An Energy Efficient Uplink Scheduling and Resource Allocation for M2M Communications in SC-FDMA Based LTE-A Networks

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Abstract. In future wireless communications, there will be a large number of devices equipped with several different types of sensors need to access networks with diverse quality of service requirements. In cellular network evolution, the long term evolution advanced (LTE-A) networks has standardized Machine-to-Machine (M2M) features. Such M2M technology can provide a promising infrastructure for Internet of things (IoT) sensing applications, which usually require real-time data reporting. However, LTE-A is not designed for directly supporting such low-data-rate devices with optimized energy efficiency since it depends on core technologies of LTE that are originally designed for high-data-rate services. This paper investigate the maximum energy efficient data packets M2M transmission with uplink channels in LTE-A network. We formulate it into a jointed problem of Modulation and-Coding Scheme (MCS) assignment, resource allocation and power control, which can be expressed as a NP-hard mixed-integer linear fractional programming problem. Then we propose a global optimization scheme with Charnes-Cooper transformation and Glover linearization. The numerical experiment results show that with limited resource blocks, our algorithm can maintain low data packets dropping ratios while achieving optimal energy efficiency for a large number of M2M nodes, comparing with other typical counterparts.

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1 Introduction

Machine-to-Machine (M2M), also known as machine-type communication (MTC) technology, emerging as a new communication technology, has recently gained a great deal of attention [1]. It allows MTC devices (MTCDs) communicate with each other intelligently without or with very little human interventions. The technology has been utilized in a variety of M2M applications, such as smart grids (SG), intelligent transportation system (ITS), e-healthcare, industrial/home automation, and so on [2].

According to Cisco, it is predicted that M2M connections will increase to 12.2 billion by 2020, accounting for nearly half of the total global connections [3]. To take advantages of the opportunities created by a global M2M communications over cellular networks, the 3rd Generation Partnership Project (3GPP) Release 10 [4] first proposed service requirements for supporting MTC in LTE-A cellular networks. LTE-A networks can offer higher capacity and more flexible radio resource management (RRM) schemes than the existing packet access data technologies [5]. In LTE-A network, evolved universal terrestrial radio access (E-UTRA) NodeBs (eNBs), home eNBs (HeNBs), and relay nodes (RNs) can be deployed to provide general wireless access in outdoor and indoor environments.

In LTE-A cellular networks, Orthogonal Frequency Division Multiple Access (OFDMA) is chosen for the LTE's downlink, while the Single-Carrier FDMA (SC-FDMA) is chosen for the uplink. Advantages of such multi-carrier access techniques include their robust communication and stable interference management [6]. However, the OFDMA technique also introduces considerable challenges when it comes to designing RRM functionalities such as resource allocation and packet scheduling. In LTE networks, the radio resources are distributed in both time and frequency domains. In the time domain, radio resources are allocated on every Transmission Time Interval (TTI), which consists of two time slots and has a duration of 1 ms. One LTE frame is composed by 20 slots or 10 TTIs. In the frequency domain, a full LTE system bandwidth (20 MHz) is divided into 100 uplink sub-channel each including 12 subcarriers. Every sub-channel has a bandwidth of 180 kHz and 7 symbols in the time domain constitute a Resource Block (RB) as shown in Fig. 1.

Originally, LTE-A networks were designed for human-to-human (H2H) communications, where the amount of uplink traffic is normally lower than the downlink traffic. However in many M2M applications, data reporting with Quality of Service (QoS) constraints is a typical requirement. For example, in the e-healthcare application, each patient is equipped with smart device which can sample several types of health-related data, such as heart beat rate, body temperature, blood glucose levels and so on. The smart devices must upload data in real time to the healthcare provider via eNB. With the reported data,

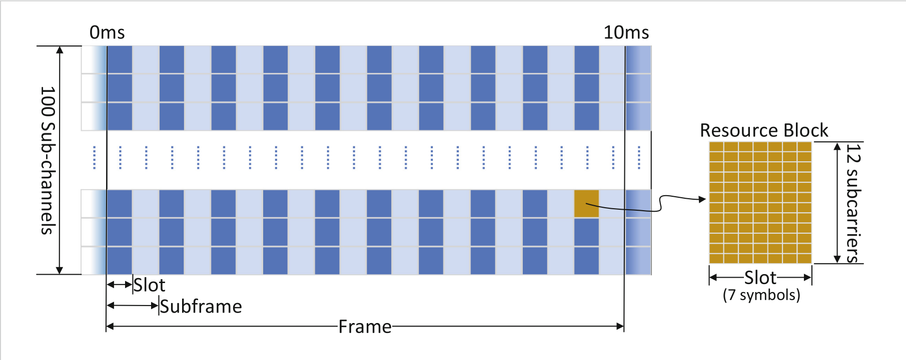

Fig. 1. The LTE-A frame structure and resource blocks.

