Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 7815916, 11 pages
https://doi.org/10.1155/2022/7815916

Research Article

Algorithm for Energy Resource Allocation and Sensor-Based Clustering in M2M Communication Systems

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Received 13 January 2022; Revised 28 March 2022; Accepted 5 April 2022; Published 22 April 2022

Academic Editor: Giovanni Stea

Recent years have seen a surge in curiosity in machine-to-machine (M2M) collaborations between academics and industry. Machine-to-machine communication devices (MTCDs) are able to communicate automatically and with minimum human intervention in an M2M communications infrastructure. While MTCDs are anticipated to deliver a range of services, resource allocation and clustering approaches in M2M transceivers face issues and limits due to the diverse quality of service (QoS) needs in various network conditions. A major issue in M2M communication systems is how to distribute and cluster resources. This article presents a clustering technique and collaborative resource allocation for MTCD resource management. The clustering and integrated resource allocation challenge is characteristic as a maximization of energy efficiency problem. As a consequence of the original optimization model's inability to tackle nonlinear fractional utilizations, we separate the issue into two subproblems: power redistribution and cluster. We begin by obtaining the optimal power distribution plan through an iterative energy efficiency maximization algorithm and then offer a modified K-means technique for clustering. The effectiveness of the proposed approach is shown by the numerical solution.

1. Introduction

When it comes to adopting the Internet of Things (IoT) in second-generation networking, machine-to-machine transmission (M2M) is one of the most effective choices available. Machine-to-machine (M2M) transceivers (MTCDs) are devices that allow machines to communicate with one another automatically and with little human intervention. Researchers should come up with effective interference control strategies to meet the quality of service (QoS) requirements of MTCDs and to improve the performance of M2M communication networks so they can meet their needs [1].

Clustering tactics might be used to increase the throughput of MTCDs' network connections. Supervised approaches separate MTCDs into clusters, which is a procedure in which each cluster has a cluster head (CH) and a certain number of cluster members, as shown in Figure 1 (CMs). Through the application of clustering algorithms, data transmission efficiency may be improved, and the amount of energy used by MTCDs to transmit data packets can be greatly reduced [2].

M2M assignment and clustering have been examined earlier, but it is clear that they are intertwined and that their solutions may impact both user QoS and network management. This research looks at M2M resource allocation and clustering. We suggest combining resource allocation and clustering to handle MTCD resources effectively. The problem is called an energy efficiency utility maximization problem. We separate the optimization problem into two subproblems, namely, power distribution and clustering, but since the basic optimization model is a nonlinear partial differential equation, continuing to fulfil cannot be simply addressed. We begin by obtaining the optimal power distribution plan through an iterative energy efficiency utility maximization algorithm and then offer a modified K-means technique for clustering. The following is a list of notable contributions made by the paper as shown in Figure 2 [3, 4].

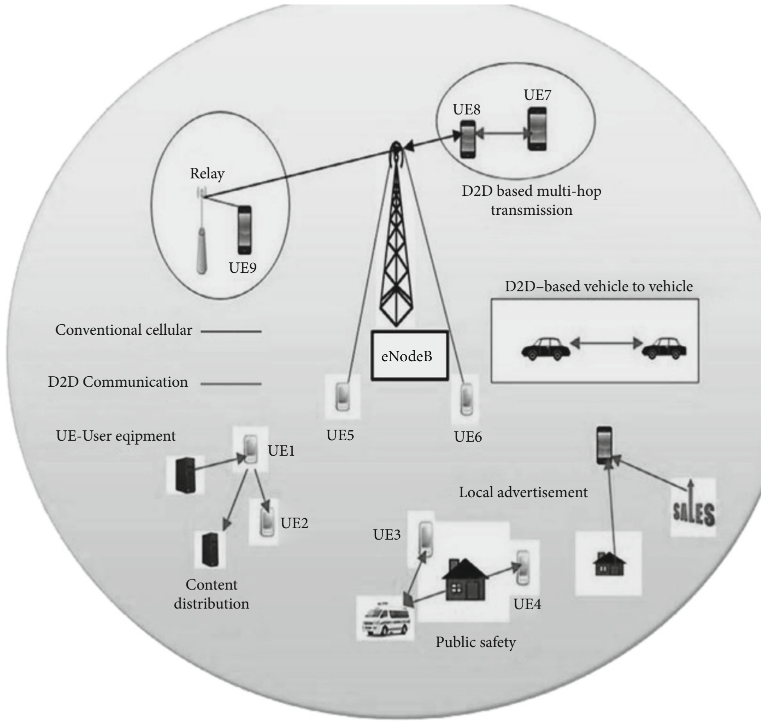

Figure 1: Model of the communication system.

