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Retraction

Retracted: 5G-EECC: Energy-Efficient Collaboration-Based Content Sharing Strategy in Device-to-Device Communication

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] N. Khan, I. A. Khan, J. U. Arshed, M. Afzal, M. M. Ahmed, and M. Arif, "5G-EECC: Energy-Efficient Collaboration-Based Content Sharing Strategy in Device-to-Device Communication," *Security and Communication Networks*, vol. 2022, Article ID 1354238, 13 pages, 2022.

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Research Article

5G-EECC: Energy-Efficient Collaboration-Based Content Sharing Strategy in Device-to-Device Communication

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In the past few years, mobile data traffic has seen exponential growth due to the emergence of smart applications. Although throughput enhancement techniques such as macro- and femtocells reduce cell size, they are relatively expensive to implement. Mobile device-to-device (*D2D*) communication has emerged as a solution to support the growing popularity of multimedia content for local service in next-generation 5G cellular networks. Content sharing is the prominent feature, which helps *D2D* communication in reducing offload traffic on the network, improving the energy efficiency of the device, and reducing backhaul connectivity costs. In traditional mapping approaches such as one to one or one to many, a massive amount of traffic is distributed among the devices resulting in high-energy consumption. In this paper, we propose a novel energy-efficient content sharing scheme called Energy-Efficient Collaboration-based Content (EECC) sharing strategy in *D2D* communication that shares content equally across devices based on their capacities and battery life under mobility. The proposed work includes cluster formation, cluster head selection, and helper node selection. In addition, we relied on a cooperative caching policy to ensure that content is distributed efficiently. The simulation results indicate a 12.05% reduction in energy compared to the state-of-the-art technique with a 2-gigabyte video file. To evaluate scalability, we increased the file size from 3 to 4 gigabytes, yet the performance in terms of energy consumption remained the same.

1. Introduction

During the past few years, mobile data traffic has experienced explosive growth due to the increasing demand for smartphone devices and multimedia applications. This rapid increase in data traffic results in demand for bandwidth [1]. To overcome this issue, different traditional solutions like decreasing cell size by using femto- and picocells were proposed for improving throughput, but still the problem remains unsolved due to their high deployment cost [2, 3]. Device-to-device (*D2D*) communication is viewed as the best solution because of features such as cellular traffic offloading, high throughput, high-energy efficiency, and resilience to infrastructure failure. It is described as a mode of communication in which mobile nodes communicate using their own communication channels without the involvement of a central entity like a base station. Conventional *D2D* communication [4, 5] works on the two-tier model and depends on cellular architecture for fetching resources. The devices are at one hop distance, so fewer resources are used, and battery life is improved, but this communication leads to the issue of interference that makes this architecture inefficient. In order to deal with interference, dedicated resources are assigned to relay nodes for long communication [6] but result in wastage of resources. Traffic on the network will increase until 2022 due to increased demand for multimedia content, with videos having the highest request factor of 78 percent. Huge demand for videos can create extensive traffic load and congestion on the devices and at backhaul affecting the battery life of devices.

Content sharing [7–10] is a novel solution to reduce multimedia traffic and accommodate the user by requesting the neighbor for content within their coverage area. In content sharing, the device requesting content, called a demander, fetches the content from neighbors rather than requesting the base station. Throughout this process, the neighboring device providing content, known as the provider, is obligated to accommodate this demander and refrain from fetching data for that period of time. This pairing of provider and demander is referred to as mapping. In literature [7–13], researchers have only focused on how efficiently multimedia traffic can be offloaded from the Internet for smartphone users. In doing so, they have achieved two common objectives, that is, improving performance and reducing load by caching popular data locally or making optimal matching between requester and demander. There is one issue that the researchers have overlooked; that is, content providers that have a high link quality and numerous social ties are more likely to be selected to provide video content to demanders. The preferred provider experiences uneven traffic distribution during the content sharing process, which reduces battery life. This problem is addressed by 5G *D2D* Comp [14], which collaborates multiple device transmission in which the traffic load is evenly distributed among devices, which improves battery life. This approach is scalable for static scenarios, but its performance suffers in terms of energy and delay when used in a mobile scenario.

The main contributions of this work are as follows:

(1) The novel 5G energy-efficient content sharing scheme called Energy-Efficient Collaboration-based Content (EECC) architecture is proposed by utilizing the reference point group mobility model for clustering groups along with a weighted algorithm for choosing cluster heads.

(2) A collaborative-based content sharing mechanism is investigated in which video caching is designed using the Multilevel Pareto Least Recently Used (MPLRU) cache algorithm approach, and content is distributed across devices while two factors considered are communication efficiency and energy consumption.

(3) Finally, the performance evaluation of video in terms of energy and delay is analyzed by changing content sizes.

The rest of the paper is organized as follows. Section 2 covers the related work about content sharing approaches in 5G *D2D* communication. Section 3 describes the proposed model. In Section 4, the experiments and results are discussed, whereas the conclusion is described in Section 5.

2. Related Work

This section outlines some content sharing approaches used in *D2D* communication. The related work is divided into two parts. In the first part, content sharing techniques are discussed that focus on caching the most requested services desired by neighboring. In the second part, matching techniques are discussed that use a pair of providers and demanders who share resources after offloading them from the base station.

