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Enhancing quality of experience using peer-to-peer overlay on device-to-device communications

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Summary

With the recent development of LTE-A/5G technologies, data sharing among mobile devices offer an attractive opportunity to reduce Internet access. However, it requires smart strategies to share the data with low trade-offs in time, cost, and energy. Several existing schemes offer a super-peer-based two-tier model using a distributed hash table (DHT) organization for smart devices having device-to-device (D2D)/Bluetooth/WiFi capabilities. The primary focus of these schemes has been to reduce Internet usage by increased D2D content sharing. However, the real challenge is not in creating a two-tier model, but evolving an efficient overlay that offers enhanced opportunities for D2D content sharing over the existing model. In this paper, we formulated a P-median-based selection of tier-1 devices in a distribution network and solved it using the Lagrangian relaxation method. The tier-2 devices become clients seeking content sharing services from tier-1 devices. A strong motivation in this work is to raise a user's perception of the grade of service known as quality of experience (QoE). We analyzed the challenge for QoE assessment in resource-constrained smartphones under the proposed model of enhanced D2D communication. Our focus is to establish a framework to evaluate QoE for applications and services over LTE-A/5G networks with an improved D2D communication level. The simulation and the experimental results validate the claim that substantial improvements in QoE are possible with the proposed mathematical model for selecting and placing tier-1 mobile devices and maintaining a DHT for D2D communication.

KEYWORDS

cellular network, distributed hash table, file-sharing application, mobile peer-to-peer, P-median, quality of experience

1 | INTRODUCTION

The mobile networks have witnessed exponential growth during the last decade or so. The digitization process is extremely convenient for any transaction involving finance, business, health care system, education, travel, entertainment, and so forth. However, most of these transactions are associated with the online sharing of digital content on smartphones either over the Internet or the cellular networks (LTE-A/5G, etc.). Excessive use of a phone's wireless interface leads to substantial cost and the drainage of the battery power.[1,2] Furthermore, the intermittent nature of the cellular network leads to wide variations in signal strengths, which increase both cost and energy consumption at end devices.

To overcome limitations of the cellular network, for content sharing under a limited coverage area with limited cost, device-to-device (D2D), Bluetooth, and WiFi capabilities of the devices can be harnessed. Different mechanisms[3-5] have been proposed to reduce the dependence on the Internet and to share files in the coverage area (vicinity) for content sharing applications (apps) The apps' performance can be improved further by creating and maintaining a distributed hash table (DHT)-based overlay of mobile devices in a cellular network such as LTE-A.[6,7] In a DHT-based implementation, the members of different vicinity communicate using only a few cellular radio links (or the Internet). Therefore, the users can use various apps and services with a better quality of experience (QoE) than the non-DHT users and at the same time bring down the charges due to cellular communication.

Of late, the requirement for quality of service (QoS) has been gradually shifting more towards the users' experience, which is known as QoE. QoE indicates the degree of a user's satisfaction from the communication services. Fiedler et al.[8] made an in-depth study to understand the differences between QoE and QoS. QoE characterizes qualitative aspects, such as a user's perception, experience, and expectations from an application and the network performance. On the other hand, QoS is primarily a quantitative measure to capture the quality aspects as perceived by a user. Therefore, QoE is more appropriate for characterizing the quality of the communication service provided by the operators.[9]

QoE-based techniques are unsuitable for resource-constrained devices though they are better alternatives to QoS-based ones for estimating the quality of applications or services. By downgrading the parameters of QoE computational metrics, it is possible to use these techniques for devices with limited capabilities. Therefore, Alfayly et al.[10] used pre-assigned user satisfaction parameters to find QoE of intelligent spectrum allocation in D2D communications. Besides, a better QoE service depends also on the organization of the network. In our previous work,[6] we proposed a DHT-based P2P overlay for efficient file sharing. A selected subset of mobile stations (MSs), known as pilots, is organized into a DHT ring over WiFi. Each pilot works as a super-peer (tier-1 device) and provides file access capability to all other mobile stations (tier-2 devices) within the D2D (or Bluetooth) range of the pilot. However, we realized that pilots' random selection would lead to their instability due to uneven drainage battery power and imbalance in the data retrieval loads. The unstable pilots drastically degrade the QoE for the end-users. Apart from that, the focus of the existing optimization methods, including pilot/super-peer selection, is on the proximity and cluster organizations. Primarily, the optimization methods focus on minimizing the difference between peers and super-peers in terms of physical and overlay connectivity. However, it is not sufficient to provide a better QoE for a P2P service, mainly when the peers (mobile phones) have limited resources such as battery capacity. To enhance the QoE, we propose a super-peers selection method based on their data serving capacity, current loads, and the hop distances from the associated peers.

In this work, we address two critical issues (selection of super-peers and evaluation of QoE) mentioned above and analyze the parameters like minimizing communication distance and data overloading in the selection of tier-1 devices or pilots. We propose an efficient heuristic for pilot selection in a DHT-based mobile P2P to balance the data retrieval load among the associated peers and minimize the distance from them. These features enhance the efficiency of each super-peer to serve an overlay without worrying about their resources, such as energy. The main contributions of this work are summarized below:

1. We present a heuristic to optimize super-peer-based DHT overlays. This mechanism selects a small number of smartphones (out of all the smartphones included in the system) as super-peer using the P-median technique and solves P-median placement using the Lagrangian Relaxation method.
2. We develop an Android application built on the Ionic-Cordova framework to study the performance of our proposed heuristic method over a mobile phone and observed that it consumes only 0.004 mAh power to execute a single round of the optimization.
3. We evaluate the performance of the content sharing mechanism and estimate QoE for both simple D2D and DHT-D2D overlay on the Vienna LTE-A simulator. The results show that the proposed heuristic enhances QoE by about 25% compared with the existing methods.

The rest of the paper is organized as follows. Section 2 presents the research related to an integrated communication environment where D2D connectivity is co-operational with cellular networks. Section 3 discusses a brief overview of DHT organization and file retrieval process, using mobile devices in DHT. The details of the optimized pilot selection process, the necessity of this selection strategy, both from theoretical and experimental perspectives, are presented in Section 4. Section 5 deals with the quality assessment framework and its analysis with a different number of parameters. Section 6 presents simulation and analysis of the proposed strategy of integrating D2D with LTE-A communication. Finally, we conclude our work and provide some future research directions in Section 7.

2 | RELATED WORKS

A fair amount of research has been carried out on the strategies that minimize the use of broadband access in GSM/LTE-A networks for retrieving shared files. McNamara et al.[4] proposed an inexpensive mobile P2P file-sharing environment called JBPeer using 3G and Bluetooth. JBPeer uses 3G for transmission of control data and Bluetooth for communicating shared data. Camps-Murr et al.[11] gave an extensive overview of the ability of mobile devices equipped with WiFi-direct facility to discover and establish connections. The main focus of their research was to design an enhanced power-saving protocol during P2P activities. Doppler et al.[12] proposed a P2P structure, with D2D connections as an underlying layer of the LTE-A network. They focused on limiting the interference of the 3GPP LTE-A network while performing D2D services. The objective of their approach is to facilitate D2D sessions in an overall communication framework within the LTE-A network. In Corson et al.,[13] the authors presented a proximity-aware communication system named Aura-net. The D2D communication in Aura-net takes place through the proximity region without involving cellular networks.

Whenever available, a smartphone user prefers to rely on a proximity-based low overhead data retrieval mechanism. Wolf et al.[14] stated the concept of super-peers to manage the vicinity of an overlay. Further, they presented a hybrid mechanism based on an evolutionary algorithm to select super-peers. This heuristic method referred to as the p-Hub median problem is suitable for super-peer selection. Merz et al.[15] presented an optimization model that selects super-peers in a distributed and self-organized way via network coordinations. The coordination adopts round trip time information and facilitates delay estimation to help the super-peer associations. Shi et al.[16] addressed the issue of load balancing among super-peers and reduced their maintenance cost in P2P overlay after implementing an extension of the Chord algorithm. In this work, all super-peers are prioritized from minimal to maximal on a virtual Chord priority ring, so that the new peer joins the super-peer who has the maximal priority. Amirazodi et al.[17] proposed an adoptive super-peer selection approach based on peers' capacity that is computed locally through learning automata. Recently, Rahmani et al.[18] developed a proximity-based cluster overlay for mobile peer-to-peer systems to minimize communication overhead and network traffic.

