Energy Efficiency Optimization-Based Joint Resource Allocation and Clustering Algorithm for M2M Communication Networks (Workshop)

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Abstract. In recent years, machine-to-machine (M2M) communications have attracted great attentions from both academia and industry. In M2M communication networks, machine type communication devices (MTCDs) are capable of communicating with each other intelligently under highly reduced human interventions. In this paper, we address the problem of joint resource allocation and clustering for M2M communications. By defining the system energy efficiency (EE) as the sum of the EE of MTCDs, the joint resource allocation and clustering problem is formulated as a system EE maximization problem. As the original optimization problem is a nonlinear fractional programming problem, which cannot be solved conveniently, we transform it into two subproblems, i,e., power allocation subproblem and clustering subproblem, and solve the two subproblems by means of Lagrange dual method and modified K-means algorithm, respectively. Numerical results demonstrate the effectiveness of the proposed algorithm.

Keywords: Machine to machine (M2M) communications · Clustering · Resource allocation · Energy efficiency (EE)

1 Introduction

Machine to machine (M2M) communications have been considered as one of the promising technologies to realize the Internet of Things (IoT) in future 5th generation network [1]. In M2M, machine type communication devices (MTCDs) are capable of communicating with each other intelligently under highly reduced human interventions. In some practical M2M applications, i.e., smart home, smart wearable device [2], massive access requests from MTCDs pose challenges and difficulties to the random access and resource allocation schemes of the traditional access networks.

In past few years, resource allocation problem has been studied for M2M communications [3–5]. In [3], the authors proposed a preamble allocation method which maximized system throughput and provides effective QoS differentiation across various random access loads. The authors in [4] studied joint resource blocks (RBs) scheduling and power allocation issues for M2M communications in long term evolution-advanced (LTE-A) networks and proposed a sum-throughput maximization-based optimal resource allocation scheme for the MTCDs. In [5], the authors studied resource

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allocation problem of energy harvesting cognitive radio sensor networks and developed an aggregate network utility optimization framework to achieve efficient resource management.

It has been demonstrated that resource allocation strategies can be jointly designed with clustering schemes to enhance the transmission performance of the MTCDs in M2M communication systems. In [6], energy efficient clustering and medium access control (MAC) problem was investigated for cellular-based M2M communication systems. To achieve the tradeoff between energy efficiency (EE), transmission delay, and spectral efficiency, and prolong the lifetime of the M2M system, the authors proposed an optimal clustering and MAC scheme. The authors in [7] proposed an energy efficient power control, user pairing and time scheduling algorithm to achieve the minimum energy consumption in non-orthogonal multiple access (NOMA)-based M2M communication systems. In [8], to accommodate massive access for MTCDs in cellular systems, relaying and resource partitioning schemes were designed for the MTCDs under the consideration of the signaling overhead in the cellular systems.

In this paper, we address the joint resource allocation and clustering problem for M2M communications. By defining system EE as the sum of the EE of MTCDs, the joint resource allocation and clustering problem is formulated as an EE maximization problem. As the original optimization problem is a nonlinear fractional programming problem, which cannot be solved conveniently, we transform it into two subproblems, i,e., power allocation subproblem and clustering subproblem, and solve the two subproblems by means of Lagrange dual method and modified K-means algorithm, respectively.

The rest of this paper is organized as follows. The system model is presented in Sect. 2. In Sect. 3, the optimization problem is formulated. Section 4 discusses the solution of the optimization problem. Section 5 analyzes the simulation results. Finally, we make a conclusion in Sect. 6.

2 System Model

In this paper, we consider the uplink transmission scenario of an M2M communication network consisting of a single base station (BS) and multiple MTCDs. Let M denote the number of MTCDs. We assume that the BS is deployed in the network center and the MTCDs are randomly deployed within the coverage area of the BS. We further assume that the MTCDs need to transmit their data packets to the BS and may apply direct transmission mode in which the MTCDs transmit their data packets the BS directly. On the other hand, to achieve highly efficient data transmission, we assume that the cluster head (CH) forwarding mode is available. More specifically, the MTCDs may form various clusters with each cluster having one CH and a number of cluster members (CMs). While the CHs in each cluster may transmit their data packets to the BS in direct transmission mode, the CMs may apply CH forwarding mode, i.e., sending their data packets to the associated CHs, which then forward the received data packets to the BS on behalf of the CMs.

We further assume that there are a number of channels with equal bandwidth. Let B denote the bandwidth of each channel. For simplicity, it is assumed that enough bandwidth resources are available and all the transmission links can be allocated with one channel, hence, no transmission interference among transmission links exists. Figure 1 shows the system model.

