Game-Theoretic Optimization for Machine-Type Communications Under Reliability Guarantee

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***Abstract*—Massive machine-type communication (mMTC) is a new focus of services in fifth generation (5G) communication networks. The associated stringent delay requirement of end-to-end (E2E) service deliveries poses technical challenges. In this paper, we propose a joint hybrid random access and data transmission protocol for mMTC to guarantee E2E service quality of different traffic types. First, we develop a priority-queueing-based access class barring (ACB) model. A novel effective capacity is derived considering device random access with short packet transmissions. Then, we model the priority-queueing-based ACB policy as a non-cooperative game, where utility is defined as the difference between effective capacity and access penalty price. We prove the existence and uniqueness of Nash equilibrium (NE) of the noncooperative game, which is also a sub-modular utility maximization problem and can be solved by a greedy updating algorithm converging to the unique NE. To further improve the efficiency, we prosent a price-update algorithm, which converges to a local optimum. Simulations demonstrate the performance of the derived effective capacity and the effectiveness of the proposed algorithms.**

***Index Terms*—Massive machine-type communications (mMTC), random access, effective capacity, quality of service (QoS), non-cooperative game, sub-modular function.**

I. Introduction

With the rapid penetration of emerging automated services, machine-type communication (MTC) has become a focus of new services in fifth generation (5G) communication networks [1], [2]. For example, the smart cities span a wide variety of service applications, from traffic management to grid power distribution, to urban security and environmental monitoring; health–oriented wearable devices offer biometric measurements such as heart rate, perspiration levels, and oxygen levels in the bloodstream. Industry analysts predict that 50 billion devices will be interconnected via mobile networks worldwide by 2020 [3]. Different from human communication, MTC involves a massive number of devices with low-complexity and low-power, referred to as massive machine-type communications (mMTC). For mMTC, traffic overloading on the random access channel (RACH) is a dominate factor causing performance bottleneck due to simultaneous activation of devices. To alleviate the traffic arrival burstiness, the access class barring (ACB) [4] and back-off procedure [5] are developed.

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Another challenge is how to guarantee heterogeneous quality of-service (QoS), i.e., delay, and reliability for devices with different traffic types. For example, MTC for industrial automation requires extremely small delay and packer error probability (PER) [6]. Although ACB or back-off procedure can prevent simultaneous massive access from activated devices, they result in a degeneration of QoS. Thus, QoS-aware random access for mMTC has recently drawn attentions from researchers. An analytical model is proposed in [7] to calculate maximum access delay for a distributed queueing-based random access protocol. In [8], the MTC network is modeled as a Beta/M/1 queueing system, where service time of the RACH procedure follows an exponential distribution. In [9], a general model is developed for RACH procedure. The impact of short packets of machine-type services on the achievable rate is considered in [10]. In traditional communications, the Shannon's channel coding theorem is employed under the assumption of infinity block-length, while for a finite block-length, a novel effective capacity is developed to guarantee statistical QoS for MTC. In [11], a cross-layer framework is proposed using the effective bandwidth theory to optimize the packet dropping policy, power allocation policy, and bandwidth allocation policy under the QoS constraint. A probabilistic bound for RACH access delay is derived using stochastic network calculus in [12].

The overall performance of MTC not only depends on the performance in the RACH phase, but also depends on the performance in data transmission phase. The backlog status of each transmission queue of MTC devices, depending on traffic arrival and service processes, affects the number of devices activated in both RACH phase and data transmission phase. As a result, a joint consideration of both RACH procedure and data transmission is a key to capture the performance of MTC. Ruan et al. in [13] consider a scenario where devices can transmit data at a random access slot only when it decides to transmit a random preamble sequence and other devices have not occupied the preamble. The transmission process is formulated as an infinite horizon average cost Markov decision process (MDP). In [14], a queueing model is developed for MTC under the assumption that a device is activated when the number of packets in its queue is larger than a threshold and all the packets in the queue are transmitted upon one successful preamble contention. Wiriaatmadja et al. derive a closed-form formula for throughput as functions of the number of resource block allocated for the PRACH and the traffic load [15]. According to the closed-form formula, a hybrid protocol is proposed to maximize the expected throughput.

How MTC devices with differentiated services should contend to access the RACH and be scheduled to transmit data for heterogeneous QoS provisioning needs in-depth investigation. First, the RACH and data transmission phases are correlated, in presence of transmission queueing dynamics among devices. A unified analytical framework to quantify the QoS-provisioning capabilities in both random access and data transmission is essential. Moreover, how to guarantee differentiated QoS requirements of MTC devices supporting multiple traffic types is challenging. For massive access from MTC devices, a centralized control solution corresponds to a large communication overhead due to global information exchange with a large number of devices. Thus, a distributed QoS provisioning scheme is desired.

In this paper, we propose a hybrid random access and data transmission protocol to guarantee the end-to-end (E2E) QoS of different traffic types in mMTC. To deal with the aforementioned challenges, we develop a priority-queueing-based ACB policy and derive a novel effective capacity, taking into account the random access and short packet transmissions. Based on the derived effective capacity, the barring policy is modeled as a non-cooperative game. We prove the existence and uniqueness of Nash equilibrium (NE) in the noncooperative game. Furthermore, a distributed iterative algorithm that converges to the equilibrium point is proposed. To improve the efficiency of NE, we provide a price-update algorithm, which converges to a locally optimal point of the effective capacity optimization problem. Simulation results show the performance of the novel effective capacity and the effectiveness of our proposed algorithms.

The remainder of this paper is organized as follows. System model is presented in Section II. In Section III, we derive a new effective capacity considering both RACH and data transmission phases. In Section IV, we present a game-theoretic barring policy with reliability guarantee. In Section V, simulation results are provided, followed by conclusions in Section VI.

II. System Model

Consider the uplink of an mMTC system, composed of a BS and N MTC devices which are randomly and uniformly distributed within the coverage of the BS, as shown in the Fig. 1. Each device generates K types of traffic, indexed by $1, 2, ...K$. We assume the smaller the index, the higher the transmission priority. Each device has K First-Input-First-Output (FIFO) transmission queues for the K types of traffic, respectively. Time is partitioned into a sequence of time slots, i.e., $t = 1, 2, 3, \ldots$, the duration of which is constant and denoted by T_d. Packet arrivals of the k-th traffic type at the n-th device over each time slot follows an independent and identically distributed Bernoulli process with probability p_n. Packet size (in the unit of bit per second) of the k-th traffic type at the n-th device at the t-th slot, denoted by $a_{n,k}[t]$, follows an exponential distribution with mean $\bar{L}_{n,k}$.

