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Energy Efficiency Optimization-Based Joint Resource Allocation and Clustering Algorithm for M2M Communication Systems

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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 systems, machine type communication devices (MTCDs) are capable of communicating with each other intelligently under highly reduced human interventions. Although diverse types of services are expected to be supported for MTCDs, various quality of service (QoS) requirements and network states pose difficulties and challenges to the resource allocation and clustering schemes of M2M communication systems. In this paper, we address the joint resource allocation and clustering problem in M2M communication systems. To achieve the efficient resource management of the MTCDs, we propose a joint resource management architecture, and design a joint resource allocation and clustering algorithm. More specifically, by defining system energy efficiency as the sum of the energy efficiency of the MTCDs, the joint resource allocation and clustering problem is formulated as an energy efficiency maximization problem. As the original optimization problem is a nonlinear fractional programming problem, which cannot be solved conveniently, we transform the optimization problem into power allocation subproblem and clustering subproblem. Applying iterative method-based energy efficiency maximization algorithm, we first obtain the optimal power allocation strategy based on which, we then propose a modified K-means algorithm to obtain the clustering strategy. Numerical results demonstrate the effectiveness of the proposed algorithm.

INDEX TERMS Machine-to-machine (M2M) communications, resource allocation, clustering, energy efficiency.

I. INTRODUCTION

Machine to machine (M2M) communication technology has been considered as one of the promising approaches to realize the Internet of things (IoT) in the 5th generation network [1]. In M2M, machine type communication devices (MTCDs) are capable of communicating with each other intelligently under highly reduced human interventions [2]. To guarantee the quality of service (QoS) requirements of the MTCDs and achieve performance enhancement of the M2M communication systems, efficient radio resource management schemes should be designed [3].

To further enhance the transmission performance of MTCDs, clustering mechanisms can be applied where the MTCDs are divided into groups or clusters with each cluster consisting of one cluster head (CH) and certain number of cluster members (CMs). By applying clustering schemes, the efficiency of data transmission can be enhanced and the energy consumption required for the MTCDs to transmit data packets can be reduced significantly [4].

Although the problem of resource allocation and clustering has been studied for M2M communications in previous research work, it can be shown that the two problems are highly related and the associated strategies may jointly affect user QoS and network performance. In this paper, we address the joint resource allocation and clustering problem in M2M communication systems. To achieve the efficient resource management of the MTCDs, we propose a joint resource management architecture, and design a joint resource allocation and clustering algorithm. More specifically, by defining system energy efficiency as the sum of the energy efficiency of the MTCDs, the joint resource allocation and clustering

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problem is formulated as an energy efficiency maximization problem. As the original optimization problem is a nonlinear fractional programming problem, which cannot be solved conveniently, we transform the optimization problem into two subproblems, i.e., power allocation subproblem and clustering subproblem. Applying iterative method-based energy efficiency maximization algorithm, we first obtain the optimal power allocation strategy based on which, we then propose a modified K-means algorithm to obtain the clustering strategy.

The major contributions of this paper are summarized as follows.

1) Although resource allocation and clustering problems have been studied for M2M communications in previous work [5]–[15], it can be shown that the two problems are highly related and jointly affect user QoS and network performance. Hence, in this paper, we jointly investigate the problem of resource allocation and clustering of the MTCDs in M2M communication systems. To achieve the efficient resource management of the MTCDs, we propose a joint resource management architecture, based on which, we design a joint resource allocation and clustering algorithm.
2) While the problem of joint resource allocation and clustering has been considered for M2M communication systems in [16]–[22], previous research work mainly aims to increase the success probability of random access [16]–[18], reduce access latency [19], [20], maximize network lifetime [21] or maximize sum-throughput [22], they fail to consider the energy efficiency of the MTCDs which is of particular importance for achieving the tradeoff between data transmission performance and energy consumption. In this paper, we jointly consider the energy efficiency of all the MTCDs in the system and formulate the joint resource allocation and clustering problem as an energy efficiency maximization problem.
3) Since the formulated joint resource allocation and clustering problem is a nonlinear fractional programming problem, which cannot be solved conveniently, we transform the optimization problem into two subproblems, i.e., power allocation subproblem and clustering subproblem. Applying iterative method-based energy efficiency maximization algorithm, we first obtain the optimal power allocation strategy based on which, we then propose a modified K-means algorithm to obtain the clustering strategy.

The rest of this paper is organized as follows. Section II presents an overview of related work. The system model and proposed joint resource management architecture are presented in Section III. In Section IV, optimization problem is formulated. Section V discusses the solution to the optimization problem. Complexity analysis of the proposed algorithm is presented in Section VI. Simulation results are presented in Section VII. Finally, we make a conclusion and discuss future work in Section VIII.

II. RELATED WORK

In this section, we present a summary on the resource allocation and clustering schemes designed for M2M communications.

A. RESOURCE ALLOCATION SCHEMES FOR M2M COMMUNICATIONS

In recent years, resource allocation problems have been addressed for M2M communications [5]–[10].

In [5], [6], the authors aim to maximize system throughput when designing optimal resource allocation strategy for the MTCDs. Vilgelm *et al.* [5] propose a preamble allocation method to maximize system throughput and design an effective QoS differentiation mechanism across a wide range of random access loads. To resolve the intra-cell pilot collision issue of M2M communications in crowded massive multiple-input multiple-output (MIMO) systems, Han *et al.* [6] propose a strongest-user collision resolution protocol which allows user equipments (UEs) to contend for the idle pilots so as to increase system throughput and decrease the number of access attempts as well.

Stressing the energy consumption of the M2M communication systems, the authors in [7], [8] develop energy-efficient resource allocation strategy for the MTCDs. Yang *et al.* [7] study energy-efficient resource allocation schemes for an M2M-enabled cellular network with nonlinear energy harvesting. Aiming to minimize the total energy consumption of the network, the authors propose a joint power control and time allocation scheme for the MTCDs applying non-orthogonal multiple access (NOMA) and time-division multiple access (TDMA) strategies. In [8], Dawaliby *et al.* tackle the challenges of scheduling M2M traffic in long-term evolution (LTE) systems and propose a cross-layer resource allocation scheme that minimizes the energy consumption of the MTCDs.

QoS or quality of experience (QoE) enhancement is considered in [9], [10]. In [9], Yin *et al.* introduce an evaluation model based on mean opinion score for various MTCDs, and propose a QoE-oriented uplink rate control and resource allocation scheme to maximize the long-term QoE of the MTCDs. The original long-term optimization problem is converted into two subproblems, i.e., admission rate control subproblem and resource allocation subproblem in each time slot, and Gale-Shapley algorithm is utilized to solve the resource allocation subproblem. In [10], Salam *et al.* propose a cooperative data aggregation (CDA) scheme by employing a fixed data aggregator (FDA) and multiple mobile data aggregators (MDAs) to collect the data packets of the MTCDs having variable QoS requirements. A distributed MDA selection algorithm is proposed to designate appropriate UEs as aggregators and a resource allocation scheme is designed to dynamically allocate channels to the MTCDs subject to their QoS requirements.

B. CLUSTERING SCHEMES FOR M2M COMMUNICATIONS

To improve the transmission performance of M2M communications, clustering schemes can be applied. The authors in [11] demonstrate that by employing relays and clustering protocols, cooperative communications can be implemented in M2M systems and network performance enhancement is expected.

In [12]–[14], the authors investigate the problem of energy-efficient clustering in M2M systems. In [12], the clustering problem is formulated as an evolutionary game, which models the interactions among a massive number of MTCDs. A utility function that captures the tradeoff between the average transmit power per cluster and the cluster size is defined. To solve the game model, a distributed algorithm is proposed which allows the MTCDs to autonomously form clusters. In [13], the clustering problem in M2M systems is formulated as a stochastic coalition formation game in which the MTCDs are the players that seek to form cooperative coalitions to optimize the utility function that characterizes the energy consumption of the MTCDs and time-varying queue length.

