massive IoT in which IoT devices with imperfect knowledge compete over limited communication resources. We show that the socially optimal solution for our resource allocation game is an NE and we propose a learning framework that can be used to converge to the NE that better utilizes the scarce communication resources. The proposed learning framework allows the IoT devices to learn and intelligently choose the communication resources, such as resource blocks, for higher system throughput. Moreover, using the proposed learning framework, the IoT devices can learn to better choose the communication resource with only local information about the resource usage of neighboring IoT devices. Simulation results show that the percentage of communication resources that are used to successfully transmit is significantly increased and the learning framework is more effective in denser IoT. In particular, the results show that the percentage of communication resources that are used to successfully transmit is increased by 7% in an IoT having 2.5 devices per square meter and by threefold in a denser IoT with 5 devices per square meter compared to a baseline case without any learning.

The rest of this paper is organized as follows. Section II presents the system model. In Section III, we introduce the IoT resource allocation game and propose a learning framework for the IoT devices. Section IV analyzes and discusses the simulation results, while Section V draws some conclusions.

II. System Model

Consider the uplink of a wireless IoT system having one BS that serves N IoT devices transmitting short packets [10], [15]. For short packet transmissions, it is known that random access transmission is more suitable than scheduled channels as it can provide lower latency [8], [9], and [16]. Hence, we consider time-slotted random access over a frequency division multiple access (FDMA) system [8]. The channel is divided into b resource blocks (RBs) each of which can be used by only one IoT device, at a given time [17]. Whenever multiple IoT devices use the same RB, their transmissions will fail due to collisions. During a time slot, each device will have a short packet to transmit with probability p, and, thus, the expected number of packets to be transmitted $\mathbb{E}[N_t]$ in a slot is $N \cdot p$, where N_t is a random variable capturing the number of transmitting IoT devices in slot t.

In an IoT, the number of IoT devices transmitting simultaneously greatly outweigh the available communication resources such that $\mathbb{E}[N_t] \gg b$. Therefore, the efficient allocation of limited communication resources among the IoT devices is critical. However, a centralized solution using which the BS allocates the communication resources to the IoT devices is impractical. This is because the short packets randomly arrive at the IoT devices, and, thus, the BS cannot predict and schedule the RB usage. A trivial solution to resource allocation would be to enforce the cooperation of all IoT devices to coordinate RB usage. However, this can be impractical due to overhead and energy constraints [1]. Furthermore, such coordination would assume that the IoT devices have perfect knowledge of all other IoT devices.

One simple solution would be to allow the IoT devices to randomly choose RBs whenever they transmit. For the case in which b RBs are chosen with equal probability, we let S_n be a random variable that captures the number of successfully transmitted short packets. The support of S_n, $\text{supp}(S_n)$, depends on both N_t and b. When $N_t \leq b$, the support of S_n is $[0, N_t]$, while the support of S_n is $[0, b-1]$ when $N_t > b$. With $N_t = n_t$, the probability of having at least s successful transmissions for $s \in \text{supp}(S_n)$ is:

$$\Pr(S_n \geq s | N_t = n_t) = \prod_{i=0}^{s-1} \frac{b-i}{b} \left(\frac{b-s}{b}\right)^{(n_t - s)}. \quad (1)$$

From (1), for given $N_t = n_t$, the probability of having s successful transmissions for $s \in \text{supp}(S_n)$ is:

$$\Pr(S_n = s | N_t = n_t) = \begin{cases} \Pr(S_n \geq s | N_t = n_t) - \sum_{i=1}^{n_t - s} \binom{n_t - s}{i} \Pr(S_n = s+i | N_t = n_t), & \text{if } n_t \leq b, \\ \Pr(S_n \geq s | N_t = n_t) - \sum_{i=1}^{b-1-s} \binom{n_t - s}{i} \Pr(S_n = s+i | N_t = n_t), & \text{if } n_t > b. \end{cases} \quad (2)$$