In *D2D* communication, content sharing is a prominent solution in reducing load and energy dissipation. The multimedia services are not only the main reason for the increase in traffic on the network but also unnecessary demand requests for multimedia service that put a load on backhaul result in congestion, and at the same time, battery life is affected [11]. A content sharing technique called proactive caching was introduced in [12], which predicted multimedia request before it has been requested by the user, and with the help of this approach, peak time demand can be reduced. Two case studies were performed to evaluate the effectiveness of the scheme. To overcome backhaul congestion, the files were cached before peak time based on their popularity and by doing association among users. *D2D* communication was facilitated in which the author predicted the influential users, proactively cached the content with these users, and distributed it with their social ties. The simulation result showed that they got important cache gain from these two scenarios with backhaul saving and a higher proportion of satisfaction rate of clients up to 22% and 26%. The work in [13] used the hypergraph framework to design a new caching model for *D2D* communication. According to the model criteria for caching, the content was to predict mobility patterns, social features of mobile clients, and multiple tier information like physical location, common interest, and social ties. The caching model formulated by this framework helped in reducing traffic burden and improving energy efficiency and spectrum efficiency. The caching model in [15] worked on *D2D*-based multicasting network-coded information. The video caching was done by assigning the coded packet to the library file, and these coded packets helped in distinguishing video files. The users can request the same content at different time intervals, which may help in improving global caching. In real life scenario, the change in popularity of the content and uncontrollable mobility makes it complex to predict the content. The limited storage and transmission capacity of devices, along with their numerous requests, makes it difficult for any potential provider to provide assistance to all. Hence, the core of matching demanders to potential providers is to choose and coordinate the providers from candidates for each demander. However, it is difficult to formulate and address this matching issue.

In [15], the author suggested this mapping problem as a maximum weighted matching problem, and weights were assigned to each pair based on the data link. This matching problem resulted in the design of a new distributed and synchronous algorithm [16]. Hypergraph-based three-dimensional problem [17] was developed with several parameters in mind such as content distribution, demander-provider pairing, and cellular resource reuse. Because global data is required in these solutions [15–17], the matching solution can only be found through centralized means. As a result, additional traffic is generated between the devices and the base station, burdening the cellular network. A local search-based method [18] was created to solve the problem

locally, without requiring the base station. The author strives to create a distributed optimal matching algorithm in order to achieve optimal matching without increasing the burden on the base station. In the formulation of these problems, *D2D* conventional content sharing matching modes [5] were taken into consideration. The work in [19] proposed a social attribute aware incentive system for cellular *D2D* video distribution. The approach encouraged core users to execute video distribution which resulted in lowering the base station transmission load. A grid-based clustering algorithm was implemented to support video distribution. A scalable video coding mechanism based on social features for video data distribution at the mobile network's edge was proposed in [20]. The suggested approach took advantage of a user's social characteristics and mobility to move some essential network functions to the network edge. Based on the user's social characteristics, a scalable video coding (SVC) sharing system was proposed through user collaboration. This strategy made video distribution more flexible at the edge of the mobile network and effectively reduced transmitter transmission energy usage. As a result, edge user collaboration reduced the amount of base station transmission.

In order to ensure reliable content sharing, a trust evaluation mechanism was presented for evaluating the cooperative capability, choice similarity, and social solidarity between mobile users [21–24]. The motivation problem in content caching was examined, and a cooperative caching game based on social trust was proposed. In order to reduce the total cost in the *D2D* network, the caching cost was described by integrating trust relations with physical distance, and an incentive caching technique was proposed.

The *D2D* multicast users clustering problem based on the social features of terminal equipment was proposed in [25] to increase the efficiency and reliability of data sharing in the *D2D* network. Software-defined network (SDN) architecture was created to ease the signaling and calculation pressures of base stations. In addition, a social-aware K-means clustering method for *D2D* multicast communication was suggested, which comprised User Entity (*UE*) clustering and core user selection. When using the *D2D* multicast clustering algorithm, both physical and social distances between UEs were taken into account. Moreover, when selecting core users in *D2D* multicast groups, the power of the *UE*, storage space, social attributes, and mobility properties were all taken into account.

The work in [26] proposed a joint downlink resource sharing and caching helper selection (*DRSCHS*) control for video applications and services in dense *D2D* 5G networks. Over clustered-based multicast *D2D* communications with downlink resource sharing, the DRSCHS was flexible in controlling the requesting users to be served, whether by the macrobase (MB) station or the caching helpers. It also optimized the process of picking the right collection of sharing users and caching helpers in order to provide maximum multicast video delivery capacity to requesting users. One demander can receive content from one provider. Communication devices with high link quality and social ties were preferred, which enhanced battery usage but at the same time resulted in resources wastage [18–28]. Cooperative *D2D* communication dealt with the problem of battery issues which was faced by previous models [14, 29, 30]. One-to-many matching was presented in this work in which one demander can get content from many providers or one provider can accommodate many demanders at the same time.

A distributed architecture based on content-centric networking and network virtualization was proposed in [31] to enable efficient content delivery. Clustering was introduced at the user level for content distribution, and a weighted multifactor clustering approach was presented for grouping *D2D* User Equipment (*DUEs*) with a common interest. Energy efficiency, area spectral efficiency, and throughput were examined for the proposed algorithm. The energy issue remained unsolved in this approach. This problem was addressed by 5G *D2D* Comp [14], which collaborated with multiple device transmission in which the traffic load was evenly distributed among devices and improved battery life as well. This approach was scalable for static scenarios, but its performance suffered in terms of energy and delay when used in a mobile scenario.