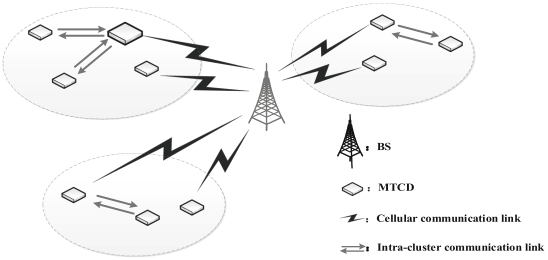

Fig. 1. System model.

3 Optimization Problem Formulation

In this section, we define system EE as the total EE of the MTCDs and formulate the joint resource allocation and clustering problem as system EE maximization problem.

3.1 Objective Function

Considering the performance of all the MTCDs, we define system EE as the sum of EE of the MTCDs, which can be expressed as

$$\eta = \sum_{i=1}^{M} \eta_i \tag{1}$$

where η_i denotes the EE of the ith MTCD. For simplicity, we denote the ith MTCD as MTCD$_i$. The expression of η_i is given by

$$\eta_i = \delta_i^{\mathrm{d}} \eta_i^{\mathrm{d}} + \sum_{j=1}^{M} \delta_{i,j}^{\mathrm{c}} \eta_{i,j}^{\mathrm{c}} \tag{2}$$

where $\delta_i^{\mathrm{d}} \in \{0, 1\}$ is the association variable of MTCD$_i$ in direct transmission mode, i.e., if $\delta_i^{\mathrm{d}} = 1$, MTCD$_i$ transmits data packets to the BS directly, otherwise, $\delta_i^{\mathrm{d}} = 0$, $1 \leq i \leq M$, η_i^{d} denotes the EE of MTCD$_i$ in direct transmission mode. The expression of η_i^{d} can be defined as follows:

$$\eta_i^{\mathrm{d}} = \frac{R_i^{\mathrm{d}}}{p_i^{\mathrm{d}} + p_{\mathrm{cir}}} \tag{3}$$

where p_{cir} is the circuit power consumption of MTCD$_i$, p_i^{d} denotes the transmit power of MTCD$_i$ when transmitting data packets to the BS directly, R_i^{d} denotes the transmit rate of MTCD$_i$ in direct transmission mode, which can be expressed as

$$R_i^{\mathrm{d}} = B \log_2 \left(1 + \frac{p_i^{\mathrm{d}} h_i^{\mathrm{d}}}{\sigma^2} \right) \tag{4}$$

where h_i^{d} denotes the channel gain of the link between MTCD_i and the BS, σ^2 denotes the noise power.

In (2), $\delta_{i,j}^{\mathrm{c}}$ is the association variable of MTCD_i and the jth CH in CH forwarding mode, i.e., if $\delta_{i,j}^{\mathrm{c}} = 1$, MTCD_i chooses jth CH to forward its data packets to the BS, otherwise, $\delta_{i,j}^{\mathrm{c}} = 0$, $1 \leq i \neq j \leq M$, for simplicity, let CH_j represent the jth CH, $\eta_{i,j}^{\mathrm{c}}$ denotes the EE of MTCD_i when transmitting data packets to CH_j, which can be expressed as

$$\eta_{i,j}^{\mathrm{c}} = \frac{R_{i,j}^{\mathrm{c}}}{p_{i,j}^{\mathrm{c}} + p_{\mathrm{cir}}} \tag{5}$$

where $p_{i,j}^{\mathrm{c}}$ is the transmit power of MTCD_i when transmitting data packets to CH_j, $R_{i,j}^{\mathrm{c}}$ denotes the transmit rate of MTCD_i when transmitting data packets to CH_j. The expression of $R_{i,j}^{\mathrm{c}}$ is given by

$$R_{i,j}^{\mathrm{c}} = B \log_2 \left(1 + \frac{p_{i,j}^{\mathrm{c}} h_{i,j}^{\mathrm{c}}}{\sigma^2}\right) \tag{6}$$

where $h_{i,j}^{\mathrm{c}}$ denotes the channel gain of the link between MTCD_i and CH_j.

3.2 Optimization Constraints

The optimal design of the joint resource allocation and clustering strategy should be subject to a number of constraints including maximum number of CHs, maximum number of MTCDs in clusters, etc.