Optimized selection of super-peers helps to enhance the QoE of the overlay members due to the efficient work of super-peers within the overlay. However, defining QoE factors and their relationships are critical issues.[8,19,20] Zinner et al.[21] defined the factors, like scaling, measuring, prioritizing, and weighting, would be considered for computing QoE, and it is not easy to fix these parameters as the existing QoE models extract the factors from network and multimedia playout parameters recommended by the International Telecommunication Union (ITU). Also, all these models fail to define QoE factors admissible for cellular P2P quality requirements. To overcome the stated difficulties, Liu et al.[22] proposed the perceived quality of Internet access as a measurement of QoE for the users. Generally, the Mean Opinion Score (MOS)[23] of the users is considered as the measurement of the service quality. MOS calculation is a time-consuming, static survey approach that requires participating users to give satisfaction feedback points for the available services.[24] It is typically independent of QoE computation due to time and space isolation. The process of calculation is thus tricky for a real-time comprehensive measurement.[25] The difficulty in mapping QoE to MOS is evident as the former is an objective while the latter is subjective based on an average user's perception of service.[26] Consequently, the correlation and the mutual influence between QoE and MOS factors are challenging issues to predict QoE of an overlay service.[27,28]

Recently, many works including Lycett et al.[29] and Yao et al.[30] proposed to evaluate QoE using machine-learning approaches. Unfortunately, most of the mechanisms above to calculate QoE are complex and not suitable for smart devices with limited resource capacity. It is, therefore, essential to design a lightweight QoE computation measurement for resource constraint devices. Such an efficient user satisfaction framework using a DHT-based P2P overlay is described in this work.

3 | BACKGROUND

3.1 | D2D communication

Device-to-device (D2D) communication in cellular networks enables direct communication between two mobile phone users without using the Base Station (eNodeB) or core network.[31] Based on the spectrum, it is categorized in out-band D2D communication (using an unlicensed spectrum) and in-band D2D communication (using the cellular system).[32]

Both categories use the existing D2D pairing based on the 3GPP LTE-A network, where resource allocation occurs between D2D devices using eNodeB. In this process, a D2D-enabled mobile phone sends a connection request to the associated eNodeB for data sharing with other D2D users. Consequently, eNodeB allocates resources to retrieve their data within their D2D communication range. However, a D2D device needs to broadcast a searching message for a file to find a target device within neighbor D2D devices (similar to Bluetooth or WiFi file searching procedure). Forming a DHT overlay would be suitable for efficient file sharing.

3.2 | DHT-based D2D communication

A DHT-based D2D communication (V-Chord[6]) consists of mobile stations (MSs) or devices with multiple communication interfaces such as infrared wireless (IR), Bluetooth, D2D, WiFi, or cellular networks (4G/LTE-A), as depicted in Figure 1. Some MSs might not have enabled data service over their cellular interfaces, but can avail data services through D2D (or Bluetooth) low range wireless interfaces within a vicinity. MSs that have enabled broadband data service or WiFi connection are eligible for the role of pilots. MSs within vicinity either communicate through WiFi-connected pilots (vicinities 1 and 2) without using Internet access or through Internet gateway (vicinity 3), as shown in Figure 1. Each MS is assigned with a unique ID to map into the V-Chord ring using DHT over a cellular network infrastructure. In this, each ID is assigned with an m-bit DHT overlay ID. The b most significant bits out of m bits specify the corresponding *eNodeB*. The next p bits specify the associated pilot, and the remaining h bits define the MS-ID under the pilot.

Each MS_i can connect to its neighbor through Bluetooth (or other low range wireless interfaces) while $Pilot_i$ can communicate directly with its $eNodeB_i$. The user of an MS may be motivated to volunteer the device for a pilot's role through inducements such as discounted data tariff rate, high data transfer speed, and so forth. Each eNodeB maintains a list of selected pilots and their corresponding pilot overlay ID (*PID*) for the V-Chord ring.

3.3 | File retrieval using D2D and DHT-based D2D communication

The procedure retrieving a file using D2D communication without DHT overlay is presented in *case 0* of Figure 2. In this case, an (MS_i) initiates the registration process by sending a request containing its ID, status, and traffic type to $eNodeB_i$. The $eNodeB_i$ executes Algorithm *Algo-A* to allocate resources to MS_i for communicating with another mobile station MS_j. Each eNodeB allocates suitable pairing resources for establishing communication between the MSs.

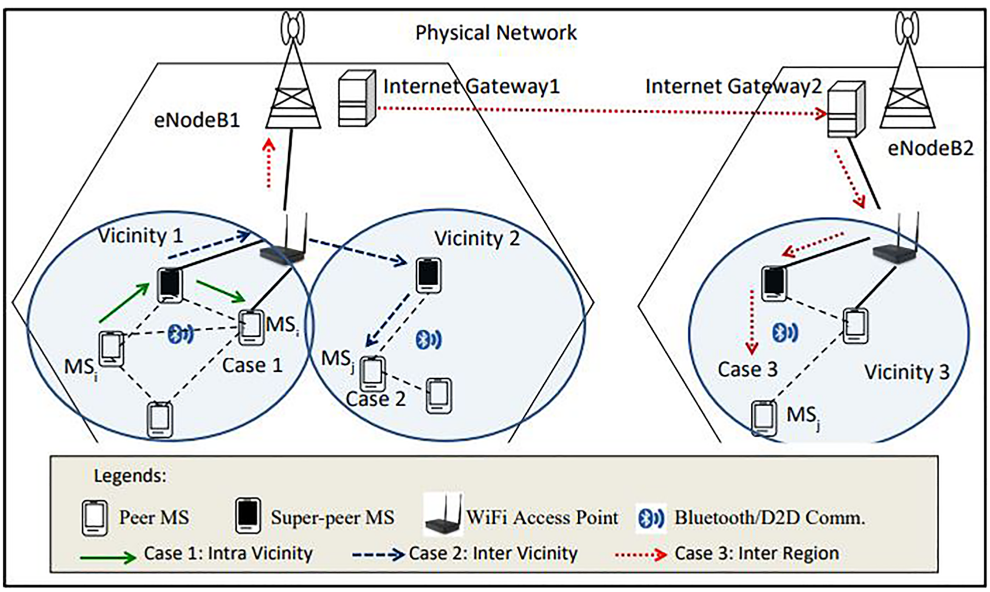


FIGURE 1 An overlay with underlay connection and different cases of file sharing in mobile P2P

