IEEE Access Multidisciplinary | Rapid Review | Open Access Journal

SPECIAL SECTION ON SMART CACHING, COMMUNICATIONS, COMPUTING AND CYBERSECURITY FOR INFORMATION-CENTRIC INTERNET OF THINGS

Received March 2, 2019, accepted March 27, 2019, date of publication April 1, 2019, date of current version April 13, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2908681

QoE-Oriented Rate Control and Resource Allocation for Cognitive M2M Communication in Spectrum-Sharing OFDM Networks

JUNJIE YIN[1], YAPENG CHEN[1], (Student Member, IEEE), GAN SANG[1], BIN LIAO[1], AND XIAOYAN WANG[2], (Member, IEEE)

[1]State Key Laboratory of Alternate Electrical Power System With Renewable Energy Sources, School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China

[2]Graduate School of Science and Engineering, Ibaraki University, Mito, Japan

Corresponding author: Yapeng Chen (yapeng_chen@ncepu.edu.cn)

ABSTRACT With the development of wireless communication systems, it is particularly essential to maximize the quality of experience (QoE) of machine-to-machine (M2M) communication. In this paper, we propose a new QoE-oriented uplink rate control and resource allocation scheme for the Internet of Things (IoT) network, by introducing an evaluation model based on mean opinion score (MOS) for different machine-type communication (MTC) devices. The existing works are only dedicated to solving the short-term resource allocation problems by considering the current transmission time slots, which cannot handle long-standing problems. To this end, based on the recently developed Lyapunov optimization, we convert the original long-term optimization problem into the admission rate control subproblem and the resource allocation subproblem in each time slot. To solve the joint power optimization and sub-channel selection subproblems, Gale–Shapley algorithm is utilized to formulate it as a two-dimensional matching problem, and the preference lists are established by the transmission rate and signal to interference plus noise ratio (SINR). In the proposed algorithms, a priority mechanism is employed to ensure fairness. The simulation results demonstrate that without prior knowledge of the data arrivals and sub-channel statistics, the proposed algorithms can significantly improve the overall perceived quality from the users' perspective.

INDEX TERMS M2M communication, QoE, Lyapunov optimization, Gale-Shapley algorithm, rate control, resource allocation.

I. INTRODUCTION

A. BACKGROUND

With the rapid advancement of communication technologies and increase of massive access from user terminals, there is a huge shift from traditional Person-to-Person (P2P) communication to novel Machine-to-Machine (M2M) communication. M2M communication enables networked services and applications based on intelligent interaction of machine-type communication (MTC) devices [1], [2]. M2M communication, as the key technology for the composition and operation of the Internet of Things (IoT) network, is also crucial for implementation of industrial automation and smart grid on account of its excellent self-configuration, self-organization and self-healing capabilities [3], [4]. The proposal of M2M provides a comprehensive solution integrating data collection, transmission, analysis and business management for all walks of life, leading to more automated business and industrial processes [5].

Cellular network is widely considered as the ideal carrier for M2M communication because of its wide coverage, high reliability and support for high-speed mobile devices. However, due to the heterogeneity caused by the variety of the MTC devices and the interference problems inherent in traditional cellular networks, the classic resource allocation methods designed for Human-to-Human (H2H) will not appease the new requirements of M2M communication [6]. Despite experiencing the considerable development and wide-range

The associate editor coordinating the review of this manuscript and approving it for publication was Jun Wu.

of applications for M2M, there still exist several urgent problems and challenges to be resolved, which are summarized as follows [7].

1) *Stability of the data queue:* In a realistic scenario, due to the dynamic and unpredictable arrival of data flow, coupled with the time-varying characteristic of the transmission channel, the data queue is generally not properly planned and organized. In order to achieve predominant stability of data queue, it is necessary to control the channel access and data arrival rate to avoid channel congestion and packet loss [8]. To solve this problem, both protocol design at high-level layer for channel access control, and bits stream processing at low-level layer for data arrival rate control are required. Previous data control methods majorly only focus on the physical or data link layer, therefore a cross-layer control scheme is required.
2) *QoE-oriented performance optimization:* Excessive proliferation of data and traffic will inevitably lead to insufficient wireless spectrum resources, which impacts the users' quality of experience (QoE) and network operators' quality of service (QoS). Specifically, QoE is an evaluation metric for subjective perception of the end users' service performance provided by the mobile network. Unfortunately, existing researches majorly focused more on optimizing the network overall performance than QoE of individual users. Thus, how to enhance the QoE by optimally exploiting finite communication resources is a key challenge, and deserves more in-depth research.
3) *Long-standing system performance optimization:* Huge amount of real-time data generated by a variety of MTC devices and mobile terminals with diverse functions influxes into cellular networks, which may overwhelm the base station (BS), and even pose the collapse of control system. The widely studied queuing theory based network performance optimization algorithms can only realize short-term optimal performance, where part of key factors are assumed to be constant. Nevertheless, multiple and complicated environment always attaches the uncertainty and randomness of communications. Therefore, there still is a challenge to design a long-term performance optimization scheme to comply the data queue stability, resource utilization and power minimization.

Based on the discussions above, in this paper, we propose a QoE-oriented rate control and resource allocation algorithm, where the Lyapunov optimization and Gale-Shapley algorithm are applied for M2M communication in spectrum-sharing OFDM networks to maximize the network performance and meet high user's demands [9] [10]. The detail of the proposal are addressed as follows.

1) At first, we decompose the original long-term optimization problem into a series of admission rate control and the resource allocation subproblems in each time slot.
2) Next, we establish a two-sided preference list according to the transmission rate of M2M pairs and signal to interference plus noise ratio (SINR) for cellular user equipments (CUEs).
3) Finally, based on Lyapunov optimization and Gale-Shapley matching, we dynamically control the data rate and select the sub-channels to attain queue stability and power optimization.

B. RELATED WORK

In order to reduce the delay and enhance the energy efficiency, the appropriate resource allocation method in M2M communication has attracted intensive research interests. In [11], the authors presented a novel design of the software-defined M2M for smart energy management to realize cost reduction, fine granularity resource allocation, and end-to-end quality of service guarantee. In [12], the authors proposed a scheduling scheme to efficiently use the spectrum based on the received signal strength of MTC devices. However, the proposed scheme was preferred for MTC devices with better signal-to-noise ratio (SNR), and the heterogeneity of MTC devices with various QoE and queue delay was not considered. In [13], the authors investigated a resource allocation algorithm of cellular M2M communication networks to obtain initial access to the network for data transmission by a random access mechanism. In [14], the authors proposed an iterative energy-efficient game-theoretical random access algorithm to solve the overload problem caused by massive connections of M2M devices in overlapped cellular networks. However, they only considered the physical layer optimization, and left the problem at upper layer and users' QoE to future work.

To improve the users' QoE [15], promoting the service queue stability are widely considered. In [16], the authors developed a framework with dynamic data arrival in cluster-based heterogeneous mobile vehicular network, where the Markov queuing model was adopted to expand the whole-network performance. In [17], the authors designed a joint subcarrier selection and power allocation framework in the downlink of OFDMA networks by means of geometric-programming and monomial approximation techniques to guarantee the stability of queue. However, unlike traditional human-centered communication, MTC' applications typically need long-term optimization at the uplink, while most of the current works show solicitude for a short-term optimal performance at downlink. To realize a long-term queue stability without prior statistical information, Lyapunov optimization based online algorithm are utilized. In [18], the authors leveraged the Lyapunov optimization framework to convert the original long-term optimization problem into a series of online rate control and power allocation problems in each time slot. In [19], new design methodologies for green cellular networks with the help of Lyapunov optimization techniques were proposed, in which the network service cost, was adopted as the performance metric and optimized via BS assignment and power control (BAPC). Further for cognitive M2M communication in the OFDM mechanism, matching theory is suitable for solving the sub-channel selection problem, in which the two-sided preferences is taken into account when M2M devices multiplex CUEs' channels. In [20], the authors developed an iterative power allocation algorithm to generate mutual preferences list based on nonlinear fractional programing. In [21], a two-sided two-stage matching scheme was presented to address a joint route planning and task assignment problem from an energy efficiency perspective by exploring the Gale-Shapley algorithm. Combining those promising theories, a long-standing optimization in multiple time slots can be realized.

C. CONTRIBUTIONS

To solve the aforementioned problems, in this paper, we propose a QoE-oriented rate control and resource allocation method for M2M communication with cross layer design in OFDM network. The main contributions are enumerated as follows.