Note that $\Pr(S_n = s | N_t = n_t) = \Pr(S_n \geq s | N_t = n_t)$ when $s = n_t \leq b$ and when $s = b - 1$ and $n_t > b$. Since $N_t \sim B(N, p)$, the probability of having n_t IoT devices transmitting in a given slot is:

$$P(N_t = n_t) = \binom{N}{n_t} p^{n_t} (1-p)^{N - n_t}. \quad (3)$$

Using (2) and (3), the probability of having s successful transmissions will be:

$$\Pr(S_n = s) = \sum_{i=s}^{N} \binom{i}{s} \Pr(S_n = s | N_t = i) \Pr(N_t = i). \quad (4)$$

For all possible values of N_t, the maximum number of successfully transmitted packets is b, and, thus, the expected number of successfully transmitted packets in a slot is:

$$\mathbb{E}[S_n] = \sum_{s=1}^{b} s \Pr(S_n = s). \quad (5)$$

In a massive IoT with very large N, the probability of having s successful transmissions in (4) will be very low, and, thus, the expected number of successful transmissions will also be low. In other words, the scarce communication resources will not be used efficiently, because very few RBs are used to successfully transmit. Therefore, there is a need for a distributed resource allocation for the IoT devices to intelligently choose the RBs given their incomplete knowledge on the RB usage of other devices.

III. Game-Theoretic Resource Allocation

The RB allocation among the IoT devices can be seen as one-to-one association between RBs and IoT devices, because one RB must be allocated to one device for a successful transmission. Furthermore, the IoT devices will decide which RB to use based on the incomplete knowledge about the RB usages of other devices. This competition among the IoT devices to choose an RB without overlap can be formulated as a *game* [18], [19] since the successful transmission of an IoT device depends on the actions of other devices due to collisions. One suitable framework is the so-called *Kolkata paise restaurant game* [14] which is a repeated game in which n customers (players) simultaneously go to one of n restaurants (actions), each of which can only serve one customer. Although the restaurants have the same price, there is a preference ranking (utilities) of restaurants commonly known among the customers based on food quality. A customer can only visit one restaurant at any given iteration, and a restaurant will randomly select to serve one of the visiting customers. In the KPR game, when the utility of the least preferred restaurant is at least half of the utility of most preferred restaurant, the NE is achieved when the *service rate*, which is the fraction of restaurants with customers, is 1 [14]. Moreover, the NE of the KPR game coincides with the socially optimal solution. Therefore, various learning methods that achieve higher service rate than random selection are analyzed [14].

We model the one-to-one association between RBs and IoT devices as a KPR game whose players are N IoT devices in a set $\mathcal{P}$. Each player $i \in \mathcal{P}$ has a set of actions $\mathcal{A}_i$, which represents the set of b RBs. Furthermore, we assume that the IoT devices transmit via Rayleigh fading channel. Moreover, the channel gains for different RBs are different for the IoT devices, and the IoT devices prefer to transmit using an RB with higher channel gain. We let $a_{i,t}$ be an action by IoT device i at time t and $g_{i,j}\ \forall\ i \in \mathcal{P}, j \in \mathcal{A}_i$ be the fading channel gain of RB j when used by IoT device i. Therefore, the utility function is:

$$u(a_{i,t}) = \begin{cases} g_{i,a_{i,t}} & \text{if } a_{i,t} \neq a_{k,t}\ \forall\ k \in \mathcal{P}, k \neq i, \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

The IoT resource allocation game differs from the classical KPR game in various aspects. For instance, the preference ranking of the RBs based on their channel gains will be different for different IoT devices. Unlike the classical KPR game, here, the number of players is random at each iteration, and the number of RBs may not be equal to the number of devices. Moreover, if multiple devices choose an RB, they will all fail to transmit resulting in zero utility. Despite the significant differences from the original KPR, next, we show that the proposed IoT resource allocation game has an NE that may also be a socially optimal solution.