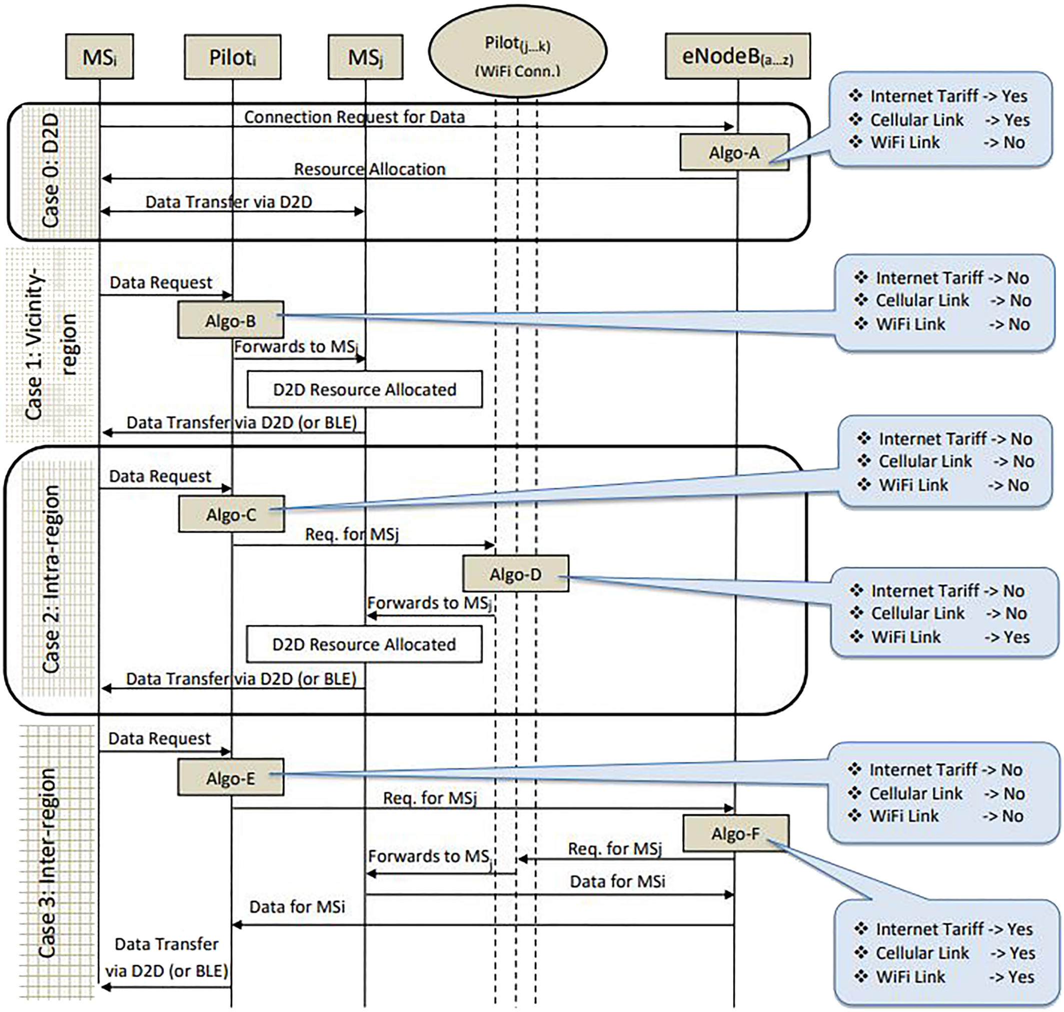


FIGURE 2 DHT and non-DHT communications under LTE-A network

The retrieval of a file using D2D communication with DHT overlay is illustrated in *case 1*, *case 2*, and *case 3* of Figure 2. The approaches to handle the different possible cases are described below. The basic algorithms (Algo-B to F in Figure 2) are implemented as mentioned in the V-Chord P2P overlay.[6]

Case 1 (MS_i and MS_j in the vicinity of a single pilot)
In this case, MS_i initiates the process by sending a search request with the ID, *FID* of the file to $Pilot_i$. $Pilot_i$ locates MS_j ($MSID_j$) having the ID with nearest prefix match for *FID* using algorithm *Algo-B*. Pilot forwards the request to MS_j for transferring the file to MS_i. This communication can be carried out either on the Bluetooth link or the D2D link.

Case 2 (MS_i and MS_j are in vicinity of a WiFi connected pilots)
In this case, on receiving a request from MS_i, $Pilot_i$ uses algorithm *Algo-C* for forwarding the request to the nearest prefix match for $Pilot_j$ (PID_j) within the WiFi range. $Pilot_j$ runs algorithm *Algo-D* for a look-up in its table for the IDs of MSs having the nearest prefix match for *FID* (of the requested file) along with their status information and availability. If found, $Pilot_j$ fetches the data from MS_j and forwards it to $Pilot_i$. After receiving the file, $Pilot_i$ transmits it to the requested station MS_i.

Case 3 (MS_i and MS_j under inter region pilots)
If file requested by MS_i is not available within the WiFi range of $Pilot_i$, it executes algorithm *Algo-E* and forwards the request to its corresponding $eNodeB_i$. In response to the request from $Pilot_i$, $eNodeB_i$ executes algorithm *Algo-F* to determine an appropriate $eNodeB_j$. If an MS_j ($MSID_j$) has closest prefix match with ID available in the neighborhood of $Pilot_j$ within $eNodeB_j$'s range, then it forwards the data to the requested MS_i.

It can be observed that in any of the three cases discussed above, most of the DHT super-peer based overlays would suffer from load balancing and peer association issues. To address these issues, there is a call for an efficient heuristic mechanism for assigning super-peers in DHT-based overlays, specifically for resource sharing applications.

3.4 | P-median problem and Lagrangian relaxation

The P-median problem can be viewed as a facility location problem where the P number of super-peers (pilots) is selected to serve all peers in an overlay. There can be multiple such selections of P pilots, but the selection with minimum cost would be challenging. The P-median problems can be mathematically expressed as a linear programming problem. However, these linear programming problems are NP-hard (non-polynomial). Therefore, we employ the Lagrangian relaxation (LR) method to approximate the P-median linear programming problem into a simpler problem by removing some complex constraints. As a cost of violations, the relaxed constraints are penalized in the objective function using Lagrange multipliers. This simpler problem gives an approximate solution, which takes less computation than the original problem. For example, if the objective

$$\min_{(\mathbf{x})} \; cx \tag{1}$$

subject to constraints

$$\left.\begin{aligned} Ax = b, \\ Cx = d, \text{ and } \; x \in X, \end{aligned}\right\} \tag{2}$$

where the first set of constraints is challenging to deal with. Then the modified Lagrangian problem is

$$\min_{(\mathbf{x})} \; cx + \mu(Ax - b) \tag{3}$$

subject to constraints

$$Cx = d, \; x \in X. \tag{4}$$

Since the modified problem does not me et all the primary constraints, it will produce a solution $f(\mu)$, which will always be better (lower bound) or equal to the solution of the original problem. Therefore, we seek a solution

$$\max_{(\boldsymbol{\mu})} \; f(\mu) \tag{5}$$

known as Lagrangian dual of the original problem.

In the next section, we propose an efficient pilot selection strategy using the P-median approach, and then we explain our user satisfaction framework to analyze QoE in such overlays.

4 | THE PROPOSED EFFICIENT PILOT SELECTION PROCESS

The most critical step in the realization of efficient D2D communication is the selection process for the pilot MSs. Table 1 summarizes the notations used in the present work. Algorithm 1 employs the idea of facility allocation (P-Median) problem[33] for the same. During the setup phase, each *eNodeB* executes the Algorithm 1 (*Assign*(*Pilot_No*)) providing total number of pilots as a parameter. Subsequently, the pilots who exceed their capacities for serving requests for data in its neighborhood execute Algorithm 1. It splits the workload and reassigns the MSs to another pilot correspondingly and re-balances the load in the vicinity using the provided parameters (the maximum data serving capacity and distance) from the MSs at the bootstrapping time. Each pilot will be offered some awards (financially or socially) for consuming its resources, such as channel and energy, to participate in the pilot assignment process. Thus, all pilot collaboration is required during setup only, which is executed by *eNodeB*.