1) We propose a long-standing online optimization algorithm with information asymmetry for data queue rate control and resource allocation. In particular, with the assistance of recently-developed Lyapunov optimization approach, we convert the long-standing performance optimization problem to a series of short-term optimization problems. Furthermore, Gale-Shapley matching theory is applied for further completing sub-channel selection and power allocation where interference for cellular user equipments CUEs) is minimized.
2) To deal with the problem of cross-layer resource allocation with random queue generation and time-varying channel condition, our algorithm considers both bits stream at physical layer and data control transmission at network layer. The problem is converted into a mixed integer nonlinear optimization problem, and the complexity of the algorithm has been greatly reduced by utilizing the existing convex function optimization tool.

The remaining parts of this paper are organized as follows. The system model is introduced in Section II. Section III describes the problem formulation and transformation. Simulation results are provided in Section V. Section VI concludes this paper.

II. SYSTEM MODEL

As shown in FIGURE 1, we consider a cognitive M2M network, which consists of a centralized BS, K CUEs, and N M2M pairs.

Each CUE occupies one orthogonal spectrum sub-channel of equal bandwidth to perform uplink communication with the BS. The sets of CUEs and sub-channels are denoted as $\mathcal{C} = \{C_1, C_2, \ldots, C_k, \ldots, C_K\}$ and $\mathcal{S} = \{S_1, S_2, \ldots, S_k, \ldots, S_K\}$, respectively. The sets of indices are denoted as $\mathcal{K} = \{1, 2, \ldots, k, \ldots, K\}$.

TABLE 1. Summary of key notations.

Notation	Meaning
N	Number of M2M pairs
K	Number of sub-channels/ CUEs
B_w	Bandwidth of each sub-channel
n, k, t	Indices of M2M pair, sub-channels/ CUEs and time slots
$\omega_n^k(t)$	Binary decision variable on whether to allocate S_k occupied by C_k to M_n at time slot t
$A_n(t)$	Admission rate for M_n at time slot t
$R_n(t)$	Transmission rate of M_n at time slot t
$\eta_n(t)$	Priority parameter set by the BS on M_n at time slot t
$p_n(t)$	Transmission power of MT of M_n at time slot t
$p_k(t)$	Transmission power of C_k on S_k at time slot t
$g_n(t)$	Multipath channel gain from MT to MR in M2M pair M_n at time slot t
$g_k(t)$	Multipath channel gain from C_k to BS at time slot t
$g_{n,k}(t)$	Multipath channel gain between C_k and M_n at time slot t
α_C	The pathloss exponent corresponding to the CUEs
α_M	The pathloss exponent corresponding to the M2M pairs
N_0	Power of the additive white Gaussian noise
$d_{C_k,BS}$	Distance between C_k and the BS
$d_{MT_n,BS}$	Distance between MT of M_n and the BS
d_{MT_n,MR_n}	Distance between MT and MR in M2M pair M_n
d_{C_k,MR_n}	Distance between C_k and the MR of M_n
$\gamma_{C_k}(t)$	SINR of C_k sharing its sub-channel with M_n at time slot t
$\gamma_{M_n}(t)$	SINR of M_n reusing S_k occupied by C_k at time slot t
a_n	Time-averaged admission rate for M_n
O_n	Rate requirement of M_n on S_k
ρ_n	Time-averaged delay of M_n
D_n	Upper bound of the time-averaged delay of M_n
$F_{M_n,S_k}(t)$	Degree of preference of M_n to S_k at time slot t
$F_{S_k,M_n}(t)$	Degree of preference of S_k to M_n at time slot t

Each M2M pair is composed of a M2M transmitter (MT) and a M2M receiver (MR). To implement the cognitive M2M communication, each M2M pair has to reuse the sub-channel allocated to a CUE. Denote the sets of M2M pairs as $\mathcal{M} = \{M_1, M_2, \ldots, M_n, \ldots, M_N\}$ and the set of corresponding indices as $\mathcal{N} = \{1, 2, \ldots, n, \ldots, N\}$. And the sets of MTs and MRs of M2M pairs are denoted as $\mathcal{MT} = \{MT_1, MT_2, \ldots, MT_n, \ldots, MT_N\}$ and $\mathcal{MR} = \{MR_1, MR_2, \ldots, MR_n, \ldots, MR_N\}$, respectively.

A M2M pair is allowed to reuse the CUE's sub-channel for data dissemination if and only if certain constraints are satisfied, *e.g.*, the rate and the delay constraints. Intuitively, a CUE is more willing to share its sub-channel with a M2M pair which causes less interference to it.

In this paper, we assume that the peer discovery process of M2M pairs between MTs and MRs is already finished. We focus on how to maximize the QoE of all M2M pairs, which involves the joint optimization of rate control, power allocation, and sub-channel selection. In the following, the data backlog of the dynamic queueing model is discussed in Section II-A. The admission rate and the QoE model are described in Section II-B. Section II-C presents the data transmission model. The long-term constraints of transmission rate and delay are considered in Section II-D.

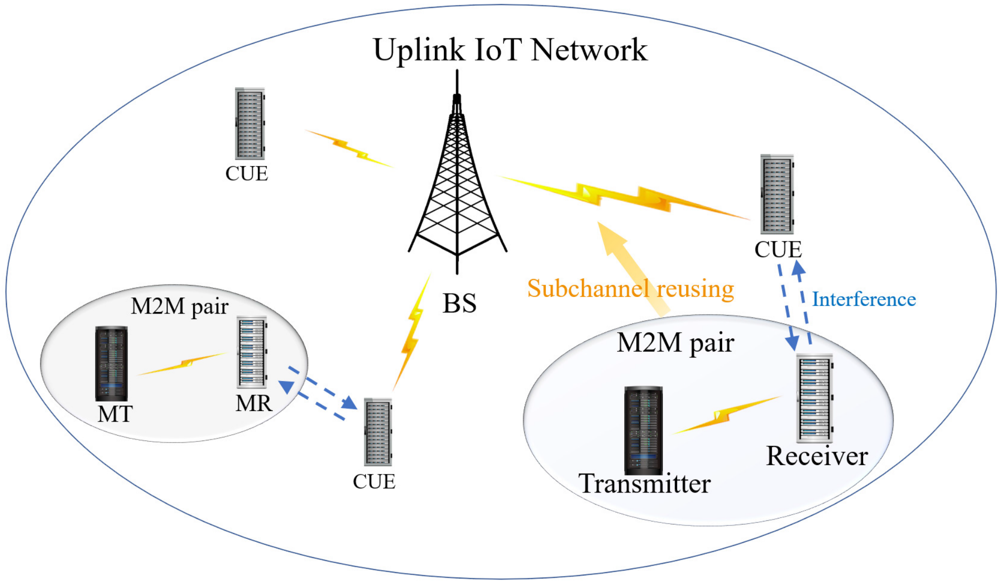


FIGURE 1. System model of M2M-based uplink IoT network.

A. QUEUE MODEL AND SYSTEM DYNAMICS

The M2M network operates in a time-slotted manner with a time-slot index $t \in \{0, 1, 2, \cdots, T\}$. At each time-slot, the data are firstly collected by MT_n and then sent to MR_n for processing. Denote the admission rate for MT_n at the t-th slot as $A_n(t)$ and the transmission rate of MT_n as $R_n(t)$.

Due to the unbalance between $A_n(t)$ and $R_n(t)$, data are firstly stored in a finite memory buffer before transmission. Denote the data backlog of M_n as $Q_n(t)$, which represents the queue length at time slot t. Then the admission rate $A_n(t)$ and the data transmission rate $R_n(t)$ can be considered as the input and the output of $Q_n(t)$, respectively. To avoid blocking, the adjustment of $A_n(t)$ and $R_n(t)$ is referred as rate control. It is noticed that $A_n(t)$ is a network-layer parameter, while $R_n(t)$ is a physical-layer parameter.

$Q_n(t)$ evolves over time as follows:

$$Q_n(t+1) = [Q_n(t) - R_n(t)]^+ + A_n(t), \tag{1}$$

where $[x]^+ = \max(x, 0)$.

Theorem 1: $Q_n(t)$ is strongly stable if

$$\lim_{T\to\infty} \sup \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{Q_n(t)\} < \infty. \tag{2}$$

Proof: Please see ***Appendix A***.

In order to guarantee that $Q_n(t)$ is strongly stable, we need to jointly optimize $A_n(t)$ and $R_n(t)$, the model of which are introduced as follows.

B. QOE MODEL

$A_n(t)$ is a network-layer parameter that reflects the admission rate, which has a direct effect on the QoE performance. In order to characterize QoE, we employee the MOS model proposed in [22]– [26], which allows us to associate user-perceived application quality metrics directly with QoS parameters such as rates.

