Social-Aware Clustering for D2D Multicast Content Sharing in 5G Networks

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***Abstract*—The fifth generation (5G) cellular networks are expected to produce a massive amount of traffic due to the rapid development of 5G applications and Internet of Things (IoT) services. Content sharing through the device to device (D2D) multicast communication can effectively mitigate the burden of the cellular network and add to network capacity. To achieve effective content sharing among users, appropriate clustering strategy is needed. In this paper, we first present an integration of Software Defined Network (SDN) and millimeter wave based heterogeneous network (mmWave-based HetNet) for 5G networks to handle the massive traffic load. Then, we propose a clustering strategy for sharing the requested content by a group of users through D2D multicast communication to mitigate the burden of the cellular networks. Moreover, we formulate an optimization problem to maximize the efficiency of the D2D multicast clusters formation. Finally, we perform a simulation study to examine the impact of the maximum D2D communication distance, minimum social relation, and minimum distance among cluster heads on the clustering performance, so to evaluate the effective parameters needed to tune a desirable D2D multicast clustering strategy.**

***Index Terms*—5G, D2D, Clustering, Multicasting, Content Sharing.**

I. Introduction

The tremendous growth of user equipment (UE) along with the expansion of the bandwidth-demanding applications such as video streaming, online gaming, and multimedia sharing has contributed to a 74% increment in the network traffic over the last years [1] [2]. According to the smart devices developments and the network traffic growth rate, the number of cellular network subscribers is expected to reach 7.7 billion by 2021 [3] [4]. Moreover, by the implementation of the fifth generation (5G) network and the introduction of its applications (e.g., augmented reality, virtual reality, autonomous driving), the network traffic is expected to increase by 8-fold, whereas the network resources are scarce. Therefore, the radio access network (RAN) would be overloaded by this predicted huge traffic demand. Since upgrading RAN needs high capital investment and requires more licensed bands, directly upgrading the RAN is undesirable. Nowadays, the cellular networks have been paving the way toward a multi-tier architecture, in which a dense-deployment of heterogeneous small cells underlaid the macrocells [5]. Hence, the heterogeneous cellular networks (HetNets) in addition to present the required structure for approaching the 5G cellular network, they provide an effective way to handle the ever-increasingly network traffic. Despite the benefits of small cells dense deployment, the cellular networks still suffer from resource scarcity and enormous strain on base stations (BSs).

To mitigate the tremendous pressure on cellular BSs, establishing device-to-device (D2D) communication enables UEs to directly communicate with each other in a licensed spectrum leading to higher spectral efficiency and cellular capacity, lower energy consumption, and better traffic delay [6]. Since modern devices and smartphones have a significant storage capacity to store the data, they can share the requested data with neighboring UEs through D2D communication, which effectively relieve the burden on cellular BSs.

Content sharing is one of the common services in the content-centric networks, such as 5G networks, because Users constantly produce new content with the aim of sharing with the interested users by social media and video streaming applications. As the local users are likely to request the same content, sharing the content among UEs can significantly mitigate the burden on cellular BSs [7]. According to the conducted research in [8], the number of requests and popularity of given content follow the Zipf distribution. Thus, it is expected the users in a congested area like public events, stadiums, concerts, central malls require to access identical types of data. To cope with this challenge, D2D multicast communication can be utilized to share the content among users, in which instead of sending the requested content one-by-one by the BS, it would be relayed through the D2D link. Hence, part of users act as D2D multicast transmitters, which receive the content from cellular BS and directly forward it to intended users. Since the cellular BSs don't need to send the data multiple times, the scarce resources of the network are saved, which improves the Quality of Service (QoS) [9].

According to the literature, the clustering concept can improve the efficiency of the D2D multicast communication [10], and the formation of appropriate clusters influence the performance of the underlay cellular network [11]. Hence, clusters are formed, in which one UE is chosen as the cluster head (CH) that is responsible for synchronization and radio resource management of its cluster members. Thus, CH receives the requested data from the respective BS and multicast it among the intended members through D2D links. Most of

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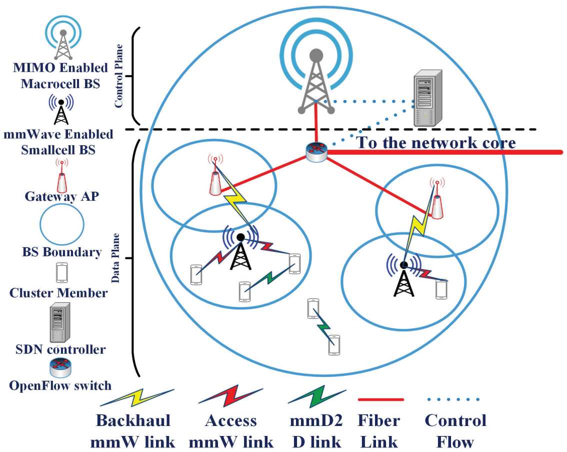

Fig. 1: Integration of SDN and mmWave-based HetNet for 5G networks.