TABLE 1 Notations used to analyze and evaluate the optimized pilot assignment and proposed QoE framework

Description	Notation (value)
Mobile station i and its overlay identity	$MS_i/MSID_i$
Pilot i and its overlay identity	$Pilot_i/PID_i$
Vicinity i and its overlay identity	$Vicinity_i/VID_i$
eNodeB i and its overlay identity	$eNodeB_i/BID_i$
Number of pilots	P
A shared file key	FID_i
Value of user satisfaction i and rank of its preference	US_i/i
Size of shared data at each MS (MS_i)	d_i
Size of shared data at each pilot ($Pilot_j$)	d_j
Number of MSs under each region	m
Distance from $Pilot_j$ to MS_i	h_{ij}
Number of eligible pilots under each WiFi-connected location	e
Number of required pilots under a region	P_{num}
Maximum data serving capacity for a pilot	$=P_{cap}$
Initial penalties of Lagrangian relaxation for data capacity P_{cap}	λ'_j $(=1/d_j)$
Initial penalties of Lagrangian relaxation for MS association with pilots	$\mu i'$ (=m)
A constant value on kth iteration for subgradient method	$A^{(k)}$
Decision variable for pilot assignment	Z_j
Decision variable for MS to pilot assignment	Y_{ij}

4.1 | Pilot assignment process

We introduce two decision variables (Z_j and Y_{ij}) for assignment of the required number of pilots (P) that may cover the region of participating *DHT MSs*.

$$Z_j = \begin{cases} 1 & \text{if } \ Pilot_j \ \text{ is assigned} \\ 0 & \text{otherwise} \end{cases} \qquad Y_{ij} = \begin{cases} 1 & \text{if } \ MS_i \ \text{ is associated by } \ Pilot_j \\ 0 & \text{otherwise} \end{cases}$$

The objective is to minimize the distance, that is, hop count h_{ij} (from $pilot_j$ to MS_i) and data overload d_i (of MS_i) on each pilot. Thus, the objective can be formulated as in Equation 6:

$$\min_{(\textbf{data},\, \textbf{distance})} \sum_j \sum_i d_i h_{ij} Y_{ij}. \tag{6}$$

Subject to the following constraints.

$$\sum_j Z_j = P \tag{7}$$

$$\sum_j Y_{ij} = 1 \ \forall (MS_i) \tag{8}$$

$$\sum_i (d_i + d_j) Y_{ij} \leq P_{cap} \ \forall (Pilot_j) \tag{9}$$

$$Y_{ij} = 0, 1 \ \forall (Pilot_j) \tag{10}$$

$$Z_j = 0,1 \; \forall (MS_i, Pilot_j) \tag{11}$$

$$d_i \geq 0,\; d_j \geq 0 \; and \; h_{ij} \geq 0 \tag{12}$$

Each constraint reflects a specific purpose. For example, constraint (7) ensures that exactly P pilots should be assigned, while constraint (8) ensures that each MS is connected to precisely one pilot. To ensure the load (shared data) on each pilot is not higher than the predefined data serving capacity (P_{cap}), constraint (9) is being used. Constraints (10) and (11) are for appropriate settings of the decision variables. For example, Y_{ij} is set to 1 or 0 depending on whether MS_i is served by $Pilot_j$ or not. Similarly, variable Z_j is set to 0 or 1 depending on whether an MS_j is selected as a pilot or not. Constraint (12) states that fixed variables (i.e., d_i, d_j, and h_{ij}) are positive integers.

In the formulation of constraints, variables Z_j and Y_{ij} are restricted to be either 0 or 1. So, it is difficult to solve the objective function (Equation 6) applying the linear programming technique. Therefore, we have used Lagrangian relaxation (LR), which removes some complicated constraints by adding a penalty to each removal objective function.

Let $\lambda = \{\lambda_j,\ j \in [1,\ P]\}$ and $\mu = \{\mu_i,\ i \in [1,\ m]\}$ are two sets of Lagrangian multiplier penalties associated with constraints (9) and (10), respectively. Thus, the corresponding Lagrangian function becomes

$$\begin{aligned} M(\lambda,\mu) = \sum_j \sum_i d_i h_{ij} Y_{ij} + \sum_j \lambda_j \left(\sum_i (d_i + d_j) Y_{ij} - P_{cap} \right) \\ + \sum_i \mu_i \left(1 - \sum_j Y_{ij}\right). \end{aligned} \tag{13}$$

Now, the Lagrangian dual objective function $M(\lambda, \mu)$ would be

$$\max\ M(\lambda,\mu). \tag{14}$$

Moreover, as $M(\lambda, \mu)$ is linear in λ and μ, the maximum of $M(\lambda, \mu)$ always exists, and to obtain the best possible solution, we use subgradient optimization.[34] Subgradient optimization is an iterative procedure in which a new approximation for $k + 1$ of the Lagrangian multipliers is chosen as

$$M^{(k+1)}(\lambda,\ \mu) = \max\{M(\lambda^1,\ \mu^1), M(\lambda^2,\ \mu^2), \ldots, M(\lambda^{k-1},\ \mu^{k-1}),\ M(\lambda^k,\ \mu^k)\}. \tag{15}$$

The solution of Equation (6) is an upper bound for Equation (14). $M^{(k+1)}(\lambda,\ \mu)$ would be optimal or near-optimal solution of Equation (6), as shown in Figure 3, for $k \rightarrow \infty$.

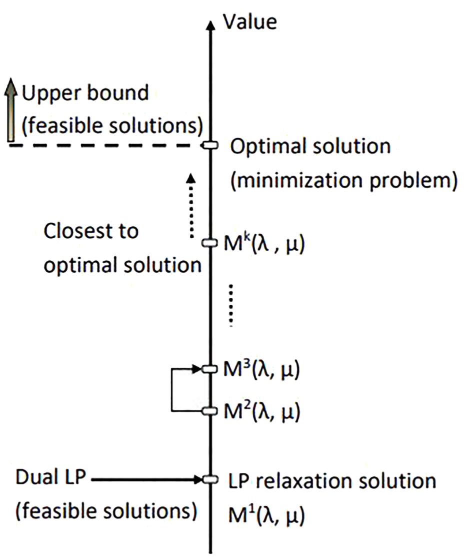


FIGURE 3 Lagrangian dual problem with subgradient solution

The overall optimization process is captured by Algorithm 1. The step-size value $t^{(k)}$ is updated by Polyak-type step-size rule.[34] Polyak proved that if $\epsilon < A^{(k)} \leq D$ for any fixed $\epsilon > 0$, the subgradient method is guaranteed to converge, where D depends on the problem definition.

Algorithm 1 *Assign*(P)

Initialize $A^{(1)} = D$, $\lambda = \frac{1}{\sum_{j=1}^{e} d_j}$, $\mu = m$, $Z_j = 1$ and $Y_{ij} = 1$, where $j \in [1, e]$ and $i \in (1, m)$
for q = 1 : e **do** $V_q = \sum_i min\{0, [d_i h_{iq} + \lambda_q(d_i + d_q) - \mu_i]\}$
Select P Pilots from $V[1, \ldots, e]$, where V_q is minimum
  for r = 1 : P **do**
    for i = 1 : m **do**
      if (Z_r =1 and $[d_i h_{ir} + \lambda_r(d_i + d_r) - \mu_i] < 0$) **then** **Assign** MS_i to $Pilot_r$ (i.e., V_r)
    for k = 1 : iteration **do** **Compute** $t^{(k)} = \frac{A^{(k)}(0.01M(\lambda,\mu))}{\sum_r^P\{\sum_i^m(d_i+d_r)Y_{ir} - P_{cap}\}^2 + \sum_i\{1-\sum_r^P Y_{ir}^{(k)}\}^2}$
      for s = 1 : P **do** $\lambda_s^{(k+1)} = max\{0, [\lambda_s^{(k)} - t^k(\sum_i^m(d_i + d_s)Y_{is}^{(k)} - P_{cap})]\}$
        for i = 1 : m **do** $\mu_i^{(k+1)} = max\{0, [\mu_i^{(k)} - t^k(1 - \sum_j^P Y_{ij}^{(k)})]\}$
          if $(|M(\lambda^{k+1}, \mu^{k+1}) - M(\lambda^k, \mu^k)| \leq \delta)$ **then** $A = \frac{A}{2}$; k=1;