Maximum Number of CHs. Let $\delta_{j,j}^{\mathrm{c}} = 1$ denote the CH identifier, i.e. if $\delta_{j,j}^{\mathrm{c}} = 1$, MTCD_j acts as a CH, otherwise, $\delta_{j,j}^{\mathrm{c}} = 0$, $1 \leq j \leq M$. Denote the maximum number of CHs in the network as $N_{\max}$, we may express the constraint on the maximum number of CHs as:

$$\mathrm{C1}: \sum_{j=1}^{M} \delta_{j,j}^{\mathrm{c}} \leq N_{\max},\ \forall i. \tag{7}$$

Maximum Number of MTCDs in Clusters. Assuming that the number of MTCDs that one CH can associate is at most K, hence, we obtain the following constraint:

$$\mathrm{C2}: \sum_{i=1, i \neq j}^{M} \delta_{i,j}^{\mathrm{c}} \leq K,\ 1 \leq j \leq M. \tag{8}$$

CH Association Constraint. Assuming each MTCD can choose at most one CH for association, i.e.,

$$\mathrm{C3}: \sum_{j=1, i \neq j}^{M} \delta_{i,j}^{\mathrm{c}} \leq 1,\ 1 \leq i \leq M. \tag{9}$$

Mode Selection Constraint. Assume that each MTCD can either choose direct transmission mode or CH forwarding mode, i.e.,

$$\mathrm{C4}: \delta_i^{\mathrm{d}} + \sum_{j=1, j \neq i}^{M} \delta_{i,j}^{\mathrm{c}} \leq 1,\ 1 \leq i \leq M. \tag{10}$$

Maximum Transmit Power Constraints. As the transmit power of each MTCD must be less than the maximum transmit power, we obtain

$$\mathrm{C5}: p_i^{\mathrm{d}} \leq p_i^{\max},\ 1 \leq i \leq M, \tag{11}$$

$$\mathrm{C6}: p_{i,j}^{\mathrm{c}} \leq p_i^{\max},\ 1 \leq i \neq j \leq M \tag{12}$$

where $p_i^{\max}$ denotes the maximum transmit power of MTCD_i.

Transmit Rate Constraint. Considering the various QoS requirements of different MTCDs, we assume that there is a minimum rate requirement for each MTCD. The transmit rate of the MTCDs should be higher than the minimum transmit rate, i.e.,

$$\mathrm{C7}: R_i \geq R_i^{\min},\ 1 \leq i \leq M \tag{13}$$

where $R_i^{\min}$ is the minimum transmit rate, R_i denotes the actual transmit rate of MTCD_i, $1 \leq i \leq M$, which can be expressed as

$$R_i = \delta_{i,j}^{\mathrm{d}} R_i^{\mathrm{d}} + \sum_{j=1, j \neq i}^{M} \delta_{i,j}^{\mathrm{c}} R_{i,j} \tag{14}$$

where $R_{i,j} = \min\left\{R_{i,j}^{\mathrm{c}}, R_j^{\mathrm{d}}\right\}$.

3.3 Optimization Problem

Considering the aforementioned objective function and optimization constraints, we formulate the EE maximization-based joint resource allocation and clustering problem as

$$\begin{aligned} \max_{\delta_i^{\mathrm{d}}, \delta_{i,j}^{\mathrm{c}}, p_i^{\mathrm{d}}, p_{i,j}^{\mathrm{c}}} \quad & \eta \\ \text{s.t.} \quad & \mathrm{C1} - \mathrm{C7} \\ & \mathrm{C8}: \delta_i^{\mathrm{d}} \in \{0, 1\}, 1 \leq i \leq M, \\ & \mathrm{C9}: \delta_{i,j}^{\mathrm{c}} \in \{0, 1\}, 1 \leq i \neq j \leq M. \end{aligned} \tag{15}$$

4 Solution of the Optimization Problem

The optimization problem in (15) is a nonlinear fractional programming problem, which cannot be solved conveniently, however, it can be demonstrated that given the clustering strategy, the power allocation strategy of the MTCDs in various transmission modes can be designed independently. Hence, we may transform the optimization problem formulated in (15) into two subproblems, i.e., power allocation subproblem and clustering subproblem.

4.1 Power Allocation Subproblem

In this subsection, we suppose MTCD$_i$ transmits its data packets to CH$_j$ in CH forwarding mode, i.e., $\delta^{\mathrm{c}}_{i,j} = 1$, $1 \leq i \neq j \leq M$, the power allocation subproblem of MTCD$_i$ can be expressed as

$$\begin{aligned} \max_{p^{\mathrm{c}}_{i,j}} \quad & \eta^{\mathrm{c}}_{i,j} \\ \text{s.t.} \quad & \mathrm{C1}: p^{\mathrm{c}}_{i,j} \leq p^{\max}_i, 1 \leq i \leq M, i \neq j, \\ & \mathrm{C2}: R^{\mathrm{c}}_{i,j} \geq R^{\min}_i, 1 \leq i \leq M, i \neq j \end{aligned} \tag{16}$$

Iterative Algorithm-Based Energy Efficiency Maximization. The optimization problem formulated in (16) is a non-convex problem with the objective function being a nonlinear fractional function, which cannot be solved directly using traditional optimization tools. In this subsection, we apply an iterative algorithm to solve the optimization problem.