In [14], the size of clusters is determined and an energy-efficient CH selection scheme is proposed to minimize the energy consumption of the MTCDs and maximize network lifetime. The communications protocols for both intra-cluster and inter-cluster communications are investigated and an energy-efficient and load-adaptive multiple access scheme is designed, which achieves a tunable tradeoff between the energy efficiency, delay and spectral efficiency of the network.

Clustering schemes can also be applied to achieve energy-efficient routing in M2M communication systems [15]. To offer data transmission from terminal nodes to a sink node via CHs, the authors in [15] study the routing problem in a hierarchical M2M communication system. A multilevel clustering scheme is designed and a self-organized routing algorithm from CHs to the sink node is proposed to prolong network lifetime and enhance the transmission performance of the terminal nodes.

C. JOINT RESOURCE ALLOCATION AND CLUSTERING SCHEMES FOR M2M COMMUNICATIONS

Some recent research work jointly considers resource allocation and clustering schemes for M2M communications [16]–[22].

In order to increase the success probability of random access, Jang *et al.* [16] propose a spatial group based random access mechanism and a non-orthogonal resource allocation scheme. To achieve the spatial multiplex of the preambles, the MTCDs are divided into groups, then for the MTCDs belonging to individual group, non-orthogonal channel resources are allocated. To accommodate massive access for MTCDs in cellular system, Tefek and Lim [17] propose two single-hop relaying schemes, i.e., signal-to-interference ratio-based relaying and location-based relaying. Specifically, the MTCDs are divided into into different clusters based on their locations and service requirements, then, a local access point is chosen to forward data packets for the MTCDs in each cluster. Location-based random access scheme is also proposed in [18] where the MTCDs are grouped into different clusters based on their location information in order to mitigate the severe collision of the MTCDs that access to the base station (BS) concurrently. The communication of MTCDs is controlled by a CH, which is assumed to be a Decode-and-Forward (DF) relay to decode and forward the information from the MTCD to the BS.

Aiming to achieve low access delay and high resource efficiency and in a co-existing environment of delay-sensitive and delay-tolerant services, Wu *et al.* [19] propose a dynamic resource allocation scheme with QoS guarantee for clustered M2M communications. Based on the minimum delay requirement, the MTCDs are divided into into different clusters, then the available physical random access channel (PRACH) resources are dynamically allocated to the MTCDs in each cluster. In [20], Vu *et al.* propose a two dimension proactive uplink resource allocation with clustering algorithm to reduce the latency in event-based M2M communications. The MTCDs in the disturbance region are spatially clustered into rings based on their distance to the original event. Then, these rings are proactively allocated resources for uplink transmissions.

Stressing the highly limited energy resources of the MTCDs, Riker *et al.* [21] propose a two-tier aggregation approach for multi-target applications in M2M communications to maximize network lifetime. In the first aggregation tier, data aggregation is executed to reduce data redundancy, and in the second tier, the cost incurred by the message overhead is reduced by further applying data aggregation. Ghavimi *et al.* [22] study joint power allocation and clustering issues for M2M communications in LTE-advanced (LTE-A) systems. By applying clustering schemes, the MTCDs are grouped based on transmission protocols and further clustered based on QoS characteristics and requirements. Then, a sum-throughput maximization-based resource allocation scheme is proposed of the MTCDs in the clusters.

While the problem of joint resource allocation and clustering has been considered for M2M communication systems, previous research work mainly aims to increase the success probability of random access [16]–[18], reduce access latency [19], [20], maximize network lifetime [21] or maximize sum-throughput [22], they fail to consider the energy efficiency of the MTCDs which is of particular importance for achieving the tradeoff between data transmission performance and energy consumption. Furthermore, in previous clustering schemes, the intra-cluster resource allocation is mainly discussed, however, the transmission performance evaluation and mode selection for both direct transmission and CH forwarding mode fail to be considered extensively. In this paper, we address the joint resource allocation and clustering problem for M2M communications and propose a system energy efficiency maximization-based joint optimal strategy.

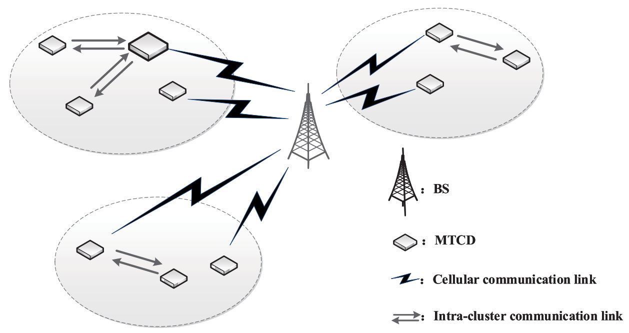

FIGURE 1. System model.

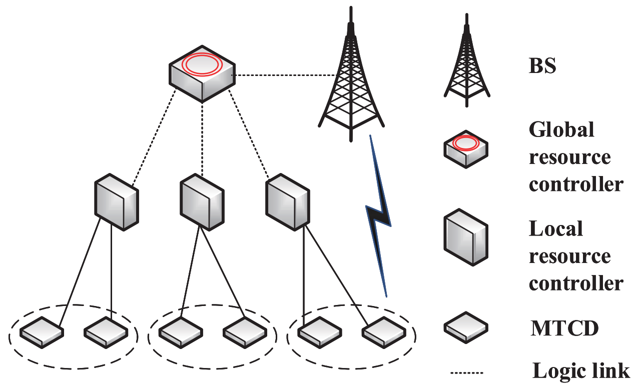

FIGURE 2. Proposed joint resource management architecture.

III. SYSTEM MODEL AND PROPOSED JOINT RESOURCE MANAGEMENT ARCHITECTURE

A. SYSTEM MODEL

In this paper, we consider an M2M communication system consisting of a single BS and a number of MTCDs where the BS is deployed at the center of certain area and the MTCDs are randomly deployed within the coverage area of the BS. We further assume that the MTCDs have collected required information and need to transmit their data packets to the BS. For convenience, we denote the ith MTCD as MTCD_i, $1 \leq i \leq M$, where M denotes the number of MTCDs.

To enable efficient data transmission, we assume that the MTCDs may communicate with the BS in direct transmission mode, i.e., the MTCDs are allowed to access the BS and transmit their data packets directly. Alternatively, the MTCDs may also transmit their data packets to the BS in CH forwarding mode. More specifically, the MTCDs are grouped into various clusters with each cluster consisting of one CH and certain number of CMs. While the CHs in different clusters 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. Figure 1 shows the system model considered in this paper.

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 exists among transmission links.

B. PROPOSED JOINT RESOURCE MANAGEMENT ARCHITECTURE

To achieve the efficient resource management in M2M communication systems, we propose a joint resource management architecture. Figure 2 shows the proposed architecture, in which two functional controllers, i.e., global resource controller (GRC) and local resource controller (LRC), are introduced to tackle the resources of the system and to conduct joint resource allocation and clustering for the MTCDs. The major roles and functions of GRC and LRC are as follows.

1) LOCAL RESOURCE CONTROLLER

Being deployed at the BS and the MTCDs, and each LRC acts as a local controller of the BS or that of one MTCD. Through interacting with the associated BS and the MTCDs, the LRCs collect the state information of the BS and the MTCDs, and then forward the collected information to the GRC. In addition, the LRCs receive the joint resource allocation and clustering strategy from the GRC, and forward the strategy to the associated BS and the MTCDs.

