

Time-Critical Data Dissemination Under Flash Crowd Traffic

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ABSTRACT How to rapidly disseminate a large-sized file to many recipients in flash crowd arrival patterns is a fundamental challenge in many applications, such as distributing multimedia content. To tackle this challenge, we present the Bee, which is a time-critical peer-to-peer data dissemination system aiming at minimizing the maximum dissemination time for all peers to obtain the complete file in flash crowd arrival patterns. Bee is a decentralized system that organizes peers into a randomized mesh-based overlay, and each peer only works with local knowledge. We introduce the slowest peer first strategy to boost the speed of dissemination and present a topology adaptation algorithm that adapts the number of connections based on upload bandwidth capacity of a peer. Bee is designed to support network heterogeneity and deals with the flash crowd arrival pattern without sacrificing the dissemination speed. We also show the lower bound analysis of the data dissemination problem, and present the experimental results to demonstrate that the performance of Bee can roughly approximate the lower bound of the data dissemination problem under flash crowd traffic.

INDEX TERMS Peer-to-peer, content distribution, flash crowd.

I. INTRODUCTION

How to rapidly distribute a large file in flash crowd arrival patterns [1] has become more and more attractive in the networking research community and mobile cloud computing applications, such as the emerging techniques for mobile content caching [2] and fast delivery [3] or updating the software patches of Massively Multiplayer Online Games (MMOG) [4] and operating systems [5]. Suppose that a large file is initially held by a single server, we have to disseminate it to other n peers, and it is the dissemination problem we defined: how to minimize the maximum dissemination time for all peers to obtain the complete file, especially in heterogeneous and dynamic networks? Furthermore, when a popular content is released, the peer arrival rate results in a flash crowd [1] as shown in Fig. 1. It should increase the difficulty of system design and significantly impact on the system performance.

Under flash crowd traffic, several characteristics make it not easy to design a scalable system that organizes resources, such as computing power and network bandwidth, for disseminating content to a large number of clients, including:

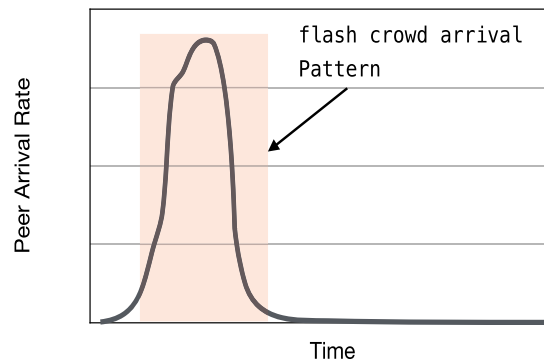


FIG. 1. An example of a flash crowd arrival pattern.

1) **Scalability:** the number of participating nodes must be in the thousands or even more. 2) **Churn:** the behavior of participating users is characterized by the dynamics with

which the peers join, leave, and rejoin the system at an arbitrary time, making it difficult to maintain an overlay network among a large number of participators. **3) Heterogeneity:** the resources, such as bandwidth, computing power of participating peers are heterogeneous, which make it difficult to make a schedule in polynomial time. **4) Network dynamic:** routers, links in the Internet, and the peers may fail, incurring more communication cost and longer transmission time to deliver content. Thus, it is not easy to maintain a large-scale data dissemination system that minimizes the maximum dissemination time under flash crowd traffic.

A famous peer-to-peer (P2P) content delivery protocol is the BitTorrent [6], which is one of the pioneers of content dissemination. However, BitTorrent is designed to minimize the dissemination time of **each peer** egoistically. On the other hand, previous studies, including Slurpie [7], Bullet [8], M2M-ALM [9] and ReCREW [10], O-Torrent [11], [12] and [13], have proposed to construct and maintain an overlay network of multiple trees, rings, or a random mesh to deliver content from a single server. In the design of these P2P protocols, content are usually divided into m parts of equal size, each being called a block. A peer may download any one of these blocks either from the server or from a peer who has downloaded that block. Besides, many researchers, including [14]–[18], have studied the performance of these P2P protocols, and have shown that the P2P protocol is both efficient and scalable, even it lacks a centralized coordination and scheduling mechanisms. Nevertheless, these previous studies related to content dissemination do not force on minimizing the maximum dissemination time for all requesting peers under flash crowd traffic.

In this article, we investigate the data dissemination problem that arises as an attractive application in the current Internet, such as content caching in [19], fast content delivery among mobile edge nodes [20], updating software patches or distributing multimedia content, especially in a flash crowd scenario. More specifically, we investigate and address the following two questions:

- i) what is the lower bound of the data dissemination problem?
- ii) how to design a distributed system that can achieve or approach to the lower bound of the data dissemination problem under flash crowd traffic?

We begin by giving a formal definition of the data dissemination problem. We then derive the lower bound of the ideal dissemination time both in homogeneous and heterogeneous networks.

Then we present Bee, a time-critical P2P data dissemination protocol to address the data dissemination problem under flash crowd traffic. Bee is designed from a *best-effort* service concept, to increase the system throughput and peer concurrency. Based on the *best-effort* service concept, a peer allocates uploading bandwidth for all its neighbors and attempts to serve all of them. Peers in Bee begin by self-organizing into a random overlay mesh and download blocks from their neighbors as soon as possible.

We present the slowest peer first strategy and the topology adaptation algorithm to maximize the speed of content dissemination. Based on the slowest peer first strategy, a peer transmits blocks to the higher priority neighbors that have the fewest number of downloaded blocks. The topology adaptation algorithm is for a peer to adapt the number of connections to neighbors based on its uploading capacity. Our experimental results demonstrate that the maximum dissemination time of the Bee can approximately approach the lower bound of the data dissemination problem. To the best of our knowledge, this work is the first that studies the effects of P2P protocols with respect to minimizing **maximum** data dissemination time under flash crowd traffic.

The rest of the article is organized as follows. In Section II, we first define the data dissemination problem. Section III describes an overview and design details of the Bee system. We give a detailed analysis of Bee in Section IV. Section V explains our simulation methodology and presents the performance results of the simulation study. In Section VI, we discuss related work. Section VII concludes this paper with a summary of the main research results of this study.

II. DATA DISSEMINATION PROBLEM

In this section, we formally define the data dissemination problem and show the lower bound of this problem.

Let us consider the problem of disseminating a file F to a set of n peers, $\mathcal{N} = \{1, 2, \dots, n\}$. We assume that a peer leaves the system once completely receiving the file. Let S be the server (we called it *seed* in the rest of this paper) that has the file F in the beginning, and let $Size(F)$ denote the size of file F in bytes. Each peer $i \in \mathcal{N}$ in this system has its upload capacity U_i and download capacity D_i . U_i and D_i respectively represent the upper bound of the upload and download bandwidth for peer i . We also assume that $U_i \leq D_i$, to model the Internet technologies. Let $t_i(F)$ denote the time it takes for peer i to download the complete file F . Note that $t_i(F)$ denotes the time interval starting at the time peer i sends its request to the server and ending at the time it receives the entire file F . Before formally defining the data dissemination problem, we define the following two performance metrics first.