To transform the objective function of the optimization problem defined in (16), we denote q as the EE of MTCD$_i$, i.e., $q = \dfrac{R^{\mathrm{c}}_{i,j}}{p^{\mathrm{c}}_{i,j} + p_{\mathrm{cir}}}$, q^* is the maximum EE, and $p^{\mathrm{c},*}_{i,j}$ as the optimal power allocation strategy of MTCD$_i$, i.e.,

$$q^* = \frac{R^{\mathrm{c}}_{i,j}\left(p^{\mathrm{c},*}_{i,j}\right)}{p^{\mathrm{c},*}_{i,j} + p_{\mathrm{cir}}} = \max_{p^{\mathrm{c}}_{i,j}} \frac{R^{\mathrm{c}}_{i,j}}{p^{\mathrm{c}}_{i,j} + p_{\mathrm{cir}}}. \tag{17}$$

It can be proved that the maximum EE q^* is achieved if and only if the following condition meets:

$$R^{\mathrm{c}}_{i,j}\left(p^{\mathrm{c}}_{i,j}\right) - q^*\left(p^{\mathrm{c}}_{i,j} + p_{\mathrm{cir}}\right) = 0. \tag{18}$$

Thus, the optimization problem formulated in (16) can be transformed into the following problem:

$$\begin{aligned} \max_{q, p^{\mathrm{c}}_{i,j}} \quad & R^{\mathrm{c}}_{i,j} - q\left(p^{\mathrm{c}}_{i,j} + p_{\mathrm{cir}}\right) \\ \text{s.t.} \quad & \mathrm{C1}: p^{\mathrm{c}}_{i,j} \leq p^{\max}_i, 1 \leq i \leq M, i \neq j, \\ & \mathrm{C2}: R^{\mathrm{c}}_{i,j} \geq R^{\min}_i, 1 \leq i \leq M, i \neq j. \end{aligned} \tag{19}$$

While the objective function in the above optimization problem is a nonlinear function of q and $p^{\mathrm{c}}_{i,j}$, which cannot be solved directly, it can be observed that given q, the optimization problem in terms of local power allocation strategy can be obtained based on which the value of q can be updated and the local power allocation strategy can be re-designed.

Applying iterative algorithm, the optimal EE q^* and power allocation strategy $p^{\mathrm{c},*}_{i,j}$ can be obtained. The problem solving process can be summarized briefly: starting from an initial value of q, the locally optimal power allocation strategy can be obtained through applying traditional convex optimization tools, then the EE q can be updated based on the obtained power solution. Then given the updated q, the power allocation process can be re-conducted to obtained power allocation strategy, the process continues until the algorithm converges, i.e., $\left|R^{\mathrm{c}}_{i,j}\left(p^{\mathrm{c}}_{i,j}\right) - q\left(p^{\mathrm{c}}_{i,j} + p_{\mathrm{cir}}\right)\right| \leq \varepsilon_0$, where ε_0 denotes the maximum tolerance.

Lagrange Dual Method-Based Power Allocation Algorithm. For a given value of q, the power allocation subproblem can be expressed as follows:

$$\begin{aligned} \max_{p^{\rm c}_{i,j}} \quad & R^{\rm c}_{i,j} - q\left(p^{\rm c}_{i,j} + p_{\rm cir}\right) \\ \text{s.t.} \quad & \text{C1}: p^{\rm c}_{i,j} \le p^{\max}_i, 1 \le i \le M, i \ne j, \\ & \text{C2}: R^{\rm c}_{i,j} \ge R^{\min}_i, 1 \le i \le M, i \ne j. \end{aligned} \tag{20}$$

The optimization problem formulated in (20) is a constrained convex optimization problem which can be solved by applying Lagrange dual method. The Lagrange function can be formulated as [9]

$$L\left(\varphi, \mu, p^{\rm c}_{i,j}\right) = R^{\rm c}_{i,j} - q\left(p^{\rm c}_{i,j} + p_{\rm cir}\right) - \varphi\left(p^{\rm c}_{i,j} - p^{\max}_i\right) - \mu\left(R^{\min}_i - R^{\rm c}_{i,j}\right) \tag{21}$$

where φ, μ are Lagrange multipliers.

The optimization problem in (20) can then be transformed into Lagrange dual problem:

$$\begin{aligned} \min_{\varphi,\mu} \ & \max_{p^{\rm c}_{i,j}} L\left(\varphi, \mu, p^{\rm c}_{i,j}\right) \\ \text{s.t.} \ & \varphi \ge 0, \ \mu \ge 0. \end{aligned} \tag{22}$$

The optimization problem formulated in (22) consists of two subproblems, i.e., internal maximum subproblem and external minimum subproblem, which can be solved iteratively. For a set of fixed Lagrange multipliers, the internal maximum subproblem can be solved to obtain the locally optimal power allocation strategy, which can then be applied to solve the external minimum subproblem to obtain the updated Lagrange multipliers.