4.2 | Analysis

The proposed pilot selection mechanism is simplified using Lagrangian relaxation and analyzed its convergence rate towards an optimal solution using MATLAB R2016a on a PC with Intel Core i5 processor with 8 GB of main memory. The simulations are performed over 500 mobile phones, where 20 phones are eligible for super-peer selection. We consider 10 pilots out of 20 to manage all peers. Further, a pilot is allowed to connect with a peer within seven hop count distance while its data serving capacity is up to 500 MB. The distance from the pilot and data sharing information of each peer is cached at each pilot. This information is generated randomly and keeps consistent for each solution, that is, P-median, random, and relaxed. Figure 4 shows an optimal solution using P-median (star line), a random solution (dotted line), and a relaxed solution after implementing P-median (solid line). It is observed that the relaxed solution provides an optimal solution after a few iterations (8–9) of our proposed solution. The convergence rate of our simplified mechanism depends significantly on the initial assignment of $A^{(k)}$, which would be chosen according to Pearson's correlation coefficient. Pearson's correlation coefficient ($\sqrt{R^2}$) is found to be 0.965 from Figure 5. Further, the relation between the number of MSs (m) and $A^{(k)}$ is derived to be $A^{(k)}$=0.017m−2.9412. The observed relation helps us to determine initial value $A^{(k)}$ of our proposed relaxed solution to converge the optimal solution in short computational iterations.

4.3 | Implementation

We evaluated the performance of the proposed optimized pilot selection mechanism using an Android application (App)-based smartphone. An app has been built on the Ionic framework using Cordova plug-in to run on a smartphone having android OS.[35] The implementation is configured to optimize a vicinity of 20 MSs with sharing the capacity of (up to) 500 MB (for each MS). The optimized process performs for 250 times on Motorola Nexus 6 smartphone having

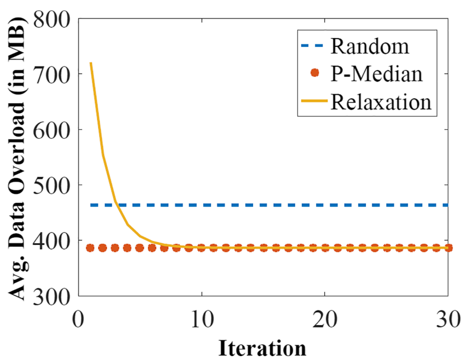


FIGURE 4 Convergence of simplified mechanism (using Lagrangian relaxation) towards the optimized solution

OS (Android 7.1.1), CPU (Quad-core 2.7 GHz Krait 450), internal memory (3 GB), and battery (3220 mAh). The results are displayed in Figure 6A,B. It is observed that the App requires 1.3 MB memory, 18 s CPU time with the energy consumption of 1 mAh.

4.4 | Discussion

According to our problem, D would be $0.017m - 2.9412$ (derived from Figure 5). To compute $t^{(1)}$ (in Algorithm 1), $A^{(1)}$ is initialized with D, and to compute $M(\lambda, \mu)$, λ and μ are initialized with $\frac{1}{\sum_{j=1}^{e} d_j}$ and m, respectively. If the solution does not improve significantly, $A^{(k)}$ needs to be reduced (e.g., $A^{(k+1)} = 0.5A^{(k)}$). Thus, $A^{(k)} \geq A^{(k+1)}$.

The overall time complexity of the proposed pilot assignment is $O(2kmP)$. However, we observe from our simulation that the algorithm converges with a small k (e.g., 8), so the complexity would be $O(mP)$.

4.5 | Benefit of overlay optimization

In cellular networks, QoE for file-sharing applications depends mostly on network traffic. User satisfaction decreases as network traffic increases. The performance bottleneck due to data traffic can be avoided using D2D communication when supported by DHT-based overlays. The pilots handle much of the file-sharing loads over short-range wireless

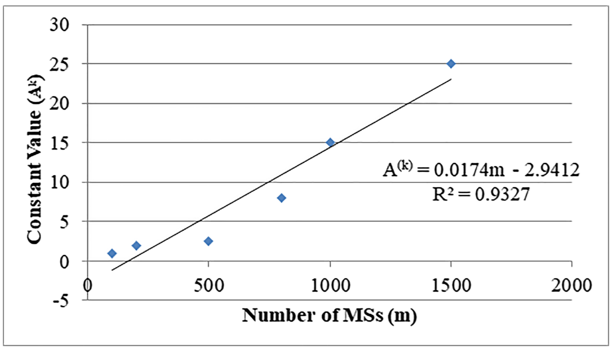
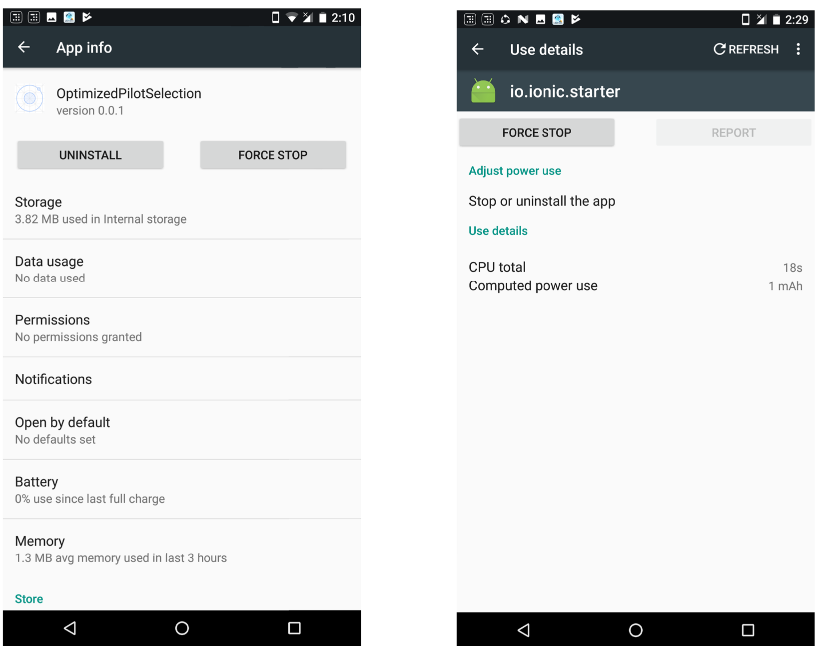


FIGURE 5 Pearson's correlation coefficient between MS and $A^{(k)}$



(A) App information regarding memory and battery consumption.

(B) Computational power to perform pilot optimization process up to 250 times.

FIGURE 6 Optimization process of pilots on a smartphone

FIGURE 7 An example of optimized pilot selection where MSs = 10, ISD = 250 m, D2D range = 20 m

MSID	1	2	3	4	5	6	7	8	9	10
Position (x, y)	(185, 212)	(105, 174)	(125, 185)	(130, 200)	(120, 190)	(190, 217)	(115, 185)	(190, 200)	(170, 210)	(120, 202)
Data (in MB)	150	200	175	250	550	75	300	150	200	450

Random Pilot Selection- Case 1:

PilotID	Assoc. MSIDs	Total Data
P1 (MSID-7)	2, 3, 5, 10	**1675 MB**
P3(MSID-4)	--	250 MB
P2(MSID-1)	6, 8, 9	575 MB

Random Pilot Selection- Case 2:

PilotID	Assoc. MSIDs	Total Data
P1 (MSID-3)	4, 5, 10	**1425 MB**
P2(MSID-7)	2	500 MB
P3(MSID-1)	6, 8, 9	575 MB

Optimized Pilot selection with $\mathbf{P_{Cap}}$= **1GB**:

PilotID	Assoc. MSIDs	Total Data
P1 (MSID-3)	4, 5	975 MB
P2(MSID-7)	2, 10	950 MB
P3(MSID-1)	6, 8, 9	575 MB

networks such as Bluetooth and WiFi. It reduces Internet usage on LTE-A networks. Therefore, user satisfaction is expected to increase substantially. However, without proper pilot selection procedure, the load distribution may be unbalanced, which may turn some of the selected pilots inactive due to fast drain out of energy.