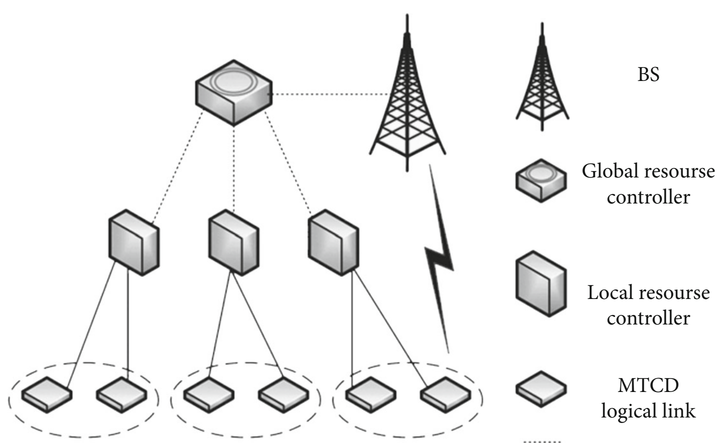

Figure 2: Proposed architecture for cooperative resource management.

Although issues of dispersion and clustering have been explored before for M2M interactions, it has been shown that the two are inextricably related and have an impact on the user's quality of service and signal strength. Because of this, the issue of the allocation of resources and clustering for MTCDs in M2M communication networks is being investigated in this study. A single strategic planning architecture is given, from which we build a solution for the efficient administration of MTCDs and other things [4, 5].

The energy consumption of MTCDs has been overlooked in prior studies on the problem of joint resource allocation and clustering for M2M transceivers. To make the most of the renewable power that is available, this analysis looks at how much energy each MTCD in the system uses [6].

We partition the optimization system into multiple subproblems, one for power allocation and another for clustering, since the given combined resource distribution and segmentation problem is a fractional derivative that cannot be simply addressed. We begin by obtaining the optimal power distribution plan through an iterative energy efficiency utility maximization algorithm and then offer a customized K-means technique for clustering.

2. Related Works

This section summarizes the distribution of resources and clustering techniques developed for M2M communications.

2.1. Resource Allocation Schemes for M2M Communication. Resource allocation for M2M communications has been fixed recently. The endeavor is to optimize system performance while efficiently utilizing MTCD resources. Vilgelm et al. offer a preamble allocation technique for a range of random access demands in order to increase system performance and QoS differentiation. Pei et al. propose a method for addressing intracell pilot conflicts in crowded MIMO systems. This protocol allows UEs to negotiate for idle pilots, increasing the transmission rate and reducing access attempts [6].

The authors devised an MTCD emission resource allocation method based on M2M transceiver energy usage. Naeem et al. investigate nonlinear M2M-enabled cellular networks with nonlinear energy harvesting. The authors suggest a way to control the power and time allocation of MTCDs that combines NOMA and TDMA techniques to save energy on the whole network [7].

To compare the mean opinion rating for different MTCDs to enhance long-term QoE, it divides the long-term optimization problem into two parts: admission rate control and resource allocation. Chang et al. propose a technique for combining data packets from MTCDs with varying QoS requirements [8]. A distributed MDA selection process is demonstrated to dynamically allocate channels to MTCDs according to QoS requirements [9].

2.2. Clustering Schemes for M2M Communications. A method known as clustering may be utilized to increase the transmission performance of M2M communications. This presentation demonstrates how collaborative connections may be made in M2M networks via the use of relays and cluster analysis protocols, resulting in a better network performance.

The study calculates the cluster size and presents an energy-efficient CH selection technique for lowering MTCD energy usage and extending network longevity. The protocols used for intra- and intercluster connectivity are analyzed, and a resource and load-adaptive channel access technique is presented, allowing for a tunable trade-off between energy efficiency, latency, and spectrum efficiency [10, 11].

When it comes to M2M communication networks, clustering algorithms may also be used to produce resource routing and allocation. Researchers who work on M2M data transmissions are looking into how to make sure data can move between terminal nodes and sink nodes through CHs in the network [12, 13].

2.3. M2M Resource Allocation and Clustering Schemes. A recent study explores resource allocation and M2M communication clustering.

A spatial group-based random access strategy is proposed by Yang et al. [14]. After grouping MTCDs, nonorthogonal channel resources are assigned to each group. It offers 2 single-hop relaying strategies based on SIR and LIR for MTCDs in cellular networks. Each MTCD cluster is assigned a local access point depending on its location and service needs. It is easier to avoid major collisions between MTCDs when they try to get to the base station (BS) if they are grouped together by location in [15, 16].

The PRACH resources are dynamically assigned among the MTCDs in each cluster based on the least delay requirement. Vu et al. It is ringed depending on its distance from the initial occurrence. These rings allocate proactive resources for uplink communications.

For M2M communications, Riker et al. offer an aggregation strategy to extend the network lifespan. The first layer decreases data redundancy, while the second reduces message overhead. Li et al. investigate M2M LTE-A power allocation and clustering. MTCDs are clustered by a transmission protocol and then by QoS features and needs. Thus, resource allocation is based on sum throughput maximization [17].

Previously, research on M2M communication networks focused on improving random access success probability, lowering access latency, prolonging network lifespan, or increasing total quantity. They ignored the MTCDs' energy efficiency, which is crucial for balancing data transmission performance. Additionally, prior clustering algorithms did not analyze transmission reliability and adaptive control for direct extension and CH forwarding. This article provides a combined optimum solution for M2M communication systems' resource distribution and a clustered understanding of the system's energy conservation optimization [18].