the proposed methods to form the multicast clusters take only into account the physical location of users for selecting CHs and cluster members. The mobility of UEs affect the stability of clusters. Selecting a UE with a high level of mobility as a CH, frequently interrupts the D2D multicast transmission links because its stay time in the cluster is too short to complete the transmission processes. The residual energy is another factor in cluster stability. The CH without enough battery energy could lead to unwanted interruptions in transmission. The frequent interruptions extremely reduce cellular network performance. Moreover, the signal strength between the selected CH and corresponding BS significantly affects the QoS, so that a weak received signal by the CH extremely increases the transmission delay. Due to the importance of received signal strength by selected CH, the cross-interference among D2D multicast communications should be considered in the CH selection procedure, as well. Therefore, an optimal D2D multicast CH selection strategy should be designed reducing the transmission delay while increasing the network capacity and performance.

In this paper, we propose a clustering strategy for content sharing through the D2D multicast communication in 5G networks to improve the network capacity and spectral efficiency. Moreover, we formulate an optimization problem to maximize the efficiency of the proposed clustering strategy. Furthermore, we utilize a genetic algorithm to solve the optimization problem.

The major contributions of this work are listed as follow:

- An integration of Software Defined Network (SDN) and millimeter wave (mmWave)-based HetNet for 5G networks is presented to increase the network capacity through reusing the cellular resources for establishing the D2D communication.
- A cluster-based, social-aware D2D multicast content sharing is proposed to mitigate the burden of cellular small cell BSs (SBSs). Hence, UEs join the cluster that is related to the community of the requested content. Then, the CH shares the content among the members through the D2D links.
- A greedy cluster formation is proposed to maximize the number of admitted D2D UEs, which improve the spectral efficiency. The social strength, achievable data rate, node density, and residual energy are evaluated by the SDN controller to choose the optimal CH for each community.
- We utilize a genetic algorithm to solve the optimization problem, which ensures finding of global optima.

The rest of the paper is organized as follow. Section II provides a brief review of the related work. Section III presents the proposed system model. Section IV describes the proposed cluster-based multicast content sharing that includes the CH selection and joining the users to the selected cH. In Section V, the problem formulation and the solution of the optimization problem is presented. Performance analysis is demonstrated in Section VI, and conclusions are drawn in Section VII.

II. Related Work

It is reported in the literature that the cellular network can benefit the D2D multicast communication advantages to significantly mitigate the burden of massive traffic on cellular BSs [12] [13]. Clustering the users with similar interest can significantly improve the spectral efficiency through the sharing content by the D2D multicast communication [14] [15]. Authors in [16] presented an energy-efficient multi-hop clustering algorithm for multiple-input and multiple-output (MIMO) Internet of Things (IoT) systems to accomplish the energy-efficient and Quality of Experience (QoE) supported communication. It is a user behavior and context-aware clustering approach aiming to facilitate CH selection for IoT devices. In [17], the authors presented an adaptive vehicle clustering for SDN enabled 5G vehicular networks, in which vehicles in proximity are clustered using the road condition gathered by the SDN. In [18], the authors proposed a SDN-enabled, social-aware clustering in 5G vehicular networks. They utilized a social pattern prediction model to enhance the stability of clusters causing the improvement of user experience. To model the movement of vehicles, a discrete time-homogeneous semi-Markov model used. To do so, integration of state transition probability and sojourn time probability distribution presented, in which the social pattern of vehicles generate as the output of the model. Then, the predicted social pattern is used for cluster formation. Due to the importance of the vehicle's distance and speed, the cluster head selection strategy is formulated based on the inter-vehicle distance and their relative speed. In [19], the authors presented a cluster selection method for content-centric 5G networks, where a combination of the node density and the neighboring degree is proposed as a metric to select nodes. The focus is on how a BS selects the appropriate CHs that are very influential in the community of requested content, and on designing a suitable cashing mechanism for system model to increase the hit ratio.

Different from the existing efforts, in this paper, we take into account the cluster transmission rate, social relation, node density, and residual energy to maximize the efficiency of cluster formation. We consider a SDN controller as the responsible entity to manage all activities in the cell. Hence, for each recognized community, the SDN selects an optimal CH such that a large number of UEs would desire to join the formed D2D multicast cluster.

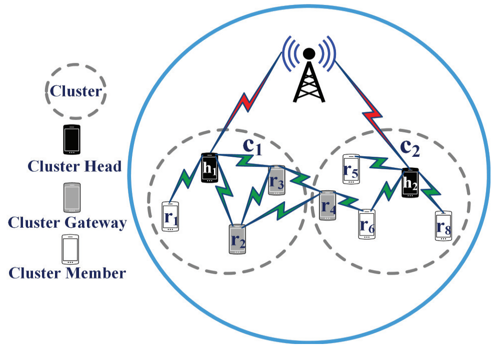

Fig. 2: D2D multicast clustering scenario.