A conventional device initiates access attempts to the BS at the time when the transmission queue is non-empty. However, the simultaneous activation of a large number of devices causes

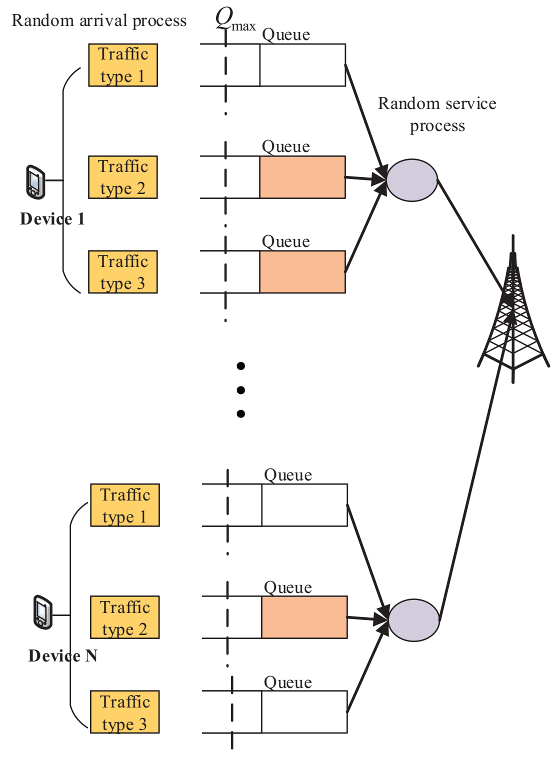

Fig. 1. An example of system model including one BS and N devices with three queue to transmit three types of traffic .

performance degradation for mMTC. To deal with massive access attempts with bursty traffic arrivals, a priority-queueing-based ACB is employed to alleviate contention collisions of random access for QoS provisioning. Suppose the k-th queue of the n-th device is non-empty. If all the $k-1$ queues that have a lower index but higher priority than the k-th queue are empty, the k-th queue can be activated with probability $d_{n,k}$.

For uplink transmissions, time is partitioned into a sequence of transmission superframes, each of which consists of a *random access phase* followed by a *data transmission phase*, depicted in Fig. 2. The durations of a random access phase and a data transmission phase are denoted by T_s and T_f, respectively, and the total transmission duration is denoted by T_u. The activated devices contend for preambles in T_s. Upon a successful contention, data is transmitted within a duration of T_f using Orthogonal Frequency Division Multiple Access (OFDMA) techniques. Otherwise, the device will try again to access the BS in the random access phase of next superframe. We assume that $T_s \ll T_f$ to alleviate the signaling overhead due to random access. The wireless channel from a device to the BS is modeled as a Rayleigh block fading, i.e., the channel remains unchanged during a time superframe T_u, and changes between consecutive superframes.

In the *random access phase*, a device attempts to connect to the BS based on a standard four step random access (RA) procedure. The detailed RA procedure for the uplink is as follows: 1) The device uniformly and randomly selects and then transmits one RA preamble from M preambles in the physical random access channel (PRACH); 2) The BS sends random access responses (RARs) through the physical down-

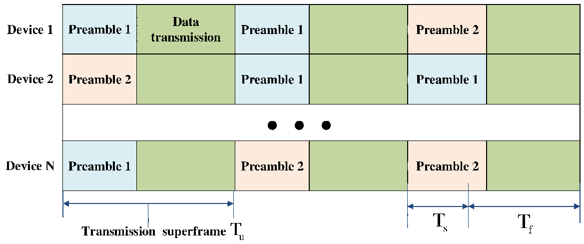

Fig. 2. An illustration of MAC operations in each transmission superframe, including the random access phase with two preambles and the data transmission phase.

link shared channel (PDSCH) to devices whose preambles are decoded successfully; 3) Devices specified in the received RAR send the connection setup request messages; 4) If the BS correctly decodes a connection request, it replies with an acknowledgement to the device. In the *data transmission phase*, we assume that the k-th queue of the n-th device successfully occupies a data transmission channel with the allocated bandwidth B_n during the slot T_f, which consists of S_n OFDM symbols. We calculate S_n as $S_n = \frac{T_f}{a}\frac{B_n}{c}$, where a is the duration of a OFDM symbol, c is the bandwidth of a OFDM symbol.

III. The QoS Analysis of Multi-class MTC

In this section, a new analytical approach is proposed to analyze the performance of the priority-queueing-based ACB model, jointly considering the *random access phase* and the *data transmission phase*.

In the context of large deviation theory [16], QoS is characterized statistically by employing the QoS exponent $\boldsymbol{\theta} = \{\theta_{n,k}, n = 1, \cdots, N, k = 1, \cdots, K\}$, as given by [17]

$$\theta_{n,k} = -\lim_{Q^{\text{th}}_{n,k}\to\infty} \frac{\log(\Pr\{Q_{n,k}[\infty] > Q^{\text{th}}_{n,k}\})}{Q^{\text{th}}_{n,k}}, \tag{1}$$

where $Q_{n,k}[t]$ is the length of transmission queue at the k-th queue of the n-th device at slot t, $Q^{\text{th}}_{n,k}$ is the threshold of the queue length to guarantee the QoS of the k-th traffic type, and $\Pr\{Q_{n,k}[\infty] > Q^{\text{th}}_{n,k}\}$ is the QoS-violation probability that the queue length exceeds $Q^{\text{th}}_{n,k}$. In (1), $\theta_{n,k}$ provides the exponential decaying rate of the probability that the threshold is violated.

A. Effective Bandwidth of Multi-class MTC

For the arrival process $a_{n,k}[t]$ at the k-th queue of the n-th device, the effective bandwidth, denoted by $A_{n,k}(\theta_{n,k})$, specifies the minimum constant service rate for probabilistic QoS guarantee. Given the Bernoulli traffic arrival, the effective bandwidth (in bit/s) of the traffic is given by [18]

$$\begin{aligned} A_{n,k}(\theta_{n,k}) &= \lim_{t\to\infty}\frac{1}{\theta_{n,k}t}\log(\mathbb{E}\{e^{\theta_{n,k}\sum\limits_{i=0}^{t}a_{n,k}[i]}\}) \\ &= \frac{1}{\theta_{n,k}T_d}\log(\frac{p_n}{1-\theta_{n,k}\bar{L}_{n,k}} + 1 - p_n). \end{aligned} \tag{2}$$

B. Effective Capacity of Multi-class MTC

Service for the k-th queue at the n-th device can have one of three states:

- **Successful access state** accounts for the case that all queues of higher priority are empty, while the k-th queue is not empty, and tries to access to the BS, and the chosen preamble is occupied only by the n-th device;
- **Collided access state** accounts for the case that all queues of higher priority are empty, while the k-th queue is not empty, and tries to access to the BS, and the chosen preamble is occupied by more than one device;
- **Silence state** accounts for the case that more than one queue of higher priority is non-empty, or the k-th queue does not try to access to the BS.