According to literature [18–22, 32, 33], a one-to-one mapping policy for *D2D* communication was imposed, allowing one demander to receive content from one provider. Communication devices with high link quality and social ties were preferred resulting in a significant increase in battery usage. The problem of battery issues was addressed in [26–30] in which the cooperative *D2D* communication approach was used. The energy issue remained unsolved due to the fact that uneven traffic distribution of content on single preferred devices results in an increase in battery usage. The problem was addressed by 5G *D2D* Comp [8], which collaborated with multiple device transmission in which the traffic load was evenly distributed among devices and improved battery life as well. 5G *D2D* Comp approach was scalable for static scenarios, but its performance suffered in terms of energy and delay when used in a mobile scenario. Comparative analysis of related work is illustrated in Table 1, and the symbols used in 5G-EECC modeling are illustrated in Table 2 along with their definitions.

3. Proposed 5G-EECC Modeling

In this section, we discuss the working of the proposed methodology for cluster head selection, cache placement, and content discovery models.

3.1. Overview of EECC. Over the past few years, mobile multimedia streaming, especially video streaming, has grown exponentially. Local providers face energy challenges due to the high volume of video requests and unequal resource distribution. In this work, we propose a 5G *D2D* architecture that employs reference point group mobility for cluster formation and a maximum weighted-based algorithm for cluster head selection. The cluster head utilizes the collaborative cache decision model to choose the best helper nodes for caching content based on battery

Table 1: Comparative analysis of related work.

Year	Paper	Research methodology	Matching mode	Proactive caching	Content type	Advantage	Disadvantage	Limitation
2017	[12]	Proactive caching based on social ties	N/A	Yes	N/A	Improved throughput delay and energy efficiency	Change in popularity will affect the performance of the network	Popularity of content is not considered
2017	[13]	Hypergraph framework-based proactive caching	N/A	Yes	Mobile multimedia	Improved battery life and local cache gain	Under mobility, caching does not perform well	Mobility factor is not focused on
2018	[14]	MDS codes-based proactive caching approach	N/A	Yes	Video	High global cache hit ratio	Different video preference is not considered	Mobility is considered, but cache strategy considers only popular videos
2019	[5, 17]	5G *D2D* communication	One to one	N/A	Mobile multimedia	Improved throughput delay and energy efficiency	The devices with high link quality are selected, which increases battery usage	Centralized approach
2019	[18–20]	Cooperative *D2D* communication	One to many	Yes	Mobile multimedia	Battery life improved	Simultaneous request for resources by multiple demanders can result in a burden on single provider end	Centralized approach
2020	[8]	*D2D* coordination Multiple point transmission	Many to many	N/A	Mobile multimedia	Improved energy efficiency by equal distribution of resources	Mobility will affect the scalability	This approach works when demander and provider are equal and static

Table 2: Symbols used in the 5G-EECC modeling.

Symbols	Definition
T	Time period
M_i	Mobility
D_i	Distance between two neighbors
RE_i	Residual energy
cc	Content capacity
N_iV_n	Number of content views
H_c	Hit count
M_c	Miss count
V_n	Request for content
LC_n	Content at a lower level of cache

life and capacity. For cache placement, Multilevel Pareto Least Recently Used cache algorithm and Zipf probability model are utilized, which determine the popularity of content. The entire procedure is depicted by using a flowchart as shown in Figure 1.

3.2. Cluster Formation and Cluster Head Selection. According to our cluster formation model, the base station computes mobility and clusters mobile users based on their speed and direction using the reference point group mobility model. When the devices are clustered, the next step is the selection of cluster head and helper node. The cluster head selection process is stated in Algorithm 1. Algorithm 1 is categorized into four parts as discussed in the following:

(i) From lines 1 to 4, each node advertises itself in order to notify its neighbors. The ID and position value of a node are included in a node discovery message. Each node builds its neighbor table based on the advertisement.

(ii) From lines 5 to 13, every node calculates its weights and broadcasts them to its neighbors. The node with the highest weight value is considered a cluster head.

(iii) From lines 15 to 26, the cluster head selection process is terminated. The cluster head selection process is concluded when the node with the highest weight broadcasts "CHMSG" to its neighbors to stop selection and declares itself cluster head.

(iv) From lines 26 to 31, the cluster head selects helper nodes based on three parameters such as willingness of neighbor, residual energy, and cache capacity. Furthermore, the base station uses a weighted round-robin algorithm to distribute video content between the cluster head and helper node based on their energy and cache space as shown in Figure 1.

The weight function used in Algorithm 1 is affected by numerous factors, including mobility, distance, cache size, residual energy, and degree of connectivity as discussed in the following.

Mobility plays an important role in cluster head selection, allowing clusters to remain stable and avoiding frequent head selection. Cluster heads are chosen from nodes with low relative mobility at current time T determined by equation (1):