the healthcare provider can assess each patient's health condition and react to an emergency situation immediately. In such applications, M2M traffic is distinct from the H2H traffic, in which more application data will be generated in uplink channels than that on downlink channels. Thus, congestion and packet drop would happen due to concurrent transmit messages from massive MTCDs, which leads to a low successful rate of random access (RA) [5,7]. Therefore, different M2M applications impose challenges to the designs of efficient radio resource allocation algorithms for M2M communications in LTE-A networks [8]. First, the radio resource allocation scheme should accommodate a large number of MTCDs with finite resources and diverse requirements. Second, it should have extreme low complexity to schedule the massive MTCDs efficiently. Finally, it should also maximize the energy efficiency to keep the M2M network alive for at least several years. In most of M2M application, usually an observation period is defined for each type of sensory data due to the real-time constraint. A MTCD must upload all the sampled data packets within the specified reporting period, otherwise the data will be dropped. On the other hand, if a MTCD is not allocated to transmit any data in a certain time slot, it can switch to sleep mode to reduce its energy consumption.

Some research efforts have been made to design effective resource allocation scheme [9]. [1,10] design scheduling algorithms for M2M communications wherein devices report multiple types of real-time data. They investigated the energy minimized scheduling problem for real-time reporting of data critical M2M applications, and proposed heuristic energy efficient algorithms. However, the algorithms only considered the data packets scheduling problem, without the resource allocation and MCS selection, which are the important parts in LTE-A network. In [11], the authors proposed two uplink scheduling algorithms in a MTCD/UE hybrid network that schedule MTCD based on their delay tolerance. The algorithm first allocated UE traffic, then allocated the remaining RBs to MTCDs. In [12], a greedy algorithm for solving approximate optimal solution is proposed, which effectively solves the NP-hard problem. [13] studied the joint optimization problem including the quality of service (QoS)-driven resource allocation and the layer selection, and proposed a tabu search-based metaheuristic algorithm for resource allocation. The authors in [14] presented a clustering-based approach to scheduling devices in LTE-A network by clustering machines based on a their QoS requirements, with a scheduling period defined for each cluster and is adapted based on jitter of clusters. Similar to [11], the algorithms are designed to accommodate with a M2M/H2H hybrid network, is not suitable to a real-time M2M application. In [15], the authors formulated the energy-optimal routing and multiple-sink aggregation into a mixed-integer programming problem, and presented a throughput-optimal scheduling algorithm to allocate the resource blocks under physical interference model in the pure aggregation case. However, as mentioned above, usually several different types of sensors with different QoS constraints are equipped on the MTCDs, which are not considered in [15].

Besides, although 3GPP has introduced some new enhanced power modes and more energy efficient signaling techniques to better handel M2M communications based on the LTE infrastructure, the size of data packets is not considered in the Modulation and Coding Scheme (MCS) selection process. In general, MCS is controlled by channel quality (e.g., receive power, Signal-to-Interference-plus-Noise Ratio (SINR) and so on). Usually when the channel quality between MTCD and eNB is good, a higher MCS selection can be used, or vice versa. For a higher MCS selection, a larger transport block (TB) can be transmitted in LTE-A [16], leading to a higher data rate. Obviously as the restriction of receiver's SINR and data packet size, a higher MCS may be over-qualified to a certain MTCD, which would cause extra energy consumption. Therefore, the resource allocation scheme in uplink M2M communications based on SC-FDMA LTE-A network is a jointed problem of MCS assignment, resource allocation, data scheduling and power control.

To the best of our knowledge, prior works have not proposed a resource allocation scheme to jointly consider MCS assignment, resource allocation and power control. Therefore, we present a resource allocation and data scheduling scheme to maximize the overall energy efficiency which is defined by the ratio of total transmitted data to the energy consumed. In this paper, we formulate the joint allocation and scheduling scheme into a Mixed Integer Linear Programming (MILP) problem, and then reconstruct it Charnes-Cooper transformation and Glover linearization scheme to obtain the global optimum.

The remainder of this paper is organized as follows. Section 2 formulates the energy efficiency optimization scheduling problem. Then, Sect. 3 introduces the reconstruction method of the original NP-hard problem to obtain it's global optimum. In Sect. 4, we evaluate the performance of the proposed algorithm. Finally, this paper is concluded in Sect. 5.

2 Problem Formulation

In this paper, we consider a typical scenario that consists of only one eNB and a number of MTCDs, within the coverage area of the eNB. Different types of sensors are equipped on each MTCD, which can sample data with different fixed intervals. The eNB can perform a scheduling procedure to decide the transmission time of the sampled data. All the MTCDs will transmit data to eNB according to the scheduling decision.

2.1 Assumptions

Without losses of generality, we make some assumptions in this paper. The sampling time of each sensor is short and can be neglected compared with LTE time slot. And each type of sensors will generate constant small size of data, and can only be transmitted in one time slot. Due to different usages and applications of different sensors, we assume different data packets can not be aggregated and have to be transmitted separately.