Definition 1 (Average Dissemination Time, ADT(F)):

$$ADT(F) = \frac{1}{|\mathcal{N}|} \sum_{i \in \mathcal{N}} t_i(F).$$

Definition 2 (Maximum Dissemination Time, MDT(F)):

$$MDT(F) = \max\{t_i(F)\}, i \in \mathcal{N}.$$

Assume that the server S and all n peers exist in the system from time $t = 0$, then $MDT(F)$ is the time it takes for all peers to finish receiving the complete file F . Now we define the data dissemination problem as follows.

Definition 3 (Data Dissemination Problem): Given a server S and n peers in the system, and each peer i has the upload capacity U_i and download capacity

151 D_i , where $i = \{1, 2, \dots, n\}$, the data dissemination prob- 196
 152 lem is to find a transmission mechanism \mathcal{M} to min- 197
 153 imize the $MDT(F)$. According to the Definition 2, 198
 154 the data dissemination problem can be treated as a min-max 199
 155 problem as follows.

$$\min\{\max\{t_i(F)\}\}. \quad (1)$$

156 Note that the data dissemination problem is somewhat
 157 different from the broadcast network problem [21] where a
 158 node is required to broadcast a message to all other nodes
 159 as fast as possible. In the broadcast network problem, a node
 160 can either transmit a message to or receive a message from
 161 other nodes, but not both. Many researchers have studied
 162 the broadcast network problem in homogeneous networks
 163 for more than 40 years [21]. The broadcast network prob-
 164 lem becomes NP-hard [22] in heterogeneous networks, and
 165 Deshpande *et al.* [23] proposed two centralized heuristics for
 166 the broadcast network problem in heterogeneous networks. In
 167 the data dissemination problem, however, a node can transmit
 168 and receive messages simultaneously. Goetzmann *et al.* [24]
 169 show that the data dissemination problem becomes NP-hard
 170 for equal upload and download capacities per peer. Thus, it
 171 also is more difficult to analyze algorithmic complexity of the
 172 data dissemination problem in heterogeneous networks.

173 A. IDEAL DISSEMINATION TIME (LOWER BOUND)

174 In this section, we focus on studying the lower bound of the
 175 data dissemination time, denoted as the **ideal dissemination**
 176 **time** in homogeneous or heterogeneous networks. We assume
 177 that peers are highly cooperative and altruistic, so that each
 178 peer is willing to forward data to other peers as fast as possible
 179 (*best-effort* service concept) and to benefit other peers than
 180 itself.

181 Let's denote the actual amount of data uploaded by peer i as
 182 f_i , where $f_i \leq U_i \times t_i(F)$ and the peer i receives in return as
 183 r_i , where $r_i \leq D_i \times t_i(F)$. Without loss of generality, we may
 184 assume that the total amount of download data must be equal
 185 to the total amount of upload data for the seed S and all peers.
 186 Hence, we have the following equation,

$$f_s + \sum_{i=1}^n f_i = \sum_{i=1}^n r_i. \quad (2)$$

187 Since we are interested in estimating the lower bound of
 188 the data dissemination time, we assume that upload capacity
 189 of each peer i is to be fully utilized, i.e., we have $f_i = U_i \times$
 190 $t_i(F)$. Besides, the total amount of download bandwidth must
 191 be equal to $n \times \text{Size}(F)$, because all peers have the entire file
 192 F at the end. Then, we can extend the Eq. 2 as follows to deal
 193 with the ideal dissemination time for the general case,

$$U_s \times t_s(F) + \sum_{i=1}^n U_i \times t_i(F) = n \times \text{Size}(F). \quad (3)$$

194 Here, we have a min-max problem with its objective func-
 195 tion in Eq. 1 subject to the constraints given by Eq. 3. Since

the constraint is a linear equation, a hyperplane in $(n + 1)$ -
 dimension, we show that an optimal solution for the con-
 strained optimization problem can be obtained if and only if
 when all t_i are the same, i.e.,

$$t_s(F) = t_1(F) = t_2(F) = \dots = t_n(F). \quad (4)$$

Lemma 1: Given a file F to a set of n peers, $\mathcal{N} =$
 $\{1, 2, \dots, n\}$ and a seed S , the ideal dissemination time can
 be obtained if and only if when all t_i are the same.

Proof: We prove Lemma 1 by contradiction. We assumed
 there is an optimal solution α and $t_j^\alpha(F) < t_s^\alpha(F) = t_1^\alpha(F) =$
 $t_2^\alpha(F) = \dots = t_n^\alpha(F)$, where $1 \leq j \leq n$. So,

$$U_s \times t_s^\alpha(F) + \sum_{i=1}^n U_i \times t_i^\alpha(F) < U_s \times t_s(F) + \sum_{i=1}^n U_i \times t_i(F).$$

Eq. 3 implies that the assumption is a contradiction. Thus,
 we have Lemma 1. ■

Applying Eq. 4 to Eq. 3, we then have a lower bound of
 $MDT(F)$, denoted by $\bar{T}(F)$, for file F , as follows.

$$\bar{T}(F) = \frac{n \times \text{Size}(F)}{U_s + \sum_{i=1}^n U_i}. \quad (5)$$

Now, we are ready to show the following Lemma 2.

Lemma 2: Let $T^*(F)$ denote the $MDT(F)$, of a feasible
 schedule of the data dissemination problem for a given file F .
 Then we have:

$$T^*(F) \geq \max \left\{ \bar{T}(F), \frac{\text{size}(F)}{U_s}, \frac{\text{size}(F)}{\min\{D_i\}} \right\}, \quad (6)$$

where the right-hand right of Eq. 6 is the lower bound of the
 dissemination time in any algorithm for the data dissemination
 problem.

Proof: Note that the lemma merely says that $T^*(F)$ must
 be greater than 1) the lower bound (the ideal dissemination
 time), the Eq. 5 we derived in the above; 2) the time for
 the seed S to transmit the file F , the bottleneck is in the
 uplink capacity of the seed S ; 3) the time for the slowest
 peer to download the file F , the bottleneck is in the download
 capacity of the slowest peer. ■

This analysis indicates that if someone has to design a
 time-critical data dissemination system to approach the ideal
 dissemination time in a general network environment, the
 two prerequisite concepts should be considered: 1) the sys-
 tem should enforce the peers to leave the system at almost
 the same time, and 2) the system should always fully utilize
 the upload capacity of each peer. Based on the two observa-
 tions, we present our design of the Bee protocol in the next
 Section III.