Consider a scenario, as shown in Figure 7, to understand the energy consumption of pilots under V-Chord. In this case, eNodeB is situated at point (0, 0) with an intersight transmission distance (ISD) of 250 m. All D2D devices are placed under eNodeB with a transmission range of 20 m. We assume that all the pilots have a uniform transmission range of $r = 20$ m. An MS at position (x_i, y_i) is a member of a group of MSs connected to a pilot at (x, y) if $(x_i - x)^2 + (y_i - y)^2 \leq r^2$.

We evaluate different cases for selecting the pilots while forming a DHT overlay. In random selection (case 1) as shown in Figure 7, three *MSIDs* (7, 4, 1) are selected randomly as pilots. Pilot ID PID_1 has four (*MSIDs* MS_2, MS_3, MS_5, and MS_{10}) D2D MS members. PID_2 has no D2D *MS* within its range, while PID_3 has three (MS_6, MS_8, and MS_9) *MSs*. So, pilots PID_1, PID_2, and PID_3 serve data to associated MSs up to 1675, 250, and 575 MB, respectively.

Figure 7 illustrates another random selection of pilots where MS_3 is selected before MS_7. In this case, pilots PID_1, PID_2, and PID_3 serve data to associated *MSs* up to 1425, 500, and 575 MB, respectively. In both cases, the selection of pilots could not balance their data serving capacity. Unbalanced load (for data serving) distribution would cause higher energy drain outs from some pilots.

The most simple solution would be to put a cap on the data serving capabilities of each pilot. We experiment with an optimal pilot selection mechanism with P_{cap} (equal to 1 GB); the load distribution becomes balanced as shown in Figure 7. However, it can be viewed as an optimized pilot selection solution. However, it is highly inadequate as many MSs may not find a pilot nearby. Therefore, optimal or near-optimal placement of the pilots through location analysis is required to provide a high level of user satisfaction.

5 | THE PROPOSED FRAMEWORK FOR COMPUTING QOE

QoE is referred to as "degree of the delight in using a service."[36] The perceived QoE may change in an end-to-end communication service, due to the dynamic temporal and spatial conditions (remaining battery energy, interest in the use of Internet service, a distance between smartphones, etc.) of mobile users. The communication requirements in QoE can be influenced by the content, the network, the device, the application, the context of use, the user expectations, and the goals.

According to Sousa et al.,[9] the estimation of QoE is influenced by several factors related to a system, service, application, the user's preferences, or context whose actual state or setting may have an influence on the QoE for the user. These factors can be categorized as a human, system, and contents based. A user's preferences are largely influenced by attributes such as gender, age, audio-visual capabilities, and so forth. Sometimes, intellectual abilities such as motivation, encouragement, and spatial and temporal mood, can also be critical and may affect the QoE. QoE is also affected by the systems through which it is perceived, for example, multimedia streaming that goes through compression and decompression at multiple levels of transmission. Apart from the above factors, the other important factor is the external environment. These can be the temporal aspects, like the day of the weak or time of the day, duration of the content and its popularity, and service type.[9]

However, QoE can depend on the multiple factors mentioned above, and therefore, it may be measured by various qualitative and quantitative metrics. An application dependent QoE is quantified by a mean opinion score (MOS) value, which is calculated using the degree of subjective satisfaction for the end-users of a particular application.[37] In cellular networks, smartphone users satisfy with an application such as the effect of the app on their smartphone components, tariff, and battery consumption using the service such as file sharing. Table 2 shows a few parameters that can be used to analyze smartphones in such applications.

TABLE 2 User satisfaction parameters

Preference	Parameter
1	Number of accessed files without using the Internet
2	Accessing time for all file chunks
3	Energy consumption of user's mobile during file retrieval
4	Search rank file within vicinity
5	Search file with keyword within vicinity
6	Target file at single (or multihop) hop D2D
7	Connecting time with target D2D
8	Associated pilot at single (or multihop) hop
9	New peer joining time

The MOS can be computed from the statistical analysis of the data provided by all users, and QoE of the service can be calculated using MOS values. But MOS computation becomes complex as the number of application-dependent metrics increases. Therefore, the calculation of QoE is challenging. A visual solution is to reduce the metric size. For example, Liotou et al.[37] use only one parameter (Internet access) to reduce complexity. So, we decided to propose a lightweighted framework to compute user satisfaction providing a preference for parameters. Further, we analyze the framework of how it helps to reduce the complexity.

5.1 | Computing user satisfaction score

This section describes the proposed user satisfaction framework. A user chooses an application based on a perceived satisfaction score for using the application. It is possible to define a priority range of values for a set of parameters that a user would find important. Then, a user's feedback can be gathered by seeking a satisfaction score for each parameter from the corresponding predefined absolute category rating (ACR) scale. ACR maps ratings between bad and excellent to numerical values within the range 1 through 5.[38] However, in this work, we modify the rating values within the range [−2,+2]. More specifically, the value for a parameter i is denoted by $US_i \in \{2\ (\textit{Excellent}),\ 1\ (\textit{Good}),\ 0\ (\textit{Satisfactory}),\ -1\ (\textit{Poor}),\ \textit{or} -2\ (\textit{Bad})\}$. The primary reason behind the proposed modification is to obtain a smooth convex surface with its minima at 0 that helps in the optimization process and reduces the requirement to compute large values. Next, we define the overall user satisfaction score ($US_{overall}$) as follows.

$$US_{overall} = \frac{\sum_{i=1}^{\mathbb{k}} (US_i / i)}{\sum_{i=1}^{\mathbb{k}} (1/i)}, \tag{16}$$

where $\mathbb{k}$ denotes the number of parameters chosen by the user about an application. The overall satisfaction depends on the chosen parameters (see Table 2) and lies between −2 and 2, that is, $-2 \leq US_{overall} \leq 2$. We analyze the behavior of Equation (16) with the help of random harmonic distribution,[41] to determine the acceptance (or rejection) of the application without computing large MOS value for a small and broad set of user satisfaction parameters.

5.1.1 | Small set of user satisfaction parameters

Proposition 1 If value of each US_i $(1 \leq i \leq \lfloor \frac{\mathbb{k}}{2} \rfloor)$ is 2 (-2), $US_{overall}$ QoE score becomes positive (negative).

Proof. Considering the value of $US_i \in \{2\}\ \forall (1 \leq i \leq \lfloor \frac{\mathbb{k}}{2} \rfloor)$.

$\sum_{i=1}^{\mathbb{k}} \frac{US_i}{i} = \sum_{i=1}^{\lfloor \frac{\mathbb{k}}{2} \rfloor} \frac{US_i}{i} + \sum_{j=\lceil \frac{\mathbb{k}+1}{2} \rceil}^{\mathbb{k}} \frac{US_i}{j} > 2\sum_{i=1}^{\lfloor \frac{\mathbb{k}}{2} \rfloor} \frac{1}{i} - 2\sum_{j=\lceil \frac{\mathbb{k}+1}{2} \rceil}^{\mathbb{k}} \frac{1}{j} > 0.$

Therefore, $US_{overall} > 0$.

Similarly, we can show that $US_{overall} < 0$, when $US_i = -2\ \forall (1 \leq i \leq \lfloor \frac{\mathbb{k}}{2} \rfloor)$.

Proposition 2 If value of each US_i $(1 \le i \le \lceil \frac{\Bbbk}{2} \rceil)$ is $\in\{1,2\}$ $(\in\{-1,-2\})$, $US_{overall}$ QoE score becomes positive (negative).

Proof. Considering the value of $US_i \in \{1,2\}\ \forall (1 \le i \le \lceil \frac{\Bbbk}{2} \rceil)$.