The locally optimal power allocation strategy can be obtained by calculating the derivative of formulated Lagrange function with respect to $p^{\rm c}_{i,j}$ and let the computed derivative equal to zero, i.e.,

$$\frac{\partial L\left(\varphi, \mu, p^{\rm c}_{i,j}\right)}{\partial p^{\rm c}_{i,j}} = \frac{(1+\mu)\, B h^{\rm c}_{i,j}}{\ln 2\left(\sigma^2 + p^{\rm c}_{i,j} h^{\rm c}_{i,j}\right)} - q - \varphi = 0, \tag{23}$$

we can obtain

$$p^{{\rm c},*}_{i,j} = \left[\frac{(1+\mu)\, B}{(q+\varphi)\, ln2} - \frac{\sigma^2}{h^{\rm c}_{i,j}}\right]^+ \tag{24}$$

where $[x]^+ = \max\{x, 0\}$, denote $\eta^{{\rm c},*}_{i,j}$ as the optimal EE of MTCD$_i$ obtained from $p^{{\rm c},*}_{i,j}$.

To solve the external minimum subproblem, we apply gradient descent algorithm to calculate the Lagrange multipliers, i.e.,

$$\varphi\left(t_1+1\right) = \left[\varphi\left(t_1\right) - \omega_1\left(p^{\max}_i - p^{\rm c}_{i,j}\right)\right]^+, \tag{25}$$

$$\mu\left(t_1+1\right) = \left[\mu\left(t_1\right) - \omega_2\left(R^{\rm c}_{i,j} - R^{\min}_i\right)\right]^+ \tag{26}$$

where t_1 denotes the iteration index, ω_1 and ω_2 are step size. The proposed Lagrange dual method-based power allocation algorithm is shown in Algorithm 1. The above

Algorithm 1. Lagrange Dual Method-based Power Allocation Algorithm

```
Set the maximum number of iterations $T_1$, and the maximum tolerance $\varepsilon_1$
Initialize the Lagrange multipliers $\varphi(t_1)$, $\mu(t_1)$ for $t_1 = 0$
repeat
    Compute the power allocation strategy
    $p_{i,j}^{\mathrm{c},*} = \left[\frac{(1+\mu) f_i B}{(q+\varphi)\ln 2} - \frac{\sigma^2}{h_{i,j}^{\mathrm{c}}}\right]^+$
    Update the Lagrange multipliers:
    $\varphi(t_1+1) = \left[\varphi(t_1) - \omega_1\left(p_i^{\max} - p_{i,j}^{\mathrm{c}}\right)\right]^+$
    $\mu(t_1+1) = \left[\mu(t_1) - \omega_2\left(R_{i,j}^{\mathrm{c}} - R_i^{\min}\right)\right]^+$
    if $|\varphi(t_1+1) - \varphi(t_1)| + |\mu(t_1+1) - \mu(t_1)| \le \varepsilon_1$ then
        The algorithm terminates
        Convergence = true
        return $p_{i,j}^{\mathrm{c},*}$
    else
        $t_1 = t_1 + 1$
    end if
until Convergence = true or $t_1 = T_1$
```

algorithm can be extended to the case that MTCD$_i$ communicates with BS in direct transmission mode, let $p_i^{\mathrm{d},*}$ denote the optimal value of p_i^{d}, $\eta_i^{\mathrm{d},*}$ denotes the optimal EE corresponding to $p_i^{\mathrm{d},*}$.

4.2 Clustering Subproblem

In this subsection, based on the optimal power allocation strategy obtained from previous subsection, we address the clustering subproblem and solve the subproblem by means of the modified K-means algorithm.

Direct Transmission Mode Selection. It can be understood easily that one MTCD may tend to transmit its data packets to the BS directly provided that it achieves the maximum EE in direct transmission mode compared to CH forwarding mode. Hence, we may first assign the direct transmission mode to the MTCDs simply by comparing the EE of the MTCDs obtained at different transmission modes.

In Table 1, we plot the optimal EE of the MTCDs obtained in different transmission modes. As we can see from the table, different rows in the table represent the EE of different MTCDs, and different columns correspond to different transmission modes of the MTCDs. In particular, in CH forwarding modes, we consider the case that any MTCD can be selected as the CH of other MTCDs. For simplicity, we define the EE of MTCD$_i$ as 0 when the MTCD selects itself as CH for data forwarding, i.e., $\eta_{i,i}^{\mathrm{c},*} = 0$, $1 \le i \le M$.