We denote successful access indicator variable as $s_{n,k}$:

$$s_{n,k} = \begin{cases} 1, \text{if the state is successful access state;} \\ 0, \text{otherwise.} \end{cases}$$

Let $P^{n,k}_{idle}$ denote the probability of having an empty buffer at the k-th queue of n-th device. Then, the probability that the packet at the head of the k-th queue of the n-th device tries to access the BS is given by

$$P^{n,k}_{a} = d_{n,k}\prod_{j=1}^{k-1} P^{n,j}_{idle}(1 - P^{n,k}_{idle}). \tag{3}$$

The activation probability of n-th device is

$$D_n = \sum_{k=1}^{K} P^{n,k}_{a}. \tag{4}$$

As a result, the successful access probability of the k-th queue of the n-th device is given by

$$\begin{aligned} F^{n,k}_{s} &= \sum_{m\in M}\frac{1}{M}P^{n,k}_{a}\prod_{l\neq n, l\in N}\left(1 - \frac{D_l}{M}\right) \\ &= P^{n,k}_{a}\prod_{l\neq n, l\in N}\left(1 - \frac{D_l}{M}\right) \end{aligned} \tag{5}$$

where $\left(1 - \frac{D_l}{M}\right)$ is the probability that the l-th device does not operate on the m-th preamble, and M is the number of preambles.

For the short packet transmission, the achievable channel coding rate (bits per channel use) of the successful access state not only depends on the channel condition, but also depends on the finite blocklength S_n and the packet error probability $\varepsilon_{n,k}$, which is given by [10]

$$\begin{aligned} r_{n,k} \approx &\log_2(1 + \frac{P^{n,k}_{tx}G_n|H_n|^2}{N_0}) \\ &- \sqrt{\frac{1}{S_n}\left(1 - \frac{1}{\left(1 + \frac{P^{n,k}_{tx}G_n}{N_0}|H_n|^2\right)^2}\right)}Q^{-1}(\varepsilon_{n,k})\log_2(e) \end{aligned} \tag{6}$$

where $Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}}e^{\frac{-t^2}{2}}dt$ is the Gaussian Q-function, and $Q^{-1}(\cdot)$ represents its inverse, N_0 is the power of the additive white Gaussian noise, $P^{n,k}_{tx}$ is the transmit power of the k-th queue of the n-th device, G_n is the large-scale fading coefficient from n-th device to the BS, H_n is the Rayleigh fading coefficient with unit variance, and $|H_n|^2, n=1,2,...N$ are independent and exponentially distributed random variables with unit mean, i.e., $|H_n|^2 \sim \exp(1)$. From (6), we notice that there is a penalty on the maximum achievable rate since the finite blocklength makes the decoding error probability nonnegligible.

Given the block Rayleigh fading during different transmission superframes, the effective capacity (in bit/s), denoted by $C_{n,k}(\theta_{n,k}, d_{n,k}, \vec{d}_{-n}, P_{tx}^{n,k})$, specifies the maximum, consistent, steady-state arrival rate at the input of the k-th queue of the n-th device, given by [10], [17]

$$\begin{aligned}&C_{n,k}(\theta_{n,k}, d_{n,k}, \vec{d}_{-n}, P_{tx}^{n,k}) = \\ &-\frac{1}{\theta_{n,k}T_u}\log\left\{F_s^{n,k}(1-\varepsilon_n)\mathbb{E}_{H_n}\{e^{-\theta_{n,k}r_{n,k}S_n}\}\right. \\ &\left.+1-F_s^{n,k}(1-\varepsilon_n)\right\}\end{aligned} \tag{7}$$

where $\mathbb{E}_{H_n}\{\cdot\}$ is the expectation operation on small-scale channel fading for the n-th device, $\vec{d}_{-n} = \left\{\vec{d}_j, j \in \mathcal{N}-n\right\}$ and $\vec{d_n} = [d_{n,1}, d_{n,2}, \ldots d_{n,K}]$ is barring strategy vector for player n.

C. Composition Results

We note that if the assumptions of Gartner-Ellis theorem hold [1] [18], [19] and there is a unique QoS exponent $\theta_{n,k}^*$ that satisfies

$$A_{n,k}(\theta_{n,k}^*) = C_{n,k}(\theta_{n,k}^*, d_{n,k}, \vec{d}_{-n}, P_{tx}^{n,k}) \tag{8}$$

then the k-th queue of the n-th device is stable and $P(Q_{n,k}[\infty] \geq Q_{n,k}^{\text{th}})$ can be approximated by [18]

$$P(Q_{n,k}[\infty] \geq Q_{n,k}^{\text{th}}) \approx (1-P_{idle}^{n,k})e^{(-\theta_{n,k}^* Q_{n,k}^{\text{th}})}. \tag{9}$$

Given a delay bound $D_{\max}^{n,k}$, the probability that the steady-state packet delay at the k-th queue of the n-th device exceeds $D_{\max}^{n,k}$ is given by [19]

$$P_{th}^{n,k} \approx (1-P_{idle}^{n,k})e^{-\theta_{n,k}^* A_{n,k}(\theta_{n,k}^*)D_{\max}^{n,k}}. \tag{10}$$

Given the Bernoulli traffic arrivals, $P_{idle}^{n,k}$ is approximated as $\theta_{n,k}^*\bar{L}_{n,k}$ [18]. The empty buffer probability of the queue can be also estimated by learning the parameters of the network environments.

Theorem 1. *Given QoS exponents $\boldsymbol{\theta} = \{\theta_{n,k}, n=1,\cdots,N, k=1,\cdots,K\}$, the barring policy $\{d_{n,k}, n \in N, k \in K\}$ and the traffic arrival process, the transmit power $P_{tx}^{n,k}$ of the k-th queue at the n-th device is obtained by solving*

$$\begin{aligned}&C_{n,k}(\theta_{n,k}, d_{n,k}, \vec{d}_{-n}, P_{tx}^{n,k}) \\ &= \frac{1}{\theta_{n,k}^* T_d}\log\left(\frac{p_n}{1-\theta_{n,k}\bar{L}_{n,k}} + 1 - p_n\right).\end{aligned} \tag{11}$$

Note that (11) is obtained by substituting (2) and (7) into (8), and is solved using a bisection method, since $C_{n,k}$ monotonically increases with $P_{tx}^{n,k}$, the proof of which is provided as follows:

The first-order derivative of (6) with respect to $P_{tx}^{n,k}$ is

$$\begin{aligned}&\frac{\partial r_{n,k}}{\partial P_{tx}^{n,k}} = \frac{\sigma_n}{\ln 2(1+P_{tx}^{n,k}\sigma_n)} \\ &\left(1 - \frac{Q^{-1}(\varepsilon_{n,k})}{\sqrt{S_n}}\frac{1}{\sqrt{\left(1+P_{tx}^{n,k}\sigma_n\right)^4 - \left(1+P_{tx}^{n,k}\sigma_n\right)^2}}\right)\end{aligned} \tag{12}$$

where $\sigma_n = \frac{G_n|H_n|^2}{N_0}$. When the number of OFDM symbols is enough larger, $\sqrt{S_n} \geq Q^{-1}(\varepsilon_{n,k})$. Thus, $\frac{\partial r_{n,k}}{\partial P_{tx}^{n,k}} \geq 0$. According to (7), we can readily prove that $C_{n,k}$ is increasing with $r_{n,k}$. As a result, $C_{n,k}$ increases with $P_{tx}^{n,k}$.