The MOS is defined as a concave function of the admission rate $A_n(t)$:

$$MOS[A_n(t)] = \eta_n(t) \log_2[A_n(t)], \tag{3}$$

where $\eta_n(t) \in [0, 1]$ is a priority parameter, which characterize the importance of data associated with M_n at time slot t [27].

Remark 1: $\eta_n(t)$ is a predefined parameter that can be controlled by the BS. Its role is to guarantee that some important M2M pairs will have higher priority than those M2M pairs with less importance.

The logarithmic expressions have been utilized in a number of previous works, which can be found in subjective tests [28] or previously proposed related economic theories [29], [30]. The first derivative of MOS decreases with $A_n(t)$, which represents the increment of MOS per unit $A_n(t)$ decreases with $A_n(t)$. Particularly, when the value of $A_n(t)$ is small, the change in MOS is more significant. If $A_n(t)$ exceeds a certain value, the MOS changes less significantly as $A_n(t)$ increases.

C. TRANSMISSION RATE MODEL

Given K CUEs, the total bandwidth is divided equally into K sub-channels and each sub-channel's bandwidth is denoted as B_w.

The SINR of C_k which shares its sub-channel with MT_n can be expressed as

$$\gamma_{C_k}(t) = \frac{p_k(t) g_k(t) d_{C_k,BS}^{-\alpha_C}}{N_0 + p_n(t) g_{n,k}(t) d_{MT_n,BS}^{-\alpha_M}}. \tag{4}$$

In the numerator, $p_k(t)$ represents the transmission power for C_k at time slot t. $g_k(t)$ denotes the multipath channel gain from C_k to BS at time slot t. $d_{C_k,BS}^{-\alpha_C}$ denotes the pathloss channel gain for C_k at time slot t, where $d_{C_k,BS}$ stands for the distance between C_k and the BS and α_C is the pathloss exponents corresponding to the CUEs. In the denominator, N_0 denotes the power of the additive white Gaussian noise (AWGN). $p_n(t)$ represents the transmission power of MT_n. $g_{n,k}(t)$ denotes the multipath channel gain between MT_n and the BS. $d_{MT_n,BS}^{-\alpha_M}$ denotes the pathloss channel gain from MT_n to the BS, where $d_{MT_n,BS}$ stands for the distance between MT_n and the BS and α_M is the pathloss exponent corresponding to the M2M pairs. In conclusion, the interference caused by MT_n is denoted as $p_n(t)g_{n,k}(t)d_{MT_n,BS}^{-\alpha_M}$.

Similarly, the SINR of the associated MR_n can be expressed as

$$\gamma_{M_n}(t) = \frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0 + p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}. \tag{5}$$

In the numerator, $g_n(t)$ denotes the multipath channel gain between MT_n and MR_n. $d_{MT_n,MR_n}^{-\alpha_M}$ denotes the pathloss channel gain, where d_{MT_n,MR_n} stands for the distance between between MT_n and MR_n. $d_{C_k,MR_n}^{-\alpha_C}$ denotes the pathloss channel gain from C_k to MR_n, where d_{C_k,MR_n} stands for the distance between C_k and MR_n.

The transmission rate of M_n is given by:

$$R_n(t) = \omega_n^k(t)B_w \log_2\left(1+\gamma_{M_n}(t)\right), \tag{6}$$

where $\omega_n^k \in \{0,1\}$ is a binary decision of sub-channel selection. $\omega_n^k = 1$ means that M_n reuses the sub-channel S_k allocated to C_k and otherwise $\omega_n^k = 0$.

D. LONG-TERM ADMISSION RATE AND DELAY CONSTRAINTS

In practice, many M2M applications typically require an upper bound on delay and a lower bound on admission rate [31]. In the following, the time-averaged constraint of admission rate and delay are introduced.

Time-averaged constraint of admission rate is expressed as

$$a_n = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}A_n(t) \geq O_n, \tag{7}$$

where a_n is the time-averaged admission rate for M_n and O_n denotes the long-term minimum rate requirement of M_n, independent of specific time slot t.

Time-averaged constraint of delay is defined as the time length that a packet waits in a queue until it can be transmitted. Since we consider a network with heavy load, the transmission delay is negligible compared with the queuing delay. By *Little's theorem*, the time-averaged delay ρ_n is approximated [35] by

$$\rho_n = \frac{\lim\limits_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{Q_n(t)\}}{\lim\limits_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{R_n(t)\}} \leq D_n, \tag{8}$$

where D_n is the upper bound of the time-averaged delay of M_n.

III. PROBLEM FORMULATION

The optimization of the QoE performances of all M2M pairs requires solving a joint admission rate control, power allocation, and sub-channel selection problem. Denote the sets of sub-channel selection strategies, power optimization strategies, and rate control strategies as $\Omega = \{\omega_n^k\}$, $\mathbf{P} = \{p_n\}$, and $\mathbf{R} = \{R_n\}$, respectively. The joint optimization problem is formulated by maximizing the weighted MOS of all M2M pairs as

$$\max_{\mathbf{R},\Omega,\mathbf{P}} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{n=1}^{N}\mathbb{E}\{MOS[A_n(t)]\}, \tag{9}$$

$$\begin{aligned}
\text{s.t.}\ & C1: \omega_n^k(t) \in \{0,1\}\ \forall M_n \in \mathcal{M}, S_k \in \mathcal{S},\\
& C2: \sum_{S_k\in\mathcal{S}} \omega_n^k(t) \leq 1, \forall M_n \in \mathcal{M},\\
& \quad \sum_{M_n\in\mathcal{M}} \omega_n^k(t) \leq 1, \forall S_k \in \mathcal{S},\\
& C3: 0 \leq \sum_{k=1}^{K}\sum_{n=1}^{N}\omega_n^k(t)p_n(t) \leq P_{\max},\\
& C4: \gamma_{C_k} \geq \gamma_{C_k,thd}, \forall S_k \in \mathcal{S},\\
& \quad \gamma_{M_n} \geq \gamma_{M_n,thd}, \forall M_n \in \mathcal{M},\\
& C5: MOS[A_n(t)] \geq MOS_{thd}, \forall M_n \in \mathcal{M},\\
& \quad 0 \leq \sum_{n=1}^{N}A_n(t) \leq A_{\max}, \forall M_n \in \mathcal{M},\\
& C6: \text{Queues } Q_n(t) \text{ are strongly stable}, \forall M_n \in \mathcal{M},\\
& C7: a_n \geq O_n\ \forall M_n \in \mathcal{M}, S_k \in \mathcal{S},\\
& C8: \rho_n \leq D_n\ \forall M_n \in \mathcal{M}, S_k \in \mathcal{S}.
\end{aligned} \tag{10}$$

C1 and C2 ensure that each sub-channel $S_k \in \mathcal{S}$ can be reused by at most one M2M pair at each time slot t to avoid the excessive interference to existing cellular communication and vice versa. C3 specifies the transmission power constraint of M2M pairs. C4 is the SINR thresholds of CUEs and M2M pairs. C5 ensures that the MOS of each M2M pair must be larger than the threshold. C6 is the queue stability constraint of M2M pairs. C7 and C8 ensure that the rate requirement and time-averaged delay constraints of M2M pairs should be guaranteed simultaneously.

IV. JOINT RATE CONTROL AND RESOURCE ALLOCATION BASED ON LYAPUNOV OPTIMIZATION AND GALE-SHAPLEY ALGORITHM

Lyapunov optimization which enables online optimization without knowing the statistical knowledge of data arrivals and channel states is applied to solve the formulated problem.

First of all, the long-term constraints in (9) are transformed into queue stability constraints based on the concept of virtual queue [32], [33]. The virtual queue $Y(t)$ associated with the average rate constraint evolves as follows:

$$Y_n(t+1) = [Y_n(t) - A_n(t)]^+ + O_n. \tag{11}$$

Theorem 1: If the virtual power queue $Y(t)$ is mean rate stable, then the average power constraint C7 holds automatically.

Proof: Please see ***Appendix B***.

The virtual queue $Z(t)$ associated with the delay constraint evolves as follows:

$$Z_n(t+1) = [Z_n(t) - D_n R_n(t)]^+ + Q_n(t). \tag{12}$$

Remark 2: From the above analysis and according to the ***Theorem 1***, if the two virtual queues (Y, Z) are stable for all M2M pairs, both the delay and rate constraints are satisfied.