2) GLOBAL RESOURCE CONTROLLER

Being deployed over the BS and the MTCDs, the GRC acts as the centralized controller of the system. Through interacting with the LRC associated with the BS, the GRC receives the status information of the M2M communication system, such as the channel bandwidth, the maximum allowable number of CHs in the network and the maximum number of CMs that associate with one CH, etc. Similarly, through interacting with the LRCs associated with the MTCDs, the GRC receives the status information and QoS requirement of the MTCDs, such as the channel characteristics, the maximum transmit power and the minimum transmission rate of the MTCDs, etc. Based on the obtained information, the GRC may conduct the proposed energy efficiency maximization-based joint resource allocation and clustering algorithm, obtain the power allocation and clustering strategy of the MTCDs and send the strategy to the LRCs.

IV. OPTIMIZATION PROBLEM FORMULATION

The power consumption is one of the important metrics for MTCDs, as in many MTCD applications, MTCDs can be battery-driving sensors or small-size devices with radio frequency identity (RFID) embedded. Charging or replacing the battery of these MTCDs is in general very difficult or impractical. In the case that the battery of one MTCD runs out, the MTCD cannot work properly any more. Since data transmission consumes considerable energy of the MTCDs, designing energy efficient data transmission schemes to achieve low power consumption and long lifetime of the MTCDs is highly desired. On the other hand, while minimizing power consumption is important, the transmission performance of the MTCDs should be guaranteed. To achieve the tradeoff between transmission performance and energy consumption, we may stress the metric of energy efficiency, which is defined as the ratio of the achievable data rate to the overall power consumption of the MTCD.

In this section, we examine the energy efficiency of the MTCDs in various data transmission modes and define system energy efficiency as the total energy efficiency of the MTCDs. Then, jointly considering the constraints on transmission mode selection, the minimum data rate requirement and the maximum transmit power of the MTCDs, etc., we formulate the joint resource allocation and clustering problem as system energy efficiency maximization problem.

A. OBJECTIVE FUNCTION

The system energy efficiency of the M2M system can be expressed as

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

where η_i denotes the energy efficiency of MTCD$_i$. The expression of η_i is given by

$$\eta_i = \delta_i^{\mathrm{d}} \eta_i^{\mathrm{d}} + \sum_{l=1, l \neq i}^{M} \sum_{k=1}^{K_1} \alpha_{l,k} \delta_{i,k}^{\mathrm{c}} \eta_{i,l}^{\mathrm{c}} \tag{2}$$

where $\delta_i^{\mathrm{d}} \in \{0, 1\}$ is the direct transmission mode selection variable of MTCD$_i$, i.e., $\delta_i^{\mathrm{d}} = 1$, if MTCD$_i$ transmits its data packets to the BS in direct transmission mode, otherwise, $\delta_i^{\mathrm{d}} = 0$, η_i^{d} denotes the energy efficiency 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 R_i^{d} and p_i^{d} denote respectively the transmission rate and transmit power of MTCD$_i$ in direct transmission mode, p_{cir} denotes the circuit power consumption of MTCD$_i$. Without loss of generality, we assume that p_{cir} is a constant for various MTCDs. R_i^{d} 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} and σ^2 denote respectively the channel gain and the noise power of the transmission link between MTCD$_i$ and the BS.

In (2), $\alpha_{l,k}$ is the CH selection variable, i.e., $\alpha_{l,k} = 1$, if MTCD$_l$ is selected as the CH of the kth cluster, otherwise, $\alpha_{l,k} = 0$. For convenience, we denote CH$_k$ as the CH of the kth cluster. $\delta_{i,k}^{\mathrm{c}}$ is the association variable of MTCD$_i$ and CH$_k$ in CH forwarding mode. We set $\delta_{i,k}^{\mathrm{c}} = 1$, if MTCD$_i$ is the CM of the kth cluster and chooses CH$_k$ to forward its data packets to the BS, otherwise, $\delta_{i,k}^{\mathrm{c}} = 0$. $\eta_{i,l}^{\mathrm{c}}$ denotes the energy efficiency of MTCD$_i$ when transmitting data to MTCD$_l$ in CH forwarding mode. $\eta_{i,l}^{\mathrm{c}}$ can be computed as

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

where $R_{i,l}^{\mathrm{c}}$ and $p_{i,l}^{\mathrm{c}}$ denote respectively the transmission rate and transmit power of MTCD$_i$ when forwarding data packets to MTCD$_l$. $R_{i,l}^{\mathrm{c}}$ is given by

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

where $h_{i,l}^{\mathrm{c}}$ denotes the channel gain of the link between MTCD$_i$ and MTCD$_l$. In (2), K_1 denotes the number of CHs, i.e.,

$$K_1 = \max k, \; \exists\, \alpha_{l,k} = 1, \quad \forall\, 1 \le l \le L. \tag{7}$$

B. OPTIMIZATION CONSTRAINTS

The optimal design of the joint resource allocation and clustering strategy should be subject to certain constraints as discussed in detail in this subsection.

1) MAXIMUM NUMBER OF CHS

The clustering strategy should meet the constraint on the maximum number of CHs. Let $N_{\max}$ denote the maximum allowable number of CHs in the network, we may express the constraint on the maximum number of CHs as:

$$\mathrm{C1}: K_1 \le N_{\max}. \tag{8}$$

2) MAXIMUM NUMBER OF CMS IN EACH CLUSTER

Assuming that the maximum number of CMs that associate with one CH is M_1, hence, we obtain the following constraint:

$$\mathrm{C2}: \sum_{i=1}^{M} \delta_{i,k}^{\mathrm{c}} \le M_1, \quad 1 \le k \le K_1. \tag{9}$$

3) CH ASSOCIATION CONSTRAINT

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

$$\mathrm{C3}: \sum_{k=1}^{K_1} \delta_{i,k}^{\mathrm{c}} \le 1, \quad 1 \le i \le M. \tag{10}$$

4) CH SELECTION CONSTRAINT

As each CH can only be selected from individual MTCD, we obtain

$$\mathrm{C4}: \sum_{l=1}^{M} \alpha_{l,k} \le 1, \quad 1 \le k \le K_1. \tag{11}$$

Similarly, each MTCD can at most be selected as one CH, i.e.,

$$\mathrm{C5}: \sum_{k=1}^{K_1} \alpha_{l,k} \le 1, \quad 1 \le l \le M. \tag{12}$$

5) MODE SELECTION CONSTRAINT

We further assume that each MTCD can either choose direct transmission mode or CH forwarding mode, i.e.,

$$C6 : \delta_i^{d} + \sum_{k=1}^{K_1} \delta_{i,k}^{c} \leq 1, \quad 1 \leq i \leq M. \tag{13}$$

It should be noticed that the CHs can only apply direct transmission mode to transmit their own data packets to the BS. Furthermore, to forward the data packets received from their associated CMs, the CHs also apply direct transmission mode. Hence, we obtain the following constraint on the transmission mode of the CHs:

$$C7 : \delta_l^{d} = 1, \text{ if } \sum_{k=1}^{K_1} \alpha_{l,k} = 1, \quad 1 \leq l \leq M. \tag{14}$$

6) MAXIMUM TRANSMIT POWER CONSTRAINTS

As the transmit power of the MTCDs must be less than their maximum transmit power, we obtain

$$C8 : p_i^{d} \leq p_i^{\max}, \quad 1 \leq i \leq M, \tag{15}$$
$$C9 : p_{i,l}^{c} \leq p_i^{\max}, \quad 1 \leq i \neq l \leq M \tag{16}$$

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

7) TRANSMISSION RATE CONSTRAINT

Stressing the various QoS requirements of MTCDs, we assume that there is a minimum rate requirement for each MTCD, thus, the achievable transmission rate of the MTCDs should be higher than the minimum transmission rate requirement, i.e.,

$$C10 : R_i \geq R_i^{\min}, \quad 1 \leq i \leq M \tag{17}$$

where $R_i^{\min}$ and R_i denote respectively the minimum transmission rate and the actual achievable transmission rate of MTCD$_i$, $1 \leq i \leq M$. R_i can be expressed as

$$R_i = \delta_i^{d} R_i^{d} + \sum_{l=1, l\neq i}^{M} \sum_{k=1}^{K_1} \alpha_{l,k} \delta_{i,k}^{c} R_{i,l} \tag{18}$$

where $R_{i,l}$ denotes the transmission rate of the two-hop link between MTCD$_i$ and the BS via MTCD$_l$ and can be expressed as $R_{i,l} = \min\left\{R_{i,l}^{c}, R_l^{d}\right\}$.