2.4. Interest and Energy-Aware Machine Clustering. This section explains how to cluster M2M devices using a Chinese restaurant process- (CRP-) based admission control policy. Assume we want to group a set of entities, in this case, M2M devices. In the Chinese restaurant metaphor, each group represents a table, and each entity represents a customer. The Chinese restaurant has an infinite number of tables labelled 1, 2,…. In this case, the tables are the clusters. Customers arrive and sit at a table. Contrary to a popular belief, a new customer will always sit at an empty table. (a) The first customer always selects the first table, and (b) the m^{th} customer selects an occupied table with probability $c/(m-1+a)$ (where c is the number of customers already seated at that table) and the first unoccupied table with probability $a/(m-1+a)$, where a is the CRP's "concentration parameter," indicating each customer's willingness M1A to remain alone and form a new cluster. The analysis below uses CRP to classify M2M devices. Our goal is to make the clustering results more practical by including M2M-related factors like device desire to communicate, proximity, and energy availability [19].

The CRP method can group M2M devices into clusters based on interest similarity and physical proximity. The proposed interest and physical-aware CRP (IP-CRP) method will use interest-based and distance-based graphs to intelligently form clusters. Furthermore, the M2M devices' energy availability will be used to select the cluster head ch_c of each cluster $c, c \in C$ [20].

2.5. Modelling and Architecture and Collaborative Resource Management (CRM). One BS and numerous MTCDs are examined in this M2M communication system. The BS lies in the center of an area, surrounded by MTCDs.

Additionally, it is assumed that perhaps the MTCDs are supposed to receive their data from BS. Each MTCD is denoted by the abbreviation MTCDi, where M is the actual population of MTCDs [21].

To assure data transfer, we believe MTCDs should be allowed to directly contact the BS. MTCDs may use CH forwarding to deliver data to the BS. The MTCDs are grouped, with a CH and CMs in each cluster. We assume equibandwidth too. Assume B is the bandwidth. There is adequate bandwidth to prevent transmission congestion [21, 22].

Consistent energy supply is critical to extending the battery life of M2M devices as well as the overall IoT network. An alternative to battery-powered operation or energy harvesting from natural sources such as the sun or wind is the wireless-powered communication (WPC). It allows M2M devices to harvest and store energy from radio frequency signals via dedicated neighbor devices, e.g., cluster heads. It is then possible to use the saved energy to transmit information to the cluster head or evolve NB (eNB) during the WIT phase. In the literature, several studies have addressed energy efficiency through wireless communication and intelligent resource management. With limited initial battery energy and minimal system throughput limits, this proposes a hybrid time allocation and power control methodology for optimal network energy efficiency. By defining the optimal energy and time resource allocation for various mobile devices, the maximization problem of uplink sum rate network performance is studied. With infinite or finite capacity energy storage, this work has been extended. On the other hand, to maximize system sum rate, this investigated the problem of combined subcarrier scheduling and power allocation using OFDM and WPC approaches. There has also been extensive research on energy-efficient distributed resource management, with either single or multiple control parameters (e.g., power and rate) [23, 24].

Despite the fact that the above approaches support (a) energy-efficient communication among M2M devices and (b) resource management efforts using the WPC technique that show significant results in improving overall system energy efficiency and M2M device battery life, their main drawbacks are as follows: their joint effect in prolonging M2M device battery life has not been studied and exploited yet [25, 26].

The IoT envisions a society in which common things are connected to the Internet, allowing them to provide contextual services collectively and autonomously. As a result, the Internet of Things is a digital overlay of information over the physical world. This work tries to deal with these difficult problems and fill the gap in the research literature that comes with them [26, 27].

2.6. The Proposed Joint Resource Management Architecture. A shared resource management paradigm for M2M networks is proposed. To manage the system's resources, the recommended design uses global and local resource controllers, as well as cooperative distribution of resources and clustering for MTCDs, which are the key responsibilities of LRC and GRC [28].

2.6.1. Resource Management. Each LRC controls either the BS or a single MTCD. The GRC may receive state information from linked BS and MTCDs. The LRCs get the GRC's resource allocation and clustering strategy for their BS and MTCDs.

2.6.2. GR Administration. Inputs are controlled by GRC. This data is sent to the GRC by the BS's LRC. This data includes communication range, network size, and maximum CMs per CH. It captures MTCD LRC channel parameters, max transmit power, and min transmit rate. So, the GRC can understand the MTCD allocation scheme and clustering.

2.6.3. Defining the Optimization Issue. The power consumption of MTCDs is critical since they are battery-powered sensors or small devices with RFID. The batteries in these MTCDs are often difficult or impossible to charge. The MTCD stops operating when one of its batteries runs out. Designing energy efficient data transmission systems is critical for low power consumption and a long MTCD lifespan since data transmission consumes a lot of energy. On-time, low-power MTCD transmission performance must be ensured. Focusing on the energy efficiency indicator allows for a trade-off between transmission performance and energy usage.

The power generation of all the MTCDs in different data communication standards is added together. With transmit channel estimation, data rate, and MTCD transmit power limits, this job becomes a problem for the whole system.