Therefore, we can transform the original problem in (9) into a problem of maximizing the MOS of the M2M pairs subject to the queue stability constraints along with C1∼C5. The transformed problem is rewritten as follows:

$$\begin{aligned} \max_{\mathbf{R},\Omega,\mathbf{P}} \quad & \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{k=1}^{K} \sum_{n=1}^{N} \mathbb{E}\left\{MOS[A_n(t)]\right\} \\ \text{s.t.} \quad & \text{C1, C2, C3, C4, and C5,} \\ & \text{Queues } Q_n(t),\ Y_n(t), \text{ and } Z_n(t) \text{ are stable,} \\ & \forall M_n \in \mathcal{M}. \end{aligned} \tag{13}$$

Let $\mathbf{Q} = \{Q_n(t)\}$, $\mathbf{Y} = \{Y_n(t)\}$, $\mathbf{Z} = \{Z_n(t)\}$ denote the sets of the queue backlogs of Q, Y, and Z, respectively.

Definition 1: Let $\mathbf{G}(t) = [\mathbf{Q}(t), \mathbf{Y}(t), \mathbf{Z}(t)]$ denote the concatenated queue backlog of the M2M pair. Define the following Lyapunov function:

$$L(\mathbf{G}(t)) \triangleq \frac{1}{2} \sum_{M_n\in\mathcal{M}} (Q_n^2(t) + Y_n^2(t) + Z_n^2(t)). \tag{14}$$

Without loss of generality, we assume that all queues are empty when $t = 0$, such that $L(\mathbf{G}(t)) = 0$.

Definition 2: Define the one-slot conditional Lyapunov drift $\Delta(\mathbf{G}(t))$as follows:

$$\Delta(\mathbf{G}(t)) \triangleq \mathbb{E}\{L(\mathbf{G}(t+1)) - L(\mathbf{G}(t)) \,|\mathbf{G}(t)\}. \tag{15}$$

Subtracting the conditional expectation of $MOS[A_n(t)]$ from (12), we obtain the following drift-minus-reward term:

$$\Delta(\mathbf{G}(t)) - V\mathbb{E}\{MOS[A_n(t)]|\mathbf{G}(t)\}. \tag{16}$$

where V is a nonnegative tunable parameter and is sufficiently large. According to the design principle of Lyapunov optimization [32], [34], the rate control and resource allocation decisions should be chosen to minimize the upper bound of (16) at each time slot t.

Theorem 2 (Upper Bound of the Drift-Minus-Reward Term): Under any control algorithms, the drift-minus-reward term is upper bounded by [32], [34]:

$$\begin{aligned} &\Delta(\mathbf{G}(t)) - V\mathbb{E}\{MOS[A_n(t)]|\mathbf{G}(t)\} \\ &\leq B + \frac{1}{2}\sum_{n=1}^{N} \mathbb{E}\{2Q_n(t)A_n(t) - 2Y_n(t)A_n(t) \\ &\quad - VMOS[A_n(t)]|\mathbf{G}(t)\} \\ &\quad - \sum_{n=1}^{N} \mathbb{E}\{Q_n(t)R_n(t) + 2D_n Z_n(t) R_n(t)|\mathbf{G}(t)\} \\ &\quad + \sum_{n=1}^{N} \mathbb{E}\{Y_n(t)O_n + Z_n(t)Q_n(t)|\mathbf{G}(t)\}. \end{aligned} \tag{17}$$

where B is a positive constant which satisfies the following inequality:

$$\begin{aligned} B &\geq B(t) \\ &= \tfrac{1}{2} \textstyle\sum_{n=1}^{N} \mathbb{E}\{R_n^2(t) + 2A_n^2(t) + O_n^2 + Q_{max}^2(t) \\ &\qquad + D_n^2 R_n^2(t)\}. \end{aligned} \tag{18}$$

Proof: Please see ***Appendix C***.

By ***Theorem 2***, we have transformed the problem defined in (13) into minimizing the right-hand side (RHS) of (17) at each time slot t subject to the rate control constraint C5 and the resource allocation constraints C1, C2, C3, and C4. Thus, the original stochastic long-term optimization problem in (9) is converted into a series of successive instantaneous static optimization subproblems, which are separated into rate control subproblems and resource allocation subproblems.

A. RATE CONTROL SUBPROBLEM

Since the second term in the RHS of (17) involves only the admission rate control decision $A_n(t)$, the minimization of this term can be decomposed into admission rate control subproblems as follows:

$$\begin{aligned} \min_{\mathbf{R}} \; & \sum_{n=1}^{N} f_1[A_n(t)], \\ \text{s.t.} \; & \text{C5.} \end{aligned} \tag{19}$$

where

$$\begin{aligned} f_1[A_n(t)] &= 2Q_n(t)A_n(t) - 2Y_n(t)A_n(t) \\ &\quad - VMOS[A_n(t)]. \end{aligned} \tag{20}$$

Because $MOS[A_n(t)]$ is a concave function of $A_n(t)$, we can verify that the problem in (19) is a convex optimization problem. Take the derivative of $2Q_n(t)A_n(t) - 2Y_n(t)A_n(t) - VMOS[A_n(t)]$ with respect to $A_n(t)$:

$$2Q_n(t) - 2Y_n(t) - \frac{V\eta_n}{A_n(t)\ln 2}. \tag{21}$$

Set the derivative to be zero, we obtain:

$$A_n(t) = \frac{\eta_n V}{2[Q_n(t) - Y_n(t)]\ln 2}. \tag{22}$$

According to the Karush-Kuhn-Tucker (KKT) conditions [36], the optimal admission rate control decision is expressed as follows:

$$A_n^*(t) = \min\left\{\frac{\eta_n V}{2[Q_n(t) - Y_n(t)]\ln 2}, A_{n,\max}\right\}, \tag{23}$$

where $A_{n,\max}$ is the maximum of admission rate for M_n corresponding to $MOS[A_n(t)]$ according to the QoE function in (3). When $A_n^*(t)$ is determined, the associated quality $MOS^*[A_n(t)]$ can be determined directly by the QoE function.

Remark 3: The admission rate control strategy in (23) means that the algorithm adjusts the admission rate associated with the MOS based on the M2M pairs' requirements and the current data queue backlog. As an example, the M2M pairs will decrease the amount of admitted data when the queue backlog is large in order to avoid data overflow or congestion. Furthermore, for a particular sub-channel, provided that the nonnegative tunable parameter V is larger, the M2M pair will implement a more relaxed rate control strategy to allow more data to be accepted. Therefore, the corresponding MOS value of the M2M pair is also increased.

B. RESOURCE ALLOCATION SUBPROBLEM

We can observe that the third term in the RHS of (17) involves only the resource allocation decision $p_n(t)$ and $\omega_n^k(t)$. The maximization of this term can be decomposed into subproblems as follows:

$$\max_{\Omega,\mathbf{P}} \sum_{n=1}^{N} f_2[R_n(t), \omega_n^k(t)],$$
$$\text{s.t.} \quad \text{C1, C2, C3, and C4.} \tag{24}$$

where

$$f_2[R_n(t), \omega_n^k(t)] = Q_n(t)R_n(t) + Z_n(t)D_nR_n(t). \tag{25}$$

The resource allocation problem is a mixed combinatorial problem because the variable $\omega_n^k(t)$ is discrete, e.g., $\omega_n^k(t) \in \{0, 1\}$, while the variable $p_n(t)$ is continuous. In practical applications, the exhaustive search for optimal solutions is prohibitive because of its high complexity.

In order to solve the above-mentioned resource allocation subproblem with high complexity, a low-complexity sub-optimal algorithm based on matching theory is proposed to decouple sub-channel selection and power allocation.

PART 1: Sub-Channel Selection Problem:

- *Definition of Gale-Shapley Matching:*

The sub-channel selection problem can be transformed into a two-dimensional matching problem involving N M2M pairs on one side and K sub-channels on the other side.

We give the following definition:

Definition 3: A matching ϕ is a one-to-one correspondence from set $\mathcal{M} \cup \mathcal{S}$ onto itself, denoted as $\phi : \mathcal{M} \cup \mathcal{S} \to \mathcal{M} \cup \mathcal{S}$, *i.e.*, $\phi(M_n) \in \mathcal{S}, \forall n \in \mathcal{N}$. And $\phi(M_n) = S_k$ reperesents that M_n is matched with sub-channel S_k, *i.e.*, $\omega_n^k(t) = 1$. $\phi(M_n) \neq S_k$ reperesents that M_n is not matched with sub-channel S_k, *i.e.*, $\omega_n^k(t) = 0$. If $\phi(S_k) = \emptyset$, it denotes that sub-channel S_k has no matching partner, *i.e.*, $\omega_n^k(t) = 0, \forall M_n \in \mathcal{M}$.

Provided that M_n and S_k prefers to be matched each other while $\phi(M_n) \neq S_k$ and $\phi(S_k) \neq M_n$, which means that the current matching ϕ is unstable. In other words, (M_n, S_k) is a blocking pair for ϕ.