2.2 Network Architecture and System Model

We consider the uplink channel in a single cell of a multiuser 3GPP LTE-A network with SC-FDMA channel access for sensor data reporting, and the network architecture is shown in Fig. 2.

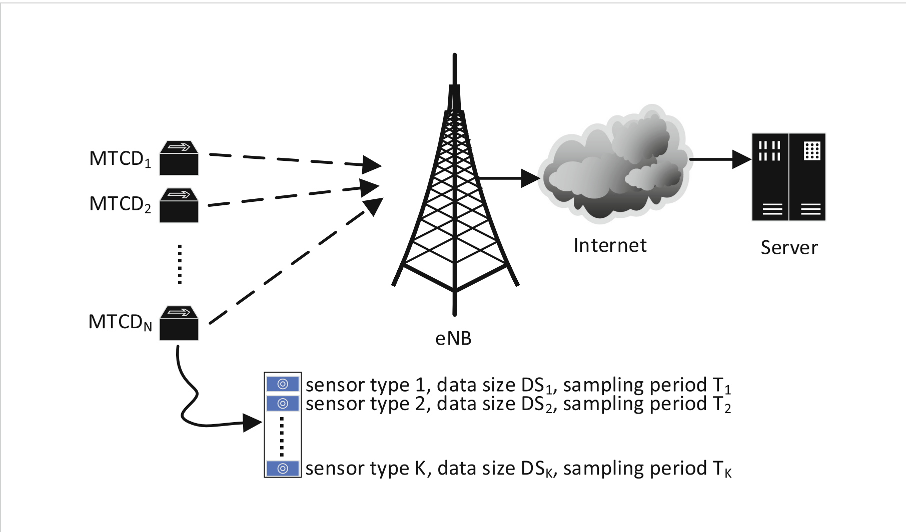

Fig. 2. Network architecture.

There are N MTCDs in the network, and all the MTCDs are equipped with K types of sensors and sample data. Let DS_k is data packet size sampled by sensor k, and T_k is sampling and reporting period of sensor k. Similar to [1], we also define a observation period T (time slots), which is the Least Common Multiple

(LCM) of the all the sampling periods of each sensor type in the networkwide. Obviously, the data reporting of all the N MTCDs will repeat every T time slots, thus eNB can perform a scheduling algorithm every T in a centralized manner. Let $d_{n,k,j}$ denote the jth data packet sampled by sensor K in MTCD n, Y the total RBs ready to allocate in every time slot, and M total MCS selections available for each MTCD.

2.3 Problem Statement

In this paper, we consider how to determine an efficient reporting schedule and resource allocation scheme which can maximize Energy Efficiency (EE) of all the N MTCDs, in which EE is defined as a ratio of all the data packets (bytes) transmitted to all the power (Joule) consumed. In a typical application all the MTCDs are used to monitor some certain physical values collaboratively, which makes EE a very important metric to evaluate the lifetime of the whole M2M network [17]. Thus this energy efficiency maximized scheduling problem can be formulated as follows:

$$(P0) \quad \max EE = \frac{\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{T/T_k} DS_k}{\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{T/T_k}\sum_{t=1}^{T}\sum_{b=1}^{Y}(\varphi_{n,k,j,t,b} \times P_{n,k,j,t,b})} \tag{1}$$

where $\varphi_{n,k,j,t,b}$ is a binary variable, $\varphi_{n,k,j,t,b} = 1$ when the RB b in time slot t is allocated to data $d_{n,k,j}$, otherwise $\varphi_{n,k,j,t,b} = 0$. $P_{n,k,j,t,b}$ is the consumed power when transmitting data $d_{n,k,j}$ on RB b time slot t.

The constraints are:

$$P_{n,k,j} \le P_{max}, \forall n \in N, k \in K, j \in J \tag{2}$$

$$\begin{aligned} \varphi_{n,k,j,t,b_1} \times P_{n,k,j,t,b_1} = \varphi_{n,k,j,t,b_2} \times P_{n,k,j,t,b_2}, \\ \forall n \in N, k \in K, j \in J, t \in T, b_1 \in Y, b_2 \in Y, and\ \varphi_{n,k,j,t,b_1} = \varphi_{n,k,j,t,b_2} \end{aligned} \tag{3}$$

$$\sum_{b=1}^{Y} \varphi_{n,k,j,t,b} \times R(m_{n,k,j,t}) \ge DS_k, \forall n \in N, k \in K, j \in J, t \in T \tag{4}$$

$$P_{n,k,j,t,b} + 10 \times \log(\sum_{b=1}^{Y} \varphi_{n,k,j,t,b}) + (\alpha - 1) \times PL_n - IoT \ge SINR(m_{n,k,j,t}) \tag{5}$$

$$\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{T/T_k}\sum_{b=1}^{Y} \varphi_{n,k,j,t,b} \le Y,\ \forall t \in T \tag{6}$$

$$\begin{cases} \varphi_{n,k,j,t}^{max} - \varphi_{n,k,j,t}^{min} = \sum_{b=1}^{Y} \varphi_{n,k,j,t,b} - 1 \\ \varphi_{n,k,j,t}^{max} = \max\{b \mid \varphi_{n,k,j,t,b} = 1\} \\ \varphi_{n,k,j,t}^{min} = \min\{b \mid \varphi_{n,k,j,t,b} = 1\} \end{cases} \tag{7}$$

$$\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{T/T_k}\varphi_{n,k,j,t,b} \leq 1,\ \forall t \in T, b \in Y \tag{8}$$

Constraint 2 means the total transmission power of MTCD n can not exceed the maximum power P_{max}.