(1) (1) Objective Function. The system's energy efficiency is stated as follows:

$$\psi = \sum_{j=1}^{M} \psi_i, \tag{1}$$

where ψ_i represents the MTCDi's energy consumption.

The term for ψ_i is as follows:

$$\psi_i = L_i^{\mathrm{d}} \psi_i^{\mathrm{d}} + \sum_{l=1, l\neq i}^{M} \sum_{k=1}^{K_1} \alpha_{l,k} L_{i,k}^{\mathrm{c}} \psi_{i,l}^{\mathrm{c}}, \tag{2}$$

where $L_i^{\mathrm{d}} \in 0, 1$ is the MTCD_i transmitter and the receiver dynamic load balancing variable, i.e., $L_i^{\mathrm{d}} = 1$; in this case, MTCD_i sends data packets directly to the BS. Otherwise, $L_i^{\mathrm{d}} = 0$, ψ_i^{d} represents $\mathrm{MTCD}_{\underline{i}}$'s power consumption in a direct transmission mode.

The following is a definition of the phrase ψ_i^{d}:

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

With directly transmission mode, R_i^{d} and p_i^{d} represent the transmission rate and transmit power of MTCD_i, respectively, while p_{cir} signifies the circuit power consumption of MTCD_i.

We assume that p_{cir} is consistent for all MTCDs without sacrificing generality. R_i^{d} may be written as follows:

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

where h_i^{d} and σ^2 in this case (MTCD$_i$) transmits its data packets to the BS using the direct transmission methods (the MTCD$_i$ and the BS), respectively.

$$\psi_{i,l}^{\text{c}} = \frac{R_{i,l}^{\text{c}}}{p_{i,l}^{\text{c}} + p_{\text{cir}}}. \tag{5}$$

When transmitting data packets to MTCD$_i$, $R_{i,l}^{\text{c}}$ and $p_{i,l}^{\text{c}}$ signify the transmission rate and transmit power MTCD$_i$, respectively. $R_{i,l}^{\text{c}}$ is denoted by the following:

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

The channel gain of the connection between MTCD$_i$ and MTCD$_l$ is denoted by $h_{i,l}^{\text{c}}$. K_1 specifies the number of CH$_s$ in Equation (2), i.e.,

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

(2) (2) Constraints on Optimization. This section discusses restrictions on efficient utilization of resources and clustering design.

(1) Number of CHs that may be used as a maximum

The clustering approach should adhere to the maximum number of CH$_s$ limitation. If the term $N_{\max}$ is used to refer to the CH$_s$, we may specify the maximum number of CH$_s$ as follows:

$$K_1 \le N_{\max} -- > C1. \tag{8}$$

(2) Maximum number of clustered CMs

By assuming that a single CH may be connected with a maximum of one hundred fifty-one CMs (M1), the following constraint is obtained:

$$\sum_{i=1}^{M} L_{i,k}^{\text{c}} \le M_1, \quad 1 \le k \le K_1 -- > C2. \tag{9}$$

(3) Constraint on CH association

Assuming that each MTCD may associate with no more than one CH,

$$\sum_{k=1}^{K_1} L_{\text{i},k}^{\text{c}} \le 1, \quad 1 \le i \le M -- > C3. \tag{10}$$

(4) Constraint on CH selection

Due to the fact that each CH may be picked exclusively from its own MTCD, we receive the following:

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

Similarly, each MTCD may only be assigned to a single CH, i.e.,

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

(5) Constraint on mode selection

Each MTCD may choose among direct transmission and CH forwarding, i.e.,

$$L_i^{\text{d}} + \sum_{k=1}^{K_1} L_{i,k}^{\text{c}} \le 1, \quad 1 \le i \le M -- > C6. \tag{13}$$

Notably, CHs can only send data directly to the BS. CHs employ reliable communication to relay CM data packets. The derivative transmission mode is as follows:

$$L_l^{\text{d}} = 1, \text{if} \sum_{k=1}^{K_1} \alpha_{l,k} = 1, \quad 1 \le l \le M -- > C7. \tag{14}$$

(6) Transmit power capacity

Due to the low transmit power need, this is achievable.

$$p_i^{\text{d}} \le p_i^{\max}, \quad 1 \le i \le M -- > C8, \tag{15}$$

$$p_{i,l}^{\text{d}} \le p_i^{\max}, \quad 1 \le i \ne l \le M -- > C9, \tag{16}$$

where $p_i^{\max}$ signifies the MTCD$_i$'s maximum transmit power.

(7) Constraint on transmission rate

Various QoS needs are for MTCDs; each MTCD has a minimum transmission rate requirement.

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

where $R_i^{\min}$ and R_i indicate the lowest and maximum possible transmission rates of $\mathrm{MTCD}_i 1 \leq i \leq M$, respectively. R_i may be written as follows:

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

where $R_{i,l}$ signifies the two-hop transmission rate between MTCD_i and the BS through MTCD_i and may be represented as $R_{\{i,l\}} = \min\left\{R_{i,l}^{\mathrm{c}}, R_i^{\mathrm{d}}\right\}$.