- *Establishment of preference list:*

In order to achieve double-sided matching between M2M pairs and sub-channels, it is necessary for each M2M pair to construct its preference list by comparing and ordering the sub-channels on the other side according to preferences. For the M2M pair M_n, when multiplexing different sub-channels (i.e., pairing with different sub-channels), the data transmission rate of M_n is very different. Therefore, in order to maximize the data transmission rate of all M2M pairs in the network, we can define that the preference of M2M pair towards sub-channels is proportional to the data transmission rate.

The preference list of the M2M pairs to the sub-channels is a $N \times K$ matrix, which is defined as $\mathcal{F}_{\mathcal{M},\mathcal{S}}$. The element of the n-th row and the k-th column of the matrix is denoted as $F_{M_n,S_k}(t)$, indicating the degree of preference of M_n to S_k. The value of $F_{M_n,S_k}(t)$ is the data transmission rate of M_n multiplexing S_k. The preference is calculated as

$$F_{M_n,S_k}(t) = R_n(t) = \omega_n^k(t)B_w \log_2\left(1 + \gamma_{M_n}(t)\right). \tag{26}$$

Similarly, the preference list of the sub-channels to the M2M pairs is a $K \times N$ matrix, which is defined as $\mathcal{F}_{\mathcal{S},\mathcal{M}}$. The element of the k-th row and the n-th column of the matrix is denoted as $F_{S_k,M_n}(t)$, indicating the degree of preference of S_k to M_n. The value of $F_{S_k,M_n}(t)$ is denoted by SINR of C_k. The preference is calculated as

$$F_{S_k,M_n}(t) = \gamma_{C_k}(t) = \frac{p_k(t)g_k(t)d_{C_k,BS}^{-\alpha_C}}{N_0 + p_n(t)g_{n,k}(t)d_{MT_n,BS}^{-\alpha_M}}. \tag{27}$$

By temporarily paring sub-channels with M2M pairs, all of the value of elements in $\mathcal{F}_{\mathcal{S},\mathcal{M}}$, which shows interference of the M2M pairs on each sub-channel can be obtained. Note that a CUE can be more robust against the interference if it can have a higher SINR $\gamma_{C_k}(t)$. Also, one with bigger SINR $\gamma_{C_k}(t)$ can experience a less amount of interference. If the interference caused by M2M pairs to existing uplinks of CUEs are very serious, it is possible for CUEs to reject sharing sub-channels with certain M2M pairs.

- *Matching process and algorithm:*

The matching process is implemented in multiple iterations, and the detailed process is summarized as ***Algorithm 1***. Note that resource allocation based on matching is implemented by BS. Specifically, each M2M pair first uploads its preference list to BS. Then, BS determines the stability of the match based on the preference list of CUEs. Finally, BS derives a stable match between the CUEs and the M2M pairs to implement internal data transmission of the M2M pairs. The steps of the detailed implementation process of ***Algorithm 1*** are explained below.

Phase 1: Initialization of preference list

- Calculate $F_{M_n,S_k}(t)$ for each M2M pair $M_n \in \mathcal{M}$.
- Calculate $F_{S_k,M_n}(t)$ for each sub-channels $S_k \in \mathcal{S}$.
- ϕ is initialized as empty set firstly. M2M pairs submit applications to their most preferred sub-channel based on the established preference list $\mathcal{F}_{\mathcal{M},\mathcal{S}}$.

- Define Ω' as the set of sub-channels which receive multiple matching requests from M2M pairs, for it is possible for more than one M2M pairs to prefer the same sub-channel at the same time-slot. Note that $\Omega' = \emptyset$ at $t = 0$.

Phase 2: Iterative matching

- Declare the availability of each M2M pair and sub-channel.

Repeat the following process iteratively (n from 1 to N, k from 1 to K).

- if $\phi(M_n) = \emptyset$ ($\forall n \in \mathcal{M}$), then set $\omega_n^k = 1$(i.e.,S_k is engaged to M_n).
- if $\phi(M_n) \neq \emptyset$ ($\omega_m^k = 1$) and $F_{S_k,M_n} > F_{S_k,M_m}$, then set $\omega_n^k = 1$(i.e.,S_k is re-engaged to M_n) and set $\omega_m^k = 0$ (i.e., re-declare the availability of M_m).

Until Every M2M pair has been matched with a sub-channel, i.e., $\phi(M_n) \neq \emptyset, \forall M_n \in \mathcal{M}$, or there exists none of unmatched M2M pairs.

Phase 3: Sub-channel selection implementation

MTs multiplex the specified subchannel to send the data to MRs, according to the matching result obtained in **Phase 2**. In the case considered in this paper, the number of M2M pairs is less than the number of sub-channels. Therefore, each M2M pair is paired with one sub-channel, but some sub-channels have no matching objects. For the set of sub-channels not matched, they only carry out communication with BS due to the characteristics CUEs current time slot. In the next time slot, $\mathcal{F}_{\mathcal{M},\mathcal{S}}$ and $\mathcal{F}_{\mathcal{S},\mathcal{M}}$ are cleared, and the subchannel selection process is restarted from **Phase 1**.

PART 2: Power Allocation Problem:

When $\phi(M_n) = S_k$, in other words, $\omega_n^k(t) = 1$, the maximum value of $f_2[R_n(t)|\omega_n^k(t) = 1]$ can be obtained by solving the following power optimization problem:

$$\max_{\mathbf{P}} \quad \sum_{n=1}^{N} f_2[R_n(t)|\omega_n^k(t) = 1],$$
$$\text{s.t.} \quad \text{C1, C2, C3, and C4.} \tag{28}$$

Problem (28) is also a convex optimization problem, where the optimal solution exists, which is denoted as $p_n^*(t)$ and the convexity of power optimization problem is proved in ***Appendix D***.

Substitute $R_n(t)$ specific expression in (6) into the $f_2[R_n(t)|\omega_n^k(t) = 1]$ in formula (28). The following formula can be obtained:

$$[Q_n(t) + Z_n(t)D_n] * \log_2\left(1 + \frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0 + p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}\right). \tag{29}$$

Since$[Q_n(t) + Z_n(t)D_n]$ in formula (29) does not contain $p_n(t)$ and $R_n(t)$ is a concave function of $p_n(t)$, take the derivative of $R_n(t)$ with respect to $p_n(t)$ and the result is shown as follows:

$$\frac{dR_n(t)}{dp_n(t)} = \left[\log_2\left(1 + \frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0 + p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}\right)\right]'$$

$$= \frac{1}{1 + \frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0+p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}} * \frac{d\frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0+p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}}{dp_n(t)}. \tag{30}$$

Algorithm 1 Gale-Shapley Matching Based Sub-Channel Selection Algorithm

$\mathcal{M}$: The set of M2M pairs
$\mathcal{S}$: The set of sub-channels
for $n = 1$ to $|\mathcal{M}|$ **do**
  sort the sub-channels of each M2M pair according to $R_n(t)$ in decreasing order
end for
for $k = 1$ to $|\mathcal{S}|$ **do**
  sort the M2M pair of each sub-channel according to $\gamma_{C_k}(t)$ in decreasing order
end for
Declare the availability of each M2M pair and sub-channel
for $n = 1$ to $|\mathcal{M}|$ **do**
  while M_n is available **do**
    S_k:= the first sub-channel on the preference list of M_n to whom M_n has not yet proposed
    if S_k is available ($\omega_n^k = 0, \forall n \in \mathcal{M}$) **then**
      S_k is engaged to M_n, set $\omega_n^k = 1$
    else
      if S_k prefers M_n to its 'fiance' M_m ($m \neq n$) **then**
Re-engage
        S_k to M_n, set $\omega_n^k = 1$;
Re-decare
        the availability of M_m, set $\omega_m^k = 0$
      else
        S_k rejects M_n, set $\omega_n^k = 0$
      end if
    end if
  end while
end for
The matching results of the N couples are declared

Set the derivative to be zero, we obtain:

$$p_n(t) = \arg_{\mathbf{P}} \frac{dR_n(t)}{dp_n(t)}. \tag{31}$$

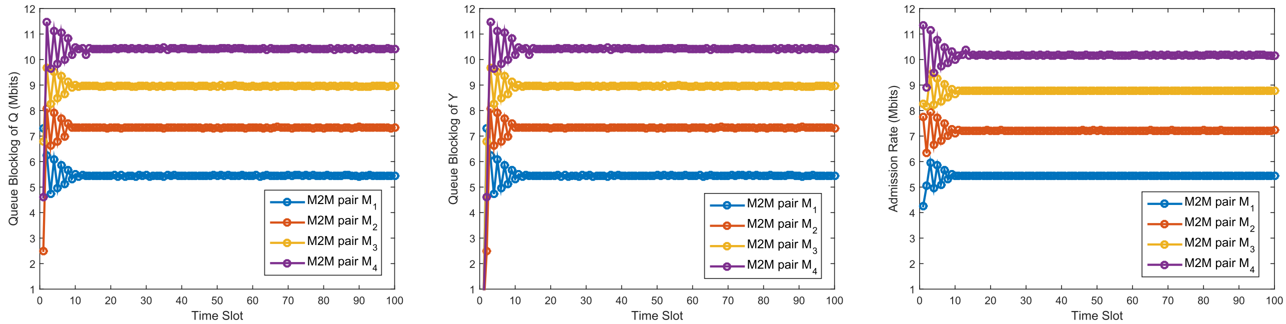
According to the Karush-Kuhn-Tucker (KKT) conditions [36], the optimal power optimization decision is expressed as follows:

$$p_n^*(t) = \min\left\{\arg_{\mathbf{P}} \frac{dR_n(t)}{dp_n(t)}, p_{n,\min}\right\}, \tag{32}$$

where $p_{n,\min}$ is the minimum of transmission power of M_n.