C. OPTIMIZATION PROBLEM

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

$$\max_{\alpha_{l,k}, \delta_i^{d}, \delta_{i,k}^{c}, p_i^{d}, p_{i,l}^{c}} \quad \eta \qquad \text{s.t. } C1 - C10. \tag{19}$$

V. SOLUTION TO THE OPTIMIZATION PROBLEM

The optimization problem in (19) 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 MTCDs in various transmission modes can be designed independently. Hence, we may transform the optimization problem formulated in (19) into two subproblems, i.e., power allocation subproblem and clustering subproblem, and solve the two subproblems successively.

A. POWER ALLOCATION SUBPROBLEM

In this subsection, we suppose MTCD$_i$ chooses CH forwarding mode and transmits its data packets to MTCD$_l$ which is selected as CH$_k$, i.e., $\alpha_{l,k} = 1$, $\delta_{i,k}^{c} = 1$, $1 \leq i \neq l \leq M$, $1 \leq k \leq K_1$, the power allocation subproblem of MTCD$_i$ in CH forwarding mode can be expressed as

$$\begin{aligned} \max_{p_{i,l}^{c}} \quad & \eta_{i,l}^{c} \\ \text{s.t. } & C1 : p_{i,l}^{c} \leq p_i^{\max}, \\ & C2 : R_{i,l}^{c} \geq R_i^{\min}, 1 \leq i \neq l \leq M. \end{aligned} \tag{20}$$

1) ITERATIVE METHOD-BASED ENERGY EFFICIENCY MAXIMIZATION ALGORITHM

The optimization problem formulated in (20) 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.

Let q denote the energy efficiency of MTCD$_i$ when transmitting to MTCD$_l$, i.e., $q = \frac{R_{i,l}^{c}}{p_{i,l}^{c} + p_{\mathrm{cir}}}$, $p_{i,l}^{c,*}$ denote the optimal transmit power of MTCD$_i$ and q^* denote the maximum energy efficiency, we obtain [24]

$$q^* = \frac{R_{i,l}^{c}\left(p_{i,l}^{c,*}\right)}{p_{i,l}^{c,*} + p_{\mathrm{cir}}} = \max_{p_{i,l}^{c}} \frac{R_{i,l}^{c}(p_{i,l}^{c})}{p_{i,l}^{c} + p_{\mathrm{cir}}}. \tag{21}$$

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

$$R_{i,l}^{c}\left(p_{i,l}^{c}\right) - q^*\left(p_{i,l}^{c} + p_{\mathrm{cir}}\right) = 0. \tag{22}$$

Hence, the optimization problem formulated in (20) can be transformed into the following problem:

$$\begin{aligned} \max_{q, p_{i,l}^{c}} \quad & R_{i,l}^{c} - q\left(p_{i,l}^{c} + p_{\mathrm{cir}}\right) \\ \text{s.t. } & C1 : p_{i,l}^{c} \leq p_i^{\max} \\ & C2 : R_{i,l}^{c} \geq R_i^{\min}. \end{aligned} \tag{23}$$

While the optimization problem formulated in (23) is a non-convex optimization problem of the optimization variables q and $p_{i,l}^{c}$, which cannot be solved easily, it can be demonstrated that by applying iterative method, the optimization problem can be solved, and the maximum energy efficiency q^* and the optimal power allocation strategy $p_{i,l}^{\mathrm{c},*}$ can be obtained.

The iterative method-based energy efficiency maximization algorithm can be summarized briefly as follows.

a) Starting from an initial value of q, the locally optimal power allocation strategy can be obtained through applying traditional convex optimization tools;

b) The energy efficiency q can be updated based on the obtained power allocation strategy;

c) Given the updated q, the power allocation process can be re-conducted;

d) The process continues until the algorithm converges, i.e., $\left|R_{i,l}^{\mathrm{c}}\left(p_{i,l}^{\mathrm{c}}\right) - q\left(p_{i,l}^{\mathrm{c}} + p_{\mathrm{cir}}\right)\right| \leq \varepsilon_0$, where ε_0 denotes the maximum tolerance, and the optimal energy efficiency and power allocation strategy can be obtained.

Let $\eta_{i,l}^{\mathrm{c},*}$ denote the maximum energy efficiency corresponding to the optimal power allocation strategy $p_{i,l}^{\mathrm{c},*}$. The proposed iterative method-based energy efficiency maximization algorithm is summarized in Algorithm 1 and the convergence of the algorithm can be guaranteed [25].

Algorithm 1 Iterative Method-Based Energy Efficiency Maximization Algorithm

1: Set the maximum number of iterations T_0 and the maximum tolerance ε_0
2: Set the initial energy efficiency $q = 0$ and iteration index $t_0 = 0$
3: **repeat**
4: Given q, solve the power allocation subproblem to obtain the locally optimal power allocation strategy $p_{i,l}^{\mathrm{c},0}$
5: **if** $\left|R_{i,l}^{\mathrm{c}}\left(p_{i,l}^{\mathrm{c},0}\right) - q\left(p_{i,l}^{\mathrm{c},0} + p_{\mathrm{cir}}\right)\right| \leq \varepsilon_0$ **then**
6: Convergence = **true**
7: **return** $q^* = \frac{R_{i,l}^{\mathrm{c}}\left(p_{i,l}^{\mathrm{c},0}\right)}{p_{i,l}^{\mathrm{c},0} + p_{\mathrm{cir}}}$, $p_{i,l}^{\mathrm{c},*} = p_{i,l}^{\mathrm{c},0}$
8: **else**
9: Set $q = \frac{R_{i,l}^{\mathrm{c}}\left(p_{i,l}^{\mathrm{c},0}\right)}{p_{i,l}^{\mathrm{c},0} + p_{\mathrm{cir}}}$ and let $t_0 = t_0 + 1$
10: **end if**
11: **until** Convergence = **true** or $t_0 = T_0$

2) LAGRANGE DUAL METHOD-BASED POWER ALLOCATION ALGORITHM

In Algorithm 1, given energy efficiency q, we need to solve the local power allocation subproblem and obtain the locally optimal power allocation strategy. In this subsection, we propose a Lagrange dual method-based power allocation algorithm to solve power allocation subproblem.