Table 1. EE of the links between BS and MTCDs and between MTCDs

	Direct transmission mode	CH forwarding mode			
		MTCD$_1$	MTCD$_2$	$\cdots$	MTCD$_M$
MTCD$_1$	$\eta_1^{\mathrm{d},*}$	0	$\eta_{1,2}^{\mathrm{c},*}$	$\cdots$	$\eta_{1,M}^{\mathrm{c},*}$
MTCD$_2$	$\eta_2^{\mathrm{d},*}$	$\eta_{2,1}^{\mathrm{c},*}$	0	$\cdots$	$\eta_{2,M}^{\mathrm{c},*}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
MTCD$_M$	$\eta_M^{\mathrm{d},*}$	$\eta_{M,1}^{\mathrm{c},*}$	$\eta_{M,2}^{\mathrm{c},*}$	$\cdots$	0

Examining Table 1, we can see that in the case that MTCD$_i$ achieves the maximum EE when forwarding data packets to MTCD$_j$ (CH$_j$), i.e., $\eta_i^{\mathrm{d},*} \geq \eta_{i,j}^{\mathrm{c},*}$, $\forall\ 1 \leq j \neq i \leq M$, we should assign direct transmission mode to MTCD$_i$, i.e., $\delta_i^{\mathrm{d},*} = 1$. Let Φ_{d} denote the set of MTCDs which are assigned direct transmission mode, i.e., $\Phi_{\mathrm{d}} = \left\{\mathrm{MTCD}_i \middle| \delta_i^{\mathrm{d},*} = 1,\ 1 \leq i \leq M\right\}$. It should be mentioned that MTCD$_i \in \Phi_{\mathrm{d}}$ cannot be the CM of any clusters, however, it may act as CH for other CMs. Let Φ denote the set of all the MTCDs, i.e., $\Phi = \{\mathrm{MTCD}_i, 1 \leq i \leq M\}$.

Candidate CH Selection. To reduce the computation complexity of the clustering scheme, we propose a candidate CH selection scheme which selects the qualified CHs based on the transmission performance of the MTCDs.

Since the selected CHs should forward data packets for their associated CMs within the clusters, the characteristic of the link between the CHs and the BS, i.e., the direct transmission link of the CHs, is of particular importance as it may affect the transmission performance of data packets significantly. To avoid selecting the MTCDs with highly limited transmission performance, we set a threshold on the EE of the direct transmission link of the MTCDs and set the MTCDs with the EE of the direct transmission link being greater than the threshold as the candidate CHs.

Let $\eta_{\min}$ denote the EE threshold of the direct transmission link of the MTCDs, MTCD$_i$ can be set as a candidate CH provided that $\eta_i^{\mathrm{d},*} \geq \eta_{\min}$, $1 \leq i \leq M$. Denoting Φ_0 as the set of the candidate CHs, we obtain

$$\Phi_0 = \{\mathrm{MTCD}_i | \eta_i^{\mathrm{d},*} \geq \eta_{\min},\ 1 \leq i \leq M\}. \tag{27}$$

Let K_0 denote the number of candidate CHs, i.e., $K_0 = |\Phi_0|$, where $|x|$ represents the number of elements in set x.

Modified K-Means Algorithm-Based Clustering Scheme. The K-means algorithm is commonly used for solving clustering problems [10]. In this paper, we propose a modified K-means algorithm to solve the clustering problem of the MTCDs.

The basic idea of the proposed algorithm can be summarized briefly. We first set the initial number of CHs, i.e., $K_1 = \min\{N_{\max}, K_0\}$, then, select the CHs which offer the highest EE of both the direct link and the association links with other MTCDs. Given the initial CHs, associate the CMs with the CH offering the maximum EE of the association links. Within each cluster, the CH selection and association processes are repeated until the algorithm achieves convergence.

The steps of modified K-means algorithm-based clustering scheme are as follows:

(a) *Initialization*: Set the maximum number of iterations T', the maximum tolerance $\varDelta$, set $t' = 1$, and determine the number of CHs, i.e., $K_1 = \min\{N_{\max}, K_0\}$.

(b) *Initial CH selection*: For $\mathrm{MTCD}_i \in \varPhi$, $1 \le i \le M$, calculate the sum of EE of both the direct link and the association links with other MTCDs, denoted as ψ_i, i.e.,

$$\psi_i = \eta_i^{\mathrm{d},*} + \sum_{j=1, j\neq i}^{M} \eta_{i,j}^{\mathrm{c},*},\ 1 \le i \le M.$$

Select K_1 MTCDs which offer the largest EE as the CHs. More specifically, ordering $\mathrm{MTCD}_i \in \varPhi$ according to ψ_i, i.e.,

$$\psi_{i_1} \ge \psi_{i_2} \ge \cdots \ge \psi_{i_k} \ge \cdots \ge \psi_{i_{K_0}}, \forall\, \mathrm{MTCD}_{i_k} \in \varPhi.$$

The first K_1 MTCDs will be selected as the CHs. Let $\varPhi_{\mathrm{ch}}$ denote the set of CHs, we set

$$\varPhi_{\mathrm{ch}} = \{\mathrm{MTCD}_{i_k} \mid 1 \le k \le K_1,\ \mathrm{MTCD}_{i_k} \in \varPhi\}.$$