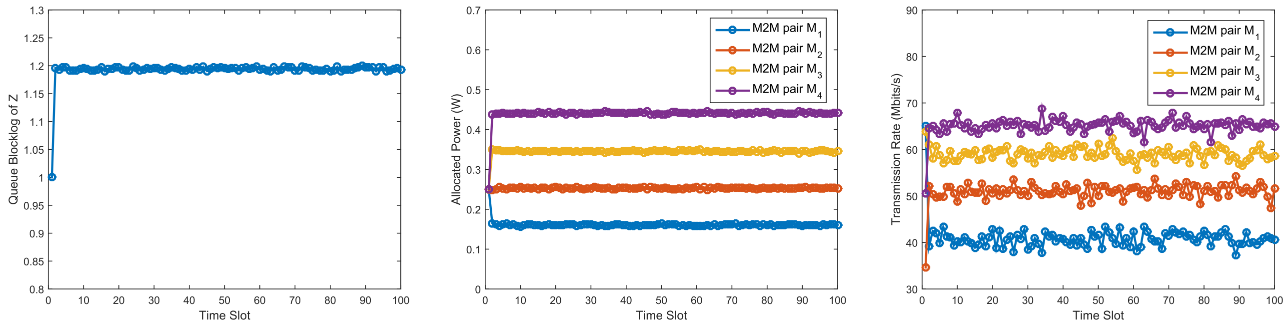
V. SIMULATION RESULTS

In this section, the performance of the proposed Gale-Shapley matching based resource allocation algorithm is validated



(a) (b) (c)

FIGURE 2. Rate control.



(a) (b) (c)

FIGURE 3. Power allocation and sub-channel selection.

TABLE 2. Simulation parameters.

Simulation Parameters	Value
Number of M2M pairs N	4
Number of Sub-channels/ CUEs K	5
Network Radius	200 m
Bandwidth of each Sub-channel	20 MHz
Priority parameter $\eta_n(t)$	0.2,0.3,0.4,0.5
Transmission power of M_n at $t = 0$ $p_n(0)$	0.25 W
SINR threshold of $\gamma_{C_k,thd}$ and $\gamma_{M_n,thd}$	12 dB
Additive white Gaussian noise N_0	-110 dBm
Upper bound of delay versus M2M pair M_n	0.2,0.3,0.4,0.5s
Upper bound of total transmission power $P_{\max}$	1.2 W
Upper bound of total admission rate $A_{\max}$	30 $Mbits/s$

through simulations. CVX, which is a Matlab-based modeling system for convex optimization, is utilized to solve the problem mentioned above. CVX turns Matlab into a modeling language, allowing constraints and objectives to be specified using standard Matlab expression syntax. Table 2 presents the simulation parameters.

FIGURE 2 shows the backlogs changes of different queues versus time slot. We can observe that when random initial backlogs is given, each queue tend to stabilize near a corresponding value after only several slots. The numerical results prove that the rate control can be achieved by exploiting our method to continuous backlogs of the queues or excessive processing capacity of the BS. It is worth mentioning that the size of the backlogs is positively related to the priority for the reason that the M2M pair with higher priority has more data collection and more frequent data transmission leading to more queue backlogs.

FIGURE 3 shows the joint resource allocation and sub-channel selection versus time slot. Specifically, similar stable simulation result for virtual queue Z is shown in FIGURE 3-(a), where the value represents total allocated power P_{max}. FIGURE 3-(b) reveals the power optimization results with four gradients varying from device to device. The transmission rate of the sub-channels is as shown in FIGURE 3-(c) after allocation. Above results demonstrate that combinatorial algorithm with Lyapunov optimization and Gale-Shapley matching can not only maintains the stability of the system, but also avoid the influence of the time-varying channel as much as possible.

FIGURE 4 compares the total system stability analysis of our proposed algorithm and Lyapunov optimization with random matching from the perspective of queue backlogs and power allocation, in which two box-plots are shown to display a set of data dispersion. Whatever referring to backlogs or power allocation, the overall distribution of proposed scheme is more concentrated than that of random sub-channel selection on account of the possibility matching a poor-performance sub-channel to the high queue with high priority.

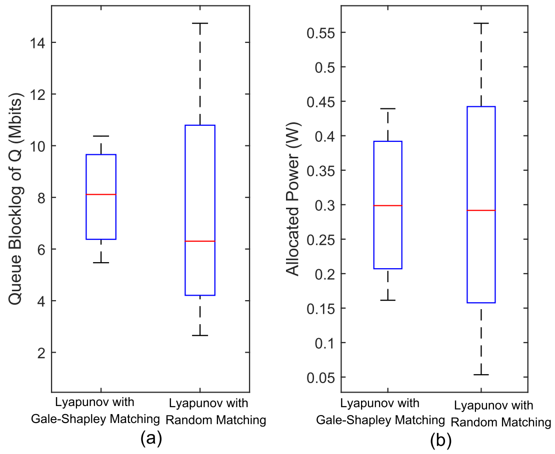


FIGURE 4. Total system stability.

VI. CONCLUSION AND FUTURE RESEARCH

In this paper, we have proposed novel QoE-oriented uplink rate control and resource allocation schemes for IoT using time-varying channels. We utilize the rate control associated with QoE adjustment, and the resource allocation associated with sub-channel selection and power optimization to perform the dynamic resource management. MOS model is designed to measure the degree of assesses QoE. We employ a stochastic optimization model to maximize the time-averaged MOS of all M2M pairs subject to the network stability constraint, the admission rate control constraint and the delay constraint intrinsic of the OFDM network.

We convert the original long-term optimization problem into admission rate control subproblem and resource allocation subproblem in each time slot, based on the recently developed Lyapunov optimization, without prior knowledge of channel statistics. In particular, we exploit the special structure of the resource allocation subproblem to develop extremely simple and low-complexity but optimal Gale-Shapley matching based resource allocation algorithm for the resource allocation subproblem. We show that the optimal decisions achieved without any prior knowledge of channel statistics can arbitrarily approach the optimal decisions achieved by the algorithm with complete knowledge of channel statistics. The simulation results verify that the Gale-Shapley matching based resource allocation algorithm can significantly improve the MOS compared with the random matching algorithm.

In our future work, we will:

1) investigate the rate control and resource allocation issues with externalities;
2) extend the work to more complex type of QoE model, considering more measuring standards;
3) consider the problem closer to the actual situation of life, *e.g.*, three-dimensional matching between transmitters, receivers and sub-channels, which involves joint peer discovery, sub-channel selection and power optimization problem.

APPENDIX A
PROOF OF THEOREM 1

A multiqueue network is strongly stable if all the individual queues are strongly stable. According to the strong stability theorem in [32], for finite variables $A_n(t)$ and $R_n(t)$, strong stability implies the rate stability of $Q_n(t)$. The definition of rate stability can be found in [32] and omitted here. According to the rate stability theorem in [32], the discrete queue $Q_n(t)$ is rate stable if and only if the time-average transmission rate r satisfies

$$r \geq a \tag{33}$$

where $r = \lim\limits_{T\to\infty} \frac{1}{T}\sum\limits_{t=0}^{T-1} R_n(t)$, $a = \lim\limits_{T\to\infty} \frac{1}{T}\sum\limits_{t=0}^{T-1} A_n(t)$. The assumption is reasonable since all physical quantities, such as the admission rates, the transmission rates, and the transmit power, are all bounded in real condition. Thus, if a queue is strongly stable, the time-averaged transmission rate r satisfies $r \geq a$.