The improved energy value enhancement combined allocation of resources and clustering issue is defined as follows.

$$\begin{aligned} &\max_{\alpha_{l,k}, L_i^{\mathrm{d}}, L_{i,k}^{\mathrm{c}}, p_i^{\mathrm{d}}, p_{i,l}^{\mathrm{c}}} \quad \psi \\ &\text{s.t.} \quad C1 - C10. \end{aligned} \tag{19}$$

(3) (3) Subproblem of Clustering. The clustering subproblem may be expressed as follows using the optimum power allocation approach derived in the preceding subsection:

$$\begin{aligned} &\max_{\alpha_{l,k}, L_i^{\mathrm{d}}, L_{i,k}^{\mathrm{c}}} \quad \eta \\ &\text{s.t.} \quad C1 - C7, C10. \end{aligned} \tag{20}$$

This article proposes a modified K-means method in this paragraph to acquire the clustering approach.

(1) Mode for direct transmission

It is simple to understand why an MTCD would select direct transmission over CH forwarding if the latter saves the most energy. Thus, by analyzing MTCDs' energy efficiency in different transmission modes, one may assign them to direct transmission.

(2) CH candidate selection

This paper proposes a candidate CH selection approach based on MTCD transmission performance.

A direct transmission link between a CH and the BS is critical because the CH delivers data packets to its appropriate CM within a cluster. Accordingly, only MTCDs with better threshold energy conservation is regarded as possible CHs.

Let $\psi_{\min}$ be the energy conservation limit of the MTCDs, a direct transmission connection. We pick MTCD_i as a candidate CH.

$\psi_{\min}^{d,*} \geq \psi_{\min}$, $1 \leq i \leq M$. We get by denoting 0 as the set of candidate CHs.

Table 1: Simulation parameters.

Parameters	Values
MTCDs numbers	15
Fading distribution on a small scale	Rayleigh fading
Model of channel path loss	$128.1 + 37.6\log(d)$ dB
One RB's bandwidth	180 kHz
Transmission power at its maximum	0.15 W
Noise power	-104 dBm
Consumption of circuit power	0.3 W

$\Phi_0 = \left\{\mathrm{MTCD}_i | \psi_i^{\mathrm{d},*} \geq \psi_{\min} \quad 1 \leq i \leq M\right\}$. Let $K0$ signify the total number of candidate CHs, i.e., $K0 = |0|$, where $|x|$ denotes the total number of items in the set x.

(3) Clustering method using the modified K-means algorithm

K-means classification methods are often employed to solve clustering difficulties [25].

For example, starting CHs are picked at random, and CH updates are based on Euclidean distance, which may not result in optimal energy efficiency. Given that K-means concentrates on CH selection and user correlation, it ignores direct transmission ties between CHs and BSs. We provide a modified K-means MTCD aggregating approach.

The suggested individual's fundamental concept may be stated quickly. We begin by setting the initial number of CHs, i.e., $K1 = \min N \max, K0$, and then assess the energy efficiency total of the straightforward and associative linkages between each MTCD, selecting the CHs with the greatest energy efficiency sum. CH association may be performed using the first CHs. Researchers who want to be CMs choose environmentally friendly CHs as linked CHs based on how efficient they are with their energy.

In this updated K-means algorithm-based clustering technique, data transfer modes show $L_i^{\mathrm{d}*} = 1$ or MTCDi. Direct mode selection variable for MTCD shows $L_i^{\mathrm{d}*} = 1$. We determine the energy efficiency of the system.

$$\psi_{t'} = \sum_{\mathrm{MTCD}_i \in \Phi_{\mathrm{d}}'} \psi_i^{\mathrm{d},*} + \sum_{\mathrm{MTCD}_i \in \Phi_{\mathrm{ch}}} \psi_i^{\mathrm{d},*} + \sum_{\mathrm{MTCD}_i \in \Phi_{\mathrm{cm}}} \sum_{\mathrm{MTCD}_{i_{k'}} \in \Phi_{\mathrm{ch}}} \psi_{i,i_{k'}}^{\mathrm{c},*}. \tag{21}$$

CH reselection: Considering that $\mathrm{MTCD}_{i_{k'}}$ is chosen as a single CH, we refer to k' as the set of CMs corresponding with $\mathrm{MTCD}_{i_{k'}}$, i.e.,

$$\Phi_{k'} = \left\{\mathrm{MTCD}_i \middle| \mathrm{MTCD}_i \in \Phi_{\mathrm{cm}}, \delta_{i,i_{k'}}^{\mathrm{c},*} = 1\right\}. \tag{22}$$

Energy efficiency is calculated using the single link MTCD_i and the base station.

The connection between MTCD_i and $\mathrm{MTCD}_{i_{k'}}$, and the links between MTCD_i and $\mathrm{MTCD}_{i'_{k'}, i_{i'}}$, for $\mathrm{MTCD}_{i_{k'}}$.