IV. Barring Policy under QoS Guarantee

A. Distributed Game-Theoretic Barring Policy

The activation probability of the queue determines the arrival rate and the QoS of the traffic. The total performance in terms of effective capacity can be optimized by adaptively allocating the activation probability of all the queues over time based on the channel condition and the system delay requirement. As a result, the effective capacity maximization problem with constraints on barring policy is formulated as

$$\begin{aligned}&(P1): \max_{\{d_{n,k}\}} \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} C_{n,k}(d_{n,k}, \vec{d}_{-n}) \\ &s.t.\ d_{min} \leq d_{n,k} \leq d_{max}\end{aligned} \tag{13}$$

where $\{d_{n,k}\}$ is the activation probability of k-th queue at n-th device. Due to the non-convexity of the (P1), it is difficult to obtain the optimal solution. Besides, accurate channel information is required for centralized computation, which is cost-ineffective in the mMTC system.

The successful access in its essence is network resource competition (e.g., preambles) among devices. As a result, it can be modeled as a non-cooperative game, which is effective to analyze the interactions among distributed decision makers and to improve the performance of decentralized networks. Specifically, the priority-queuing-based access class barring policy across different devices is formulated as a non-cooperative game, denoted by $\mathcal{G} = \left[\mathcal{N}, \left\{\vec{d_n}\right\}_{n\in\mathcal{N}}, \{U_n\}_{n\in\mathcal{N}}\right]$, where $\mathcal{N} = \{1,\ldots,N\}$ is a set of players (i.e., devices), U_n is an utility (payoff) function of player n, as given by

$$U_n(\vec{d_n}, \vec{d}_{-n}) = \sum_{k\in\mathcal{K}} C_{n,k}\left(d_{n,k}, \vec{d}_{-n}\right). \tag{14}$$

In (14), the effective capacity $C_{n,k}\left(d_{n,k}, \vec{d}_{-n}\right)$ can be regarded as the profit from channel access, given by

$$C_{n,k}\left(d_{n,k}, \vec{d}_{-n}\right) = -\frac{1}{\theta_{n,k}T_s}\log\left\{1 - d_{n,k}\Phi_{n,k}(\vec{d}_{-n})\right\} \tag{15}$$

[1] The Gartner-Ellis theorem assumptions require the function (i) exists for all real θ, (ii) is strictly convex, and (iii) is essentially smooth.

where

$$\Phi_{n,k}(\vec{d}_{-n}) = \left(1 - E_{H_n}\{e^{-\theta_{n,k} r_{n,k} S_{n,k}}\}\right)(1-\varepsilon_n) \prod_{j=1}^{k-1} P_{idle}^{n,j}(1-P_{idle}^{n,k}) \prod_{l\neq n, l\in N}\left(1 - D_l \frac{1}{M}\right). \quad (16)$$

Given the game formulation, it is required to prove and derive the Nash equilibrium point. Since $C_{n,k}$ increases with $d_{n,k}$, and there is no penalty for high activation probability, it is verified that the NE point is $\{d_{n,k} = d_{\max}\}$. The NE can be far from the optimal solution of (P1).

In order to improve the efficiency of the game, we design the utility function of player n based on pricing techniques [20], given by

$$U_n(\vec{x}_n, \vec{x}_{-n}) = \sum_{k\in\mathcal{K}} \left(C_{n,k}\left(x_{n,k}, \vec{x}_{-n}\right) - \lambda_{n,k} x_{n,k}\right) \quad (17)$$

where $d_{n,k} = 1 - e^{-x_{n,k}}$, and $\lambda_{n,k}$ is regarded as a penalty price to prevent devices from always trying to access the channel and causing a heavy collision. To this end, we give Lemma 1 and Lemma 2, to prove the existence and uniqueness of NE of the new game $\mathcal{G}' = \left[\mathcal{N}, \{\vec{x}_n\}_{n\in\mathcal{N}}, \{U_n\}_{n\in\mathcal{N}}\right]$.

Lemma 1. *$U_n(\vec{x}_n, \vec{x}_{-n})$ is a concave function of $\vec{x}_n$.*

Proof: The first-order derivative of U_n with respect to $x_{n,k}$ is

$$\frac{\partial U_n}{\partial x_{n,k}} = \frac{e^{-x_{n,k}}\Phi_{n,k}(\vec{x}_{-n})}{\theta_{n,k}T_s\left(1-\Phi_{n,k}(\vec{x}_{-n}) + e^{-x_{n,k}}\Phi_{n,k}(\vec{x}_{-n})\right)} - \lambda_{n,k}, \quad (18)$$

and the second-order derivative of U_n with respect to $x_{n,k}$ is

$$\frac{\partial^2 U_n}{\partial^2 x_{n,k}} = \frac{e^{x_{n,k}}\left(\Phi_{n,k}(\vec{x}_{-n}) - 1\right)\Phi_{n,k}(\vec{x}_{-n})}{\theta_{n,k}T_s\left(e^{x_{n,k}} + \Phi_{n,k}(\vec{x}_{-n}) - e^{x_{n,k}}\Phi_{n,k}(\vec{x}_{-n})\right)^2}. \quad (19)$$

According to (16), we have $0 < \Phi_1(\vec{x}_{-n}) < 1$, and $\frac{\partial^2 U_n}{\partial^2 x_{n,k}} < 0$. Thus, this concludes the proof. ■

Lemma 2. *$U_n(\vec{x}_n, \vec{x}_{-n})$ is a sub-modular function.*

Proof: We have

$$\frac{\partial U_n}{\partial x_{n,k}\partial x_{j,k'}} = \frac{\partial}{\partial x_{j,k'}}\left(\frac{e^{-x_{n,k}}}{\theta_{n,k}T_s\left(\frac{1}{\Phi_{n,k}(\vec{x}_{-n})} - 1 + e^{-x_{n,k}}\right)}\right)$$

$$= \frac{e^{-x_{n,k}}}{\theta_{n,k}T_s\left(\frac{1}{\Phi_{n,k}(\vec{x}_{-n})} - 1 + e^{-x_{n,k}}\right)^2}\frac{1}{\Phi_{n,k}(\vec{x}_{-n})^2}\frac{\partial\Phi_{n,k}(\vec{x}_{-n})}{\partial x_{j,k'}}. \quad (20)$$

According to (16), we have $\frac{\partial\Phi_{n,k}(\vec{x}_{-n})}{\partial x_{j,k'}} < 0$. As a result, $\frac{\partial^2 U_n}{\partial x_{n,k}\partial x_{j,k'}} < 0$. Since $U_n(\vec{x}_n, \vec{x}_{-n})$ is twice differentiable, and $\frac{\partial^2 U_n}{\partial x_{n,k}\partial x_{j,k'}} < 0$, the utility function $U_n(\vec{x}_n, \vec{x}_{-n})$ is a sub-modular function [21]. ■

Informally, the sub-modularity of the game implies that the best-response of player n is a non-increasing function of another players' decision [21]. The strict mathematic proof will be given in the following.