III. System Model

We propose a mmWave-based D2D multicast communication for 5G HetNets to increase the network capacity and improve the spectral efficiency, as depicted in Fig. 1. We consider a single-cell cellular network with a massive MIMO-enabled Macrocell BS (MBS) located in the center, and a number of mmWave-enabled small cell BSs (SBSs) densely underlaid the macrocell. The objective of the dense deployment of SBSs is to bring the RAN closer to UEs, which ensures the high-quality transmission links. Since establishing the fiber-optics link between all SBSs and the network core is difficult, because of urban cabling restrictions and the expensive costs, wireless communication can be a proper alternative for deployment the small cells due to easy deployment, cost-effectiveness, and flexibility. Therefore, in our proposed system model, the integrated access and backhaul (IAB) scheme is considered for connecting SBSs to each other and to the network core, in which SBSs use the mmWave frequency band for both backhaul links and access links. Hence, SBSs transmit the backhaul traffic to a gateway Access Point (AP) via mmWave link and then the gateway AP forwards the received traffic toward the network core.The key to establishing a high-performance backhauling by the mmWave links is to provide the exact line-of-sight (LOS) among SBSs. Since it is difficult to acquire LOS for backhaul links in an urban environment, the multi-hop relays are considered for backhaul traffic, using short-distance and highly capable links. Thus, SBSs can reach the gateway AP using multi-hop relays if there is not any direct backhaul link to the gateway AP.

Small Cells dual connectivity (DC) is applied to increase the per-user throughput and mobility robustness, in which UEs simultaneously are connected to an MBS and an SBS. It enables the separation of control plane and data plane such that MBS manages the connection and mobility, while the SBSs deal with data delivery. An SDN controller is deployed to facilitate the management of the cellular network by the separation of the control plane and data plane. The SDN controller deals with all control signaling and instructs the OpenFlow (OF) switches through the OpenFlow interface to handle the data flow. The SDN needs to collect and maintain the up to date information about all the network entities. Since UEs are simultaneously connected to one MBS and one SBS (dual connectivity), SDN is up to date about the UEs' status. SDN can communicate with the application and services over the network through the application program interfaces (APIs), like RESTful APIs, to facilitate orchestration and automation of the different applications' requirements. Moreover, OF interfaces connect the SDN controller to OF switches for implementing the SDN in networking equipment. The OF switch proceeds with a lookup of the received packet into the flow table, and if there is a match then the OF switch runs a set of actions and forwards the packet to the destination. Otherwise, the SDN controller decides how to deal with the packet without valid flow entry. The OF switch is programmable by the SDN controller through adding or deleting flow entries. Since the OF switch provides communication between the MBS and the SBS via the fiber links, transferring the backhaul traffic among them will be fast with negligible delay since they are all connected to the same switch.

IV. Proposed Cluster-Based Multicast Content Sharing

To mitigate the burden of SBSs, a cluster-based D2D multicast content sharing is defined to distribute the requested content among a group of UEs through mmWave D2D links. We assume there are k UEs $U = \{u_1, u_2, ..., u_k\}$ in a small cell area, where all k UEs requested the specific contents. If the content is valuable for the users just in a short period of time, it is forwarded to UEs by the cellular link; otherwise, it is delivered to the UEs by the D2D multicast communication. The key to ensuring the performance of content sharing through the D2D multicast communication is the formation of D2D clusters, which consists of CH selection and joining UEs to the proper cluster. In general, clustering aims to achieve network scalability, stability, and improve performance through the load balancing. In 5G networks, clustering caters to meet the ultra-densification, network heterogeneity, and high variability.

For the sake of generality, there are n clusters $G = \{c_1, c_2, ..., c_n\}$. As depicted in Fig. 2, each cluster includes one CH as the transmitter and plenty of cluster members (CM) as the receivers. CHs are selected among UEs and comprise of $\Upsilon = \{h_1, h_2, ..., h_n\}$, where h_n denotes the CH of cluster c_n. The rest of UEs are considered as CMs and they collectively form $\Psi = \{r_1, r_2, ..., r_m\}$. Each cluster might have a CM who can establish a D2D link with a member of the adjacent cluster that is called the cluster gateway (CG). Note that, each UE can only be the member of one cluster and there is no overlapping among the clusters.

For content sharing through D2D communication, first, an SBS receives the request for sharing specific content from a group of UEs. According to the different interested contents, UEs can form the communities denoted as $\Lambda = \{g_1, g_2, ..., g_l\}$. UEs with strong social strength can form the D2D multicast cluster, if they can satisfy the D2D communication conditions. For each community, there are some active UEs denoted as $\Lambda_U(g_l) = \{r_{g_l,1}, r_{g_l,2}, ..., r_{g_l,k}\}$. The SDN controller selects CHs for each community and broadcasts CH identification and location to active UEs. Then, each UE decides whether to join selected CHs or not based on the received information, i.e., a UE might not discover the desirable CH, thus UE who can not join a proper cluster receives the content by the cellular link. After clusters are formed, SBS transmits the content to the CHs and the UEs that are operating in cellular mode. Once a CH receives the content will share it with its CMs through the

D2D multicast communication. The re-clustering formation occurs when changes appear in the current clustering structure, including joining/leaving of UEs to/from the cluster. The re-clustering is essential, because of managing a large number of joining and leaving of UEs, rotating the role of CHs, and offering load balancing.