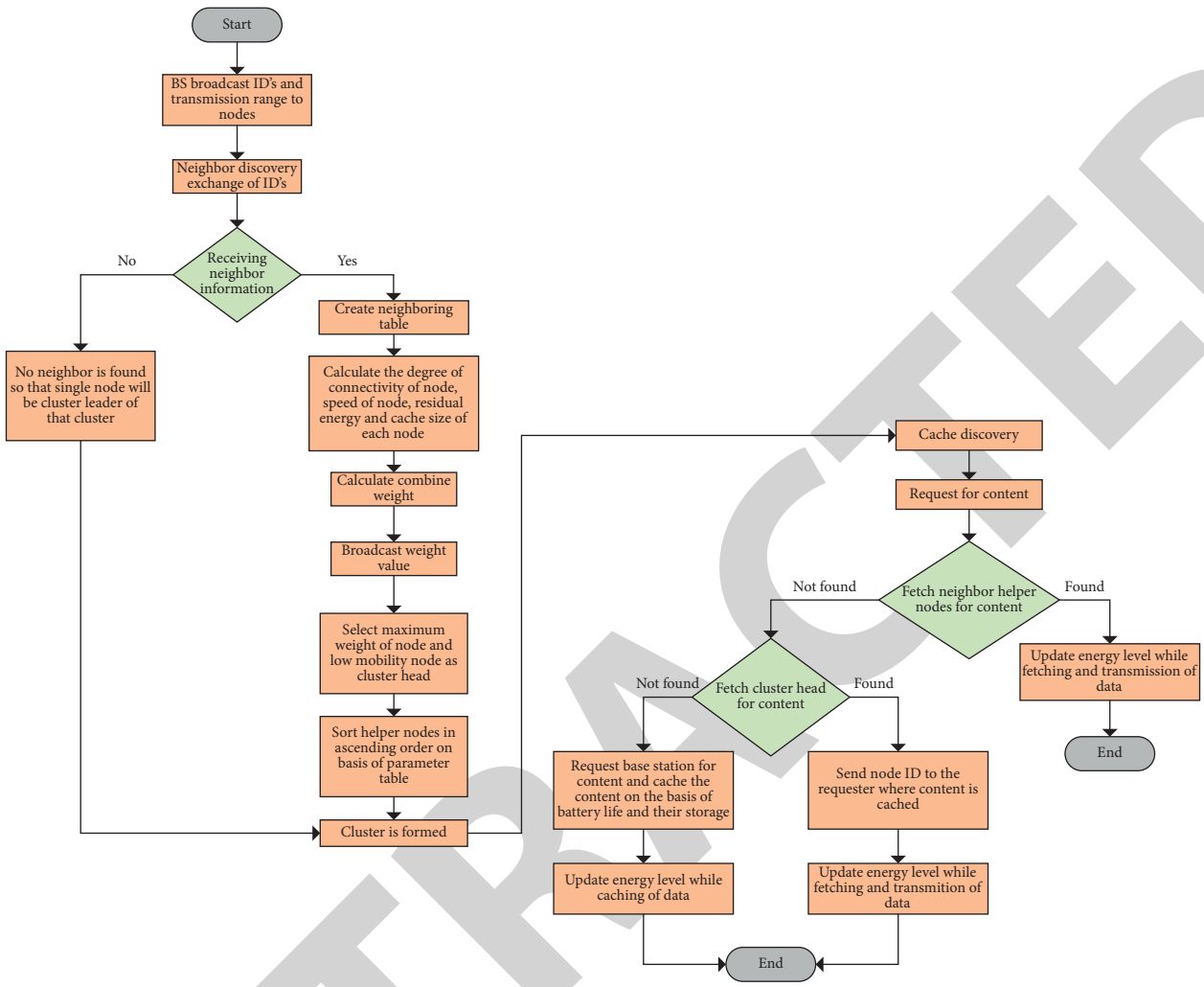

Figure 1: Flowchart of the proposed 5G-EECC.

Input:
(i) List of device ids and their transmission range
(ii) Coefficients of w_1, w_2, w_3, w_4, w_5
(iii) List of device ids and transmission range
Output: Cluster formation and cluster head selection
Steps
(1) Begin
(2) **for** any node $ne_i \in G$
(3) then
(4) ne_i form a neighboring list $N(j)$ by broadcasting the hello message;
(5) Calculate the coefficient of equation (6) and calculate W_V
(6) Initialize time cluster and state vector for all node $ne_i \in G$
(7) Vector state (id, weight, list neighbor, CH, Helper);
(8) Initially CH = 0, helper = 0;
(9) **if** $ne_i \in G$ broadcast hello message && $N(j)! = \varnothing$
(10) **then**
(11) V_n is set at the header of C_i
(12) **else**
(13) Choose cluster leader = $\max\{\text{weight}(w)/W_V \in N(j)\}$
(14) **end if**
(15) State vector of elected CH is updated

Algorithm 1: Continued.

```
        CH = id;
        helper = 0;
        CH send "CHMSG" to neighbor N[CH] to stop selection
        K = Count[N[CH]];
      end for
      for i = 1 to K Do
        then
          if ne_i ∈ N[CH] receive "CHMSG"
          then
            Stop cluster head selection and become member of cluster
          if ne_i ∈ N[CH] energy > threshold energy && ne_i ∈ N[CH] capacity > threshold capacity
              then
              CH sort helper in ascending order based on energy and capacity
            else
            Nodes become ordinary member
          end if
        else
            Continue selection process
        end if
        State vector of selected helper is updated
        helper = id;
      end for
    end
```

Algorithm 1: Cluster formation and cluster head selection.

$$\text{Mobility}_{\text{i}} = \frac{1}{T}\sum_{t=1}^{T}\sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}, \quad (1)$$

where (x_t, y_t) and (x_{t-1}, y_{t-1}) represent the coordinates of node at time t and t_1, respectively.

The cluster head can communicate more effectively with its neighbors who are closer within its transmission range. The sum of distance D_i from neighbor i and j is computed by using the equation (2):

$$D_i = \sum_{j \in N(i)} \{\text{Dist}(i, j)\}. \quad (2)$$

Residual energy is an important factor for the cluster head selection process, as devices with a sufficient amount of energy are able to communicate and provide services better than devices with low residual energy. Within transmission range, node energy can be efficiently utilized; that is, if two nodes are nearby, they require less energy to communicate with each other. The remaining energy of the node is calculated by using equation (3):

$$\text{Re}_u = \text{Energy}_{\text{Curr}} - (\text{Energy}_{\text{TX}} + \text{Energy}_{\text{RX}}), \quad (3)$$

where $\text{Energy}_{\text{Curr}}$ represents the node's current energy, $\text{Energy}_{\text{TX}}$ represents the energy consumed sending a video packet, and $\text{Energy}_{\text{RX}}$ indicates the energy consume receiving a video chunk.