Theorem 2 (NE Existence)**.** *The game $\mathcal{G}' = \left[\mathcal{N}, \{\vec{x}_n\}_{n\in\mathcal{N}}, \{U_n\}_{n\in\mathcal{N}}\right]$ has at least one pure-strategy Nash equilibrium $\{x^*_{n,k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}\}$.*

Proof: For every player, $d_{n,k}$ is within the interval $[d_{\min}, d_{\max}]$.Thus, we have $-\ln(1-d_{\min}) \le x_{n,k} \le -\ln(1-d_{\max})$. Let $x_{\min} = -\ln(1-d_{\min})$ and $x_{\max} = -\ln(1-d_{\max})$. Obviously, the set $x_{n,k} \in [x_{\min}, x_{\max}]$ is compact and convex. The utility function $U_n(\vec{x}_n, x_{-n})$ is a continuous function of the probability vector $\vec{x}_n$. In addition, $U_n(\vec{x}_n, \vec{x}_{-n})$ is a concave function of $\vec{x}_n$ (See Lemma 1). According to the theorem 3.2 in [22], we prove the existence of Nash equilibrium. ■

Theorem 3. *The best-response function of player n can be given by*

$$x_{n,k} = b_{n,k}(\vec{x}_{-n}) = \left[\ln\left(\frac{1}{\lambda_{n,k}\theta_{n,k}T_s} - 1\right) - \ln\left(\frac{1}{\Phi_{n,k}(\vec{x}_{-n})} - 1\right)\right]_{x_{\min}}^{x_{\max}}, \quad (21)$$

and is a decreasing function with $\vec{x}_{-n}$, where $[x]_{x_{\min}}^{x_{\max}} = \min\left[\max\left(x, x_{\min}\right), x_{\max}\right]$.

Proof: Intuitively, the best-response function of player n is the point at which the derivative of $U_n(\vec{x}_n, \vec{x}_{-n})$ with respect to $x_{n,k}$ equals zero. According to (18), it can be calculated by

$$\frac{e^{-x_{n,k}}\Phi_{n,k}(\vec{x}_{-n})}{\theta_{n,k}T_s\left(1-\Phi_{n,k}(\vec{x}_{-n}) + e^{-x_{n,k}}\Phi_{n,k}(\vec{x}_{-n})\right)} = \lambda_{n,k}. \quad (22)$$

After some algebraic manipulation, (21) can be obtained, which decreases with $\vec{x}_{-n}$. This is because

$$\frac{\partial b_{n,k}(\vec{x}_{-n})}{\partial x_{j,k'}} = \frac{1}{\Phi_{n,k}(\vec{x}_{-n}) - \Phi_{n,k}(\vec{x}_{-n})^2}\frac{\partial\Phi_{n,k}(\vec{x}_{-n})}{\partial x_{j,k'}}.$$

where $0 < \Phi_{n,k}(\vec{x}_{-n}) < 1$ and $\frac{\partial\Phi_{n,k}(\vec{x}_{-n})}{\partial x_{j,k'}} < 0$, and we have $\frac{\partial b_{n,k}(\vec{x}_{-n})}{\partial x_{j,k'}} < 0$. The proof has been accomplished. ■

According to Lemma2 and Theorem 3, a greedy updating algorithm is developed to iteratively for search the Nash equilibrium point. At iteration t, each player chooses the best strategy to the opponent strategy chosen in iteration $t-1$. For the game of the minimization of sub-modular cost function, the greedy updating algorithm is proved to converge monotonically to an equilibrium (the equilibrium depends on the initial state of the algorithm) [23], [24]. However, the conclusion cannot fit to the maximization of sub-modular utility function. In the following, we prove the convergence of the algorithm for the case of maximization of sub-modular utility function, and the uniqueness of the equilibrium.

Theorem 4 (Convergence and Uniqueness)**.** *Consider a non-cooperative game, where the payoff functions are sub-modular, players maximize, and the strategy spaces are continuous and compact. Then, the following hold.*

1) *If each player n initially uses the policy satisfying $x^0_{n,k} \le b_{n,k}(\vec{x}^*_{-n})$ and $x^0_{n,k} < x^2_{n,k}$ ($x^0_{n,k} \ge b_{n,k}(\vec{x}^*_{-n})$ and $x^0_{n,k} > x^2_{n,k}$), $\forall n \in \mathcal{N}, \forall k \in \mathcal{K}$, the sequence $\{x^t_{n,k}\}_{t=0,1,2,...}$ generated by the greedy updating algorithm converges to an Nash equilibrium $\{x^*_{n,k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}\}$.*
2) *The Nash equilibrium $\{x^*_{n,k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}\}$ is unique.*

Proof: We first prove item 1). According to the existence theorem, there is an Nash equilibrium, denoted by $\{x^*_{n,k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}\}$, satisfying $x^*_{n,k} = b_{n,k}(\vec{x}^*_{-n})$. The initial point is assume to satisfy $x^0_{n,k} \le b_{n,k}(\vec{x}^*_{-n}), \forall n \in \mathcal{N}, \forall k \in \mathcal{K}$. Due to decreasing property of the best-response function, we have

$$\begin{array}{l}
x^0_{n,k} \le b_{n,k}(\vec{x}^*_{-n}) = \vec{x}^*_{-n}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
x^1_{n,k} = b_{n,k}(\vec{x}^0_{-n}) \ge b_{n,k}(\vec{x}^*_{-n}) = \vec{x}^*_{-n}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
x^2_{n,k} = b_{n,k}(\vec{x}^1_{-n}) \le b_{n,k}(\vec{x}^*_{-n}) = \vec{x}^*_{-n}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
x^3_{n,k} = b_{n,k}(\vec{x}^2_{-n}) \ge b_{n,k}(\vec{x}^*_{-n}) = \vec{x}^*_{-n}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
\cdots \\
x^{2t}_{n,k} = b_{n,k}(\vec{x}^{2t-1}_{-n}) \le b_{n,k}(\vec{x}^*_{-n}) = \vec{x}^*_{-n}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
x^{2t+1}_{n,k} = b_{n,k}(\vec{x}^{2t}_{-n}) \ge b_{n,k}(\vec{x}^*_{-n}) = \vec{x}^*_{-n}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}
\end{array} \tag{23}$$

As a result, we can observe that the sequence $\{x^t_{n,k} - x^*_{n,k}\}_{t=0,1,2,\ldots}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}$ is an alternating sequence whose terms alternate in sign. Stated otherwise, the original sequence $\{x^t_{n,k}\}_{t=0,1,2,\ldots}$ oscillates at the Nash equilibrium $\{x^*_{n,k}\}$. In addition, we can observe that if $x^2_{n,k} - x^0_{n,k} > 0$, the following inequations are satisfied:

$$\begin{array}{l}
x^3_{n,k} - x^1_{n,k} = b_{n,k}(\vec{x}^2_{-n}) - b_{n,k}(\vec{x}^0_{-n}) < 0, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
x^4_{n,k} - x^2_{n,k} = b_{n,k}(\vec{x}^3_{-n}) - b_{n,k}(\vec{x}^1_{-n}) > 0, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
\cdots \\
x^{2t-1}_{n,k} - \vec{x}^{2t-3}_{-n} = b_{n,k}(\vec{x}^{2t-2}_{-n}) - b_{n,k}(\vec{x}^{2t-4}_{-n}) < 0, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \\
x^{2t}_{n,k} - \vec{x}^{2t-2}_{-n} = b_{n,k}(\vec{x}^{2t-1}_{-n}) - b_{n,k}(\vec{x}^{2t-3}_{-n}) > 0, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}
\end{array} \tag{24}$$