Case (i): When $\Bbbk$ is even.

$$\sum_{i=1}^{\Bbbk} \frac{US_i}{i} > \sum_{i=1}^{\frac{\Bbbk}{2}} \frac{1}{i} - 2\sum_{j=\frac{\Bbbk}{2}+1}^{\Bbbk} \frac{1}{j} = \sum_{i=1}^{\frac{\Bbbk}{2}} \left(\frac{1}{i} - \frac{2}{\frac{\Bbbk}{2}+i}\right) > 0.$$

Case (ii): When $\Bbbk$ is odd.

$$\sum_{i=1}^{\Bbbk} \frac{US_i}{i} > \sum_{i=1}^{\frac{\Bbbk+1}{2}} \frac{1}{i} - 2\sum_{j=\frac{\Bbbk+3}{2}}^{\Bbbk} \frac{1}{j} = \sum_{i=1}^{\frac{\Bbbk-1}{2}} \left(\frac{1}{i} - \frac{2}{\frac{\Bbbk+2}{2}+i}\right) + \frac{1}{\frac{\Bbbk+1}{2}} > 0.$$

Therefore, in both cases, $US_{overall} > 0$.

Similarly, we can show that $US_{overall} < 0$, when $US_i \in \{-1,-2\}\ \forall (1 \le i \le \lceil \frac{\Bbbk}{2} \rceil)$.

5.1.2 | Large set of user satisfaction parameters

If the feedback value of a large set of user satisfaction is equally distributed (not equally distributed), the application should be accepted (difficult to judge).

Proof. Let $S = US_1 + \frac{US_2}{2} + \frac{US_3}{3} + \ldots + \frac{US_i}{i} + \ldots,$

where US_i are independent random variables, which may or may not be distributed equally. In this article, we study and analyze equally distributed or unequally distributed of a large set of random variable US_i, which helps users to decide whether an application should be accepted. Our analysis covers both cases. According to Kolmogorov three-series theorem,[39] the series $\sum_{i=1}^{\infty} X_i$ (where, $(X_i)_{i \in N}$ are independent random variables) converges $\mathbb{R}$ if and only if the following three conditions (C1, C2, and C3) hold for some $A > 0$:

(C1) $\sum_{i=1}^{\infty} Pr(|X_i| \ge A)$ converges.

(C2) Let $Y_i := X_i.1_{\{|X_i| \le A\}}$, then $\sum_{i=1}^{\infty} E(Y_i)$, the series of expected values of Y_i, converges.

(C3) $\sum_{i=1}^{\infty} var(Y_i)$ converges.

where, $Pr(X)$, $var(Y)$, and $E(Y)$ are denoted as probability of X, variance, and expected values of Y, respectively.

Case (i): Let user satisfaction values be equally distributed and US_is are distributed with uniform distribution $Pr(US_i = -2) = Pr(US_i = -1) = Pr(US_i = 0) = Pr(US_i = 1) = Pr(US_i = 2) = \frac{1}{5}$. Therefore, $E(S) = 0$ and

$$E(S^2) = \sum_{i=1}^{\infty} \frac{E(US_i^2)}{i^2} = \frac{10}{5}\left(\frac{\pi^2}{6}\right) = \frac{\pi^2}{3}. \tag{17}$$

Since $\frac{US_i}{i}$ are random variables, then

(C1) $\sum_{i=1}^{\infty} Pr(|\frac{US_i}{i}| \ge 3) = 0.$

(C2) If $Y_i := \frac{US_i}{i}.1_{\{|\frac{US_i}{i}| \le 3\}}$, then

$Y_i = \frac{US_i}{i}$ and

$E(Y_i) = \sum_{i=1}^{\infty} E(Y_i) = \sum_{i=1}^{\infty} E(\frac{US_i}{i}) = 0.$

(C3) $\sum_{i=1}^{\infty} var(Y_i) = \sum_{i=1}^{\infty} var(\frac{US_i}{i})$

$= \sum_{i=1}^{\infty} \frac{1}{i^2} var(US_i)$

$= \sum_{i=1}^{\infty} \frac{1}{i^2} (E(US_i^2) - [E(US_i)]^2)$

$= \sum_{i=1}^{\infty} \frac{1}{i^2}.2 = \frac{\pi^2}{3}.$

Therefore, all three conditions of Kolmogorov's three-series theorem holds. This implies $\sum_{i=1}^{\infty} \frac{US_i}{i}$ almost surely converge. Since, $\sum_{i=1}^{\infty} \frac{1}{i}$ diverges towards $+\infty$; therefore, $US_{overall} \rightarrow 0$. It shows that the equally distributed feedback values for different parameters of an application should be acceptable by users.Moreover, from Schmuland,[41] we conclude that

(a) The probability of S having a very large value is very small, but it is never 0.
(b) Distribution of S has full support on the real line, so there is no theoretical upper bound or lower bound of S. The range of S is $\mathbb{R}$ U $\{-\infty,\infty\}$.

Case (ii): Let user satisfaction values be not equally distributed, and the satisfaction values of different parameters are provided with different probabilities. Suppose, $Pr(US_i = -2) = Pr1$, $Pr(US_i = -1) = Pr2$,$Pr(US_i = 0) = Pr3$, $Pr(US_i = 1) = Pr4$, $Pr(US_i = 2) = Pr5$, where $(Pr1 + Pr2 + Pr3 + Pr4 + Pr5) = 1$. If $A \subseteq [3, \infty)$, then condition (C2) of Kolmogorov three-series does not hold always as

$E(Y_i) = E(\frac{US_i}{i}) = (2.Pr5 + Pr4 - Pr2 - 2.Pr1) \sum_{i=1}^{\infty} \frac{1}{i}.$

Therefore, $E(Y_i)$ diverges if

$(2.Pr5+Pr4-Pr2-2.Pr1) \neq 0.$

However, if $A \subseteq (-\infty,3)$, then (C1) does not hold as

$\sum_{i=1}^{\infty} Pr(\frac{US_i}{i} < 3) = \sum_{i=1}^{\infty} 1 \rightarrow$ diverges.

Thus, $S = \sum_{i=1}^{\infty} \frac{US_i}{i}$ does not converge. In this case, $US_{overall}$ diverges towards $-\infty$ or ∞; therefore, it is difficult to judge the acceptability of the application.

6 | SIMULATION AND RESULT ANALYSIS

We used Vienna LTE-advanced open-source system-level simulator[40] to verify the proposed optimized pilot selection mechanism and user satisfaction framework. The simulator uses the object-oriented programming paradigm with a modular code structure allowing us to add extra modules with basic input parameters as described in Table 3.

6.1 | User satisfaction parameters

We implemented a look-up cost model of V-Chord[6] using the modified D2D simulator to calculate the MOS values corresponding to user satisfaction parameters mentioned in Table 2. In this model, the look-up process for the DHT file

TABLE 3 Input parameters and their values

Parameter	Value
Intersite distance (ISD)	250 m
Number of single carrier	600
Number of resource block (RB_{num})	100
Total power POW_{total}	−10 dB W
Circuit power consumption ($CPOW_{con}$)	0.05 W
Carrier frequency (C_{freq})	2.15 GHz
Tuning step (T)	$20/(\pi * 1500^2)$
Path-loss parameter (α)	3.5
Number of pilots (P_{num})	10
Number of D2D users ($D2D_{num}$)	100
Number of user satisfaction parameters (US_{param})	3, 6, 9
Vicinity Size (V_{size})	$\lceil(1+(D2D_{num}-P_{num})/P_{num})\rceil$
Number of resource block per D2D user (RB_{d2dNum})	$RB_{num}/D2D_{num}$
Vicinity radius (V_{radius})	ISD/10 m

sharing application is categorized into three categories, namely, inter-region, intra-region, and vicinity-region, as depicted in Figure 2.