Since content sharing relies on wireless transmission, there is a need to ensure the availability of link resources. For sharing the received content by the CHs with their CMs, mmWave based D2D communication is utilized due to the IAB scheme, which improves the efficiency of spectrum utilization by reusing the link resources.

As mentioned before, clustering includes two major phases, that is, the CH selection and the cluster formation, which affect the overall network performance. In the rest of this Section, we explain both in detail.

A. CH Selection

In the clustering context, CHs are chosen among the active UEs as the point of entry or sending aggregate data toward the network. In multicast systems, CHs are bridges between the SBS and CMs. It is favorable that the UE be selected as CH that can serve the highest number of CMs. This fact causes better spectral efficiency. Thus, selecting a UE with the larger node density and better social strength can be an optimal solution to improve spectral efficiency. To measure the ability of UEs for acting as CH, we introduce the centrality degree, node density, and residual energy as follow.

1) Centrality Degree: The centrality measures the ability of each UE for establishing connection with UEs in proximity in terms of the physical distance and social closeness, such that the larger the degree of centrality, the more efficient cooperation. To calculate the centrality degree, first we need to calculate the CH transmission rate and social strength as below.

- *CH Transmission Rate:* In the cluster-based multicast systems, the CH transmission rate can be measured as the lowest transmission rate between the respective CH and its CMs [20]. Hence, we defined the CH transmission rate as the minimum achievable data rate of the CMs in the corresponding cluster. Consider c_n as the n_{th} cluster with h_n as its CH. Let $\alpha_{r_m}^{h_n}$ show whether CM r_m joins cluster C_n, in which $\alpha_{r_m}^{h_n} = 1$ denotes r_m is in c_n; otherwise it is out of c_n. The achievable data rate of r_m can be calculated by
$$\varphi_{h_n,r_m} = BLog_2\left(1 + \frac{p_{h_n} g_{h_n,r_m}}{BN_0 + p_{c_g}^{h_n} g_{c_g,r_m}^{h_n}}\right) \tag{1}$$
where B denotes the link bandwidth, p_{h_n} is the transmission power of respective CH, g_{h_n,r_m} shows the gain between h_n and r_m, N_0 represents the power noise, $p_{c_g}^{h_n}$ is the transmission power of the users in cellular mode that reuse the cellular link with h_n, and g_{c_g,r_m} is the channel gain between c_g and r_m. Thus, the transmission rate of CH h_n with cluster formation strategy $\Phi = \{\alpha_{r_m}^{h_n} | r_m \in \Psi, h_n \in \Upsilon\}$ is equivalent to the minimum achievable data rate between CH h_n and its CMs in cluster c_n, which can be denoted as below.
$$\Theta_{h_n}(\Phi) = min\left\{\varphi_{h_n,r_m} | \forall \quad \alpha_{r_m}^{h_n} = 1\right\} \tag{2}$$
- *Social Strength:* Since CHs consume more energy, local storage, and bandwidth, compared with CMs, they are not perfectly happy to act as a bridge between the SBS and CMs. However, UEs with high social relations are willing to share content despite the losses even under ultra-dense networks [21]. Thus, the social relationships of UEs need to be considered for CH selection to persuade the selected CH for tight cooperation with the other UEs resulted in the improvement of the clustering performance in terms of the number of clusters and average cluster size. We define the tendency degree and contact degree to measure the social strength among UEs. Let symmetric matrix $A = \{\varepsilon_{r_i,r_j}\}_{N\times N}$, in which ε_{r_i,r_j} denotes the social strength between r_i and r_j.

  Assuming L categories of content, we denote the tendency degree of r_i and r_j as L dimensional vectors Y_{r_i} and Y_{r_j}, respectively. The tendency degree for a given category is calculated by the cumulative access time in a certain period of time. According to the cosine similarity [22], the tendency degree between r_i and r_j can be calculated and normalized as given below.
$$\gamma_{r_i,r_j} = \frac{Y_{r_i} Y_{r_j}}{|Y_{r_i}| \,.\, |Y_{r_j}|} \tag{3}$$
  The contact degree between r_i and r_j can be calculated and normalized as
$$\rho_{r_i,r_j} = \frac{b_{r_i,r_j}}{b_{r_i,r_j}^{max}} + \frac{t_{r_i,r_j}}{t_{r_i,r_j}^{max}} \tag{4}$$
  where b_{r_i,r_j} and t_{r_i,r_j} represents the contact number and the contact period, respectively. Thus, the social strength between r_i and r_j can be denoted as follow.
$$\varepsilon_{r_i,r_j} = \gamma_{r_i,r_j} + \rho_{r_i,r_j} \tag{5}$$

According to the formulated CH transmission rate and social strength in (1) and (5), respectively, the centrality degree of UE r_i can be calculated by
$$\Gamma_{r_i} = \sum_{r_j \in, i \neq j} \frac{\varphi_{r_i,r_j}}{\varphi_{max}} + \varepsilon_{r_i,r_j} \tag{6}$$