Constraint 3 means transmission power on all the RBs allocated to data $d_{n,k,j}$ should be equal, according to SC-FDMA uplink channel access protocol in 3GPP LTE-A network.

Constraint 4 means data rate $R(m)$ supported by MCS selection m should be greater than transmitted data packet size, in which $m_{n,k,j,t}$ is the MCS assigned to tranmsit data $d_{n,k,j}$ at time slot t.

Constraint 5 is the uplink channel power control model defined by 3GPP LTE-A protocol [18], in which α is the cell-specific path-loss compensation factor that can be set to 0.0 and from 0.4 to 1.0 in steps of 0.1. PL_n is the downlink path-loss measured by eNB, which can be considered as a constant value for each static MTCD n, and IoT is the Interference over Thermal, which should be equal to 0 in our single cell case. $SINR(m_{n,k,j,t})$ is the SINR requirement of MCS selection $m_{n,k,j,t}$.

Constraint 6 means total RBs allocated in one time slot can not exceed Y.

Constraint 7 is the contiguity constraint, means all the RBs allocated to one data packet should be adjacent, according to SC-FDMA uplink channel access model.

Constraint 8 means one RB can only be allocated to one MTCD.

It can be proved that energy efficiency maximized scheduling problem $P0$ is NP-hard with unlinear terms and constraints. Thus we can only perform exhaustive search algorithm with exponential complexity to obtain global optimum. However, with the rapidly development of IoT, the number of MTCDs could be enormous, and it is impossible for eNB to perform optimal scheduling with exhaustive search algorithm. Thus in this paper, we try to reformulate $P0$ into an equivalent two-dimensional knapsack problem, and then reconstruct it into a Mixed Integer Linear Programming (MILP) problem with Charnes-Cooper transformation and Glover linearization scheme [19], to find the global optimum.

3 Problem Reformulation and Proposed Algorithm

3.1 Problem Reformulation

Given the K types of sensors, each type of sensory data will be transmitted to the base-station $N \times DT_k$ times. Then the total amount of data times is $\sum_{k=1}^{K}(N \times DT_k)$. The total amount of wireless resource blocks is $T \times Y$, and there are M kinds of MCS selection methods to transmit data, which are mutual. Thus this problem can be reformulated into a two dimensional knapsack problem. We can consider the total resource blocks as a knapsack, and all the transmitted data as the items. Each item has some contribution to the EE object, and for each item there is only one method among M kinds organizations. Each data can only be inserted into the place t. If data $d_{n,k,j}$ is transmitted by m MCS at time slot t, then

1. It's capacity in the knapsack is $(1, \left\lceil \frac{DS_{n,k,j,m,t}}{R_{n,k,j,m,t}} \right\rceil)$
2. It's contribution to EE is $\frac{DS_{n,k,j,m,t}}{\left\lceil \frac{DS_{n,k,j,m,t}}{R_{n,k,j,m,t}} \right\rceil \times P_{n,k,j,m,t}}$

Thus, we can define a binary variable $x_{n,k,j,m,t}$. When the data $d_{n,k,j}$ is transmitted at time slot t with MCS selection m, $x_{n,k,j,m,t} = 1$, otherwise, $x_{n,k,j,m,t} = 0$.

Thus, the EE optimization can be reformulated into a two dimensional knapsack problem.

$$(P1) \quad \max \frac{\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{DT_k}\sum_{m=1}^{M}\sum_{t=1}^{T} x_{n,k,j,m,t} \times DS_{n,k,j,m,t}}{\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{DT_k}\sum_{m=1}^{M}\sum_{t=1}^{T}(x_{n,k,j,m,t} \times \left\lceil \frac{DS_{n,k,j,m,t}}{R_{n,k,j,m,t}} \right\rceil \times P_{n,k,j,m,t})} \tag{9}$$

s.t.