III. BEE DESIGN

In this section, we present the Bee system to approach the
 ideal dissemination time that we derived in Section II. In the
 Bee, like other P2P content delivery systems [6], the file is
 divided into many fix-sized blocks (256 KB). The proposed
 Bee consists of 3 parts: slowest peer first strategy, local rarest
 first strategy, and topology adaptation algorithm. The slowest

240 peer first strategy is used to control and balance the dissemination
 241 process of all nodes. By this strategy, nodes might have
 242 the same download process and complete the download at
 243 almost the same time with high probability. The local rarest
 244 first strategy can prevent the last block problem and increase
 245 blocks availability. The topology adaptation algorithm is used
 246 to dynamically adjust different uplink capacities and make
 247 nodes fully utilize the upload capacity with high probability.

248 At a high level overview, Bee organizes a random mesh
 249 overlay among a set of participating peers. Suppose that a
 250 large file is announced from a single seed S , then peers require
 251 to download the content at the same time. Each peer gets into
 252 contact with well-know register server and retrieves a *contact*
 253 *list* of a uniform random subsets of all peers. The size of
 254 contact list is a small constant, say 80. The initial mechanism
 255 is the same as that used in other P2P content delivery systems.

256 **A. SLOWEST PEER FIRST STRATEGY**

257 We describe the slowest peer first strategy and the procedure
 258 that each peer performs. Overall, a good peer selection strategy
 259 would be one which neither requests a peer to maintain
 260 a global knowledge, nor to communicate with many peers,
 261 but the one which is able to find peers having blocks the peer
 262 needs. In order to minimize the *MDT* of the dissemination
 263 system, our focus is the development of a distributed system,
 264 which each peer learns its nearby peers' statuses (with local
 265 knowledge) and selects a suitable peer to upload blocks.

266 The design principle of the slowest peer first strategy is to
 267 fully utilize all the upload capacity of peers in the system.
 268 It implies that a peer can always find some peers to upload
 269 blocks to utilize its upload capacity. Based on the slowest peer
 270 first strategy, a peer i always picks the slowest downloading
 271 peer among its *contact list*, where the slowest downloading
 272 peer is the peer that has the least number of blocks. Conse-
 273 quently, the peer i can always upload blocks to the picked
 274 peer to utilize its upload capacity, because there is a high
 275 probability that the peer i has some blocks that the picked
 276 peer does not have. In this point of view, the slowest peer first
 277 selection strategy makes our Bee system to be able to maintain
 278 a high level of throughput of peer's upload capacity.

279 The operation of the slowest peer first strategy is efficient
 280 and sustainable for fully utilizing the upload capacity of each
 281 peer. Figure 2 illustrates the idea of the slowest peer first
 282 strategy. After a peer joins, it periodically sends the requesting
 283 block messages to the peers in the contact list for downloading
 284 the blocks it lacks. When a peer starts to upload blocks to other
 285 peers, it maintains a **working set**, and the peer tries to utilize
 286 its upload capacity as much as possible to upload blocks to
 287 the peers in its working set. The working set is a set of peers
 288 selected from the contact list over a period of time. The size of
 289 working set is controlled by the topology adaptation algorithm
 290 that we will discuss later. We present the pseudocode of the
 291 slowest peer first algorithm in Algorithm 1 as follows.

292 The advantage of the slowest peer first strategy is to enforce
 293 peers to download blocks at approximately the same progress
 294 and the design can significantly diminish the *MDT* of the

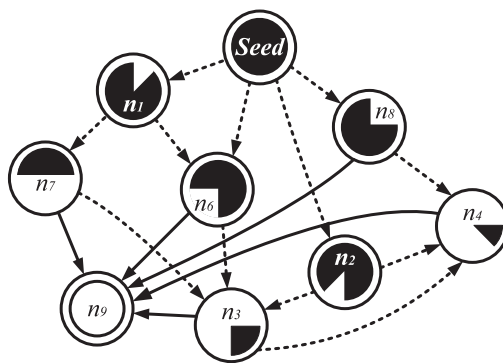


FIG. 2. An illustration of the slowest peer first strategy: The shaded content within a peer represents the percentage of the file that a peer has downloaded.

Algorithm 1: Slowest Peer First Strategy.

```

1: Begin
2: WorkingSet[]  $\leftarrow$  Null
3: for  $j \leftarrow 0$  to Sizeof(WorkingSet[]) do
4:   Pick the slowest peer  $i \in$  Contact List
5:   WorkingSet[ $j$ ]  $\leftarrow$  peer  $i$ 
6:    $j \leftarrow j + 1$ 
7: end for
8: return WorkingSet[]
9: End
    
```

system. The disadvantage is that the faster peers will be de-
 295 layed by the slower peers. However, if the faster downloading
 296 peers leave the system early, the *MDT* of the system will be
 297 prolonged undoubtedly, recalling the Lemma 1 in Section II.
 298

299 **B. BLOCK SELECTION STRATEGY**

300 Bee employs the local rarest first strategy for choosing new
 301 blocks to download from neighboring peers. The local rarest
 302 first strategy is proposed in BitTorrent [6], and it can prevent
 303 the last block problem and increase the file availability in a
 304 BitTorrent system. The main advantage of the local rarest first
 305 strategy is to overcome the last block problem [25] by favoring
 306 rare blocks. This strategy equalizes the file block distribution
 307 to minimize the risk that some rare blocks are lost when peers
 308 owning them fail or depart the system. Bharambe *et al.* [26]
 309 study the local rarest first strategy by simulations and show
 310 that this strategy can address the last block problem efficiently.
 311 Another advantage of the local rarest first strategy is to in-
 312 crease the probability that a peer is useful to its neighboring
 313 peers because it owns the blocks that others do not have. Thus,
 314 the local rarest first strategy helps diversify the range of blocks
 315 in the system.

316 **C. TOPOLOGY ADAPTATION ALGORITHM**

317 The design of Bee explicitly takes into account the capacity
 318 heterogeneity associated with each peer in P2P networks. Bee
 319 leverages the topology adaptation algorithm to dynamically
 320 adjust different uplink capacities. In general, the available

bandwidth estimation [27] is a non-trivial problem, so it is hard to decide how many upload connections a peer should have in a Bee system. However, using a fixed number of upload connections will not perform well under a wide variety of peers' uplink capacities. Hence, Bee leverages a topology adaptation algorithm that attempts to dynamically maintain the maximum number of upload connections according to the upload capacity of each peer.

We do not use the network bandwidth estimation techniques [28] to determine the precise uplink capacity of each peer. Instead, we assume that the user can configure a coarse-grained bandwidth that provides an initial maximum upload capacity U_i . In addition, we assume that peers (including the seed S) have limited upload/download bandwidth but the Internet backbone has infinite bandwidth. This assumption is reasonable because the previous study [29] shows that the Internet backbone indeed has low utilization and the bottleneck almost happens at the parts near the end hosts. Based on the assumptions, we can develop the topology adaptation algorithm.