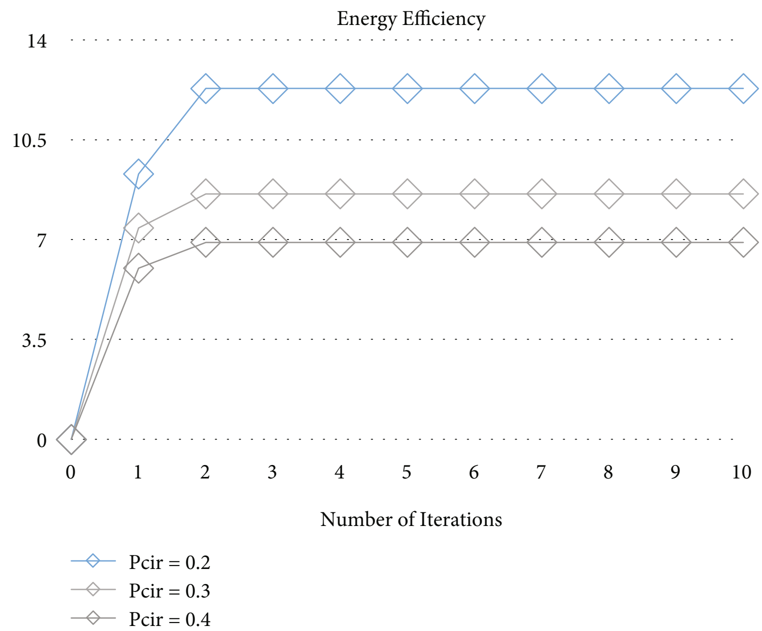

Figure 3: Efficiencies in terms of energy consumption vs. iterations (different circuit power).

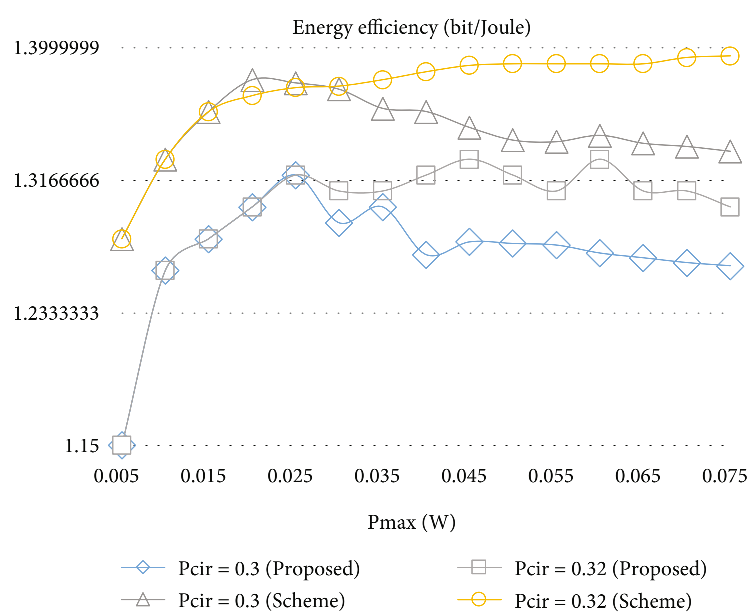

Figure 4: Energy efficiency versus transmission power maximum (different circuit power).

Energy efficient of $\mathrm{MTCD}_{i_{k'}}$ which is termed as τ_i.

$$\tau_i = \psi_i^{\mathrm{d},*} + \psi_{i,i_{k'}}^{\mathrm{c},*} + \sum_{\mathrm{MTCD}_{i'} \in \Phi_{k'}, i' \neq i} \psi'_{i,i}\mathrm{c},*. \tag{23}$$

As the upgraded CH, choose $\mathrm{MTCD}_i \in \phi_{k'}$, which has the maximum energy efficiency.

$$\mathrm{CH}_{k'} = \underset{\left\{\mathrm{MTCD}_{i_{k'}}\right\} \cup \Phi_{k'}}{\operatorname{argmax}} \{\tau_i\}. \tag{24}$$

As a result, update the list of ΦchΦcm.

Calculate the link's energy efficiency MTCD_i and $\mathrm{MTCD}_{ik} \in \phi_{\mathrm{ch}}$ for $\mathrm{MTCD}_i \in \phi_{\mathrm{cm}}$ and choose the most energy-efficient CH as the associated CH.

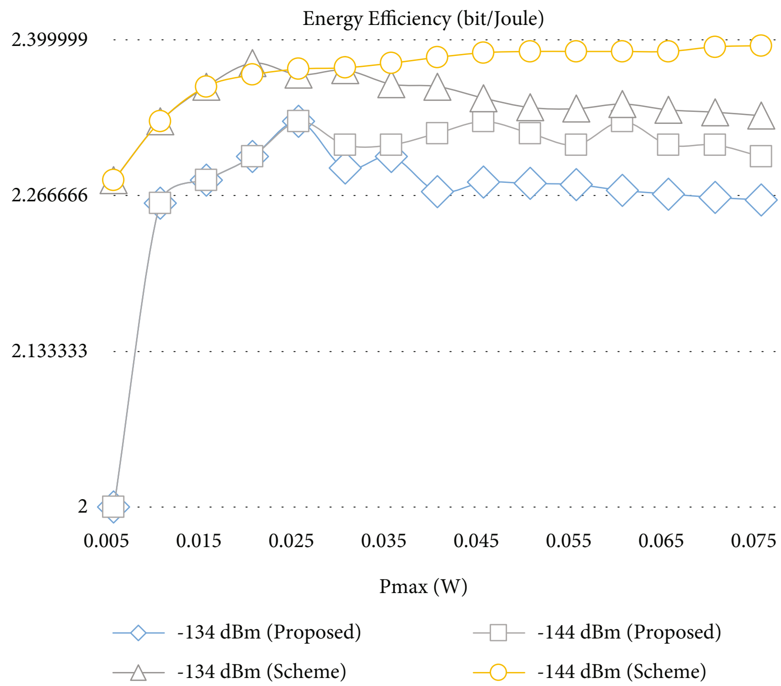

Figure 5: Energy efficiency versus transmission power maximum (different noise power).