2) Node Density: To improve spectral efficiency, a UE should be selected as CH if it can serve a large number of CMs. Thus, a UE with more node density should have a higher priority to be selected as CH. Using node density as a metric for CH selection can increase the cluster stability because the selection of a UE with higher node density enhances the probability of having a connection between the respective CH and a CM. Let t_{r_i} be the transmission range of UE r_i and d_{r_i,r_j} be the euclidean distance between r_i and r_j. Thus, r_j is within coverage of r_i if $d_{r_i,r_j} < t_{r_i}$. Hence, the normalized node density of UE r_i can be calculated by
$$\lambda_{r_i} = \frac{\sum_{\forall r_i, r_j \in \Psi, r_i \neq r_j} \left(d_{r_i,r_j} < t_{r_i}\right)}{k} \tag{7}$$

3) Residual Energy: In the 5G networks, selecting a UE that possesses higher residual energy compared to the rest of the candidate UEs can increase the network lifetime. This is due to the fact that the selection of UE with higher residual energy as CH enhances the connection time between CH and CMs and improves the load balancing. Moreover, using the residual energy as a clustering metric declines the re-clustering occurrence. Thus, it can significantly enhances the clusters stability. The normalized residual energy of r_i is denoted as $\frac{E_{r_i}}{E_{initial}}$.

B. Cluster Formation

To form the D2D multicast clusters we provide a greedy method consisting of the following steps.

Step 1: The SBS receives the communities set Λ according to the requested content by UEs. For each community g_l, we initialize the set $y^l = \Lambda_U(g_l)$.

Step 2: The SDN controller selects a UE $r_{g_l,i}$ as CH for each community. The SDN controller evaluates each active UE in y^l based on the centrality degree, node density, and residual energy to find the optimal CH. The selected CH is announced to the community to form a cluster for sharing the requested content.

Step 3: Each active UE $r_{g_l,i} \neq r_{g_l,j}$ can join the formed cluster $c(r_{g_l,i})$ if it simultaneously satisfies two conditions. First, the social strength between UE and CH should be bigger than their minimum strength relation requirements. Second, UE has a proper achievable data rate with CH or any UE who is connected to CH through the D2D link.

Step 4: After $y^l = y^l - c(r_{g_l,i})$, if $|y^l| > 1$ the SDN selects additional CH among the rest of active UEs in y^l and Step 3 is repeated; otherwise, the cluster formation terminates.

V. Problem Formulation

To maximize the efficiency of content sharing through D2D multicat communication, the key is the formation of proper clusters, in which CHs are the UEs with strong centrality, high node density, and high residual energy. Thus, we formulate an optimization problem as below.

$$\max_{\Phi} \quad \{\Theta_{h_n}(\Phi), \Gamma_{h_n}(\Phi), \lambda_{h_n}(\Phi), E_{h_n}(\Phi)\} \tag{8}$$

subject to :

$$C_1 : \sum_{i=1}^{n} \alpha_{r_j}^{h_i} \leq 1, \quad \forall r_j \in \Psi, \tag{8a}$$

$$C_2 : \sum_{j=1}^{m} \alpha_{r_j}^{h_i} \leq \omega, \quad \forall h_i \in \Upsilon, \tag{8b}$$

$$C_3 : \varphi_{h_i,r_j} \geqslant \varphi_{min}, \quad \forall r_j \in \Psi, h_i \in \Upsilon \tag{8c}$$

$$C_4 : \varepsilon_{h_i,r_j} \geqslant \varepsilon_{min}, \quad \forall r_j \in \Psi, h_i \in \Upsilon \tag{8d}$$

$$C_5 : D_{h_i,h_j} \geqslant \zeta, \quad \forall hi, hj \in \Upsilon. \tag{8e}$$

Constraint C_1 ensures that each CM only joins one cluster. Constraint C_2 limits the cluster size to ω, which is the maximum size of a cluster. Since coordination within a dense cluster is very complicated, limiting the size of clusters avoids wasting CH resources and reduces the signaling overhead. Constraint $C3$ and $C4$ ensure the transmission rate and the social strength should be greater than their minimum requirements. Constraint $C5$ states that each CH must keep the minimum distance ζ from each other to avoid wasting their capacity.

A. Solution For Optimization Problem

Since the objectives in (8) are non-conflicting, the optimization problem can be solved as a single objective problem. Thus, we employ the genetic algorithm (GA) to find the optimal CH, since GA can guarantee the convergence to the global optima for single objective optimization problems. GA is an iterative metaheuristic approach inspired by the natural process of generating chromosomes to produce new solutions in a real search space. The formal model of using GA to search the optimal solution is introduced in the GA Schema Theorem [23].

Table I: An example of problem encoding.

	Centrality degree	Node density	Residual energy	CH
$\mathbf{u}_1$	0.6	0.1	0.4	0
$\mathbf{u}_2$	0.45	0.3	0.6	0
$\mathbf{u}_3$	0.73	0.6	0.58	1
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathbf{u}_k$	0.58	0.4	0.45	0

In GA, a potential solution is represented in the form of a chromosome-like structure. The population comprises a set of solutions (individuals), which is randomly initialized within the search space. The individuals are evaluated based on a fitness function. In each iteration of GA, the individuals that present superior fit are chosen as the parents to produce the new solutions. To do that, the crossover operator is applied to the selected parents for generating the offsprings. Then, the mutation operator randomly modifies the offsprings with the aim of achieving a better generation. The offsprings replace weaker solutions in the population to progressively evolve the population toward the optimal solution.