APPENDIX B
PROOF OF THEOREM 1

From (11), we naturally have

$$Y_n(t+1) \geq Y_n(t) - A_n(t) + O_n. \tag{34}$$

Summing (34) over $t \in \{0, 1, \ldots, T\}$ and taking expectations, we obtain

$$\mathbb{E}\{Y_n(T)\} \leq \sum_{t=0}^{T-1} \mathbb{E}\{A_n(t)\} - TO_n. \tag{35}$$

Dividing by T and taking $T \to +\infty$ yield

$$\lim_{T\to+\infty} \frac{\mathbb{E}\{Y_n(T)\}}{T} \leq \frac{\sum\limits_{t=0}^{T-1} \mathbb{E}\{A_n(t)\}}{T} - O_n. \tag{36}$$

From Jensen's inequality, we have $0 \leq |\mathbb{E}\{Y_n(T)\}| \leq \mathbb{E}\{|Y_n(T)|\}$. Thus, if $Y_n(t)$ is mean rate stable, i.e., $\lim\limits_{T\to+\infty} (\mathbb{E}\{|Y(T)|\}/T) = 0$, we have

$$\lim_{T\to+\infty} \frac{\mathbb{E}\{Y_n(T)\}}{T} = 0. \tag{37}$$

Thus, we obtain

$$\frac{\sum\limits_{t=0}^{T-1} \mathbb{E}\{A_n(t)\}}{T} \geq O_n. \tag{38}$$

which proves Theorem 1.

APPENDIX C
DRIFT-MINUS-REWARD

Theorem 2: For any nonnegative real numbers x, y, and z, there holds [32]

$$[\max(x-y,0)+z]^2 \leq x^2 + y^2 + z^2 - 2x(y-z).$$

By employing ***Theorem 1*** and squaring both sides of the queue dynamics (1), (11), (12), we obtain By employing ***Theorem 1*** and squaring both sides of the queue dynamics (1), (11), (12), we obtain

$$\begin{aligned}
&\Delta(\mathbf{G}(t)) - V\mathbb{E}\{MOS[A_n(t)]|\mathbf{G}(t)\}\\
&\triangleq \mathbb{E}\{L\left(\mathbf{G}(t+1)\right) - L\left(\mathbf{G}(t)\right)|\mathbf{G}(t)\}\\
&\quad -V\mathbb{E}\{MOS[A_n(t)]|\mathbf{G}(t)\}\\
&\le \frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{R_n^2(t) + A_n^2(t) - 2Q_n(t)(R_n(t) - A_n(t))|\mathbf{G}(t)\}\\
&\quad +\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{A_n^2(t) + O_n^2 - 2Y_n(t)(A_n(t) - O_n)|\mathbf{G}(t)\}\\
&\quad +\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{D_n^2R_n^2(t) + Q_n^2(t)\\
&\quad -2Z_n(t)[D_nR_n(t) - Q_n(t)]|\mathbf{G}(t)\}\\
&\quad -\frac{1}{2}\sum_{n=1}^{N}V\mathbb{E}\{MOS[A_n(t)]|\mathbf{G}(t)\}\\
&\le \frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{R_n^2(t) + 2A_n^2(t) + O_n^2 + Q_{max}^2(t) + D_n^2R_n^2(t)\}\\
&\quad +\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{-2Q_n(t)(R_n(t) - A_n(t))|\mathbf{G}(t)\}\\
&\quad +\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{-2Y_n(t)(A_n(t) - O_n)|\mathbf{G}(t)\}\\
&\quad +\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{-2Z_n(t)(D_nR_n(t) - Q_n(t))|\mathbf{G}(t)\}\\
&\quad -\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{VMOS[A_n(t)]_n(t)|\mathbf{G}(t)\}\\
&\le B + \frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{2Q_n(t)A_n(t) - 2Y_n(t)A_n(t)\\
&\quad -VMOS[A_n(t)]|\mathbf{G}(t)\}\\
&\quad -\sum_{n=1}^{N}\mathbb{E}\{Q_n(t)R_n(t) + Z_nD_n(t)R_n(t)|\mathbf{G}(t)\}\\
&\quad +\sum_{n=1}^{N}\mathbb{E}\{Y_n(t)O_n + Z_n(t)Q_n(t)|\mathbf{G}(t)\}. \qquad (39)
\end{aligned}$$

APPENDIX D
PROOF OF CONVEXITY OF THE RESOURCE ALLOCATION SUBPROBLEM

After relaxing $\omega_n^k(t)$ to $\tilde{\omega}_n^k(t) \in [0, 1]$, the original RA subproblem is formulated as follows:

$$\begin{aligned}
\max_{\Omega,\mathbf{P}}\quad & \sum_{n=1}^{N}[Q_n(t) + Z_n(t)D_n] * \omega_n^k(t)\log_2\\
&\times\left(1 + \frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0 + p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}\right), \qquad (40)\\
\text{s.t.}\quad & 0 \le \tilde{\omega}_n^k(t) \le 1, \forall M_n \in \mathcal{M}, S_k \in \mathcal{S}, \qquad (41)\\
& 0 \le \sum_{S_k\in\mathcal{S}} \tilde{\omega}_n^k(t) \le 1, \forall M_n \in \mathcal{M}, \qquad (42)\\
& \text{C3, and C4.}
\end{aligned}$$

Assuming that $f(x)$ is concave, then its perspective function $bf(x)$ is still concave in (b, x). From this, (40) is jointly concave in $\tilde{\mathbf{W}}(t) = \{\tilde{w}_{nk}(t)\}$ and $\mathbf{P}(t)$ because it can be regarded as the perspective function of the concave function $\log_2\left(1 + \frac{p_n(t)g_n(t)d_{MT_n,MR_n}^{-\alpha_M}}{N_0+p_k(t)g_{n,k}(t)d_{C_k,MR_n}^{-\alpha_C}}\right)$. As a result, the objective in the given optimization problem is jointly concave in $\tilde{\mathbf{W}}(t)$ and $\mathbf{P}(t)$.

In addition, (41), (42), C3 and C4 are all linear constraints; thus, the sets produced by them for $\tilde{\mathbf{W}}(t)$ and $\mathbf{P}(t)$ are convex. Therefore, (41), (42), C3 and C4 together construct a convex set as well. Therefore, the given optimization problem maximizes a concave function over a convex set; thus, it is a concave optimization problem.

APPENDIX E
GALE-SHAPLEY ALGORITHM

The stable marriage problem has been stated as follows:

See ***Algorithm 2***.

Algorithm 2 Gale-Shapley Algorithm

1: Declare the availability of each M2M pair and sub-channel
2: **while** M_n is available **do**
3: S_k:= the first sub-channel on M_n's preference list to whom M_n has not yet proposed
4: **if** S_k is available ($\omega_n^k = 0, \forall n \in \mathcal{M}$) **then**
5: The S_k is engaged to M_n
6: **else**
7: **if** S_k prefers M_n to its 'fiance' M_m $(m \neq n)$ **then**
Re-engage
8: S_k to M_n, set $\omega_n^k = 1$;
Re-declare
9: the availability of M_m, set $\omega_m^k = 0$
10: **else**
11: S_k rejects M_n, set $\omega_n^k = 0$
12: **end if**
13: **end if**
14: **end while**

REFERENCES

[1] Z. Zhou, M. Dong, K. Ota, J. Wu, and T. Sato, "Energy efficiency and spectral efficiency tradeoff in device-to-device (D2D) communication," *IEEE Wireless Commun. Lett.*, vol. 3, no. 5, pp. 485–488, Oct. 2014.

[2] J. Wu, M. Dong, K. Ota, L. Liang, and Z. Zhou, "Securing distributed storage for social Internet of Things using regenerating code and blom key agreement," *Peer-to-Peer Netw. Appl.*, vol. 8, no. 6, pp. 1133–1142, Nov. 2015.

[3] Z. Zhou, H. Liao, G. Gu, K. M. S. Huq, S. Mumtaz, and J. Rodriguez, "Robust mobile crowd sensing: When deep learning meets edge computing," *IEEE Netw.*, vol. 32, no. 4, pp. 54–60, Jul. 2018.

[4] J. Wu, M. Dong, K. Ota, J. Li, and Z. Guan, "Big data analysis-based secure cluster management for optimized control plane in software-defined networks," *IEEE Trans. Netw. Service Manag.*, vol. 15, no. 1, pp. 27–38, Mar. 2018.

[5] Z. Zhou, M. Dong, K. Ota, G. Wang, and L. T. Yang, "Energy-efficient resource allocation for D2D communications underlaying cloud-RAN-based LTE-A networks," *IEEE Internet Things J.*, vol. 3, no. 3, pp. 428–438, Jun. 2016.