The topology adaptation algorithm is to set the upload rate for each upload connection to the fixed value, a rate r , for all peers and the seed S . Hence, if a peer i has maximum upload capacity of U_i , it establishes $k = \lceil \frac{U_i}{r} \rceil$ connections, where $r \leq U_i, \forall i \in \mathcal{N}$. Each peer establishes k concurrent upload connections among its working set, and intuitively a peer can upload the blocks it holds to other peers.

The basic idea behind this approach is that by serving k different peers with an uploading rate r simultaneously, the peer can fully utilize its upload capacity and thus maximize its contribution to the system throughput. For example, a peer with higher capacity might establish ten or more connections than a peer with lower capacity. However, a smaller value of r might slow down the distribution rate for blocks. The analysis of the upload rate r has been demonstrated in our previous work [30].

IV. SYSTEM ANALYSIS

In this section, we describe the $MDT(F)$ in the Bee can approach to the ideal dissemination time with a high probability. We also present the analysis for the Bee in terms of the scalability and efficiency. Here, we assume that all peers join the system at the same time and all the communications between peers are reliable. We also assume that peers do not leave the system either voluntarily or due to failures, and no transmission delay.

A. SCALABILITY

The design of Bee is very scalable. A peer only needs to maintain a random overlay mesh with a constant number of connections, regardless of the size of the system. This implies that each peer only connects to a few number of peers, so the loading in each peer should be very slight. The possible concern is the scalability of the register server in Bee. The register server in Bee serves as the same role as the tracker in BitTorrent or the rendezvous point in some application

overlay multicast systems [31], [32]. The design of the register server can be distributed, the service loading is distributed evenly to many servers. Therefore, we believe that the register server should not be a critical problem to limit the scalability of Bee.

B. EFFICIENCY

We discuss why the $MDT(F)$ in the Bee can approach to the lower bound with a high probability. We do not provide a theoretical proof on the optimality of the Bee due to the inherent difficulty of any heuristic-driven distributed systems, such as BitTorrent. To the best of our knowledge, we are not aware of any theoretical results to prove that a distributed system can achieve the lower bound. In [33], Wu *et al.* show a centralized scheduling algorithm to minimize the dissemination time with all knowledge of system capacities. However, the centralized solution only works in a static network environment and it also does not consider the dynamic behaviors of peers in real systems.

Before we analyze Bee system, we assume that the goal of Bee is to disseminate a file F from a seed S to a number of receivers under the constraints of $\frac{size(F)}{U_s} \leq \bar{T}(F)$ and $\frac{size(F)}{\min\{D_i\}} \leq \bar{T}(F)$, where $\bar{T}(F)$ is defined in the Eq. 5. When the two constraints hold, neither the seed S nor the slowest peer does not become the bottleneck in the system. In addition, we also assume that the blocks are uniformly distributed among peers, which is caused by the local rarest first strategy.

Recall the analysis in Section II, we introduced two design principles for a data dissemination system to achieve the theoretical lower bound. The first one is that all peers should leave the system at the same time as much as possible, and each peer has to utilize its upload bandwidth as much as possible. For the first principle, the slowest peer strategy could force peers to progress at approximately the same download speed. For the other, all peers may fully contribute to the uploading capacity of whole system based on the topology adaptation algorithm, thus each peer can maintain its upload contribution to the system throughput continuously.

At the beginning of the system, only the seed S has the file, so it is impossible to fully utilize the upload bandwidth of each peer. We define the period of time for the system so that each peer has enough blocks to exchange as the start-up time of the system. Assume that the size of block is $256KB$, the start-up time is at about $\frac{256KB}{r} \times \log n$, where r is the upload rate and n is the number of peers in the system. Our previous work [18] shows how to find the optimal rate r in static networks. Moreover, a peer only sends out a block when it already received a request from a peer and it should not receive duplicated blocks.

Now, we provide an example to explain the behaviors in Bee. In homogeneous networks, the upload connections k of each peer is equivalent, assume $k = 5$ ($\frac{U_i}{r} = 5$). If the number of peers is n , the number of incoming connections per peer should be 5 ($5 = \frac{n \times k}{n}$) in average, due to the overlay mesh is constructed randomly. In heterogeneous networks, each peer

TABLE 1. The upload/download Bandwidth Distribution

Network Type	Downloadlink	Uplink	Fraction
Heterogeneous	1500kbps	384kbps	50%
	3000kbps	1000kbps	50%
More heterogeneous	784kbps	128kbps	20%
	1500kbps	384kbps	40%
	3000kbps	1000kbps	25%
	10000kbps	5000kbps	15%

in Bee could have the same number of incoming connections in average based the assumption. It should be easy to expound that Bee system could enforce most of peers at the same download progress approximately and make most of peers leaving the system at roughly the same time. Thus, with a high probability, the $MDT(F)$ of a Bee system can approximately approach to the ideal dissemination time both in homogeneous and heterogeneous networks.

V. PERFORMANCE EVALUATION

We made a simulation to compare the dissemination time in Bee with the lower bound of dissemination time and the required time in BitTorrent [6]. We consider two network scenarios, each representing a different degree of heterogeneity in their upload/download capacity. Table 1 presents the bandwidth distribution of each network condition. The heterogeneous network has two types of peers. A more heterogeneous condition with four types of peers is considered, and this setting is the realistic peer bandwidth distribution of Gnutella [34]. And the arrival pattern is flash crowd, i.e., all peers join at the initial stage and leave the system when they finish their downloading.

For the parameter r in Bee, we configure the uploading rate $r = 25$ in the all experiments based on our previous results [30]. All the experiments were run using an Intel Xeon E5560 CPU at 2.80 GHz with 512 GB of RAM. These source code of the simulations and the experimental results can be accessed publicly at <https://github.com/cjwu/bee>.

Unless otherwise specified, we use the following settings in our experiments. We used a file size of 200 MB with a block size 256 KB. The seed's uplink capacity is 6000 Kbps. The number of contact list is 40 in both Bee and BitTorrent, and the maximal number of concurrent upload connections per peer is 5 in BitTorrent settings. Then the number of initial seeds is only one in all of our experiments. Finally, the endgame model [35] of BitTorrent is not enabled because it only works for a small percentage of the download time.

A. HETEROGENEOUS ENVIRONMENT

We evaluate the performance of Bee and BitTorrent in a heterogeneous network that consists of two types of peers, one of which has a higher upload/download capacity (3000/1000 Kbps) than the other (1500/384 Kbps). In this scenario, the lower bound is 2333 seconds according to Eq. 6 in Section II.

Fig. 3 shows the comparisons of Bee to BitTorrent in heterogeneous environments. Here, we use a normalized MDT metric which is the MDT dividing the lower bound. Fig. 3(a) shows the normalized MDT metric for Bee and BitTorrent. In Fig. 3(a), we present the scalability of Bee by increasing the network size from 500 to 5000 in experiments. The results demonstrate that Bee is almost twice faster than BitTorrent in the MDT metric, and also show that both Bee and BitTorrent are scalable systems.