Let $\varPhi_{\mathrm{cm}}$ denote the set of CMs, we obtain

$$\varPhi_{\mathrm{cm}} = \left\{\mathrm{MTCD}_i \,|\mathrm{MTCD}_i \in \varPhi,\ \mathrm{MTCD}_i \notin \{\varPhi_{\mathrm{ch}} \cup \varPhi_{\mathrm{d}}\}\right\}.$$

(c) *Initial CH Association*: For $\mathrm{MTCD}_i \in \varPhi_{\mathrm{cm}}$, compute the EE of the links between MTCD_i and $\mathrm{MTCD}_j \in \varPhi_{\mathrm{ch}}$, and choose the CH which offers the largest EE as the associated CH. Let $\mathrm{MTCD}_{j'}$ denote the associated CH of MTCD_i, we obtain

$$\mathrm{CH}_{j'} = \underset{\mathrm{MTCD}_j \in \varPhi_{\mathrm{ch}}}{\arg\max} \left\{\eta_{i,j}^{\mathrm{c},*}\right\},\ \mathrm{MTCD}_i \in \varPhi_{\mathrm{cm}}.$$

Accordingly, we set $\delta_{i,j'}^{\mathrm{c}} = 1$.

(d) *System EE calculation*: Update the set of direct transmission MTCDs by removing those MTCDs which are selected as CHs, denote $\varPhi_{\mathrm{d}'}$ as the updated set of direct transmission MTCDs, we express $\varPhi_{\mathrm{d}'}$ as

$$\varPhi_{\mathrm{d}'} = \{\mathrm{MTCD}_i \,|\mathrm{MTCD}_i \in \varPhi_{\mathrm{d}},\ \ \mathrm{MTCD}_i \notin \varPhi_{\mathrm{ch}}\}.$$

For $\mathrm{MTCD}_i \in \varPhi_{\mathrm{d}'}$, set the direct transmission mode selection variable $\delta_i^{\mathrm{d},*} = 1$. Based on the obtained transmission mode selection and clustering strategy, we calculate system EE denoted by $\eta_{t'}$, i.e.,

$$\eta_{t'} = \sum_{\mathrm{MTCD}_i \in \varPhi_{\mathrm{d}'}} \eta_i^{\mathrm{d},*} + \sum_{\mathrm{MTCD}_i \in \varPhi_{\mathrm{ch}}} \eta_i^{\mathrm{d},*} + \sum_{\mathrm{MTCD}_i \in \varPhi_{\mathrm{cm}}} \sum_{\mathrm{MTCD}_{j'} \in \varPhi_{\mathrm{ch}}} \eta_{i,j'}^{\mathrm{c},*} \tag{28}$$

(e) *CH reselection*: Assuming $\mathrm{MTCD}_{j'} \in \varPhi_{\mathrm{ch}}$ is selected as one CH, we let $\varPhi_{j'}$ denote the set of the CMs which are associated with $\mathrm{MTCD}_{j'}$, i.e.,

$$\varPhi_{j'} = \{\mathrm{MTCD}_i \,|\mathrm{MTCD}_i \in \varPhi_{\mathrm{cm}},\ \delta_{i,j'}^{\mathrm{c}} = 1\}.$$

For $\forall$ MTCD$_i \in \Phi_{j'}$, compute the sum of EE of the direct link between MTCD$_i$ and the BS, the link between MTCD$_i$ and MTCD$_{j'}$, and the links between MTCD$_i$ and MTCD$_{i'} \in \Phi_{j'},\ i \neq i'$. Let ζ_i denote the EE performance of MTCD$_i \in \Phi_{j'}$, we express ζ_i as

$$\zeta_i = \eta_i^{\mathrm{d},*} + \eta_{i,j'}^{\mathrm{c},*} + \sum_{\mathrm{MTCD}_{i'} \in \Phi_{j'}, i' \neq i} \eta_{i,i'}^{\mathrm{c},*}$$

and choose MTCD$_i \in \Phi_{j'}$ which offers the largest EE as the updated CH, i.e.,

$$\mathrm{CH}_i = \underset{\{\mathrm{MTCD}_{j'}\} \cup \Phi_{j'}}{\arg\max} \{\zeta_i\}.$$

Accordingly, update the set of Φ_{ch} and Φ_{cm}.

(f) *CH reassociation*: For MTCD$_i \in \Phi_{\mathrm{cm}}$, compute the EE of the link between MTCD$_i$ and MTCD$_j \in \Phi_{\mathrm{ch}}$, and choose the CH which offers the largest EE as the associated CH.

(g) *System EE update*: Re-calculate the system EE based on (28), denoted by $\eta_{t'+1}$.