$$\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{DT_k}\sum_{m=1}^{M}(x_{n,k,j,m,t} \times \left\lceil \frac{DS_{n,k,j,m,t}}{R_{n,k,j,m,t}} \right\rceil) \leq Y, \ \forall t \in T \tag{10}$$

$$\sum_{t=1}^{T} x_{n,k,j,m,t} \leq 1, \ \forall n \in N, k \in K, j \in J, m \in M \tag{11}$$

$$P_{n,k,j,m,t} + 10 \times \log \left\lceil \frac{DS_{n,k,j,m,t}}{R_{n,k,j,m,t}} \right\rceil + (\alpha - 1) \times PL_n - IoT \geq SINR_{n,k,j,m,t} \tag{12}$$

$$P_{n,k,j,m,t} \times \left\lceil \frac{DS_{n,k,j,m,t}}{R_{n,k,j,m,t}} \right\rceil \leq P_{max} \tag{13}$$

$$\sum_{m=1}^{M} x_{n,k,j,m,t} \leq 1, \ \forall n \in N, k \in K, j \in J, t \in T \tag{14}$$

$$\sum_{m=1}^{M}\sum_{t=1}^{T} x_{n,k,j,m,t} \leq 1, \ \forall n \in N, k \in K, j \in J \tag{15}$$

$$x_{n,k,j,m,t} \in \{0, 1\} \tag{16}$$

The constraint 10 means the resource blocks allocated in one time slot can not exceed Y. The constraint 11 means each item(data) can only be put in a single time slot. The constraint 12 means the power allocated to a single RB has to meet the MCS requirement. The constraint 13 means the total power allocated to all RBs can not exceed the maximum power of the device. The constraint 14 means one data packet can only be transmitted with one MCS selection. And the constraint 16 means $x_{n,k,j,m,t}$ is a binary variable.

3.2 Mixed-Integer Linear Fractional Programming Reconstruction

Regarding to the problem $(P1)$ defined in Eq. 9, first we can reconstruct the problem by simplifying the subscripts of parameters. Let $l_1 = \lceil \log_2 N \rceil$, $l_2 = \lceil \log_2 K \rceil$, $l_3 = \lceil \log_2 DT_{max} \rceil$, $l_4 = \lceil \log_2 M \rceil$, $l_5 = \lceil \log_2 T \rceil$. A, A_1, A_2, A_3, A_4, A_5 are binary numbers with length of $l_1 + l_2 + l_3 + l_4 + l_5$, among which the first l_1 bits in A_1, the $l_1 + 1$ to l_2 bits in A_2, the $l_2 + 1$ to l_3 bits in A_3, the $l_3 + 1$ to l_4 bits in A_4, the $L - 4 + 1$ to l_5 bits in A_5 are '1's, and the rest bits are '0's. Then the subscript n of $x_{n,k,j,m,t}$ can be placed at top l_1 bits of A with binary value. The subscript k of $x_{n,k,j,m,t}$ can be placed at $l_1 + 1$ to l_2 bits of A with binary value. The subscript j can be placed at $l_2 + 1$ to l_3 bits of A with binary value. The subscript m can be placed at $l_3 + 1$ to l_4 bits of A with binary value. The subscript m can be placed at $l_3 + 1$ to l_4 bits of A with binary value. The subscript t can be placed at $l_4 + 1$ to l_5 bits of A with binary value. Then we can reconstruct $(P1)$ into the following problem.

$$(P2) \quad \max \frac{\sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} DS_a \times x_a}{\sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} \left\lceil \frac{DS_a}{R_a} \right\rceil \times P_a \times x_a} \tag{17}$$

s.t.

$$\sum_{a=1+(i-1)\times 2^{l_1+l_2+l_3+l_4}}^{i\times 2^{l_1+l_2+l_3+l_4}} (\left\lceil \frac{DS_a}{R_a} \right\rceil \times x_a) \le Y, \ \forall 1 \le (A\&A_5) \le T, \ i = 1, 2, 3, \cdots, 2^{l_5} \tag{18}$$

$$P_a + 10 \times \log(\left\lceil \frac{DS_a}{R_a} \right\rceil) + (\alpha - 1) \times PL_n - IOT \ge SINR_a \tag{19}$$

$$P_a \times \left\lceil \frac{DS_a}{R_a} \right\rceil \le P_{max} \tag{20}$$

$$\begin{gathered} \sum_{j=1}^{2^{l_5}} x_{i+(j-1)\times 2^{l_1+l_2+l_3+l_4}} \le 1, \quad i = 1, 2, 3, \cdots, 2^{l_1+l_2+l_3+l_4} \\ \forall n \in N, k \in K, j \in J, m \in M \end{gathered} \tag{21}$$

$$\begin{gathered} \sum_{j=1}^{2^{l_4}} x_{i+(j-1)\times 2^{l_1+l_2+l_3}} \le 1, \forall n \in N, k \in K, j \in J, t \in T \\ i = (h-1) \times 2^{l_1+l_2+l_3+l_4} + 1, (h-1) \times 2^{l_1+l_2+l_3+l_4} + 2, \cdots, \\ (h-1) \times 2^{l_1+l_2+l_3+l_4} + 2^{l_1+l_2+l_3}, \ h = 1, 2, 3, \cdots, 2^{l_5} \end{gathered} \tag{22}$$

$$\begin{gathered} \sum_{j=1}^{2^{l_4+l_5}} x_{i+(j-1)\times 2^{l_1+l_2+l_3}} \le 1, \quad i = 1, 2, 3, \cdots, 2^{l_1+l_2+l_3}, \\ \forall n \in N, k \in K, j \in J \end{gathered} \tag{23}$$

$$x_a \in \{0, 1\} \tag{24}$$

It can be seen that the objective function $P2$ is a ratio of two linear functions, and all the constraints are linear. Thus $P2$ is a mixed-integer linear fractional programming (MILFP) problem. Besides, it can be proven that $P2$ is a NP-hard MILFP problem with quasi-convex and quasi-concave property, thus the local optimal of $P2$ is the global optimal in feasible region.