We also show the cumulative distribution of the number of complete peers in a network with 2000 peers in Fig. 3(b). The result shows that a peer with higher capacity leaves faster than the peer with lower capacity in BitTorrent. After the higher capacity peers leave BitTorrent, the total upload capacity of BitTorrent is decreased significantly, and the lower capacity peers are required to stay in the system longer to download the complete file. Thus, the MDT of BitTorrent is also prolonged, it fits our analysis in the Section II.

Compared to BitTorrent, the MDT of Bee approaches to the lower bound approximately due to the two design principles we analyzed in the section IV. More clearly, the normalized MDT of Bee is only 1.1. As we mentioned previously, any data dissemination system requires a start-up time to let peers have enough blocks to exchange and to utilize their uplink capacities. The results examine that the start-up time of an efficient system could be short.

In addition, we show the average uploading link utilization of peers, including the seed (6000 Kbps) and two type of peers (1000 Kbps and 400 Kbps) in Fig. 3(c). The result shows that the uplink utilization of each peer is over 90% (96% in Bee) in average, which means that the overall upload utilizations of the two systems are close to fully utilized. However, in BitTorrent, a peer with higher upload capacity should exchange blocks with another one with similar upload capacity, because the Tit-For-Tat (TFT) peer selection strategy [5] is likely to reward for the one with similar upload capacity. As a result, the overall uplink utilization of BitTorrent is efficient, but the design philosophy of BitTorrent is exclusively due to egoistic motivation, so the lower capacity peers need more time to download the complete file.

B. MORE HETEROGENEOUS ENVIRONMENT

In this section, we repeat the above experiments in a more heterogeneous network with four types of peer capacities, the detailed bandwidth distribution is presented in Table I. This results examine the behaviors of Bee and BitTorrent in a complex network environment and in a real P2P network condition. In this simulation setting, the lower bound is 2089 seconds, it can be derived from the Eq. 6 ($\frac{size(F)}{\min\{D_i\}} = \frac{1638400}{784}$). Thus, the bottleneck of the system is at the download link of the slowest peer.

First, we study the impacts of various network sizes by scaling from 500 to 5000 peers. Fig. 4(a) shows the normalized MDT metric of Bee and BitTorrent. This result also shows that Bee is at least two times faster than the BitTorrent in MDT metric. As a result, the bottleneck of the system (the

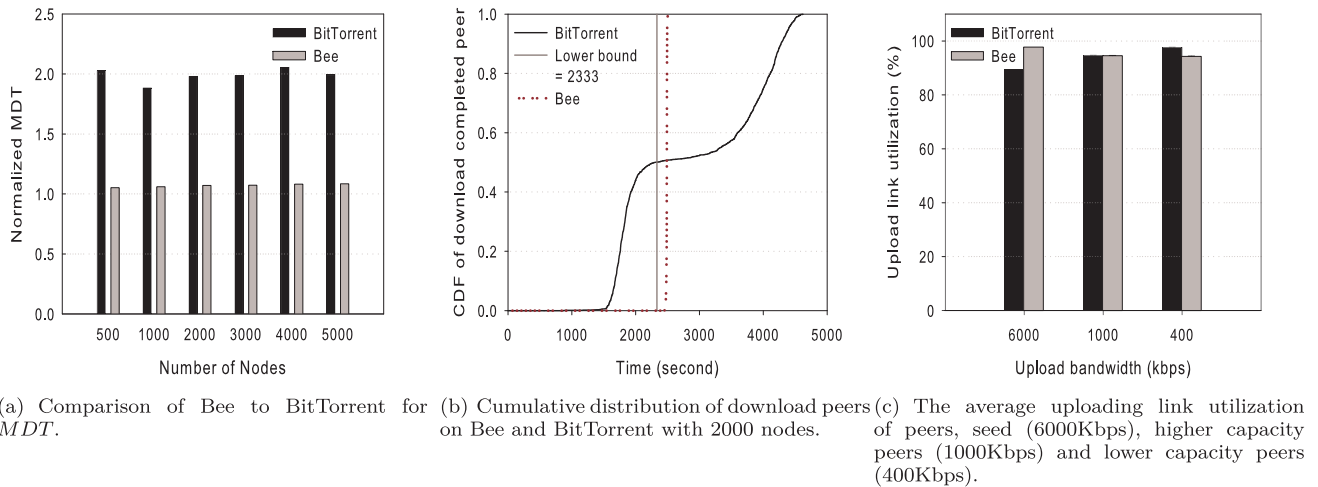


FIG. 3. The comparisons of Bee to BitTorrent in the heterogeneous environment.