1) Problem Encoding: To implement the GA, there is a need to specify the individuals and chromosomes structure. For the formulated problem, the centrality degree, node density, and residual energy of each UE are encoded by a chromosome structure. Thus, the number of chromosomes in the search space is equal to the number of UEs. The structure of an individual for our problem with k chromosomes is presented in Table I.

2) Fitness Function: The most important issue to design an effective GA is the definition of a proper fitness function to distinguish the superiority of solutions into the search space. Since it forms the basis of the selection process, it can facilitate population improvements. Fitness function is a cost function, which basically is a mathematical expression for any performance metric that should be optimized. In our optimization problem, the fitness function includes the CH transmission rate, centrality degree, node density, and residual energy as the fitness parameters. The objective functions in (8) and the constraints (8.a)-(8.e) can be used to build up the fitness function. First, we use the weighted sum method [24] to integrate the objectives into a single objective as below.

$$\max_{\Phi} f(\Phi) = \big(\alpha\Theta_{h_n}(\Phi) + \beta\Gamma_{h_n}(\Phi) + \gamma\lambda_{h_n}(\Phi) + \epsilon E_{h_n}(\Phi)\big) \tag{9}$$

$$\text{subject to:} C_1 - C_5. \tag{9a}$$

where α, β, γ, and ϵ assign the weight to each objective, such that $\alpha + \beta + \gamma + \epsilon = 1$. To convert the maximization problem to a minimization problem, the equation (9) is multiplied by -1 as follows.

$$\min_{\Phi} f(\Phi) = \max_{\Phi} -f(\Phi) \tag{10}$$

$$\text{subject to:} C_1 - C_5. \tag{10a}$$

According to [25] the constraints are relaxed through the penalty function method, in which the infeasible solutions are penalized in proportion to their constraints violation. Thus, relaxing the constraints $C_1 - C_5$, the unconstrained function can be derived as given

$$f(\tau,\Phi) = -\Big(\alpha\Theta_{h_n}(\Phi) + \beta\Gamma_{h_n}(\Phi) + \gamma\lambda_{h_n}(\Phi) + \epsilon E_{h_n}(\Phi)\Big) + \tau\Bigg[\Big(\max\big\{0, \textstyle\sum_{i=1}^{n}\alpha_{r_j}^{h_i} - 1\big\}\Big)^2 + \Big(\max\big\{0, \textstyle\sum_{j=1}^{m}\alpha_{r_j}^{h_i} - \omega\big\}\Big)^2 + \Big(\max\big\{0, \varphi_{h_i,r_j} - \varphi_{min}\big\}\Big)^2 + \Big(\max\big\{0, \varepsilon_{h_i,r_j} - \varepsilon_{min}\big\}\Big)^2 + \Big(\max\big\{0, d_{h_i,h_j} - \zeta\big\}\Big)^2\Bigg] \quad (11)$$

where τ is a coefficient value for the penalty terms.

3) Selection: To preserve the most fit individuals to generate the best offsprings, we employ the ranking selection method, in which the rank of each solution is determined based on its measured cost by the fitness function. Moreover, the elitist strategy [26] is applied to the ranking selection method to ensure the quality of the selected parents for the next iteration. Thus, after ranking the eligible solutions, elitism [26] is applied to preserve the current CH until there is a richer new solution better than the current one, which decreases the signaling overhead.

4) Genetic Operators: GA operators are applied to the selected parents to generate better new solutions (offsprings). The crossover is a binary operator in the GA theorem, which performs the mating process of two selected parents. In this work, we utilize a crossover based on a single point, in which the chromosomes exchange the bitstream after reach the single point. The crossover rate determines whether the CH is periodically changed or not. By applying the crossover to the selected parents, the new generation inherits the characteristics of the parental chromosomes. Hence, the search space remains similar to local solutions. To escape from this issue, the mutation is applied to ensure the arising of new genes into the solutions leading the search space toward the optimal solution.

5) Termination: The termination of the GA occurs after predefined iterations. Moreover, during each iteration the fitness value of each chromosome is compared with the value of the last iteration. Thus, the best chromosome or UE is selected as CH, but if there is no better solution than current CH, it will be preserved.

The GA steps to select the optimal CH are explained in Algorithm 1. First, the GA parameters are initialized including the number of chromosomes into the search space (N_{GA}), population size (S_{GA}), GA crossover rate (P_c), mutation rate (P_m), generation number (Gen), and weight coefficient for fitness parameters. After initialization, a set of chromosomes are chosen for further operations. The selected chromosomes are evaluated by the fitness function in (11). To find the best CH, the GA continues until the termination criteria is reached. The rank selection method is applied to select the fittest chromosomes. Then, 1-point crossover is applied to generate new individuals by the mating of two parents with predefined crossover rate. The new chromosomes are applied over the mutation operator to escape from getting stuck to the local solutions. In the end, the population is updated by the new solutions and the fittest is retained by the elitist strategy. Hence, if the current CH is more fit than the selected one by the GA, it remains as CH until a better solution is found.