3.3 The Proposed Algorithm

To obtain the global optimal in polynomial time, we propose a optimal algorithm based on Charnes-Cooper transformation and Glover linearization, the former of which can transform the original MILFP problem into a mixed-integer nonlinear programming (MINLP) problem, while the later can convert MINLP problem into an equivalent mixed-integer linear programming (MILP) problem.

First, we introduce a new positive variable u, and let

$$u = \frac{1}{\sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} \times P_a \times x_a} \tag{25}$$

Obviously $u > 0$. Thus the fractional objective function in $P0$ can be transformed into a linear function, i.e.

$$\max \frac{\sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} DS_a \times x_a}{\sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} \left\lceil \frac{DS_a}{R_a} \right\rceil \times P_a \times x_a} = \max \sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} DS_a \times (x_a \times u) \tag{26}$$

As u is positive, we can multiply by u on both sides of Eqs. 18, 21 and 23, and the following constraints can be obtained.

$$\sum_{a=1+(i-1)\times 2^{l_1+l_2+l_3+l_4}}^{i\times 2^{l_1+l_2+l_3+l_4}} \left(\left\lceil \frac{DS_a}{R_a} \right\rceil \times x_a \times u\right) \leq Y \times u,\ \ i = 1, 2, 3, \cdots, 2^{l_5} \tag{27}$$

$$\begin{aligned} &\sum_{j=1}^{2^{l_5}} x_{i+(j-1)\times 2^{l_1+l_2+l_3+l_4}} \times u \leq u, \quad i = 1, 2, 3, \cdots, 2^{l_1+l_2+l_3+l_4}, \\ &\qquad\qquad \forall n \in N, k \in K, j \in J, m \in M \end{aligned} \tag{28}$$

$$\begin{aligned} &\sum_{j=1}^{2^{l_4}} x_{i+(j-1)\times 2^{l_1+l_2+l_3}} \times u \leq u, \quad \forall n \in N, k \in K, j \in J, t \in T \\ &i = (h-1) \times 2^{l_1+l_2+l_3+l_4} + 1, (h-1) \times 2^{l_1+l_2+l_3+l_4} + 2, \cdots, \\ &\qquad (h-1) \times 2^{l_1+l_2+l_3+l_4} + 2^{l_1+l_2+l_3}, h = 1, 2, 3, \cdots, 2^{l_5}, \end{aligned} \tag{29}$$

$$\begin{aligned} &\sum_{j=1}^{2^{l_4+l_5}} x_{i+(j-1)\times 2^{l_1+l_2+l_3}} \times u \leq u, \quad i = 1, 2, 3, \cdots, 2^{l_1+l_2+l_3}, \\ &\qquad\qquad \forall n \in N, k \in K, j \in J \end{aligned} \tag{30}$$

$$x_a \times u \in \{0, u\} \tag{31}$$

According to definition of u, Eq. 25 can be converted to

$$\begin{aligned} 1 &= u \times \sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} \left\lceil \frac{DS_a}{R_a} \right\rceil \times P_a \times x_a \\ &= \sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} \left\lceil \frac{DS_a}{R_a} \right\rceil \times P_a \times (x_a \times u) \end{aligned} \tag{32}$$

Thus, the MILFP problem $P2$ can be transformed to an equivalent MINLP problem $P3$.

$$(P3) \quad \max \sum_{a=1}^{2^(l_1+l_2+l_3+l_4+l_5)} DS_a \times (x_a \times u) \tag{33}$$

The constraints are illustrated as Eqs. 19, 20, 27, 28, 29, 31 and 32.