(h) *Algorithm convergence*: If $|\eta_{t'+1} - \eta_{t'}| \leq \Delta$ or $t' = T'$, then algorithm stops, the corresponding clustering strategy can be obtained, otherwise, set $t' = t' + 1$, return to Step (e).

Table 2. Simulation parameters

Parameters	Value
Number of MTCDs	15
Small scale fading distribution	Rayleigh fading with unit variance
Channel path loss model	$128.1 + 37.6 \log(d)$ dB
Bandwidth of one RB	180 KHz
Maximum transmit power	0.15 W
Noise power	-104 dBm
Circuit power consumption	0.3 W

5 Simulation Result Analysis

In this section, simulation results are presented to show the performance by our proposed scheme. For comparison, we also examine the performance of the previously proposed algorithm in [4] via simulation. In the simulation, we consider an M2M communication network consisting of one BS and M MTCDs. The size of the simulation region is set as $500\,\mathrm{m} \times 500\,\mathrm{m}$, and the MTCDs are randomly located in the simulation area. Unless otherwise mentioned, the simulation parameters are listed in Table 2.

Figure 2 shows system EE versus maximum transmit power for different circuit power consumption. From the figure, we can see that for small $p_i^{\max}$, the EE increases with the increase of $p_i^{\max}$ for both schemes, indicating that a larger power threshold is desired for achieving the maximum EE. However, as the maximum transmit power reaches to a certain value, the EE obtained from our proposed scheme converges to a constant while the EE obtained from the scheme proposed in [4] decreases as the power increases. This is because the scheme proposed in [4] aims to achieve the maximum transmit rate, thus may require higher power consumption, resulting in undesired EE. It can also be observed from the figure that the EE obtained from both algorithms decreases with the increase of circuit power consumption. Comparing the curves in the graph, we can see that the proposed algorithm offers higher EE than that of previously proposed scheme.

In Fig. 3, we examine system EE versus maximum transmit power for different noise power. From the figure, we can see that the EE decreases with the increase of noise power. This is because larger noise power results in reduced transmission performance and lower EE in turn. Comparing the results obtained from two algorithms, we can see that our proposed scheme offers better performance compared with [4].

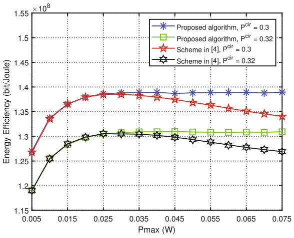

Fig. 2. Energy efficiency versus maximum transmit power (different circuit power).

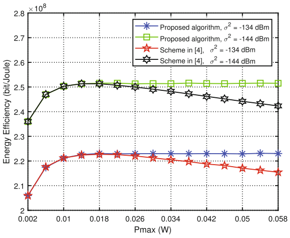

Fig. 3. Energy efficiency versus maximum transmit power (different noise power).

In Fig. 4, we plot system EE versus the number of MTCDs for different circuit power consumption. We set the number of MTCDs from 10 to 55 in the simulation. It can be see from the figure that the EE obtained from both algorithms decreases with the increase of circuit power consumption. As the number of MTCDs increases, the EE obtained from both algorithms increases accordingly. This is due to the fact that as the number of MTCDs increases, the increased amount of data flows are transmitted through the system, resulting in an increased EE. In addition, we can observe that our proposed scheme is more energy efficient than other algorithm.

Figure 5 shows system EE versus the number of MTCDs for different noise power. From the figure, we can see that the EE decreases with the increase of noise power and increases as the number of MTCDs increase. This is because larger noise power results in worse transmission performance and lower EE in turn. In addition, we can see that our proposed algorithm offers outperforms the other scheme.

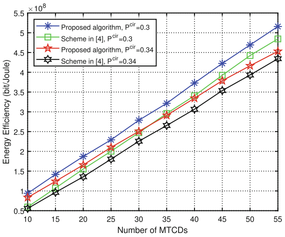

Fig. 4. Energy efficiency versus the number of MTCDs (different circuit power).

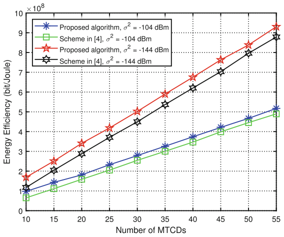

Fig. 5. Energy efficiency versus the number MTCDs (different noise power).

6 Conclusion

In this paper, we consider an M2M communication network and formulate the joint resource allocation and clustering problem as system EE maximization problem. As the formulated optimization problem is a nonlinear fractional programming problem, which cannot be solved directly, we decompose it into two subproblems, i.e., power allocation subproblem and clustering subproblem, and solve the two subproblems by means of Lagrange dual method and modified K-means algorithm, respectively. Numerical results show that our proposed algorithm outperforms previously proposed algorithm.

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