The degree of connectivity is an important factor for cluster head selection which defines how many devices are connected at time t. Each node calculates the degree of connectivity C_i with its neighbors Ne_i by using equation (4):

$$C_i = \left\{\frac{Ne_i}{\text{Dist}(i, j) \le T_R}\right\}, \quad (4)$$

where $\text{Dist}(i, j)$ represents the separation between two nodes and T_R represents transmission radius.

Nodes with enough storage space are better suited to provide cache services than others with insufficient storage space. Cache capacity of device cc is calculated by using equation (5):

$$cc = T_C - C_S, \quad (5)$$

where T_C represents the total cache size of the device and C_S represents the size of the video chunk.

The parameters that are discussed above are basically the coefficient of the proposed maximum weight-based algorithm in finding weights which is described in equation (6):

$$W_V = w_1 \times cc_i + w_2 \times RE_i + w_3 \times C_i + w_4 \times D_i + w_5 \times M_i, \quad (6)$$

where w_1, w_2, w_3, w_4, and w_5 are the respective weighing factors for the system parameters and $w_1 + w_2 + w_3 + w_4 + w_5 = 1$.

3.3. Cache Design Model. An efficient caching algorithm can significantly enhance the service quality of *D2D* communication. Considering the device's limited caching space, it is critical to place the appropriate video content. Unpopular and outdated videos should be replaced gradually. This section introduces the design of the caching replacement strategy. A good cache replacement strategy tends to keep cached videos as long available as possible in

the near future. According to our proposed design, cache index lists are divided into different levels with different cache priority. If a video is demanded that is not in the whole cache list, it is cached and labeled as low priority. Video with a lower priority level can only be promoted to the top level if it gradually breaks through the thresholds of each level. If the cache space at that level runs out, the currently most outdated video is moved to a lower level of the cache index list. The whole process is described in Algorithm 2. Algorithm 2 is categorized into three parts as discussed in the following:

(i) From lines 1 to 5, the algorithm searches for the requested content. If the content requested by the client is present in C_i (cache level), then N_iV_n (number of content views) and HC (number of hit counts) are incremented by 1.

(ii) Lines 6 to 16 are about the content upgrade and degradation for the three different cache levels. For each client request, if N_iV_n exceeds X_i (threshold value = 2), the relative video is promoted from the existing cache level to C_{i-1} (higher priority cache). If the cache level is full, the video at the end of the current cache list is demoted and moved below.

(iii) Lines 17 to 25 of the algorithm are about the placement of new content. If the requested content is not in the cache C_i, the content is placed at the head of the lowest level, but if the cache level is full, the content at the bottom level is removed.

3.4. Cache Discovery. Cache discovery focuses not only on the challenge of resolving data requests while using the least amount of power and bandwidth but also on improving a request's success rate. The goal of cache discovery is to determine how mobile nodes can work together to handle data requests in order to improve network performance. The cache discovery is described in Algorithm 3. Algorithm 3 is categorized into three parts as discussed in the following:

(i) From lines 1 to 6, the local cache is checked to see whether the required content is available or not. The cache hit or miss ratio is used to update content views, and a cache replacement policy is used for content upgradation and degradation.

(ii) From lines 7 to 13, if the content is not found in the local cache, the device checks its neighbor table for helper nodes created during node discovery. If the content is discovered, the data packet is sent to the demander; otherwise, the request is routed to the other helper nodes. At the same time, content views are updated, and the cache is replaced.

(iii) From lines 14 to 23, if the content is not found on all of the helper nodes, the request is forwarded to the cluster head. If the cluster head discovers the video content, it sends it to the requester and employs the replacement policy; otherwise, the cluster head sends a request to the base station for content. If video content is discovered on the server, the base station distributes it to the cluster head and helper nodes based on their residual energy and cache capacity. The cluster head notifies the demanders of the location of the content via the helper id.

4. Simulation Results

In this section, the results and the testing environment of the proposed architecture are described. In this work, millimeter wave technology is utilized for *D2D* communications, and *D2D* Simulator 3.0 [18] is employed to design and evaluate our proposed network. In terms of our implementation, the wireless link capacity of mobile users is assumed to be distributed equally. Using the Reference Point Group (UPG) mobility model, the devices are divided into different clusters. The number of video requests generated is 10,000, and the number of identical requests is 2,598. The video is divided into chunks, each of 4000 bytes in size. The video sizes are in the range of 30 megabytes to 4 gigabytes. Zipf's distribution is utilized with a value of 0.7 for popularity. The parameter setup is illustrated in Table 3.

4.1. Results and Discussion. In this section, we examine how the 5G-EECC approach affects network performance in terms of energy and delay when we deal with different size contents. For simulation, we use four adjacent devices and compare their energy consumption for our proposed model, that is, 5G-EECC, traditional *D2D* communication, and the previous state-of-the-art model *D2D*-Comp under mobility. The objective of the experiments is to check how mobility factors affect energy parameters while a packet is transmitted. We analyze that the energy consumption of these devices improves by segmenting 2-gigabyte files using a weight-based round-robin algorithm under mobility by considering two parameters, that is, capacity and battery life. Figure 2 depicts the whole process. The results in Figure 3 show that our proposed scheme achieves 12.05% improvement in energy consumption when the cumulative percentage of our approach is calculated for four devices and compared with the state-of-the-art *D2D*-Comp approach. Similarly, the energy consumption improves 15% for 5G-EECC when the cumulative percentage for four devices is calculated and compared with traditional *D2D*.