The only unlinear item in MINLP problem $P1$ is the bilinear one $x_a \times u$, which can be accuartely linearized by intro ducting some auxiliary variables and constraints using the Glover linearzation scheme. By introducing $w_a = x_a \times u$, the MINLP problem $P1$ can be linearized to a mix-integer linear programming (MILP) problem, i.e.

$$(PR) \quad \max Z = \sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} DS_a \times w_a, \quad a \in B \tag{34}$$

s.t.

$$\sum_{a=1+(i-1)\times 2^{l_1+l_2+l_3+l_4}}^{i\times 2^{l_1+l_2+l_3+l_4}} (\left\lceil \frac{DS_a}{R_a} \right\rceil \times w_a) \le Y \times u, \quad i = 1, 2, 3, \cdots, 2^{l_5} \tag{35}$$

$$\sum_{j=1}^{2^{l_5}} w_{i+(j-1)\times 2^{l_1+l_2+l_3+l_4}} \le u, \quad i = 1, 2, 3, \cdots, 2^{l_1+l_2+l_3+l_4} \tag{36}$$

$$\begin{aligned} &\sum_{j=1}^{2^{l_4}} w_{i+(j-1)\times 2^{l_1+l_2+l_3}} \le u, \\ i = (h-1) \times 2^{l_1+l_2+l_3+l_4} &+ 1, (h-1) \times 2^{l_1+l_2+l_3+l_4} + 2, \cdots, \\ &(h-1) \times 2^{l_1+l_2+l_3+l_4} + 2^{l_1+l_2+l_3}, h = 1, 2, 3, \cdots, 2^{l_5} \end{aligned} \tag{37}$$

$$\sum_{j=1}^{2^{l_4+l_5}} w_{i+(j-1)\times 2^{l_1+l_2+l_3}} \le u, \quad i = 1, 2, 3, \cdots, 2^{l_1+l_2+l_3} \tag{38}$$

$$P_a + 10 \times \log(\left\lceil \frac{DS_a}{R_a} \right\rceil) + (\alpha - 1) \times PL_n - IOT \ge SINR_a \tag{39}$$

$$1 = \sum_{a=1}^{2^{l_1+l_2+l_3+l_4+l_5}} \left\lceil \frac{DS_a}{R_a} \right\rceil \times P_a \times w_a \tag{40}$$

$$w_a \in \{0, u\} \tag{41}$$

$$P_a \times \left\lceil \frac{DS_a}{R_a} \right\rceil \leq P_{max} \tag{42}$$

Obviously PR is a MILP problem equivalent to the original MILFP problem $P0$, and it can be easily solved by the commercial linear programming toolbox.

4 Simulation and Performance Analysis

In this section, we evaluate the performance achieved by our scheduling and allocation algorithm. The experiments are conducted using discrete-event simulations, where the M2M communication network is considered to consist of one eNB and N MTCDs, without considerable inter-cell interference. The position of MTCDs are randomly generated in the range of [20, 300] to eNB. Table 1 lists the detailed parameters used to evaluate the network performance. The parameter values comply with the 3GPP TS25.104 and TR36.814 standards [20]. The channel gains for uplink and downlink are included in the transmit power and receiver sensitivity, respectively. According to [16], there are 28 MCS selections in physical uplink shared channel (PUSCH), and a sample of the data rate in bits and SINR requirement defined is illustrated in Table 2.

For the sensory data, we assume there as many as 10 types of sensors equipped on each MTCD. Obviously, the results of resource allocation and data scheduling are dependent on data packet size and sampling periods. Thus we randomly generate the data packet size of each type of sensor in the range of [10, 500] bytes, and sampling periods in the range of [1, 120] s, which are practical in typical M2M applications. Then the simulation is repeated for 100 times and the results are averaged.

In the simulation, we use the open source lp_solve toolbox to solve the MILP problem PR.

To evaluate our proposed algorithm, we compare two classic resource allocation and scheduling algorithms: Energy-Efficient Scheduling algorithm (EES) [1], and Greedy algorithm as provided in [9]. The Greedy algorithm determines the optimal pair of MCS and number of RBs, at which the transport block size is sufficient to transmit sensing data within the minimum transmit power. In addition, it can utilize the optimal MCS selections as main criteria for spectrum allocation has been proposed for better adapting to the sensing node requirements. The EES algorithm is a heuristic one to schedule the transmissions of a MTCD in one time slot with energy efficiency, while maintaining fairness and low data dropping. The simulation results are presented in terms of EE and packet dropping rate of all the MTCDs. With these metrics, we investigate the impacts of the number of MTCDs and sensors.

Table 1. Simulation parameters

Parameters	Values
Network topology	Random deployment
Number of MTCDs	1–80
Maximum transmit power	23 dBm
MTCD's Receiver sensitivity	−100 dBm
Path loss model	3GPP outdoor: $PL(d) = 15.3 + 37.6 \times \log_{10}(d)(\text{dB})$
Distances between MTCDs and eNB	20–300 m
Bandwidth	20 MHz
Number of RBs	100
α	0.9
Number of MCS selection	28
Number of sensor types on each MTCD	2–8
Sensory data size	10–500 bytes
Sampling period of each sensor	1–120 s

Table 2. A sample of supported data rate in bits defined in 3GPP TS 36.213 [16]

MCS selection	Number of RBs					
	1	2	3	4	5	...
...	...	...	...	...	...	...
7	104	224	328	472	584	...
8	120	256	392	536	680	...
9	136	296	456	616	776	...
10	144	296	456	616	776	...
11	176	328	504	680	872	...
...	...	...	...	...	...	...
27	616	1256	1864	2536	3112	...
28	712	1480	2216	2984	3752	...