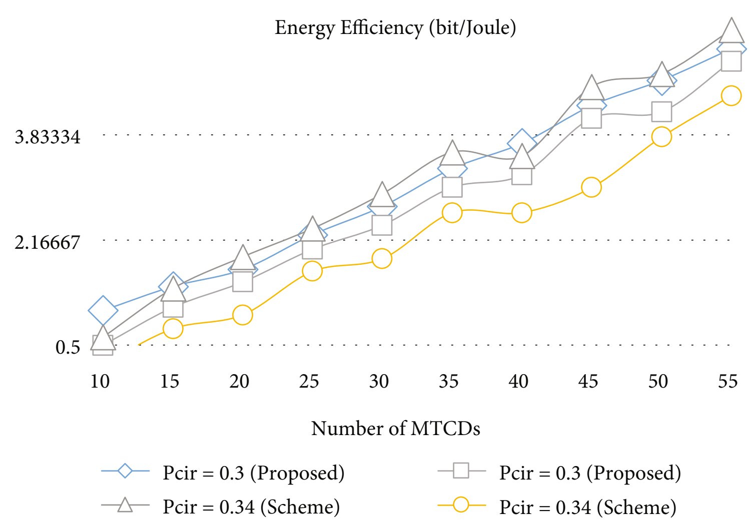

Figure 6: Energy efficiency as a function of the total no. of MTCDs (different circuit power).

Energy efficiency is defined as $\psi_{t'+1}$.

Computation convergence: If $\psi_{t'+1} - \psi_{t'} \le \Delta$, the procedure terminates, and the matching clustering method can be found; otherwise, if $t' = T'$, the method fails; anything other than that, put $t' = t' + 1$ and return to start the iteration again.

3. Complexity Analysis

The simultaneous distributing and clustering challenge in M2M networking is the subject of this research. The initial optimization process is a complex nonlinear fractional computational problem that needs simple solving. The first optimization procedure is a difficult nonlinear fractional computational problem that can be solved quickly. To establish the optimal power distribution plan, we first provide an iterative method-based energy efficiency maximization technique, followed by a modified K-means approach. This section examines the two subproblems' computational complexity [29].

3.1. Subproblem A: Power Allocation. For instantaneous BS or CH forwarding, power allocation is done for specified MTCDs. The highest bound of the difficulty is $O(MT_0T_1)$ that can directly access the BS. The complexity is low because the Lagrange multipliers and MTCDs need few iterations to attain convergence. Because each MTCD can

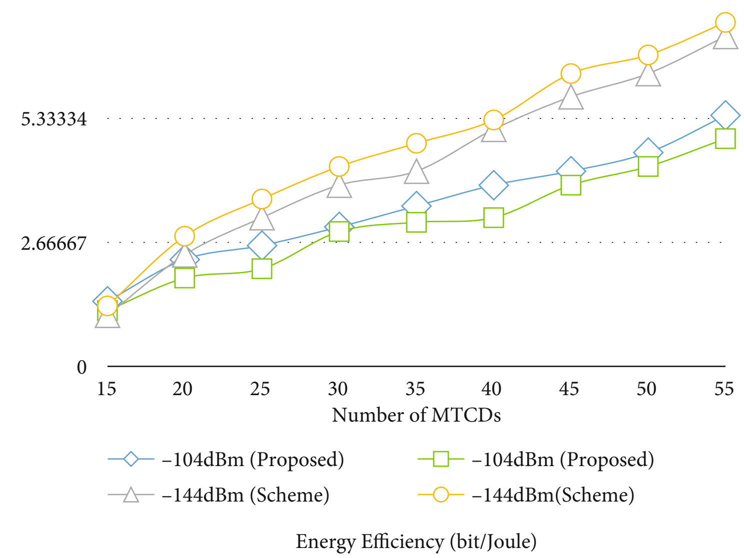

Figure 7: MTCDs' energy efficiency in relation to their bandwidth (different circuit power).