To further evaluate the energy performance, we conduct simulations with different sizes of video content to see if the performance in terms of energy is affected when the video content size is increased. Figure 4 depicts that our proposed scheme achieves 10.05% and 17.95% improvement when the cumulative percentage of our approach for four devices is calculated by increasing video content size up to 3 GB and compared with state-of-the-art approaches.

In order to validate the scalability of our proposed approach, we performed simulations with video content sizes of 4 gigabytes to see if increasing video content size

```
Input:
(i)   Devices cache capacity
(ii)  Threshold value X_i for upgrading in-cache
(iii) N_iV_n number views of content
Output: Replacement of older content with a new one
Steps
(1)   if V_n is in C_i
(2)     then
(3)     H_c++
(4)     N_iV_n++
(5)     if N_iV_n > X_i
(6)       then
(7)       V_n is set at the header of C_i
(8)     else
(9)       N_iV_n = 0
(10)      if C_{i-1} is not full
(11)        then
(12)        V_n is set at the header of C_{i-1}//upgraded from bottom to top
(13)      else
(14)        LC_i is set at the bottom of C_i//degraded from top to bottom
(15)        N_{i-1}V_{n-1} = 0
(16)        V_n is set at the header of C_{i-1}//upgraded from bottom to top
(17)        H_c++
(18)        N_iV_n++
(19)        V_n is set at the header of C_i
(20)      end if
(21)    end if
(22)  else
(23)    M_c++
(24)    LC_i is removed
(25)    V_n set header of C_i
(26)    N_iV_n++
(27)  end if
```

Algorithm 2: Cache design policy.

```
Input:
(i)   Data item ID
Output: Getting requested data (D_i) from caching node
Steps
(1)   Getting requested data from caching node
(2)   Content requester check the local cache for required data
(3)   if local cache search (requested data item = found)
(4)     then
(5)     return requested D_i
(6)     cluster leader update cluster table (energy level of nodes, cache node entry)
(7)   else
(8)     if neighboring search ((D_i) = found)
(9)       then
(10)        send reply_packet from neighbor (content provider id, data item id) to content requester
(11)        data request_packet from requester to content provider
(12)        return requested D_i
(13)        cluster leader update cluster table (energy level of nodes, cache node entry)
(14)      else
(15)        Send data request_packet (data item id) to cluster head
(16)        Cluster head start searching process Do
(17)      if Cluster head entry search (requested data item = found)
(18)        then
```

Algorithm 3: Continued.

```
        return requested D_i
      else
        Send data creation_packet msg (data item) to base station
        if (helper energy > threshold energy && helper capacity > threshold capacity)
          then
          Base station sorts helper in ascending order based on energy and capacity and distributes content
        else
          return requested D_i from base station
        end if
      end if
    end if
  end if
```

Algorithm 3: Cache discovery in *D2D*.

Table 3: Parameters setting.

Parameters	Value
Base station grid layout	$500 \times 500\,\mathrm{m}^2$
Base station radius	100 m
Mobility speed	0–5 m/s
Number of clusters	7
Zipf value	0.7
Mobility model	Reference point group
Cluster members	10–25
Range of video content size	30 MB–4 GB
Video fragment size	4000 bytes
Transmission power	1.65 W
Receiving power	1.15 W
Current	330 mA
Voltage	5 V

affects the performance in terms of energy consumption. Figure 5 illustrates the differences in energy consumption when 4 gigabytes of video content is divided into chunks and transmitted by four adjacent devices. It can be seen that the energy consumption improves 9.06% and 18% when calculating the cumulative percentage of both state-of-the-art approaches and comparing with our proposed work. Moreover, novel file segmentation can help not only in energy efficiency but also in load balancing. In order to verify it, simulation is conducted with two different video segmentation approaches, that is, random video split algorithm and our proposed algorithm. Four adjacent devices are taken, and simulation is conducted with both approaches as shown in Figure 6, with time interval on the x-axis and remaining capacity of the battery on the y-axis. It can be seen that, from time interval T to 10T, devices using our proposed split algorithm had less battery drainage and prolonged battery life as compared to the random video split algorithm. The proposed algorithm checks the remaining battery life and capacity of the device before distributing video content instead of distributing file randomly, which makes it more efficient.

Delay is an important factor that mobile users consider. We conducted simulations for video contents of sizes 2 gigabytes to 4 gigabytes. Simulation results from Figures 7 to 9 differed as the transmission size was changed. From the results, it can be seen that although the delay of our proposed work is slightly increased due to the mobility factor, still the delay is less as compared to the previous model. In the *D2D* Comp scenario, the transmission delay is increased because during the process of multiuser cooperation, a receiving device needs to establish connections with a number of other devices to transmit data packets. Figure 7 illustrates the differences between the two approaches when video content is divided into chunks and transmitted by four adjacent devices. Figure 7 shows that the cumulative percentage delay of our proposed approach improves 2.57% and 2.03% for the selected four devices as compared to the state-of-the-art *D2D* Comp and traditional *D2D* approaches, respectively. To test our approach's scalability, we conducted simulations with video contents ranging in size from 3 to 4 gigabytes to see if increasing video content size affects performance in terms of delay. Figures 8 and 9 illustrate that the differences in delay when 3 gigabytes and 4 gigabytes of video content are divided into chunks and transmitted by four adjacent devices. Figure 8 shows that the cumulative percentage delay of our proposed approach improves 1.06% and 1.03% for the selected four