Algorithm 1: Proposed GA for CH selection

```
Result: Optimal CH
Initialize the parameters of GA:
    N ← The number of UEs
    IterMax ← The maximum number of iteration
    P_c ← The crossover rate
    P_m ← The mutation rate
Initialize the parameters of fitness function:
    Θ_{h_n}(Φ) ← The cluster transmission rate
    Γ_{h_n}(Φ) ← Centrality degree
    λ_{h_n}(Φ) ← Node density
    E_{h_n}(Φ) ← Residual energy
Gen ← 0
CH ← Current CH
Initialize A set of chromosomes into X
    X={ x_1, x_2, ..., x_{S_GA} }
Evaluate Fitness value of X={ x_1, x_2, ..., x_{S_GA} }
while (Termination criteria reached) do
    Gen ← Gen + 1
    Rank X based on the fitness values
    Select the most fit chromosomes by rank selection
      Fit_X(a, b) ← Rank − selection(X)
    Apply Crossover operator into Fit_X
      Crossover(Fit_{Xa}, Fit_{Xb},   P_c) ⇒ a, b
    Apply mutation operator over new chromosomes
      Mutation( a,   P_c) ⇒ ã
      Mutation(b,    Pm) ⇒ b̃
    Update The Population with new generations
end
Apply The elitist strategy
  If (fittest(X) is better than CH) Then
    Optimal CH ← fittest(X)
  end
```

VI. Performance Analysis

In this section, simulations are conducted to study the behavior of the proposed clustering strategy for content sharing. We carry out the simulations in a single cell scenario within a $400 * 400\ m^2$ area, where BS is located in the middle of cell and UEs are randomly distributed. The simulations parameters and corresponding values are given in Table II. The performance of content sharing through D2D multicast communication relies on the CHs selection and clusters formation. Thus, we analyze the results of cluster formation with respect to the remaining cellular UEs, admitted D2D UEs, D2D multicast clusters, and average size of clusters.

Fig. 3 presents the number of cellular mode UEs versus the active UEs after performing the proposed cluster formation with different maximum D2D distances (d) and minimum social strengths (ε_{min}). It is clear that the number of cellular

Table II: NETWORK PARAMETERS.

PARAMETERS	VALUE
Network Size	400*400 m^2
Number of UEs	20-100
mmWave BS Transmission Power	30 dbm
UE Transmission Power	20 dbm
Bandwidth	2.16 GHz
Path Loss	140.7+36.7Log1(r)
Background Noise Density	-174 dBm/Hz
Fitness Parameters Weight	α=0.3, β=0.3, γ=0.2, $\epsilon = 0.2$
GA Parameters	$P_m = 0.04, P_c = 0.3$
Population Size	50

UEs that can not join any D2D clusters grows as the number of active UEs increases. As it can be seen, the curves for the maximum D2D distance $d = 60m$ are below the ones for $d = 20m$, because more UEs that have shown interest to specific content can join to D2D multicast clusters. Thus, a larger d can reduce the number of UEs in cellular mode, causing to improved spectral efficiency. Moreover, by comparing the curve, it can be seen that increasing the value of minimum social strength requirement for establishing a D2D link between two UEs or between a UE and CH, leads to an increase of the number of UEs in cellular mode. On the other hand, considering a small value for ε_{min} significantly decreases the efficiency of D2D communication.

Fig. 4 presents the admitted D2D UEs per given active UEs. It is obvious that the admitted D2D UEs grow along with the increment of active UEs. By comparing the curves, it can be seen that considering a large value for d leads to an increment in the admitted D2D UEs, because a higher number of UEs could establish a D2D link to join a D2D multicast cluster.

Fig. 5 illustrates the number of D2D multicast clusters versus the active UEs. It can be observed that the number clusters decreases as the ε_{min} increases with $d = 20m$, because it applies a strong constraint for communication of UEs through a D2D link. On the other hand, in the case of $d = 60m$, the number of D2D multicast clusters increases when ε_{min} increases for a large number of active UEs, while it decreases when ε_{min} increases for a small number of active UEs. Thus, a small ε_{min} in an area with a large number of UEs decreases the impact of d, causing more UEs to join each cluster that results in a lower number of D2D multicast clusters. Alternatively, enhancing ε_{min} leads more UEs to be rejected to establish the D2D link; thus, these UEs can either form other small clusters or switch communication mode to cellular. As a consequence, the number of clusters is enlarged, and the average size of the clusters is reduced.