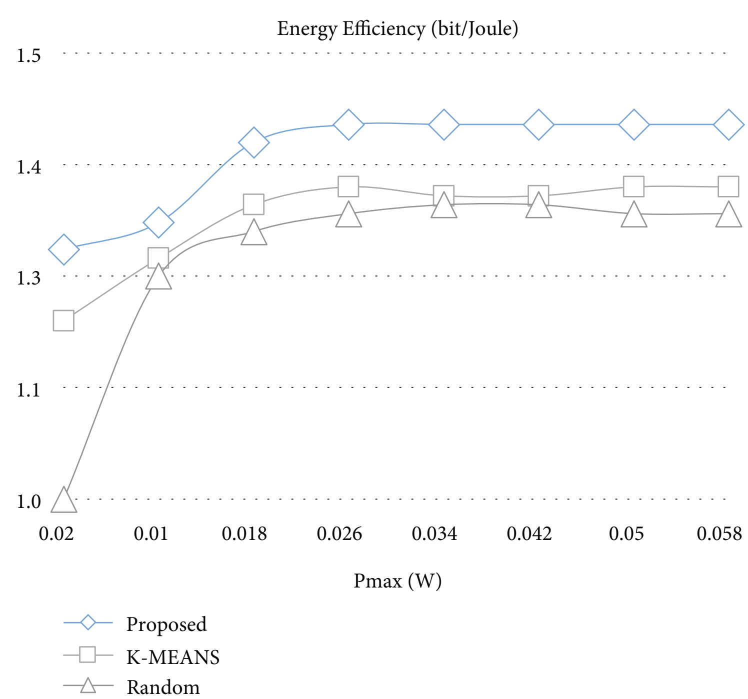

Figure 8: Energy efficiency versus transmission power maximum (different algorithms).

choose other MTCDs for data forwarding in CH forwarding mode, the needed complexity is $O(M(M-1)T_0T_1)$.

3.2. Subproblem B: Clustering. We construct the clustering subproblem using the optimal power allocation from the modified K-means approach with a preceding subproblem. The approach is as sophisticated as the K-means algorithm. The complexity is estimated as $O(M+|\phi_{\mathrm{cm}}|K_1)$ for each iteration. The computational complexity is expressed as $O(t'(M+|\phi_{\mathrm{cm}}|K_1))$ if t' denotes the number of iterations [30].

3.3. Results of the Simulation. This section uses simulation data to prove the method's efficacy. We used simulation to evaluate the prior approach. In the simulation, we have one BS and MTCDs. The simulation area is 500 m × 500 m. The BS is in the simulation space, and the MTCDs are scattered. Unless otherwise noted, the simulation parameters are in Table 1.

As seen in Figure 3, overall efficiency varies with circuit power consumption. As the graph shows, renewable energy improves with repetition. As circuit current increases, energy performance deteriorates. Figure 4 compares the system's energy efficiency to the maximum transmission power MTCDs for different circuit electricity consumption levels. The generation of power of both schemes rises as $p_{\max_i}$ grows, showing that a higher power threshold is needed to achieve maximum efficiency. However, once the maximum transmission power is achieved, our recommended system's energy efficiency remains constant, but the method described loses efficiency as power increases. Since the approach is designed to achieve the highest possible transmission rate, it may result in increased power requirements and hence worse power efficiency [31]. As shown in the illustration, both algorithms' energy conservation diminishes as the energy usage of the circuit increases.

With varying degrees of noise, we plot system energy usage against MTCDs maximum transmit power (Figure 5). As seen in the graph, noise power enhances energy efficiency because increasing noise power reduces information representation and hence energy efficiency. By comparing the outcomes of two algorithms, we can observe that our suggested scheme outperforms the proposed method. The system energy consumption vs the number of MTCDs is shown in Figure 6 for various circuit power consumption scenarios. As the number of MTCDs rises, the power generation of both procedures improves proportionately. This graph shows how the energy efficiency of both methods decreases with circuitry intensity. We can also show that our solution is eco-friendlier than the alternative. The energy performance of the network is shown against the number of MTCDs for various noise powers in Figure 7. As seen in the image, energy efficiency drops as noise power rises and increases with the number of MTCDs as shown in Figure 8. This is because increased noise power leads in decreased transmitting performance and reliability. Additionally, our suggested approach improves the technique described. The relationship between system energy efficiency and the bandwidth of MTCDs for various circuit electricity consumption levels is shown. By comparing the energy consumption of the two systems, we can see that the energy efficiency of the system grows as the bandwidth of the MTCDs increases. This is because increased bandwidth leads in increased rate of transmission, which results in increased energy efficiency. Furthermore, we can determine that our suggested system is more environmentally friendly than the suggested technique. The energy efficiency of the system against the bandwidth of MTCDs for various noise powers is shown. As seen in the image, energy efficiency rises when the bandwidth of MTCDs grows and declines as noise power increases. When the outcomes of the two methods are compared, we can see that our suggested approach outperforms the proposed algorithm.

The network's power performance is compared to the MTCDs' maximum transmission power using the specified algorithm and two other methods: K-means and randomized algorithms. Our proposed iterative energy efficiency maximization method determines the best power allocation strategy for both K-means and randomized algorithms; we then apply different clustering strategies. In the K-means method, the CHs are picked at random and then updated based on the Euclidean distance between the CMs and the CH. In the random technique, we choose CHs randomly and associate them. As seen in the graph, the proposed method outperformed the others.

4. Conclusion

This article will explore resource allocation and clustering in M2M data transfer. This article describes a collaborative strategic planning architecture, followed by a strategy for maximizing system efficiency via cooperative resource allocation and clustering. Our strategy outperforms previously reported methods numerically.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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