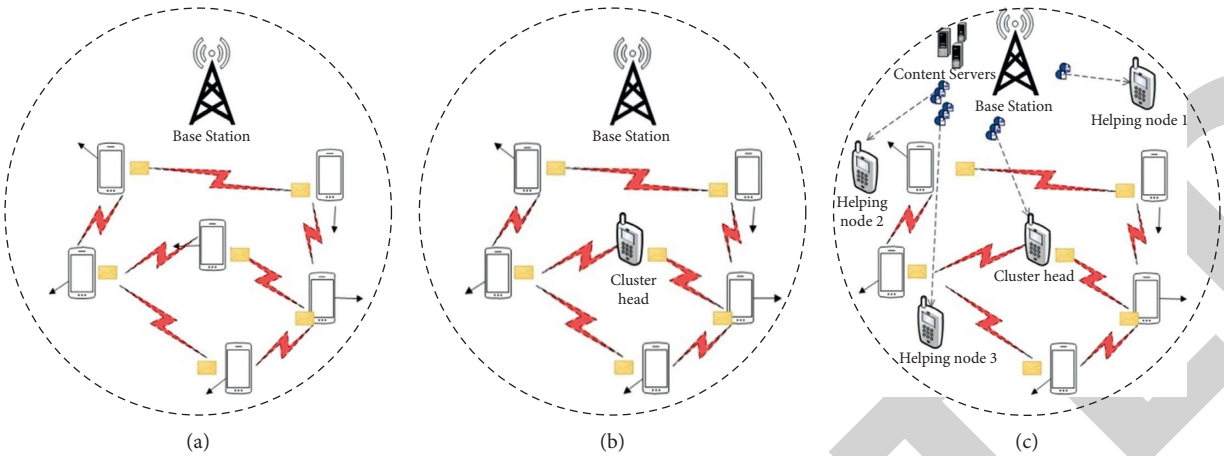

Figure 2: (a) Node discovery; (b) cluster head selection; (c) helper nodes selection and content distribution.

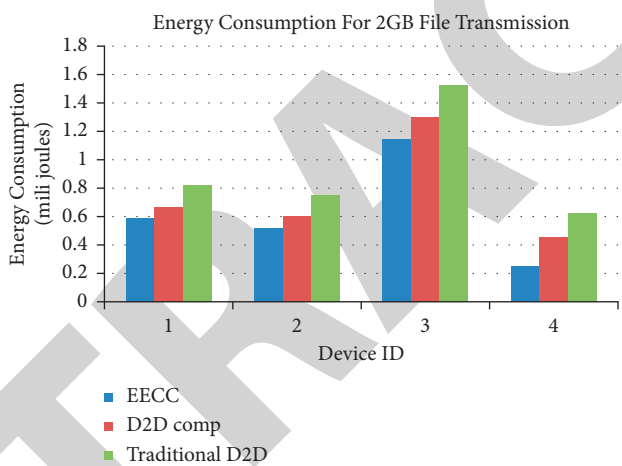

Figure 3: Energy consumption of devices to transmit 2 GB video content.

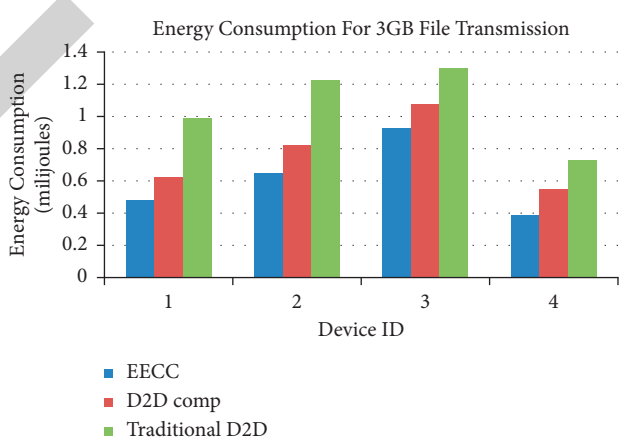

Figure 4: Energy consumption of devices to transmit 3 GB video content.

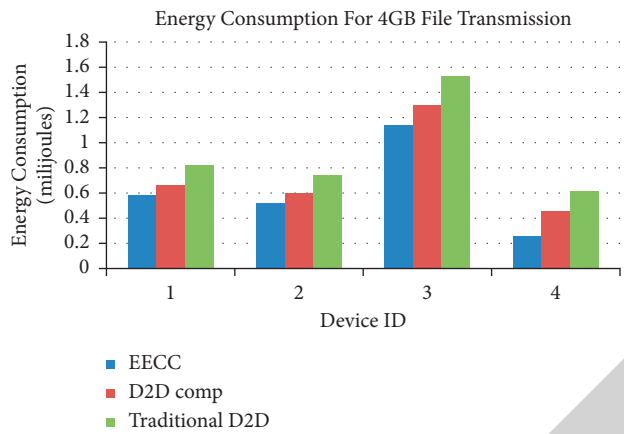

Figure 5: Energy consumption of devices to transmit 4 GB video content.