Figures 3, 4 and 5 show that our algorithm performs better than Greedy in terms of energy efficiency with different number of sensor types. First, we can observe that when N increases, the EE values of both the Greedy and our proposed methods increase and then decrease. When N increases, the data transmissions from the same MTCD are scattered over more time slots, causing higher energy consumption. Then as N keeps increasing, the available RBs is insufficient to transmit all the sensory data and some will be dropped. However, our algorithm can effectively schedule data packets and allocate resources optimally to all the MTCDs. Thus our algorithm can achieve higher energy efficiency, and have less impact of resource insufficiency on energy consumption. However, it can be seen that EES causes higher energy efficiency than ours. It is understandable as only data scheduling is considered in EES, without resource allocations. Thus although some data packets are scheduled at certain time slots, there is no sufficient RBs to transmit, leading to many infeasible scheduling.

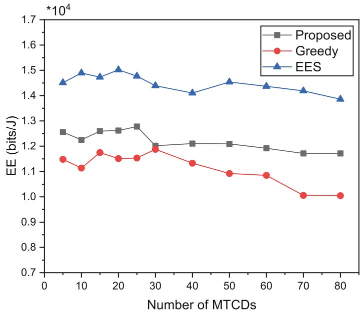

Fig. 3. Energy efficiency (K = 2) with different number of MTCDs.

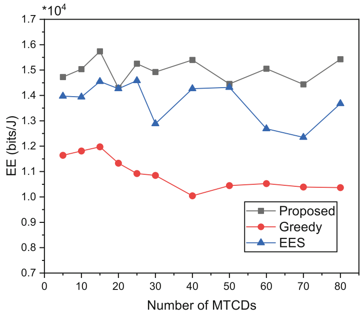

Fig. 4. Energy efficiency (K = 4) with different number of MTCDs.

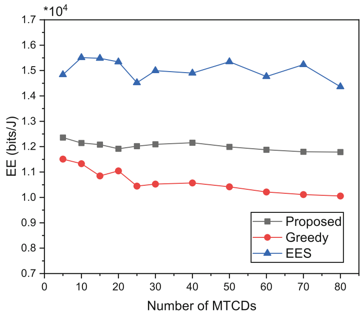

Fig. 5. Energy efficiency (K = 8) with different number of MTCDs.

Figures 6, 7 and 8 show the data packets dropping ratio of our algorithm and the counterparts. Obviously, when the number of MTCDs is small, all the sensory data can be transmitted. However, there will be no enough RBs to support the enormous data packets generated by a larger number of M2M devices. Similar to *EE*, without resource allocation EES can achieve slightly better in terms of data dropping ratio.

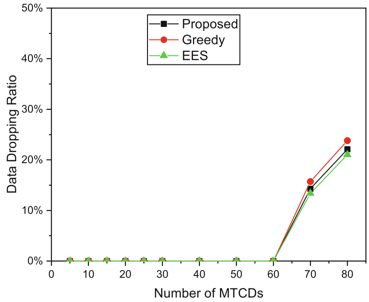

Fig. 6. Data dropping ratio (K = 2) with different number of MTCDs.

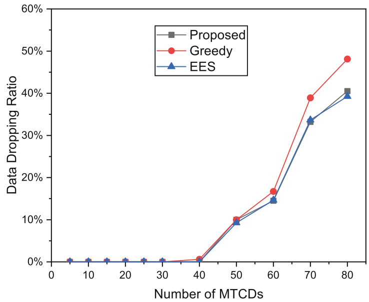

Fig. 7. Data dropping ratio (K = 4) with different number of MTCDs.

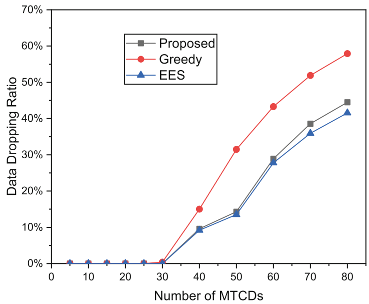

Fig. 8. Data dropping ratio (K = 8) with different number of MTCDs.

5 Conclusion

Although the LTE-A infrastructure introduces many benefits for the applications of M2M communication sensing platforms, the challenges are also considerable, especially in terms of energy efficiency of whole M2M network. In this paper, we formulate the energy efficient M2M communications in SC-FDMA based LTE-A networks into a jointed problem of MCS assignment, resource allocation, data scheduling and power control, which can be expressed as a NP-hard MILP problem.

Then we reconstruct it with Charnes-Cooper transformation and Glover linearization scheme to obtain the global optimum. Based on the optimal MCS, transmission power and resource planning scheme, the sampled data packets can be reported to eNB with maximum energy efficiency. We also compare the performance of our scheme with other typical counterparts. The numerical experiment results show that with limited resource blocks, our algorithm can maintain low data packets dropping ratios while achieving optimal energy efficiency for a large number of M2M nodes.

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