Given energy efficiency q, the power allocation subproblem of MTCD$_i$ can be expressed as

$$\begin{aligned} &\max_{p_{i,l}^{\mathrm{c}}} \; R_{i,l}^{\mathrm{c}} - q\left(p_{i,l}^{\mathrm{c}} + p_{\mathrm{cir}}\right) \\ &\text{s.t. C1}: p_{i,l}^{\mathrm{c}} \leq p_i^{\max} \\ &\quad\;\; \text{C2}: R_{i,l}^{\mathrm{c}} \geq R_i^{\min}. \end{aligned} \tag{24}$$

The optimization problem formulated in (24) is a constrained convex optimization problem which can be solved by applying Lagrange dual method. The Lagrange function can be formulated as [26]

$$\begin{aligned} &L\left(\varphi, \mu, p_{i,l}^{\mathrm{c}}\right) \\ &= R_{i,l}^{\mathrm{c}} - q\left(p_{i,l}^{\mathrm{c}} + p_{\mathrm{cir}}\right) - \varphi\left(p_{i,l}^{\mathrm{c}} - p_i^{\max}\right) - \mu\left(R_i^{\min} - R_{i,l}^{\mathrm{c}}\right) \\ &= B\log_2\left(1 + \frac{p_{i,l}^{\mathrm{c}} h_{i,l}^{\mathrm{c}}}{\sigma^2}\right) - q\left(p_{i,l}^{\mathrm{c}} + p_{\mathrm{cir}}\right) - \varphi\left(p_{i,l}^{\mathrm{c}} - p_i^{\max}\right) \\ &\quad -\mu\left(R_i^{\min} - B\log_2\left(1 + \frac{p_{i,l}^{\mathrm{c}} h_{i,l}^{\mathrm{c}}}{\sigma^2}\right)\right) \end{aligned} \tag{25}$$

where φ, μ are Lagrange multipliers.

The optimization problem in (24) can then be transformed into Lagrange dual problem:

$$\begin{aligned} &\min_{\varphi,\mu} \max_{p_{i,l}^{\mathrm{c}}} L\left(\varphi, \mu, p_{i,l}^{\mathrm{c}}\right) \\ &\text{s.t. } \varphi \geq 0, \;\; \mu \geq 0. \end{aligned} \tag{26}$$

The optimization problem formulated in (26) consists of two subproblems, i.e., internal maximum subproblem and external minimum subproblem, which can be solved iteratively. Given a set of 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.

By calculating the derivative of the Lagrange function with respect to $p_{i,l}^{\mathrm{c}}$ and setting the derivative to zero, the locally optimal power allocation strategy can be obtained. Let $p_{i,l}^{\mathrm{c},0}$ denote the locally optimal power allocation strategy of MTCD$_i$ when forwarding data packets to MTCD$_j$, we obtain

$$\frac{\partial L\left(\varphi, \mu, p_{i,l}^{\mathrm{c}}\right)}{\partial p_{i,l}^{\mathrm{c}}} = \frac{(1+\mu)\, B h_{i,l}^{\mathrm{c}}}{\ln 2\left(\sigma^2 + p_{i,l}^{\mathrm{c}} h_{i,l}^{\mathrm{c}}\right)} - q - \varphi = 0. \tag{27}$$

Solving the above equation, we obtain

$$p_{i,l}^{\mathrm{c},0} = \left[\frac{(1+\mu)\, B}{(q+\varphi)\ln 2} - \frac{\sigma^2}{h_{i,l}^{\mathrm{c}}}\right]^+ \tag{28}$$

where $[x]^+ = \max\{x, 0\}$.

To solve the external minimum subproblem in terms of the Lagrange multipliers, we apply the gradient descent algorithm. The Lagrange multipliers can be calculated as [26], [27]

$$\varphi\left(t_1 + 1\right) = \left[\varphi\left(t_1\right) - \omega_1\left(p_i^{\max} - p_{i,l}^{\mathrm{c},0}\right)\right]^+, \tag{29}$$

$$\mu\left(t_1 + 1\right) = \left[\mu\left(t_1\right) - \omega_2\left(R_{i,l}^{\mathrm{c},0} - R_i^{\min}\right)\right]^+ \tag{30}$$

where t_1 denotes the iteration index, ω_1 and ω_2 are step-size, $R_{i,l}^{\mathrm{c},0} = B\log_2\left(1 + \frac{p_{i,l}^{\mathrm{c},0} h_{i,l}^{\mathrm{c}}}{\sigma^2}\right)$. The proposed Lagrange dual method-based power allocation algorithm is shown in Algorithm 2.

Algorithm 2 Lagrange Dual Method-Based Power Allocation Algorithm

1: Set the maximum number of iterations T_1, and the maximum tolerance ε_1
2: Initialize Lagrange multipliers $\varphi(t_1)$, $\mu(t_1)$ for $t_1 = 0$
3: **repeat**
4: Compute power allocation strategy $p^{c}_{i,l} = \left[\frac{(1+\mu)B}{(q+\varphi)\ln 2} - \frac{\sigma^2}{h^{c}_{i,l}}\right]^+$
5: Update the Lagrange multipliers: $\varphi(t_1+1) = \left[\varphi(t_1) - \omega_1\left(p^{\max}_i - p^{c}_{i,l}\right)\right]^+$ $\mu(t_1+1) = \left[\mu(t_1) - \omega_2\left(R^{c}_{i,l} - R^{\min}_i\right)\right]^+$
6: **if** $|\varphi(t_1+1) - \varphi(t_1)| + |\mu(t_1+1) - \mu(t_1)| \leq \varepsilon_1$ **then**
7: The algorithm terminates
8: Convergence = **true**
9: **return** $p^{c,0}_{i,l} = p^{c}_{i,l}$
10: **else**
11: $t_1 = t_1 + 1$
12: **end if**
13: **until** Convergence = **true** or $t_1 = T_1$

The proposed iterative method-based energy efficiency maximization algorithm and the Lagrange dual method-based power allocation algorithm can be applied in a straightforward manner to solve the power allocation strategy of the MTCDs in direct transmission mode. Let $p^{d,*}_i$ denote the optimal power allocation strategy of MTCD_i in direct transmission mode, $\eta^{d,*}_i$ denote the maximum energy efficiency of MTCD_i corresponding to $p^{d,*}_i$.

B. CLUSTERING SUBPROBLEM

Based on the optimal power allocation strategy obtained from previous subsection, the clustering subproblem can be formulated as follows:

$$\max_{\alpha_{l,k},\delta^{d}_i,\delta^{c}_{i,k}} \eta \quad \text{s.t. } C1 - C7,\ C10. \tag{31}$$

In this subsection, we propose a modified K-means algorithm to obtain the clustering strategy.

1) 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 the maximum energy efficiency can be achieved in direct transmission mode compared to CH forwarding mode. Hence, we may assign direct transmission mode to the MTCDs simply by comparing the energy efficiency of the MTCDs obtained in different transmission modes.

Table 1 shows the optimal energy efficiency of the MTCDs in different transmission modes. In the table, each row represents the energy efficiency of one MTCD, and the columns correspond to different transmission modes of the MTCDs. Without loss of generality, in CH forwarding mode, we assume that any MTCD can be selected as the CH of other MTCDs. For simplicity, we define the energy efficiency of MTCD_i as 0 when the MTCD selects itself as CH for data forwarding, i.e., $\eta^{c,*}_{i,i} = 0$, $1 \leq i \leq M$.

TABLE 1. Energy efficiency of the links between MTCDs and BS, and that between MTCDs.

	Direct transmission mode	CH forwarding mode			
		MTCD_1	MTCD_2	$\cdots$	MTCD_M
MTCD_1	$\eta^{d,*}_1$	0	$\eta^{c,*}_{1,2}$	$\cdots$	$\eta^{c,*}_{1,M}$
MTCD_2	$\eta^{d,*}_2$	$\eta^{c,*}_{2,1}$	0	$\cdots$	$\eta^{c,*}_{2,M}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
MTCD_M	$\eta^{d,*}_M$	$\eta^{c,*}_{M,1}$	$\eta^{c,*}_{M,2}$	$\cdots$	0

Examining Table 1, we can see that in the case that MTCD_i achieves the maximum energy efficiency when applying direct transmission mode compared to CH forwarding mode, i.e., $\eta^{d,*}_i \geq \eta^{c,*}_{i,l}$, $1 \leq l \leq M$, $l \neq i$, we should assign direct transmission mode to MTCD_i, i.e., $\delta^{d,*}_i = 1$, $\delta^{c,*}_{i,k} = 0$, $1 \leq k \leq K_1$. For convenience, we denote Φ as the set of all the MTCDs, i.e., $\Phi = \{\text{MTCD}_i, 1 \leq i \leq M\}$ and denote Φ_d as the set of MTCDs which are assigned direct transmission mode, i.e., $\Phi_d = \left\{\text{MTCD}_i | \delta^{d,*}_i = 1, 1 \leq i \leq M\right\}$. It should be mentioned that $\text{MTCD}_i \in \Phi_d$ cannot be the CM of any clusters, however, it may act as the CH of other CMs.