Proposition 1. If the number of transmitting IoT devices in a time slot is greater than b, then the Nash equilibrium corresponds to the case in which all RBs are chosen by at least one IoT device, and the socially optimal solution achieving the highest possible service rate is Nash equilibrium.

Proof. In a massive IoT with $N \gg b$, the number of transmitting IoT devices n_t in time slot t will most likely be larger than the limited communication resources, and, thus, we assume that $n_t > b$. In such a case, any solution that has at least one IoT device choosing each RB is an NE. For those solutions, some IoT devices will transmit successfully, and other IoT devices will not transmit successfully due to collision. The IoT devices that are transmitting successfully will not deviate and choose some other RB to transmit even if they are transmitting with least preferred RB. This is because if they choose some other RB to transmit, then they will fail to transmit due to collision, resulting in zero utility. Since the successful transmission using any RB has positive utility, the IoT devices that are transmitting successfully will not deviate. On the other hand, the IoT devices that are not transmitting successfully are indifferent about deviating. This is because those IoT devices will not transmit successfully due to collision even if they deviate and choose some other RB to transmit. Since changing and not changing the RB selection will both result in zero utility for the IoT devices transmitting unsuccessfully, such IoT devices are indifferent. Therefore, the solutions such that all RBs are chosen by at least one IoT device are NE.

In a massive IoT, the socially optimal solution is when $b-1$ IoT devices transmit successfully, while $n_t-(b-1)$ IoT devices do not transmit successfully. This achieves the highest service rate, which is $\frac{b-1}{b}$. All RBs are chosen by at least one IoT devices in socially optimal solution, and, thus, the socially optimal solution is an NE. ■

In IoT resource allocation game, there exist many NE, but most NE will have very low service rates due to RB collision caused by overlapping RB selection. It is desirable to achieve NE with high service rate, such as the socially optimal NE. However, the IoT devices only have partial information about the RB usages of other IoT devices, which makes achieving the socially optimal solution challenging. Therefore, a novel framework to coordinate the RB usage of the IoT devices in a self-organizing manner using only partial information on RB usage is necessary. To this end, we propose a learning framework using which the IoT devices learn from the partial information to significantly increase the service rate compared to the baseline case of random RB selection.

A. Learning Framework

The IoT devices only have partial information about the RB usage of other IoT devices to intelligently choose an RB. For partial information, we model the IoT devices to be able to only communicate with neighboring IoT devices within a range r_c to learn about their RB usage. We let $\mathcal{T}_t$ be the set of IoT devices that transmitted during time slot t, $r_{t,i}$ be the RB used by device i in $\mathcal{T}_t$, and $\mathcal{N}_i$ be a set of neighbors of IoT device i within r_c. We let $\mathcal{S}_t$ be the set of IoT devices that transmitted successfully at slot t and $\mathcal{F}_t$ the set of IoT devices that did not transmit successfully at slot t such that $\mathcal{S}_t \cup \mathcal{F}_t = \mathcal{T}_t$ and $\mathcal{S}_t \cap \mathcal{F}_t = \varnothing$.