[6] J. Wu, S. Luo, S. Wang, and H. Wang, "NLES: A novel lifetime extension scheme for safety-critical Cyber-physical systems using SDN and NFV," *IEEE Internet Things J.* to be published. doi: 10.1109/JIOT.2018.2870294.

[7] J. Wu, M. Dong, K. Ota, J. Li, and Z. Guan, "FCSS: Fog computing based content-aware filtering for security services in information centric social networks," *IEEE Trans. Emerg. Topics Comput.* to be published. doi: 10.1109/TETC.2017.2747158.

[8] Z. Meng, Z. Wu, C. Muvianto, and J. Gray, "A data-oriented M2M messaging mechanism for industrial IoT applications," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 236–246, Feb. 2017.

[9] D. Gale and L. S. Shapley, "College admissions and the stability of marriage," *Amer. Math. Monthly*, vol. 69, no. 1, pp. 9–15, Jan. 1962.

[10] Z. Zhou, C. Gao, C. Xu, Y. Zhang, S. Mumtaz, and J. Rodriguez, "Social big-data-based content dissemination in Internet of vehicles," *IEEE Trans. Ind. Informat.*, vol. 14, no. 2, pp. 768–777, Feb. 2018.

[11] Z. Zhou, J. Gong, Y. He, and Y. Zhang, "Software defined machine-to-machine communication for smart energy management," *IEEE Commun. Mag.*, vol. 55, no. 10, pp. 52–60, Oct. 2017.

[12] U. Tefek and T. J. Lim, "Relaying and radio resource partitioning for machine-type communications in cellular networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 2, pp. 1344–1356, Feb. 2017.

[13] H. S. Dhillon, H. C. Huang, H. Viswanathan, and R. A. Valenzuela, "Power-efficient system design for cellular-based machine-to-machine communications," *IEEE Trans. Wireless Commun.*, vol. 12, no. 11, pp. 5740–5753, Nov. 2013.

[14] Z. Zhou *et al.*, "Energy-efficient game-theoretical random access for M2M communications in overlapped cellular networks," *Comput. Netw.*, vol. 129, no. 2, pp. 493–501, Dec. 2017.

[15] *Subjective Video Quality Assessment Methods for Multimedia Application*, document Rec. ITU-T 910, Sep. 1990.

[16] Q. Zheng, K. Zheng, L. Sun, and V. C. M. Leung, "Dynamic performance analysis of uplink transmission in cluster-based heterogeneous vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 12, pp. 5584–5595, Dec. 2015.

[17] S. Lakani and F. Gagnon, "Optimal design and energy efficient binary resource allocation of interference-limited cellular relay-aided systems with consideration of queue stability," *IEEE Access*, vol. 5, pp. 8459–8474, 2017.

[18] W. Bao, H. Chen, Y. Li, and B. Vucetic, "Joint rate control and power allocation for non-orthogonal multiple access systems," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 12, pp. 2798–2811, Dec. 2017.

[19] Y. Mao, J. Zhang, and K. B. Letaief, "A Lyapunov optimization approach for green cellular networks with hybrid energy supplies," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2463–2477, Dec. 2015.

[20] Z. Zhou, K. Ota, M. Dong, and C. Xu, "Energy-efficient matching for resource allocation in D2D enabled cellular networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 6, pp. 5256–5268, Jun. 2017.

[21] Z. Zhou *et al.*, "When mobile crowd sensing meets UAV: Energy-efficient task assignment and route planning," *IEEE Trans. Commun.*, vol. 66, no. 11, pp. 5526–5538, Nov. 2018.

[22] P. Li, Y. Wang, W. Zhang, and Y. Huang, "QoE-oriented two-stage resource allocation in femtocell networks," in *Proc. IEEE 80th Veh. Technol. Conf. (VTC-Fall)*, Vancouver, BC, USA, Sep. 2014, pp. 1–5.

[23] M. Eckert, T. M. Knoll, and F. Schlegel, "Advanced MOS calculation for network based QoE Estimation of TCP streamed Video Services," in *Proc. 7th Int. Conf. Signal Process. Commun. Syst. (ICSPCS)*, Carrara, Italy, 2013, pp. 1–9.

[24] R. C. Streijl, S. Winkler, and D. S. Hands, "Mean opinion score (MOS) revisited: Methods and applications, limitations and alternatives," *Multimedia Syst.*, vol. 22, no. 2, pp. 213–227, Mar. 2016.

[25] C. Sacchi, F. Granelli, and C. Schlegel, "A QoE-oriented strategy for OFDMA radio resource allocation based on min-MOS maximization," *IEEE Commun. Lett.*, vol. 15, no. 5, pp. 494–496, May 2011.

[26] D. Yuan, M. Song, Y. Teng, D. Ma, X. Wang, and G. Lu, "QoE-oriented resource allocation for multiuser-multiservice femtocell networks," *China Commun.*, vol. 12, no. 10, pp. 27–41, Oct. 2015.

[27] Y. Guo, Q. Yang, and K. S. Kwak, "Quality-oriented rate control and resource allocation in time-varying OFDMA networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 3, pp. 2324–2338, Mar. 2017.

[28] P. Reichl, S. Egger, R. Schatz, and A. D'Alconzo, "The logarithmic nature of QoE and the role of the Weber-fechner law in QoE assessment," in *Proc. IEEE Int. Conf. Commun.*, Cape Town, South Africa, May 2010, pp. 1–5.

[29] M. Fiedler, T. Hossfeld, and P. Tran-Gia, "A generic quantitative relationship between quality of experience and quality of service," *IEEE Netw.*, vol. 24, no. 2, pp. 36–41, Mar./Apr. 2010.

[30] S. Khorsandroo, R. M. Noor, and S. Khorsandroo, "A generic quantitative relationship between quality of experience and packet loss in video streaming services," in *Proc. 4th Int. Conf. Ubiquitous Future Netw. (ICUFN)*, Phuket, Thailand, Jul. 2012, pp. 352–356.

[31] B. Dimitri and G. Robert, *Data Networks*, 2nd ed. New York, NJ, USA: Prentice-Halls, 1992, pp. 1–556.

[32] N. Michael, *Stochastic Network Optimization with Application to Communication and Queueing Systems* (Synthesis Lectures on Communication Networks). San Rafael, CA, USA: Morgan & Claypool, 2010, ch. 3, sec. 1, pp. 17–18.

[33] M. J. Neely, "Energy optimal control for time-varying wireless networks," *IEEE Trans. Inf. Theory*, vol. 52, no. 7, pp. 2915–2934, Jul. 2006.

[34] L. Georgiadis, M. J. Neely, and L. Tassiulas, "resource allocation and cross-layer control in wireless networks," *Found. Trends Netw.*, vol. 1, no. 1, pp. 1–144, Jan. 2006.

[35] Y. Song, C. Zhang, Y. Fang, and P. Lin, "Revenue maximization in time-varying multi-hop wireless networks: A dynamic pricing approach," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 7, pp. 1237–1245, Aug. 2012.

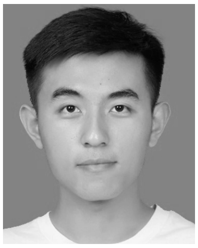
[36] S. Boyd, L. Vandenberghe, and L. Faybusovich, "Convex optimization," *IEEE Trans. Autom. Control*, vol. 51, no. 11, p. 1859, Nov. 2006.

JUNJIE YIN is currently pursuing the B.S. degree with the School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China.

His research interests include M2M communication in the IoT, smart grids, Lyapunov optimization in rate control, and resource allocation problems.

YAPENG CHEN is currently pursuing the Ph.D. degree with North China Electric Power University, China.

His research interests include green communications and smart grids.



GAN SANG is currently pursuing the B.S. degree with North China Electric Power University.

His research interests include resource allocation, rate control, and energy management in M2M communications.

BIN LIAO received the Ph.D. degree in computer applied technology from the Graduate University of Chinese Academy of Sciences, in 2003. He is currently an Associate Professor with the School of Electrical and Electronic Engineering, North China Electric Power University. His current research interests include information fusion and deep learning.

XIAOYAN WANG received the B.E. degree from Beihang University, China, and the M.E. and Ph.D. degrees from the University of Tsukuba, Japan.

He is currently an Assistant Professor with the Graduate School of Science and Engineering, Ibaraki University, Japan. Before that, he was an Assistant Professor (by special appointment) with the National Institute of Informatics (NII), Japan, from 2013 to 2016. His research interests include networking, wireless communications, cloud computing, big data, security, and privacy.