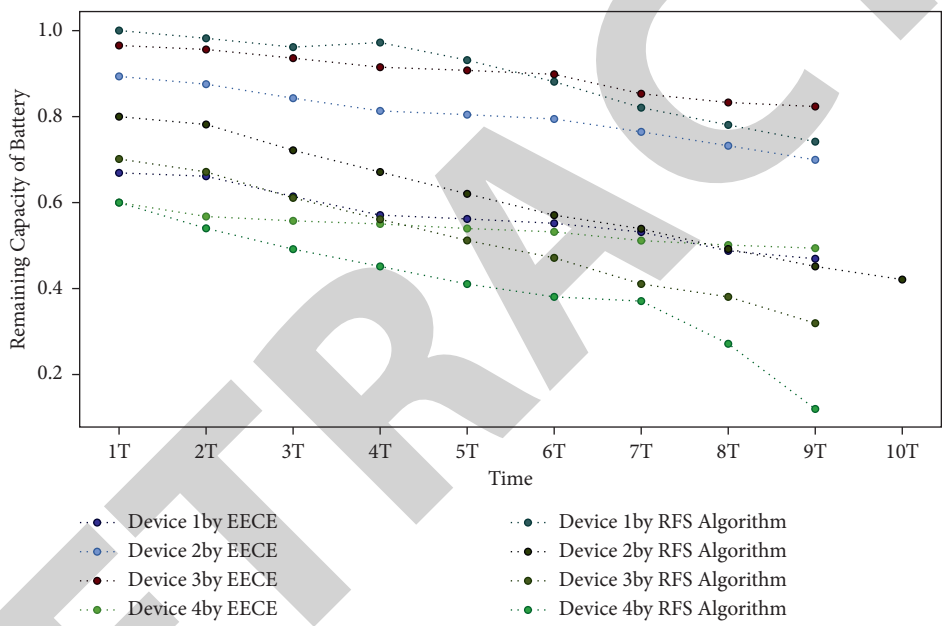

Figure 6: Time versus remaining capacity of the battery by different video segmentation models.

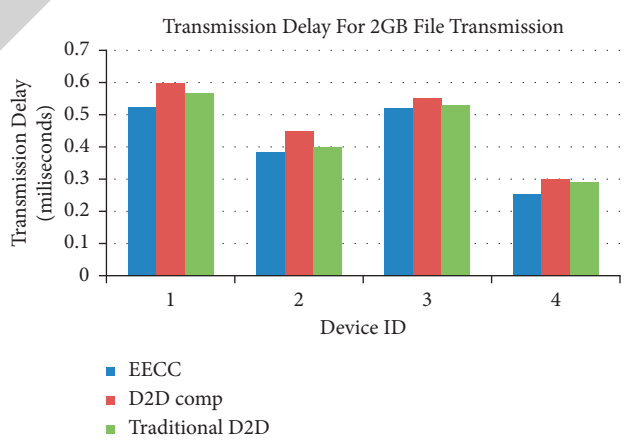

Figure 7: Transmission delay of 2 GB video file for both content sharing approaches.

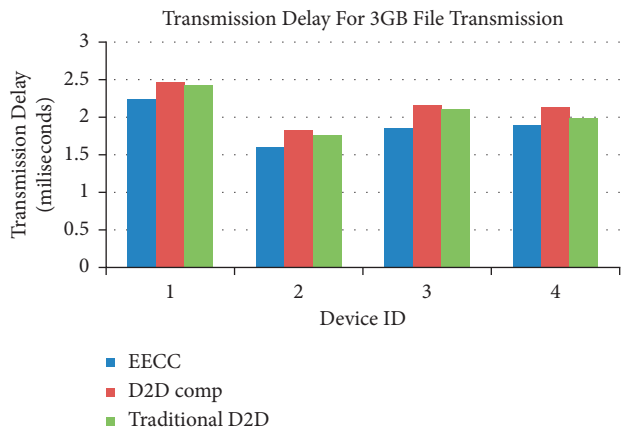

Figure 8: Transmission delay of 3 GB video file for both content sharing approaches.

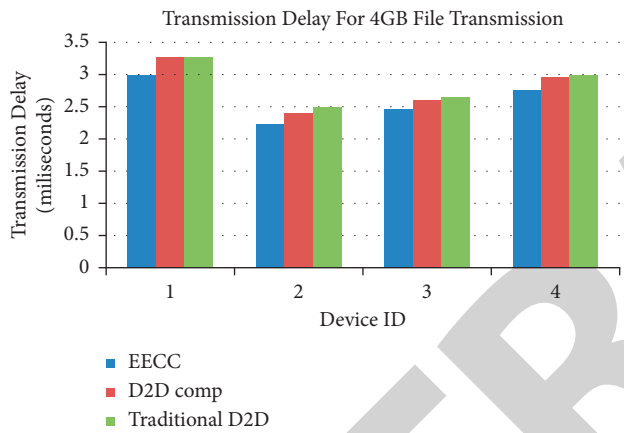

Figure 9: Transmission delay of 4 GB video file for both content sharing approaches.

devices as compared to the state-of-the-art *D2D* Comp and traditional *D2D* approaches, respectively. Similarly, the lower delay for our proposed approach can be seen in Figure 9 when compared with *D2D* Comp and traditional *D2D* approaches by 0.87% and 0.7%, respectively.

5. Conclusion

This paper proposes a 5G Energy-Efficient Collaboration-based Content (5G-EECC) technique for increasing energy efficiency while reducing delay. The proposed work includes the formation of clusters and the selection of cluster heads based on a reference point group mobility model and a weighted algorithm. A collaborative content sharing mechanism is explored using the Multilevel Pareto Least Recently Used (*MPLRU*) cache algorithm approach in which video caching is implemented on multiple devices, while energy consumption and communication efficiency factors are considered. Simulation results indicate the improvement in energy consumption and delay for our proposed 5G Energy-Efficient Collaboration-based Content (5G-EECC) approach when compared with the state-of-the-art traditional *D2D* approach and *D2D* Comp. To confirm the validity of our approach, we used the video file size ranging from 2 gigabytes to 4 gigabytes. The privacy leakage risk is one of the challenges that this technique may encounter. Distributed Denial of Service (DDoS) attacks are used by hackers to break into a network and cause service to slow down, sometimes leading to a service outage. The traditional approaches are not secure from these attacks. In the future, we will address such types of attacks to secure the network by using the deep learning approaches in consideration of the scalability of the network in terms of energy and delay.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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