2) 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 CHs should forward data packets for their associated CMs within the clusters, the characteristic of the links 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 the data packets significantly. To avoid selecting the MTCDs with highly limited transmission performance in direct transmission mode, we set an energy efficiency threshold on the direct transmission link of the MTCDs and only select the MTCDs with the energy efficiency of the direct transmission link being greater than the threshold as the candidate CHs.

Let $\eta_{\min}$ denote the energy efficiency threshold of the direct transmission link of the MTCDs, we select MTCD_i as a candidate CH provided that $\eta^{d,*}_i \geq \eta_{\min}$, $1 \leq i \leq M$. Denoting Φ_0 as the set of the candidate CHs, we obtain

$$\Phi_0 = \{\text{MTCD}_i | \eta^{d,*}_i \geq \eta_{\min},\ 1 \leq i \leq M\}. \tag{32}$$

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.

3) MODIFIED K-MEANS ALGORITHM-BASED CLUSTERING SCHEME

The K-means algorithm is commonly used for solving clustering problems [28].

According to the original K-means algorithm, the initial CHs are chosen randomly and both user association and CH update are conducted based on the Euclidean distance, which may not result in the desired performance of energy efficiency. Furthermore, the K-means algorithm mainly addresses the problem of CH selection and user association, fails to consider the direct transmission links between the CHs and the BS, and the two-hop transmission links between the CMs and the BS, hence, the original K-means algorithm cannot be applied directly to solve the formulated clustering subproblem. 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, for individual MTCDs, we examine the energy efficiency sum of both the direct link and the association links with other MTCDs, and select the CHs which offer the highest energy efficiency sum. Given the initial CHs, CH association can be conducted. More specifically, for each potential CM, the energy efficiency of the association links between the CM and the CHs is examined and the CH offering the maximum energy efficiency is chosen as the associated CH of the CM. Within each cluster, the CH selection and association processes are repeated until the algorithm achieves convergence.

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

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

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

$$\psi_i = \eta_i^{\mathrm{d},*} + \sum_{l=1, l\neq i}^{M} \eta_{i,l}^{\mathrm{c},*}, \; 1 \leq l \neq i \leq M. \tag{33}$$

Select K_1 MTCDs which offer the highest energy efficiency sum as the CHs. Specifically, ordering $\mathrm{MTCD}_{i_k} \in \Phi$ according to ψ_{i_k}, i.e.,

$$\psi_{i_1} \geq \psi_{i_2} \geq \cdots \geq \psi_{i_k} \geq \cdots \geq \psi_{i_M}, \forall\, \mathrm{MTCD}_{i_k} \in \Phi.$$

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

$$\Phi_{\mathrm{ch}} = \{\mathrm{MTCD}_{i_k} \,\big|\, \mathrm{MTCD}_{i_k} \in \Phi\,,\; 1 \leq k \leq K_1\}.$$

Let Φ_{cm} denote the set of CMs, we obtain

$$\Phi_{\mathrm{cm}} = \{\mathrm{MTCD}_i | \mathrm{MTCD}_i \in \Phi,\; \mathrm{MTCD}_i \notin \{\Phi_{\mathrm{ch}} \cup \Phi_{\mathrm{d}}\}\}.$$

c) *Initial CH association*: For $\mathrm{MTCD}_i \in \Phi_{\mathrm{cm}}$, compute the energy efficiency of the links between MTCD_i and $\mathrm{MTCD}_{i_k} \in \Phi_{\mathrm{ch}}$, and choose the CH which offers the highest energy efficiency as the associated CH. Let $\mathrm{MTCD}_{i_{k'}}$ denote the associated CH of MTCD_i, and assume that $\mathrm{MTCD}_{i_{k'}}$ is selected as the $\mathrm{CH}_{k'}$, we obtain $\alpha^*_{i_{k'},k'} = 1$, $\delta^{\mathrm{c},*}_{i,k'} = 1$, and

$$\mathrm{CH}_{k'} = \underset{\mathrm{MTCD}_{i_{k'}} \in \Phi_{\mathrm{ch}}}{\arg\max} \left\{\eta^{\mathrm{c},*}_{i,i_{k'}}\right\},\; \mathrm{MTCD}_i \in \Phi_{\mathrm{cm}}.$$

d) *System energy efficiency calculation*: The set of the MTCDs in direct transmission mode can be updated by removing those MTCDs which are selected as CHs. Let Φ'_{d} denote the updated set of the MTCDs in direct transmission mode, we may express Φ'_{d} as

$$\Phi'_{\mathrm{d}} = \{\mathrm{MTCD}_i | \mathrm{MTCD}_i \in \Phi_{\mathrm{d}},\; \mathrm{MTCD}_i \notin \Phi_{\mathrm{ch}}\}.$$

For $\mathrm{MTCD}_i \in \Phi'_{\mathrm{d}}$, 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 energy efficiency denoted by $\eta_{t'}$, i.e.,

$$\eta_{t'} = \sum_{\mathrm{MTCD}_i \in \Phi'_d} \eta_i^{\mathrm{d},*} + \sum_{\mathrm{MTCD}_i \in \Phi_{\mathrm{ch}}} \eta_i^{\mathrm{d},*} + \sum_{\mathrm{MTCD}_i \in \Phi_{\mathrm{cm}}} \sum_{\mathrm{MTCD}_{i_{k'}} \in \Phi_{\mathrm{ch}}} \eta^{\mathrm{c},*}_{i,i_{k'}} \tag{34}$$

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

$$\Phi_{k'} = \{\mathrm{MTCD}_i | \mathrm{MTCD}_i \in \Phi_{\mathrm{cm}},\; \delta^{\mathrm{c},*}_{i,i_{k'}} = 1\}.$$

For $\forall\, \mathrm{MTCD}_i \in \Phi_{k'}$, compute the energy efficiency sum of the direct link between MTCD_i and the BS, the link between MTCD_i and $\mathrm{MTCD}_{i_{k'}}$, and the links between MTCD_i and $\mathrm{MTCD}_{i'} \in \Phi_{k'}$, $i \neq i'$. Let ζ_i denote the energy efficiency of $\mathrm{MTCD}_i \in \Phi_{k'}$, we express ζ_i as

$$\zeta_i = \eta_i^{\mathrm{d},*} + \eta^{\mathrm{c},*}_{i,i_{k'}} + \sum_{\mathrm{MTCD}_{i'} \in \Phi_{k'}, i' \neq i} \eta^{\mathrm{c},*}_{i,i'}.$$

Choose $\mathrm{MTCD}_i \in \Phi_{k'}$ which offers the highest energy efficiency as the updated CH, i.e.,

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

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

f) *CH reassociation*: For $\mathrm{MTCD}_i \in \Phi_{\mathrm{cm}}$, compute the energy efficiency of the link between MTCD_i and $\mathrm{MTCD}_{i_k} \in \Phi_{\mathrm{ch}}$, and choose the CH which offers the highest energy efficiency as the associated CH.

g) *System energy efficiency update*: Re-calculate the system energy efficiency based on (34), denoted by $\eta_{t'+1}$.