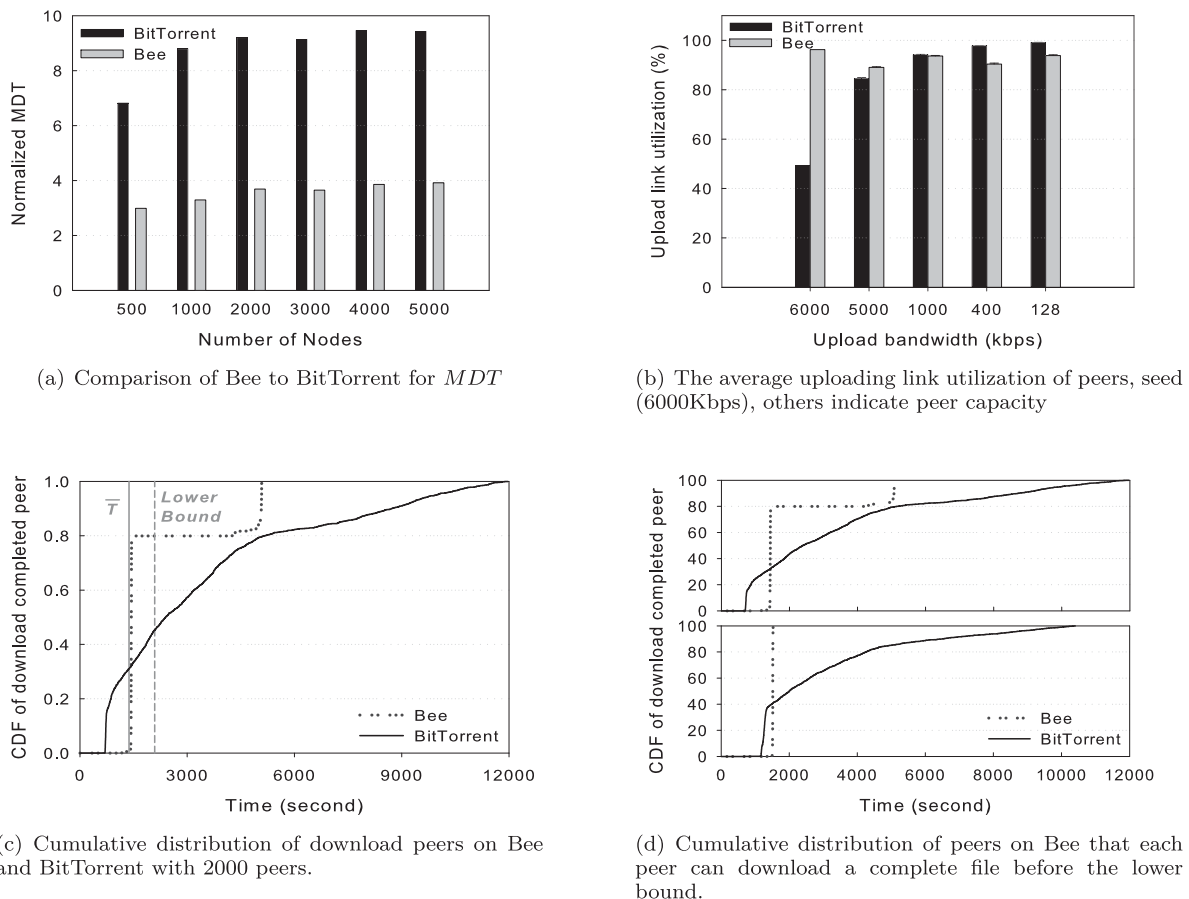


FIG. 4. The comparisons of Bee to BitTorrent in the more heterogeneous environment.

527 slowest peer) makes a significant impact on the MDT metric.
 528 Without a doubt, the result shows that both Bee and BitTorrent
 529 are scalable systems again, even in a more heterogeneous
 530 network.

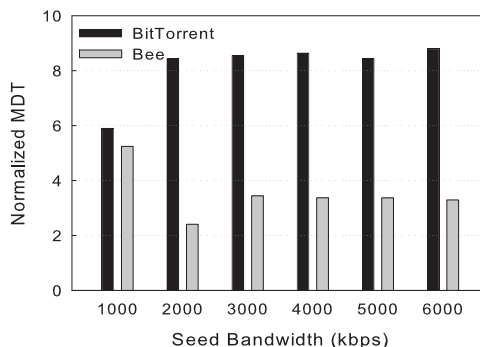
Next, we examine the uplink utilization of peers in Bee 531
 and BitTorrent in the more heterogeneous network. Fig. 4(b) 532
 shows the uplink utilization of peers in Bee and BitTorrent. 533
 The results indicate that the uplink utilization of the seed 534
 in Bee is over 90%, but only 50% in BitTorrent. From our 535

536 viewpoints, in BitTorrent, when the variance of upload capacity
 537 increases, more peers with higher capacity will leave
 538 the system early. So that the seed's uplink utilization may be
 539 limited, because the download capacity of the lower capacity
 540 peers is too small to fully utilize the uplink capacity of the
 541 seed. That might be the main reason that the uplink utilization
 542 of the seed in BitTorrent is only 50% in average, especially
 543 the upload connections of the seed is fixed to 5 in original Bit-
 544 Torrent setting. As a result, the uplink utilization of the seed
 545 decreases when the variance of download capacity increases
 546 in BitTorrent. However, the uplink utilization of seed in Bee
 547 can be fully utilized regardless of the heterogeneity degree
 548 of uplink capacity, it benefits from the topology adaptation
 549 algorithm of Bee. In Fig. 4(b), BitTorrent performs better than
 550 Bee when the upload bandwidth is less than 1000 kbps. The
 551 main reason is that the lower capacity nodes (< 1000 kbps)
 552 in Bee need more time to find the nodes to contribute their
 553 upload bandwidth to the system, especially in this simulation
 554 settings.

555 We now investigate the *MDT* metric of Bee and BitTorrent
 556 in the complex network environment. In Fig. 4(c), we show
 557 the cumulative distribution of the number of complete peers
 558 in the complex network with 2000 peers. Fig. 4(c) illustrates
 559 that 80% peers leave Bee system at the \bar{T} time (Recall that
 560 the Eq. 6) and the remained 20% peers prolong the *MDT*
 561 of Bee system. More clearly, these 80% peers are higher
 562 capacity peer (download capacity), and the dissemination time
 563 of remained peers (poor download capacity) is limited by
 564 their download capacities. Note that in this simulation, the
 565 bottleneck of the system is at the download link of the slowest
 566 peer. Again, the result shows that when the higher capacity
 567 peers leave system early, the upload capacity of overall system
 568 decreases dramatically, and that results in a longer maximum
 569 dissemination time in both Bee and BitTorrent. However, Bit-
 570 Torrent needs more than eight times to finish downloading
 571 compared to the lower bound.

572 Next, we configure the download capacities of all peers to
 573 make sure that the lower bound is not at the download capacity
 574 of peers ($\frac{size(F)}{\min\{D_i\}}$) and repeat the simulation again to examine
 575 the *MDT* metric of Bee and BitTorrent. We only increase the
 576 download capacity of the slowest peers from 784 Kbps to
 577 1200 Kbps in this network. So that the lower bound in this
 578 network is \bar{T} after the configurations are applied, here the
 579 ($\frac{size(F)}{\min\{D_i\}} = 1365.3$) is smaller than ($\bar{T} = 1374.9$).

580 Fig. 4(d) shows the cumulative distribution of the number
 581 of complete peers with the configurations. In Fig. 4(d), the
 582 top figure is the CDF with 784 Kbps (minimum download
 583 capacity) and the bottom one is the CDF with 1200 Kbps.
 584 As shown as the results, we can observe that the *MDT* in
 585 Bee can approximately approach the lower bound \bar{T} . The
 586 result implies that the performance of Bee is efficient and
 587 BitTorrent might be the network heterogeneity independent.
 588 The result also shows that the dissemination time in Bee can
 589 approach the lower bound approximately when the bottle-
 590 neck is not at the download capacity of all peers. However,



591 **FIG. 5. The comparison of Bee to BitTorrent in various uplink capacities of**
 592 **the seed.**

593 increasing the download capacity of all peers does not im-
 594 prove the *MDT* metric of BitTorrent. The result also shows
 595 that it still is a long-tail curve in the results of BitTorrent
 596 regardless of the bottleneck is at the download capacities
 597 or not.