According to (23) and (24), the sub-sequence $\{x^{2t}_{n,k}\}_{t=0,1,2,\ldots}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}$ increase with t, and the upper bound is $\{x^*_{n,k}\}$. Similarly, the sub-sequence $\{x^{2t-1}_{n,k}\}_{t=1,2,\ldots}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}$ decreases with t, and the lower bound is $\{x^*_{n,k}\}$. As a result, there is a positive integer t such that for $\forall n \in \mathcal{N}, \forall k \in \mathcal{K}$, we have $\left| x^t_{n,k} - \vec{x}^{t-1}_{-n} \right| \le \zeta$, where ζ is a small positive real number and the vertical bars denote the absolute value. Stated otherwise, the original sequence $\{x^t_{n,k}\}_{t=0,1,2,\ldots}$ is a Cauchy sequence, which converges to the Nash equilibrium.

As discussed precedingly, the convergence of the algorithm needs to be guaranteed, satisfying that $x^2_{n,k} - x^0_{n,k} > 0$. Thus, we redesign the iteration, given by

$$x^2_{n,k} = \begin{cases} b_{n,k}(\vec{x}^1_{-n}), \text{when } \ b_{n,k}(\vec{x}^1_{-n}) > x^0_{n,k} \\ x^0_{n,k} + \delta, \text{when } \ b_{n,k}(\vec{x}^1_{-n}) \le x^0_{n,k} \end{cases} \tag{25}$$

where δ is a small positive real number. For the case of $x^0_{n,k} \ge b_{n,k}(\vec{x}^*_{-n})$ and $x^0_{n,k} > x^2_{n,k}$, similar proof can be obtained.

Next, we proceed to prove item 2). Suppose $\{x^*_{n,k}\}$ and $\{x^{**}_{n,k}\}$ are distinct Nash equilibrium, satisfying $x^*_{n,k} = b_{n,k}\left(\vec{x}^*_{-n}\right)$ and $x^{**}_{n,k} = b_{n,k}\left(\vec{x}^{**}_{-n}\right)$, respectively. Without loss of generality, we assume there exist n and k such that $x^{**}_{n,k} < x^*_{n,k}$. Hence, there exists $\alpha > 1$ such that for some n and k, $\alpha x^{**}_{n,k} > x^*_{n,k}$ and that for other n and k, $\alpha x^{**}_{n,k} = x^*_{n,k}$. Thus, with n and k satisfying $\alpha x^{**}_{n,k} = x^*_{n,k}$, we have

$$\alpha b_{n,k}\left(x^{**}_{n,k}\right) = b_{n,k}\left(x^*_{n,k}\right). \tag{26}$$

Since there exists at least one n' and k' such that $\alpha x^{**}_{n',k'} > x^*_{n',k'}$, we have $\alpha \vec{x}^{**}_{-n} > \vec{x}^*_{-n}$. According to the decreasing property of the best-response function, we have

$$b_{n,k}\left(\alpha \vec{x}^{**}_{-n}\right) < b_{n,k}\left(\vec{x}^*_{-n}\right). \tag{27}$$

Algorithm 1 A distributed best-response-based algorithm for the k-th queue of the n-th device

Initialize $x_{n,k}[0]$, $t = 0$ and the error ξ.
repeat
  Estimate current channel state and the successful access probability. Update $\Phi_{n,k}(\vec{x}_{-n})$ using (28).
  $t \leftarrow t + 1$.
  Update $x_{n,k}[t]$ using (21).
until $|x_{n,k}[t] - x_{n,k}[t-1]| \le \xi$

Due to contradiction, we infer the uniqueness of Nash equilibrium. ■

However, the algorithm requires all the devices' information. Thus, we propose the following fully distributed algorithm. Substituting (5) into (16), we have

$$\Phi_{n,k}(\vec{x}_{-n}) = \left(1 - \mathbb{E}_{H_n}\{e^{-\theta_{n,k} r_{n,k} S_{n,k}}\}\right) \frac{\tilde{F}^{n,k}_s}{1 - e^{-x_{n,k}}} \tag{28}$$

where $\tilde{F}^{n,k}_s = (1 - \varepsilon_n) F^{n,k}_s$ is an estimated successful access probability, and can be obtained by observing the environment, i.e., counting the acknowledgement (ACK) sent by the BS. In this way, we do not need to estimate the empty buffer probability and exchange the information with other devices. Substituting (28) into (21), we obtain a fully distributed best-response function, requiring local information, such as current channel state and the estimated successful access probability. Thus, each device iterates by itself using the fully distributed best-response function, instead of exchanging information among devices. The proposed algorithm can be explicitly described in Algorithm 1.

B. Local Optimal Price

The price selection $\lambda_{n,k}$ is of importance to maximize the effective capacity. A smaller $\lambda_{n,k}$ implies cheap access attempts, making the signalling more conflicted. However, a larger $\lambda_{n,k}$ prevents more devices from accessing the BS. Hence, an appropriate price is necessary to the game.

The local optimal price can be obtained by comparing the Lagrangian of the centralized optimization problem (P1) and that of the maximization of each player's utility. (P1) can be rewritten as

$$\begin{aligned} (P2): & \min_{\{x_{n,k}\}} - \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} C_{n,k}\left(x_{n,k}, \vec{x}_{-n}\right) \\ & s.t. \ x_{min} \le x_{n,k} \le x_{max}. \end{aligned} \tag{29}$$

The Lagrangian function of (P2) is given by

$$\begin{aligned} L_1 = \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \{ & -C_{n,k}\left(x_{n,k}, \vec{x}_{-n}\right) + (\sigma_{n,k} - \nu_{n,k}) x_{n,k} \\ & + \nu_{n,k} x_{min} - \sigma_{n,k} x_{max} \} \end{aligned} \tag{30}$$

where $\sigma_{n,k}$ and $\nu_{n,k}$ are the Lagrange multipliers for the constraints. Let $\boldsymbol{x}^{opt}$ be the optimal device activation probability.