Inter-region look-up uses the Internet or cellular links through an Internet gateway. Access to a file located in a different region consumes more battery power in a mobile device. Therefore, a user's objective would be to reduce the inter-region look-ups. The availability of intra-region file chunks allows fast (high bandwidth) access to a file as the WiFi or Bluetooth can be used in short ranges. So, the ability to get files without Internet access would be considered as a user satisfaction parameter. Though accessing a file from a local neighborhood is cheaper, it takes some time to establish a connection and send file chunks over the Bluetooth link. So, it may be captured by two conflicting satisfaction values (one low and one high). Similarly, a user may define satisfaction parameters and give MOS feedback values according to the performance of an application, as mentioned in Table 2 with preference from 1 (top) to 9 (low). The value of each parameter is provided through a predefined policy. In the simulation, following US_i values are assigned:

$$US_i = \begin{cases} 2 & \text{if } 80\% < US_i \leq 100\% \\ 1 & \text{if } 60\% < US_i \leq 80\% \\ 0 & \text{if } 40\% < US_i \leq 60\% \\ -1 & \text{if } 20\% < US_i \leq 40\% \\ -2 & \text{if } US_i < 20\% \end{cases}$$

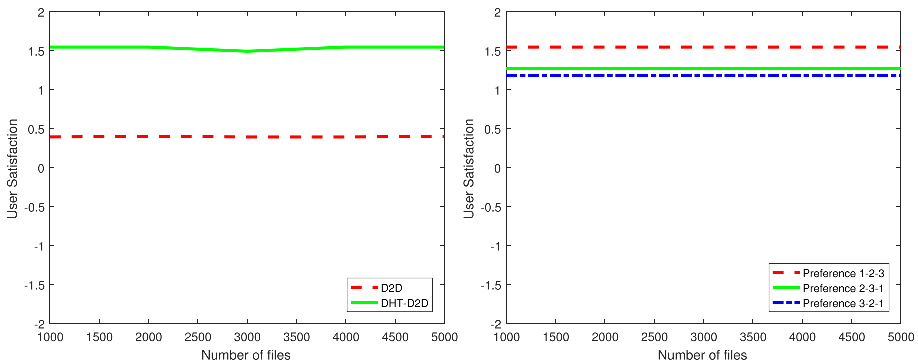
6.2 | Result analysis

The simulation is initialized with 1K shared files among users, and 500 new files are added in each iteration. Superpeers and eNodeBs of the cellular overlay keep metadata of downloaded files such as their destination peers IDs. The cache entries can be updated on the insertion or retrieval of a new shared file. A similar update of cache is performed for old files or whenever a D2D user (peer) leaves the overlay. In addition, an eNodeB includes all super-peer IDs of its region. Super-peer provides P2P services to member peers.

Figure 8 illustrates that the user satisfaction of randomly positioned D2D users under a single cell in the LTE-A simulator. It shows that each user adopts the top three parameters in their preference set. In Figure 8A, each user searches new files in its every request cycle. The result shows that the users with DHT overlay achieve three times better QoE than that without using DHT. Here, we consider the total number of intra-vicinity files as a fraction of the entire distributed files over the network among the number of assigned super-peers. Therefore, it is observed from Figure 8A that the computed user satisfaction value remains constant even if the number of files increases. Figure 8B shows the interchanging effect in preference of user satisfaction parameters, which would result in a different QoE.

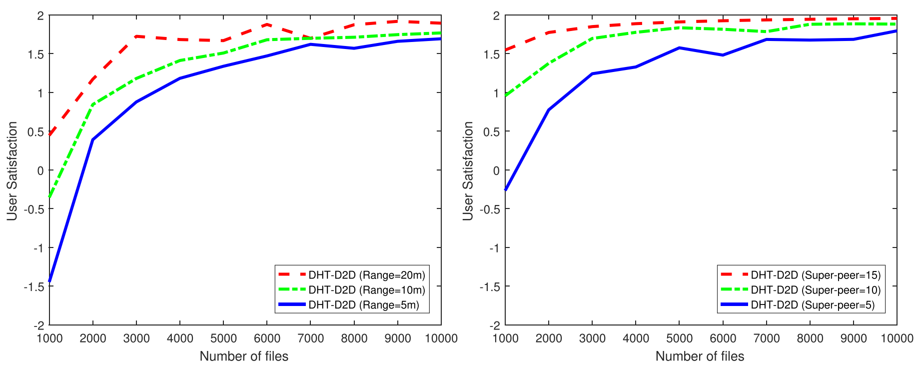
Figure 9A shows the effect of different pairing ranges (5, 10, and 20 m) of D2D devices on user satisfaction scores within DHT and non-DHT networks. It is observed that the less pairing range causes more overheads for super-peers, thus degrades the overall satisfaction score. Figure 9B shows that more super-peers would help to increase the user satisfaction score.

Further, we analyze the effect on user satisfaction scores using a single satisfaction parameter (Internet uses). It is considered that each user accesses files without Internet service, using a WiFi-connected pilot, which provides a high user satisfaction value, that is, 2. This value degrades to zero for that application, whenever a super-peer uses Internet service for accessing the requested file. In the absence of both options, a user uses his Internet service to retrieve a file and gets the minimum satisfaction score of −2. Figure 10 shows the relationship between Internet access (by peers or super-peers) during file retrieval at each iteration and overlay-wide average MOS. Initially, the shared files within a vicinity are accessed while remaining shared files are retrieved using the Internet (either through Pilot or user smart



(A) All search files are new. **(B)** Effects of user satisfaction parameters.

FIGURE 8 User satisfaction among D2D and DHT-D2D users where 1K new files are added



(A) D2D pairing ranges are 5, 10, and 20 meters. **(B)** D2D devices are managed by 5, 10 and 15 super-peers.

FIGURE 9 Comparison of user satisfaction score among D2D and DHT-D2D users, where number of devices are 50

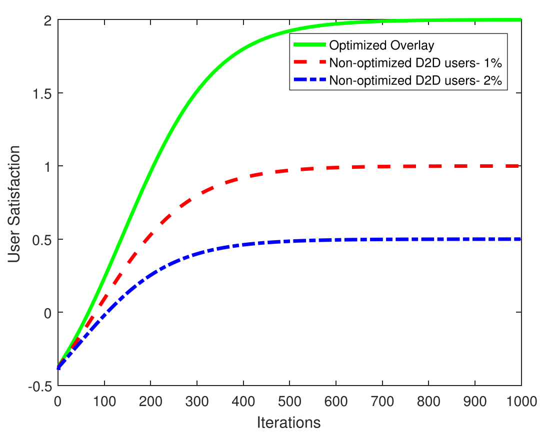


FIGURE 10 Effects of DHT-D2D mechanism over non-DHT D2D where downloaded files are available within the vicinity

devices). In this simulation, we consider 10% of the shared files among inter-region overlay members are accessed at each iteration, and then these files are kept at the appropriate peer. This metadata is available at respective super-peer or eNodeB to access them locally in the next iteration.

It is observed from Figure 10 that initially, a DHT overlay has a bad score (below average) because most of the shared files are accessible through the Internet. Once the file is downloaded, the file would be available within the WiFi-connected inter-vicinity. Thus, user satisfaction score increases. For non-optimized overlay, some D2D users are not associated with super-peers, which compels them to use their data service. Thus, the satisfaction score of the overall P2P networks increases significantly for our proposed optimization pilot selection technique. We achieved it even if 1% or 2% of D2D users are not associated with super-peer.

7 | CONCLUSION

In this paper, we evolve a mechanism to assess the Quality of Experience for applications that can take advantage of D2D communication by leveraging a structured overlay of user groups. First, we proposed a heuristic-based (P-median using Lagrangian relaxation) solutions for the selection and organization of the user devices into an optimized DHT overlay. The solution has been analyzed experimentally and found to be suitable for smartphone applications. Further, we defined a model to assess, predict, and reduces QoE computation. It allows a smartphone user to define application-specific satisfaction parameters and compute the QoE efficiently. The current work is not just limited to proof of concepts but also for creating a road-map for implementing a whole technique for content sharing through close groups of smartphone users.

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