598 **C. THE IMPACT ON SEED CAPACITY**

599 We consider the effects of various seed capacities on the
 600 performance of Bee and BitTorrent. The number of peers at
 601 the initial stage is set to 2000. In Fig. 5, Bee obviously outper-
 602 forms BitTorrent in the performance index *MDT*. However,
 603 when the uplink capacity of the seed drops to 1000 Kbps, the
 604 bottleneck of this system is at the uplink capacity of the seed
 605 ($\frac{size(F)}{U_s}$), so the *MDT* of Bee and BitTorrent both result in poor
 606 performance. This result implies that the efficiency of Bee is
 607 limited by the seed's capacity, but BitTorrent has little effect
 608 on the seed's capacity. All peers in BitTorrent have to stay in
 609 the system until all blocks have been spread to the system, it
 610 improves the *MDT* performance of BitTorrent. These results
 611 also meet our system analysis in Section IV, a poor capacity
 612 seed may make a dissemination system require more start-up
 613 time to let peers have enough blocks to stabilize exchanging
 614 process and inhibits development of spreading blocks.

615 **D. THE IMPACT ON ARRIVAL PATTERN**

616 We evaluate the effects of various arrival rates for Bee and Bit-
 617 Torrent in the more heterogeneous network conditions (with
 618 four types of peer capacities). Fig. 6 shows the normalized
 619 *MDT* performance comparisons of Bee and BitTorrent in
 620 various arrival rates. In Fig. 6, we can observe that when the
 621 arrival rate is low (0.1), a few peers join the system and con-
 622 tribute upload capacity, so that the overall upload capacity of
 623 the system is poor. And another reason is that more peers may
 624 need to wait at a longer **start-up time** to receive blocks and
 625 to exchange blocks. So the peers in Bee or BitTorrent would
 626 require more time to complete the download file. However,
 as peer arrival rate is increased, the upload capacity of the
 system also is increased promptly, that result corresponds to

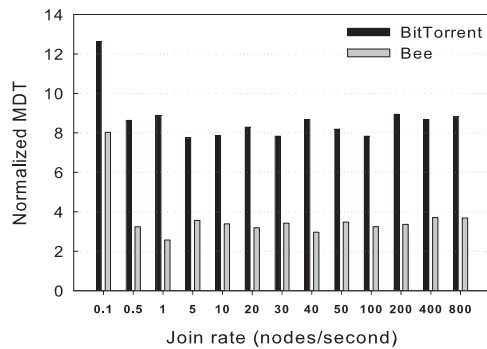


FIG. 6. The comparison of Bee to BitTorrent in various arrival rate.

627 the analysis in Section IV. Based on the results, Bee outper-
628 forms better performance than BitTorrent in *MDT* metrics
629 regardless of the arrival rate.

630 E. THE IMPACT ON FLASH CROWD TRAFFIC

631 We now evaluate Bee and BitTorrent in a realistic flash crowd
632 traffic. In this experiment, each peer joins the system accord-
633 ing to the tracker log of a Redhat 9 distribution torrent [36].
634 The capacity of each peer is randomly assigned with one of
635 four types of peer capacities, and the upload bandwidth of the
636 seed is set to 6000 Kbps. Note that the lower bound in this
637 case is $\frac{size(F)}{\min\{D_i\}} = 2089$ seconds.

638 All the results are shown in Fig. 7. Fig. 7(a) illustrates the
639 distribution of peers arrival time, the tracker log consists of
640 over 12,000 peers arrival time, almost 80% of which arrived
641 before 2000 minute. When a new version of Redhat IOS is
642 released, the flash crowd phenomenon occurs at the file release
643 time, numerous users suddenly request to download the file.
644 The flash crowd traffic model captures the most prominent
645 flash crowd characteristics observed in these traces.

646 First, we show the download completion time of each peer
647 for Bee and BitTorrent in Fig. 7(b). The result shows that
648 83% peers in Bee finish their download before 2000 seconds.
649 On the other hand, only 50% BitTorrent peers can complete
650 their download at 2000 seconds. Note that the lower bound
651 is at the poor download capacity peers (the lower bound is
652 inherently limited $\frac{size(F)}{\min\{D_i\}}$). So these poor peers need more
653 download time to complete the file, and the higher capacity
654 peers (the lower bound is \bar{T}) can receive the complete file
655 and leave the system without waiting these slow download
656 peers. So at the 10,000 time point, most of peers remained
657 in the system (17%) are poor download capacity peers, this
658 is the same behavior we found in Fig. 4(c). The result also
659 shows that the distribution of the *MDT* of BitTorrent still is
660 a long-tail curve by the same process in Fig. 4(c). Moreover,
661 compared to BitTorrent, Bee only needs 1/3 time to finish the
662 file dissemination in the more heterogeneous network.

663 Here, we demonstrate the uplink utilization of all peers in
664 Bee and BitTorrent in Fig. 7(c) and Fig. 7(d), respectively. We
665 can see that the uplink utilization of each peer in Bee is fully
666 utilized (94% in most of peers). And we see that BitTorrent

667 results most of the time in a very poor uplink utilization. One
668 reason for this should be the TFT peer selection strategy of
669 BitTorrent, it might pair a higher uplink capacity peer with
670 a lower download capacity peer, and TFT strategy keeps to
671 search the peer with better upload contributions. During the
672 peer searching process, the uplink capacity of the peer is at
673 low utilization. Thus the higher uplink capacity peers can not
674 contribute their full uplink bandwidth to the system continu-
675 ously. The main reason is that BitTorrent is inherently limited
676 by its design principles, which encourages fairness [37] in
677 peers, the TFT strategy makes all peers achieve fairness in
678 BitTorrent, considers to give and take equitably.

679 In summary, based on the simulation results, we show that
680 Bee has the ability to roughly approximate the lower bound
681 of a data dissemination system even in complex network sce-
682 narios if and only if the lower bound of the system is not at
683 uplink capacity of the seed ($\frac{size(F)}{U_s}$) and the download capacity
684 of the peers ($\frac{size(F)}{\min\{D_i\}}$). Bee is suitable as a building block in
685 a time-critical data dissemination applications, which can be
686 the virtual machine (VM) deployment in cloud computing
687 platforms [38] or distributing the urgent content in network
688 security events [39].

689 VI. RELATED WORK

690 In recent years, there are tremendous interests in building
691 content delivery systems [40] to distribute content, which
692 aims to deliver large-sized data to a large group of nodes
693 spread across a wide-area network. However, how to design
694 an efficient data dissemination system to achieve the lower
695 bound of data dissemination time has not been discussed in
696 the previous literatures, especially under flash crowd traffic.
697 In this section, we describe the recent research works about flash
698 crowd traffic and present the related work on the peer-assisted
699 content delivery systems. In addition, there are some advanced
700 coding techniques [41], [42] for content delivery, the detailed
701 survey can be reached in the article [43].

702 A. FLASH CROWD TRAFFIC

703 A flash crowd is a large traffic surge to a particular system. It is
704 not an usual event but causes poor performance at the system
705 and results in a significant number of unsatisfied users. When
706 a flash crowd occurs, the sudden arrival of numerous peers
707 may starve the capacity of a system, and degrade the quality
708 of service. Thus, it is important to understand the challenges
709 for a data dissemination system, and how flash crowds affect
710 the efficiency of data dissemination.