The first order KKT condition is given by

$$\left.\frac{\partial L_1}{\partial x_{n,k}}\right|_{\boldsymbol{x}=\boldsymbol{x}^{opt}} = -\left.\frac{\partial C_{n,k}\left(x_{n,k},\vec{x}_{-n}\right)}{\partial x_{n,k}}\right|_{\boldsymbol{x}=\boldsymbol{x}^{opt}} + \sigma_{n,k} - \nu_{n,k} - \sum_{m\neq n, m\in\mathcal{N}}\sum_{b\in\mathcal{K}}\left.\frac{\partial C_{m,b}\left(x_{m,b},\vec{x}_{-m}\right)}{\partial x_{n,k}}\right|_{\boldsymbol{x}=\boldsymbol{x}^{opt}} = 0. \tag{31}$$

The maximization of each player's utility can be formulated as

$$\begin{aligned}(P3):\ &\max_{\{x_{n,k}\}} U_n\left(x_{n,k},\vec{x}_{-n}\right)\\ &s.t.\ x_{min}\leq x_{n,k}\leq x_{max}.\end{aligned} \tag{32}$$

The Lagrangian function of (P3) is given by

$$\begin{aligned}L_2 = \sum_{k\in\mathcal{K}}\{&-\left(C_{n,k}-\lambda_{n,k}x_{n,k}\right)+(\sigma'_{n,k}-\nu'_{n,k})x_{n,k}\\ &+\nu'_{n,k}x_{min}-\sigma'_{n,k}x_{max}\}\end{aligned} \tag{33}$$

where $\sigma'_{n,k}$ and $\nu'_{n,k}$ are the Lagrange multipliers for the constraints. Let $\boldsymbol{x}^*$ be the NE point. The first order KKT condition for each player's utility at the NE point is

$$\begin{aligned}\left.\frac{\partial L_2}{\partial x_{n,k}}\right|_{\boldsymbol{x}=\boldsymbol{x}^*} =& -\left.\frac{\partial C_{n,k}(x_{n,k},\vec{x}_{-n})}{\partial x_{n,k}}\right|_{\boldsymbol{x}=\boldsymbol{x}^*} + \lambda_{n,k}\\ &+\sigma'_{n,k}-\nu'_{n,k}=0.\end{aligned} \tag{34}$$

By comparing (31) with (34), we can find that they are equivalent if

$$\lambda_{n,k} = -\sum_{m\neq n, m\in\mathcal{N}}\sum_{b\in\mathcal{K}}\left.\frac{\partial C_{m,b}\left(x_{m,b},\vec{x}_{-m}\right)}{\partial x_{n,k}}\right|_{\boldsymbol{x}=\boldsymbol{x}^{opt}}. \tag{35}$$

Denote

$$\begin{aligned}f(\boldsymbol{x}) &= -\sum_{m\neq n, m\in\mathcal{N}}\sum_{b\in\mathcal{K}}\frac{\partial C_{m,b}\left(x_{m,b},\vec{x}_{-m}\right)}{\partial x_{n,k}}\\ &= \frac{1}{T_s}\frac{1}{1-D_n\frac{1}{M}}\frac{1}{M}\prod_{j=1}^{k-1}P_{idle}^{n,j}(1-P_{idle}^{n,k})e^{-x_{n,k}}\\ &\sum_{m\neq n, m\in\mathcal{N}}\sum_{b\in\mathcal{K}}\frac{1}{\theta_{m,b}}\frac{(1-e^{-x_{m,b}})\Phi_{m,b}(\vec{x}_{-m})}{1-(1-e^{-x_{m,b}})\Phi_{m,b}(\vec{x}_{-m})}.\end{aligned} \tag{36}$$

Through updating the price using (36) and the best-response function using (21), a price-update algorithm is developed to obtain the local optimality, as described in Algorithm 2. The convergence proof of Algorithm 2 is challenging considering the dynamic price in the game and is left for future work. However, the convergence has always been observed in our simulation results. Note that, due to the non-convexity of (P2), Algorithm 2 only solves for local optimal solutions. In other words, there are some saddle points or KKT points of (P2), and the final solution of Algorithm 2 depends on the selection of initial points.

Algorithm 2 A price-update algorithm

1: Initialize $x_{n,k}[0]$, $t=0$ and the error ξ.
2: **repeat**
3: $\quad t\leftarrow t+1$.
4: $\quad$Update the price using (36).
5: $\quad$**for** $n\in\mathcal{N}, k\in\mathcal{K}$ **do**
6: $\quad\quad$Update $x_{n,k}[t]$ using (21).
7: $\quad$**end for**
8: **until** $|\boldsymbol{x}[t]-\boldsymbol{x}[t-1]|\leq\xi$

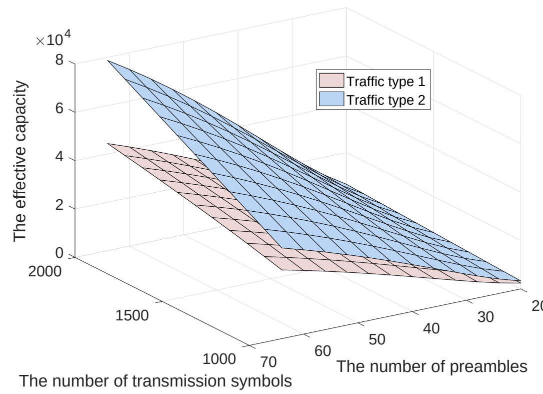

Fig. 3. The average effective capacity of one device versus the preambles resources and the data transmission resources.

V. Simulation Result

In this section, numerical results are provided. First, we evaluate the performance of the mMTC system using the proposed effective capacity. Then, the convergence and effectiveness of the distributed barring policy for maximizing each device's utility is demonstrated. Finally, we provide the results using the proposed price-update algorithm for total effective capacity maximization.

In our simulations, the BS is located in the center of an area of 500×500 m^2 and the devices are randomly and uniformly distributed with in this area. The number of traffic types is $K=2$, and the average packet length is $L=500$ bits. The QoS requirement of traffic type 1 is $\theta_{n,1}=10^{-3}, n\in\mathcal{N}$, and that of traffic type 2 is $\theta_{n,1}=10^{-5}, n\in\mathcal{N}$. The activating probability of traffic type 1 is $d_{n,1}=0.9, n\in\mathcal{N}$, and that of traffic type 2 is $d_{n,1}=0.5, n\in\mathcal{N}$. The duration of a transmission frame is $T_u=4$ ms, and that of data transmission is $T_f=3$ ms . The transmit power of each device is 10 dBm. The noise spectral density is -174 dBm/Hz. The Large-scale path loss is $PL_n=60+37.6lg(X_n)$, where X_n is the distance from the n-th device to the BS. The packet error probability $\varepsilon_{n,k}=10^{-5}$. Each point of figures is the average of 200 independent runs and for every independent run.

A. Performance analysis of the proposed effective capacity

In Fig. 3, we evaluate the joint impact of the preambles resources and the data transmission resources on the effective capacity of mMTC. The number of devices is $N=100$. The duration of a symbol is $a=66.7$ us and the bandwidth of a symbol is set to 15 KHz. We can evaluate $C_{n,k}$ by varying preambles number M and transmission bandwidth B_n. We can observe that the effective capacity grows with the preambles resources and the bandwidth in both cases of traffic types. In other words, we can joint allocated the two resources to achieve the required QoS requirement of devices.