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

VI. COMPLEXITY ANALYSIS

In this paper, we address the joint resource allocation and clustering problem in M2M communication systems. As the original optimization problem is a nonlinear fractional programming problem, which cannot be solved conveniently, we transform the optimization problem into two subproblems, i.e., power allocation subproblem and clustering subproblem. Applying iterative method-based energy efficiency maximization algorithm, we first obtain the optimal power allocation strategy based on which, we then propose a modified K-means algorithm to obtain the clustering strategy. In this section, we analyze the computation complexity of the two subproblems, respectively.

A. POWER ALLOCATION SUBPROBLEM

As power allocation is conducted for individual MTCDs when interacting with the BS directly or in CH forwarding mode. In the case that one MTCD accesses the BS directly, the upper bound of the complexity is $O(MT_0T_1)$. Since in general, the iteration number required for the Lagrange multipliers and the transmit power of the MTCDs to achieve convergence is relatively small, the complexity is relatively low. In CH forwarding mode, as each MTCD may select other MTCDs for data forwarding, the required complexity is $O(M(M-1)T_0T_1)$.

B. CLUSTERING SUBPROBLEM

Based on the optimal power allocation obtained from previous power allocation subproblem, we formulate the clustering subproblem and propose a modified K-means algorithm to obtain the clustering strategy. The complexity of the algorithm proposed in this paper is similar to that of the K-means algorithm. In each iteration, the complexity can be calculated as $O(M+|\Phi_{\text{cm}}|K_1)$. Let t' denote the number of iterations, the computational complexity can be rewritten as $O\left(t'(M+|\Phi_{\text{cm}}|K_1)\right)$.

VII. SIMULATION RESULTS

In this section, simulation results are presented to show the performance of our proposed scheme. For comparison, we also examine the performance of the previously proposed algorithm in [22] via simulation. In the simulation, we consider an M2M communication system consisting of one BS and M MTCDs. The size of the simulation region is set as 500m×500m. The BS is located at the center of the simulation area and the MTCDs are randomly located in the area. Unless otherwise mentioned, the simulation parameters are listed in Table 2.

In Figure 3, we examine system energy efficiency versus the number of iterations obtained from the proposed algorithm for different circuit power consumption. From the figure, we can see that the energy efficiency converges within a small number of iterations. Comparing the results obtained from different circuit power, we can see that the energy efficiency decreases with the increase of circuit power.

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	180KHz
Maximum transmit power	0.15W
Noise power	-104dBm
Circuit power consumption	0.3W

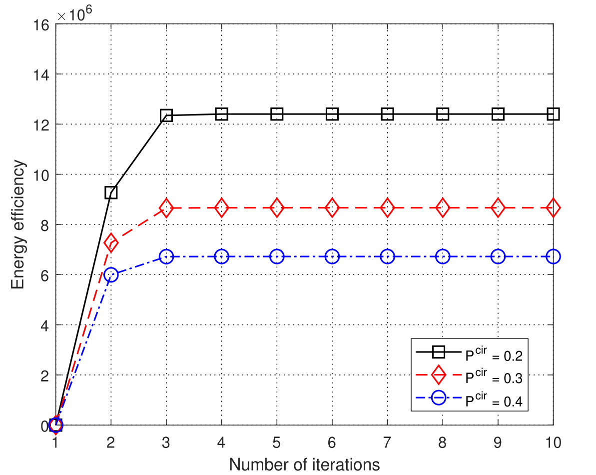

FIGURE 3. Energy efficiency versus the number of iterations (different circuit power).

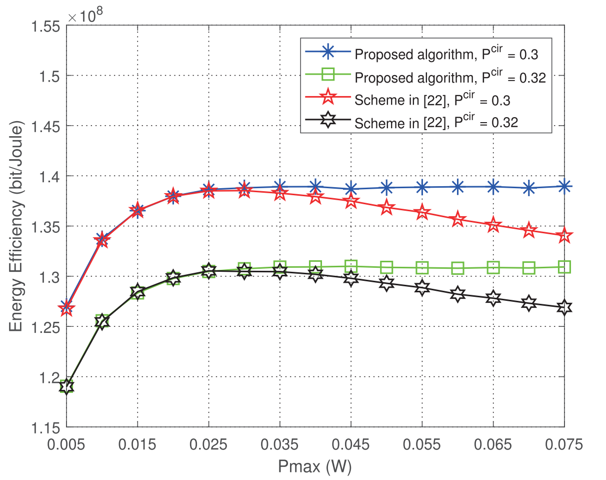

FIGURE 4. Energy efficiency versus maximum transmit power (different circuit power).

Figure 4 shows system energy efficiency versus the maximum transmit power of the MTCDs for different circuit power consumption. We can see from the figure that for small $p_i^{\max}$, the energy efficiency increases with the increase of $p_i^{\max}$ for both schemes, indicating that a higher power threshold is desired for achieving the maximum energy efficiency. However, as the maximum transmit power reaches to a certain value, the energy efficiency obtained from our proposed scheme converges to a constant while that obtained

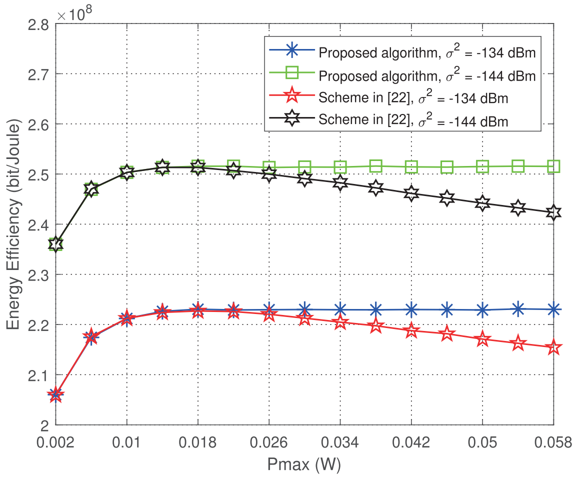

FIGURE 5. Energy efficiency versus maximum transmit power (different noise power).

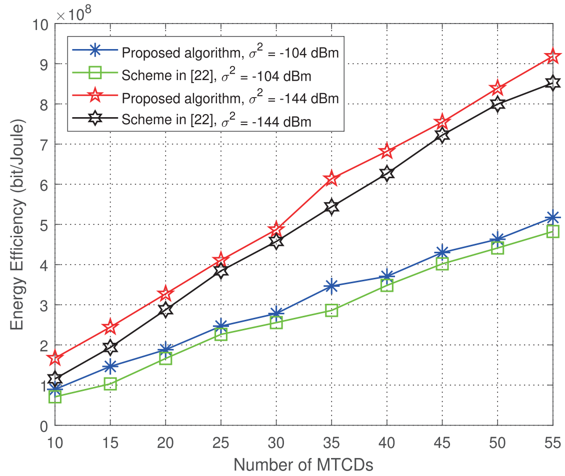

FIGURE 7. Energy efficiency versus the number of MTCDs (different noise power).

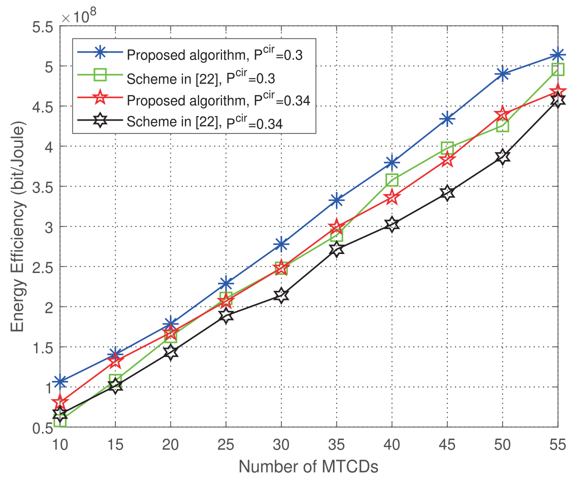

FIGURE 6. Energy efficiency versus the number of MTCDs (different circuit power).