Using limited information on RB usage within r_c, the IoT devices can intelligently choose RBs to increase the service rate, and one such approach is to learn from the most recent actions of neighboring devices. Since the transmission failures result in zero utility and the objective is to increase the service rate, an IoT device i in $\mathcal{T}_t$ will learn from the IoT devices in $\mathcal{F}_{t-1} \cap \mathcal{N}_i$ and learn from the IoT devices in $\mathcal{S}_{t-1} \cap \mathcal{N}_i$ only if $\mathcal{F}_{t-1} \cap \mathcal{N}_i = \varnothing$. If $\mathcal{F}_{t-1} \cap \mathcal{N}_i \neq \varnothing$, an IoT device $i \in \mathcal{T}_t$ will choose $r_{t,i}$ randomly among the RBs that are preferred no more than the RBs used by devices in $\mathcal{F}_{t-1} \cap \mathcal{N}_i$. If $\mathcal{F}_{t-1} \cap \mathcal{N}_i = \varnothing$, an IoT devices $i \in \mathcal{T}_t$ will choose $r_{t,i}$ randomly among the RBs that are preferred no less than the RBs used by devices in $\mathcal{S}_{t-1} \cap \mathcal{N}_i$. In a case where $\mathcal{T}_{t-1} \cap \mathcal{N}_i = \varnothing$, an IoT device i will choose $r_{t,i}$ randomly from $\mathcal{A}_i$ with higher probability for more preferred RBs. This proposed learning method primarily increases the probability of successful transmission for the IoT devices transmitting unsuccessfully by using less preferred RBs, while allowing the IoT devices transmitting successfully to use more preferred RBs. Furthermore, whether the proposed learning framework converges to the NE depends on r_c, and this will be further discussed in the next section. Moreover, it is important to note that this method only uses the immediate history of RB usage of the IoT devices in $\mathcal{T}_{t-1}$ as the IoT devices are limited in memory. The performance of the learning framework will be analyzed and compared against the baseline case of random RB selection, whose service rate is $\dfrac{\mathbb{E}[S_n]}{b}$.

IV. Simulation Results and Analysis

For our simulations, we will analyze the performance of the proposed learning framework in the resource allocation game under different communication ranges r_c, device densities λ, and transmission probabilities p. We assume that the IoT devices are deployed within a square field of dimension R meters based on Poisson point process with device density λ per square meter. In our simulations, we set the dimension R of the deployment region to be 20 meters and the number of resource blocks b to be 5. We assume that the channel gains and the preference rankings of the RBs of neighboring IoT devices are similar. Primarily, the learning framework with varying values of r_c will be compared against the baseline case of random RB selection. Furthermore, we analyze the performance of the learning framework with low device density of $\lambda = 2.5$ and high device density of $\lambda = 5$. Moreover, we study the effect of the transmission probabilities p on the performance of the proposed learning framework.

Fig. 1 shows the average service rate of RBs resulting from the proposed learning framework with $p = 0.01$ and varying r_c and λ. With lower λ, the highest service rate that can be

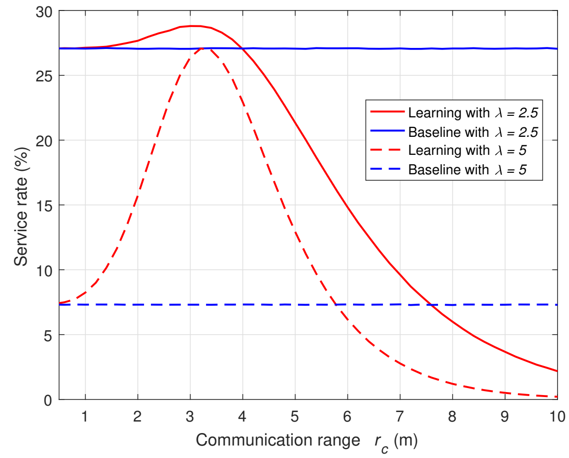

Fig. 1. Average service rate of RBs with different λ and $p = 0.01$.

achieved using our learning framework is 28.8% when $r_c = 3$ meters, which is about 7% higher than the corresponding baseline. However, with higher λ, the highest service rate that can be achieved with learning framework is 27.1% when $r_c = 3.2$ meters, which is almost threefold greater than that of the corresponding baseline. Therefore, it can be concluded that the proposed learning framework is more effective in an IoT with higher λ, and it is particularly suitable for practical, massive IoT environments [1]. For both values of λ, there is an optimal value of r_c using which the learning framework increases the service rate the most.