Fig. 4 shows the performance of mMTC in terms of different QoS requirements. In the Fig. 4(a), we evaluate the

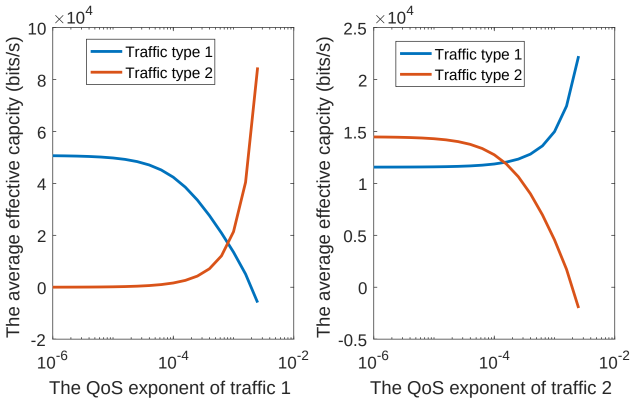

Fig. 4. The average effective capacity of one device versus different QoS requirements: (a) Given QoS requirement of traffic type 2, $d_{n,2} = 10^{-6}$; (b) Given QoS requirement of traffic type 1, $d_{n,2} = 10^{-3}$.

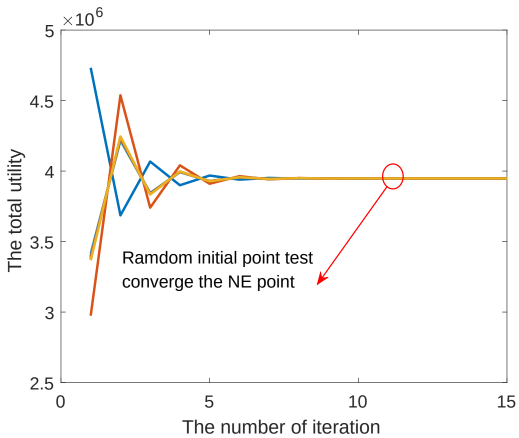

Fig. 5. Convergence of Algorithm 1.

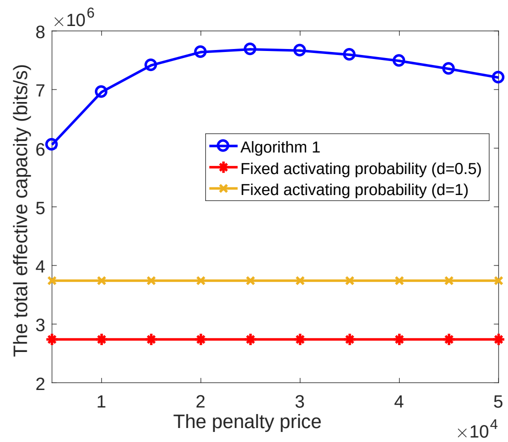

Fig. 6. Performance of different strategies with different price.

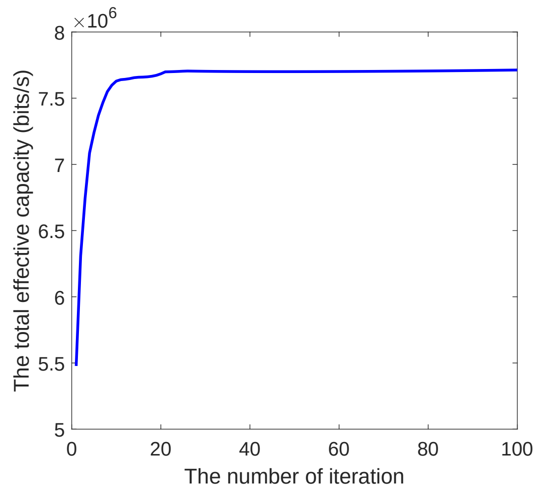

Fig. 7. Convergence of Algorithm 2.

average effective capacity with the increasing QoS exponent of traffic type 1, given $d_{n,2} = 10^{-6}$. It is shown that the effective capacity of traffic type 1 decreases with QoS exponent of traffic type 1, $\theta_{n,1}$, and is sensitive to $\theta_{n,1}$ within the region $10^{-4} \leq \theta_{n,1} \leq 10^{-2}$. On the contrary, the effective capacity of traffic type 2 decreases with $\theta_{n,1}$. This is because the larger $\theta_{n,1}$ is, the larger the queue idle probability of traffic type 1 becomes. Thus, the traffic type 2 has a higher access probability. In the Fig. 4(b), we evaluate the average effective capacity with the increasing QoS exponent of traffic type 2, given $d_{n,1} = 10^{-3}$. The conclusion is similar as that of the Fig. 4(a).

B. Convergence and performance of the distributed barring policy

In the Fig. 5, we investigate the convergence of the proposed Algorithm 1, where $\lambda_{n,k} = 1000$, $S_{n,k} = 1000$, and $M = 50$. We assume that the successful access probability of each device can be accurately estimated. In the Fig 5, we can observe that our proposed Algorithm 1 converges fast to the same NE point regardless of the initial point, which can be verified by the property of the games, as discussed in the Section IV.A.

Fig. 6 shows the total effective capacity of Algorithm 1 with different price, compared with the fixed activating probability. The simulation parameters are same as that of Fig. 5. It is shown that Algorithm 1 is superior to other strategies. This is because our proposed algorithm can search the NE point. We also observe that the penalty price has an important influence on the total effective capacity, as mentioned earlier. There is an optimal price to maximize the total effective capacity.

C. Convergence and performance of the price-update barring policy

In the Fig. 7, we investigate the convergence of the proposed Algorithm 2, where $S_{n,k} = 1000$, and $M = 50$. We can observe that our proposed Algorithm 2 converges fast to the local optimal point. Fig. 8 shows the performance of different algorithms. The price-fixed algorithm 1 cannot leverage device disparity and spatial diversity, resulting in a lower total effective capacity than that of price-update algorithm 2. We also observe that when the number of iteration is small, the gap between the two algorithms becomes bigger because the preamble resource is so scarce that the lower the price becomes, the severer the collision becomes. An appropriate price will alleviate the burst arrival.

VI. Conclusion

In this paper, we investigate a hybrid random access and data transmission protocol design to guarantee the end-to-

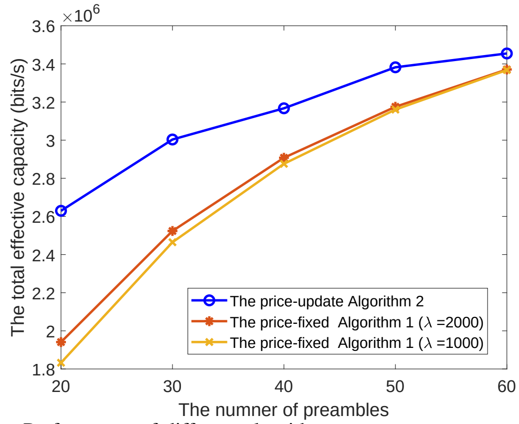

Fig. 8. Performance of different algorithms.

end QoS of different types of traffic for mMTC. First, we derive a novel effective capacity based on a priority-queueing-based ACB policy. With the proposed effective capacity, the barring policy can be modeled as a non-cooperative game. A distributed iterative algorithm that converges to the NE is then proposed. To further improve the efficiency of NE, we provide a price-update algorithm, which converges to a local optimal point for the effective capacity optimization problem. Simulation results demonstrate the performance of the novel effective capacity, where the convergence and the gains of our proposed algorithms are also verified.

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