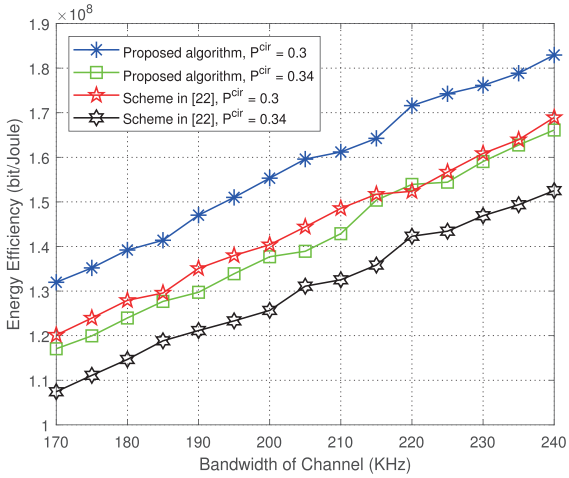

FIGURE 8. Energy efficiency versus the bandwidth of MTCDs (different circuit power).

from the scheme proposed in [22] decreases as the power increases. This is because the scheme proposed in [22] aims to achieve the maximum transmission rate, thus may require higher power consumption, resulting in undesired energy efficiency. It can also be observed from the figure that the energy efficiency obtained from both algorithms decreases with the increase of circuit power consumption.

In Figure 5, we examine system energy efficiency versus the maximum transmit power of the MTCDs for different noise power. From the figure, we can see that the energy efficiency decreases with the increase of noise power. This is because larger noise power results in deteriorated transmission performance and lower energy efficiency in turn. Comparing the results obtained from two algorithms, we can see that our proposed scheme offers better performance than that proposed in [22].

In Figure 6, we plot system energy efficiency versus the number of MTCDs for different circuit power consumption. We can observe from the figure that as the number of MTCDs increases, the energy efficiency obtained from both algorithms increases accordingly. It can be seen from the figure that the energy efficiency obtained from both algorithms decreases with the increase of circuit power consumption. In addition, we can see that our proposed scheme is more energy-efficient than the algorithm proposed in [22].

Figure 7 shows system energy efficiency versus the number of MTCDs for different noise power. From the figure, we can see that the energy efficiency decreases with the increase of noise power and increases as the number of MTCDs increases. This is because larger noise power results in worse transmission performance and lower energy efficiency. In addition, we can see that our proposed algorithm outperforms the algorithm proposed in [22].

In Figure 8, we plot system energy efficiency versus the bandwidth of MTCDs for different circuit power consumption. Examining the system energy efficiency resulted

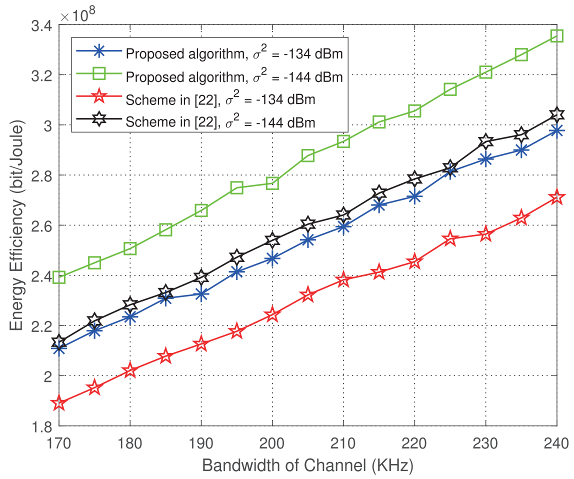

FIGURE 9. Energy efficiency versus the bandwidth of MTCDs (different noise power).

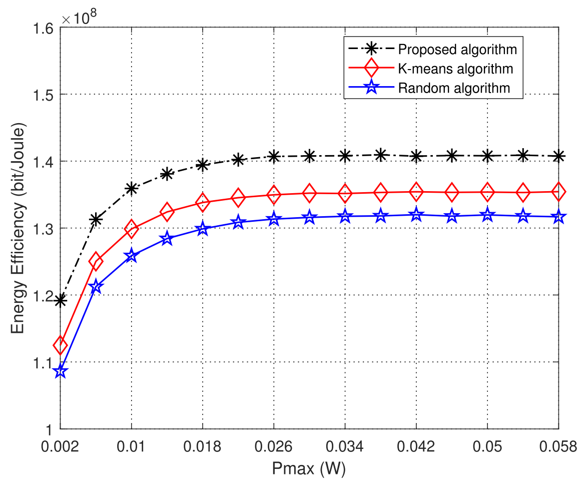

FIGURE 10. Energy efficiency versus maximum transmit power (different algorithms).

from the two schemes, we can observe that system energy efficiency increases with the increase of the bandwidth of MTCDs. This is because larger bandwidth results in higher transmission rate, and higher energy efficiency in turn. In addition, we can see that our proposed scheme is more energy-efficient than the algorithm proposed in [22].

Figure 9 shows system energy efficiency versus the bandwidth of MTCDs for different noise power. From the figure, we can see that the energy efficiency increases as the bandwidth of MTCDs increases and decreases with the increase of noise power. Comparing the results obtained from the two algorithms, we can see that our proposed algorithm outperforms the algorithm proposed in [22].

In Figure 10, we examine system energy efficiency versus the maximum transmit power of the MTCDs obtained from the proposed algorithm and two other algorithms, i.e., K-means algorithm and random algorithm. For both K-means algorithm and random algorithm, the optimal power allocation strategy is obtained through applying our proposed iterative method-based energy efficiency maximization algorithm; we then apply different clustering strategies. For K-means algorithm, the CHs are initially randomly selected, and then updated based on the Euclidean distance between the CMs and the CH. While for random algorithm, we randomly select CHs and conduct user association. It can be seen from the figure that the proposed algorithm outperforms the two other algorithms.

VIII. CONCLUSION AND FUTURE WORK

A. CONCLUSION

In this paper, we consider the resource allocation and clustering problem in an M2M communication system. To achieve the efficient resource management of the MTCDs, we first propose a joint resource management architecture, and then design a joint resource allocation and clustering algorithm which achieves the maximum system energy efficiency. Numerical results show that our proposed algorithm outperforms previously proposed algorithm.

B. FUTURE WORK

While the analysis presented in this paper is based on some simplified assumptions, the basic system model and the methodology developed can be extended to more general system models and assumptions, as briefly discussed below.

We may extend current system model to the one consisting of multiple BSs. In this case, as the MTCDs and the CHs may select different BSs for accessing, network selection schemes or user association scheme should be jointly designed with power allocation and clustering scheme. We may also extend our current assumption on spectrum utilization to a more general case. For instance, spectrum sharing can be allowed among various MTCDs. In this case, spectrum allocation or subchannel allocation should be jointly considered with power allocation and clustering in order to utilize system spectrum more efficiently. However, it should be mentioned that transmission interference may occur due to spectrum sharing, and our proposed power allocation strategy cannot be applied in a straightforward manner. To further enhance the transmission performance of the M2M communication systems, we may also consider applying NOMA schemes, or jointly applying orthogonal frequency division multiple access (OFDMA) and NOMA for offering channel access to the MTCDs.

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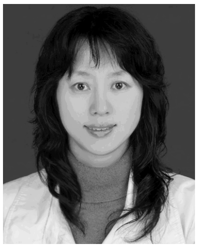

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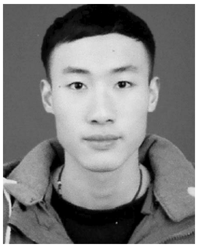

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