Moreover, we study the impact of the minimum distance among CHs ζ on the cluster formation. Fig. 6 presents the D2D multicast clusters versus given ζ for two scenarios of the proposed clustering with maximum D2D distance $d = 20m$ and $d = 60m$, respectively. It is clear that the number of D2D multicast clusters decreases as ζ increases. This highlights the fact that applying the minimum distance constraint for selecting multiple CHs avoids selecting CHs that are so physically close to each other. Reducing the number of clusters, more UEs join each formed cluster, leading to an increase in the size of clusters. As depicted in Fig. 7, the average size

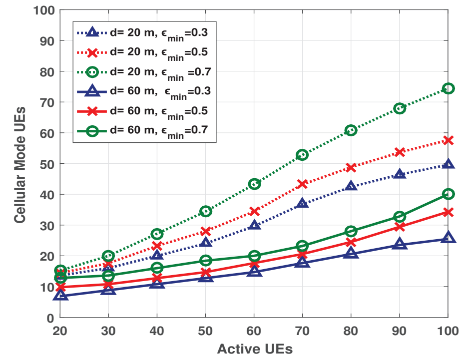

Fig. 3: Number of cellular UEs vs Active UEs.

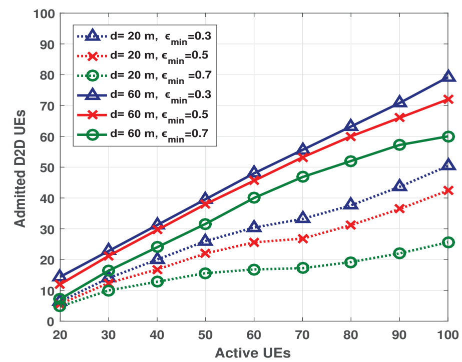

Fig. 4: Admitted D2D UEs vs Active UEs.

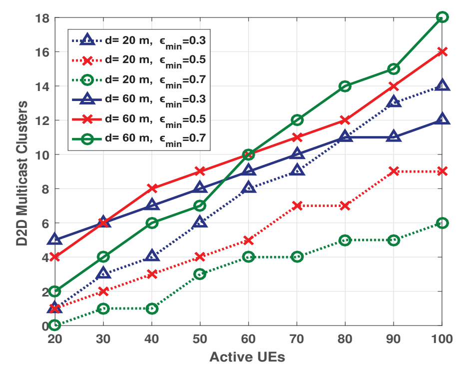

Fig. 5: D2D multicast clusters vs Active UEs.

of clusters grows with increasing ζ. However, considering a big value for ζ, the average size of clusters declines. This is due to the limitations of the cluster's size and the maximum D2D distance. In case the cluster capacity is full and there is no relay within D2D communication range, the UE has to switch to the cellular mode. As it can be observed from Fig.7, the curve $d = 20m$ declines after $\zeta = 40m$, and the curve $d = 60m$ declines after $\zeta = 70m$.

In general, the aim of D2D multicast clustering is to improve spectral efficiency. According to this objective and the observed behavior of our proposed clustering strategy, to reach a maximized performance of the proposed clustering strategy there is a need to jointly optimize the maximum D2D communication distance d, minimum social relation ε_{min}, and minimum distance among CHs ζ.

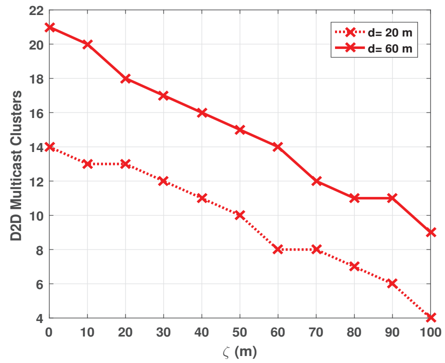

Fig. 6: D2D multicast clusters vs minimum distance among CHs, number of active UEs=100, $\varepsilon_{min} = 0.5$.

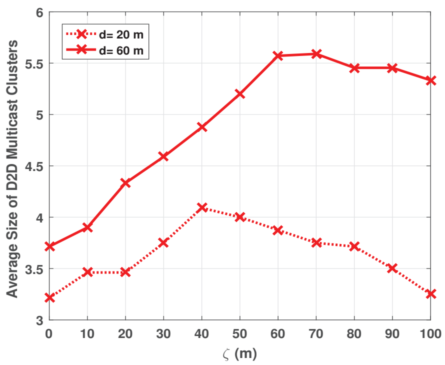

Fig. 7: Average size of D2D multicast clusters vs minimum distance among CHs, number of active UEs=100, $\varepsilon_{min} = 0.5$.

VII. Conclusion

In this paper, we proposed a social-aware D2D multicast communication for content sharing in 5G networks. We specifically designed a D2D multicast clustering strategy, which simultaneously takes into account the CH transmission rate, centrality degree, node density, and residual energy to select the optimal CH among the active UEs. Moreover, we formulated an optimization problem to maximize the efficiency of the cluster formation by solving a constrained problem. We proposed a GA to solve the formulated problem. Finally, we conducted a performance analysis through simulation study to evaluate the proposed cluster formation strategy. As future work, we would study the network performance in detail and jointly optimize the maximum D2D communication distance, the minimum social relation, and the minimum distance among CHs so to maximize the efficiency of content sharing through it applies a strong constraint for communication of UEs through the D2D communication in 5G networks.

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