The learning framework learns from both transmission failures and successes such that an IoT device learning from failure chooses less preferred RB, while an IoT device learning from success chooses more preferred RB. To learn from failures and successes, r_c can be interpreted as the amount of available information. For instance, r_c close to 0 implies that the IoT devices have almost no information, and, thus, they will choose RB randomly. Therefore, the learning framework achieves a service rate similar to the baseline, as seen in Fig. 1. The IoT devices with large r_c will almost always learn from the failures and mostly use less preferred RBs, because they first learn from the failures. Therefore, the IoT devices will be competing over fewer RBs as they all try to use less preferred RBs. This can be observed in Fig. 1 where the service rate decreases below the baseline for high values of r_c. Furthermore, the NE is not achieved with large r_c, because the RB selection is biased and not all RBs are used by at least one IoT device. There is an optimal value of r_c such that the IoT devices learn from both transmission failures and successes in choosing their RBs. Using such a value of r_c, the IoT devices do not compete over fewer RBs, and the service rate is improved compared to the baseline, as seen in Fig. 1. Furthermore, with an optimal value of r_c, the IoT devices will learn from successes and failures, and their RB selection will not be biased toward less preferred RBs. Since our learning framework enables the devices to avoid overlapping RB selections in a massive IoT to increase the

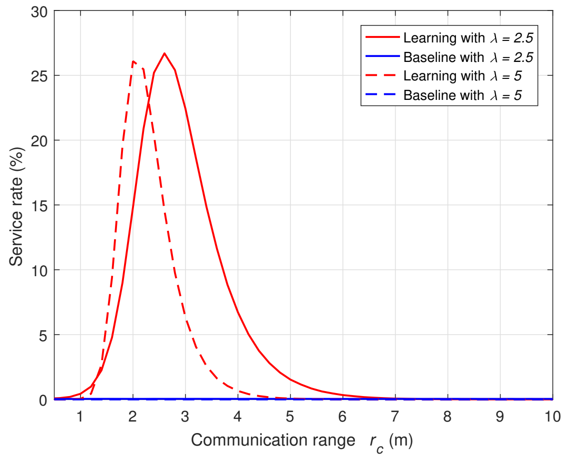

Fig. 2. Average service rate of RBs with different λ and $p = 0.05$.

service rate, all RBs will be chosen by at least one IoT device, and, thus, the NE is achieved with optimal value of r_c.

Fig. 2 shows the average service rate of RBs resulting from the proposed learning framework with $p = 0.05$ and varying r_c and λ. In an IoT, a higher value of p can be interpreted as an increase of IoT device activity due to user requests or some abnormal event. For a higher value of p, the baseline has service rates very close to 0% for both values of λ, because the number of transmissions per time slot increased greatly. For lower λ, the highest achievable service rate is 26.7% when $r_c = 2.6$ meters. For higher λ, the highest achievable service rate is 26% when $r_c = 2$ meters. Similar to Fig. 1, there is an optimal value of r_c that yields the highest service rate. Furthermore, the effect of increasing r_c on the performance of the proposed learning framework is similar to Fig. 1.

V. Conclusion

In this paper, we have formulated the problem of allocating limited communication resources among a large number of IoT devices as a KPR game and proposed a novel approach for increasing the service rate with imperfect information. In particular, we have modeled the IoT devices as players choosing which RB to use based on their preference ranking and partial information about neighboring devices. We have shown that the socially optimal solution for this game is an NE, when the utility of successful transmission is positive. Furthermore, we have introduced a learning framework that allows the IoT devices to learn from the transmission failures and successes of neighboring IoT devices and significantly increases the service rate compared to the baseline of random RB selection. Simulation results have shown that the service rate resulting from the proposed learning framework is a function of the communication range, device density, and transmission probability. Furthermore, there is an optimal value of communication range that maximizes the service rate, and the NE is achieved with certain values of communication range. Moreover, the results have shown that the learning framework is more effective in denser IoT.

Acknowledgment

This research was supported by the U.S. Office of Naval Research (ONR) under Grant N00014-15-1-2709.

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