711 There is a large body of work on the modeling of P2P
712 data dissemination systems [44] but a few work focusing
713 on flash crowd [1], [45], [46]. In reality, flash crowds may
714 result the worst case performance of P2P data dissemination
715 systems [1]. Zhang *et al.* [1] propose a model for analyzing
716 BitTorrent flashcrowds by studying millions of swarms
717 from BitTorrent trackers. They show BitTorrent flashcrowds
718 occur in very small fractions, but affect over million users.
719 Carburaru *et al.* [45] formulate an analytical model for flash

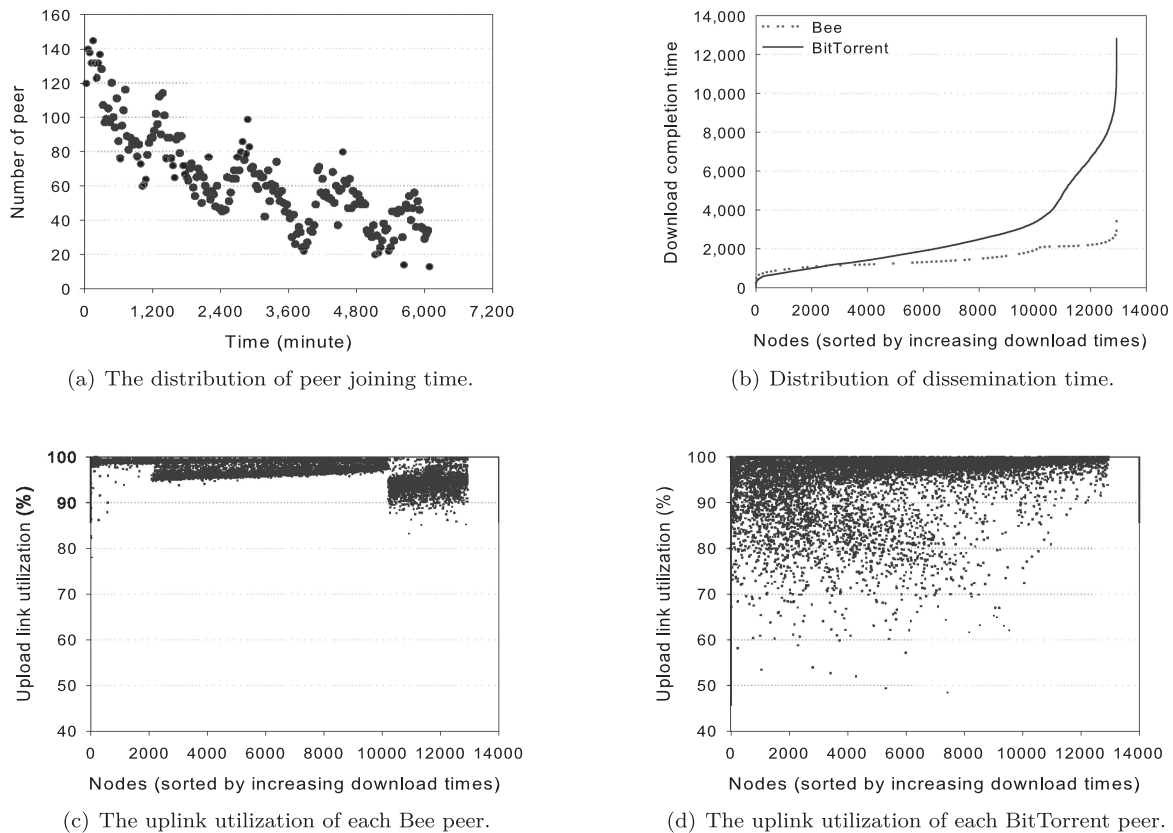


FIG. 7. Performance of Bee and BitTorrent with arrival rate from Redhat 9 tracker log.

crowds in homogeneous and heterogeneous capacity networks and focused on performance scalability of content distribution and server provisioning during flash crowds. Chen *et al.* [46] provide a fluid model study on the performance of P2P live streaming systems under flash crowds, and denote that the worst-case peer startup latency and system recovery time increase logarithmically with the flash crowd size. A key difference is that we analyze the impact of multiple classes of peers on heterogeneous networks to achieve the lower bound of the maximum dissemination time during flash crowd.

B. PEER-ASSISTED CONTENT DELIVERY SYSTEMS

The peer-assisted content delivery systems have received a lot of attention from Internet users and networking researchers [47]–[50]. Interested reader can refer to Nasreen *et al.*, [51] who present a detailed survey on this topic. The main concept of the peer-assisted content delivery is inspired from the parallel-downloading mechanism [52]. BitTorrent [6] is a popular content distribution system which is successful for its efficiency in delivering a large file. There are two mechanisms used in BitTorrent, namely, the TFT peer selection policy and the local rarest first piece selection strategy. Slurpie [7] focuses on reducing loading on servers and peer download times. Slurpie uses an adaptive downloading mechanism to improve peer’s performance according to its capacity, and adopts a random back-off algorithm to control loading on the server. Crew [53] is a gossip-based system

for data dissemination and it performs better dissemination performance than BitTorrent in experiments, but how close it approaches to the lower bound is still unknown. Kumar *et al.* [54] demonstrate a set of expressions for the minimum distribution time of a general heterogeneous peer-assisted file distribution system. Ezovski *et al.* [55] provide an analytical result of minimizing average finish time by using the water-filling technique, in an upload-constrained P2P network. The research results focused on analyzing and minimizing the download time of a single peer is presented in [56] and minimizing the average download time of a system is presented in [57]. Zheng *et al.* [58] formulate an optimization problem of content distribution as an optimal set of distribution trees for determining the rate of distribution on each tree under bandwidth limitation networks.

VII. CONCLUSION

We define the data dissemination problem and examine an analysis of the lower bound of the maximum dissemination time for this problem under flash crowd traffic. We present the design principles of Bee to capture the two following notions: 1) all peers stay the system to contribute their upload capacities (the slowest peer selection strategy), and 2) all peers fully utilize their upload capacities (the topology adaptation algorithm). Bee does not require any scheduling knowledge, each peer makes its own decision to download blocks based

717 on the local knowledge. We have conducted extensive sim-
722 ulations to evaluate the *MTD* performance of Bee, and the
723 results offer evidence that the maximum dissemination time
724 in Bee can roughly approximate the lower bound when there
725 are no bottleneck at the seed or at the download capacity of
726 the slowest peer, even under flash crowd traffic. In the current
727 Internet or the cloud computing platforms, Bee can play a
728 major role for addressing the time-critical data dissemination
729 applications in future development. It would be interesting to
730 examine the performance of Bee in the current live streaming
731 applications [59], especially in the mobile internet [60]. We
732 will implement and deploy the Bee system in cloud comput-
733 ing platforms for investigating the performance on the VM
734 deployment in our future work.

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