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RESEARCH ARTICLE

A community-based social P2P network for sharing human life digital memories

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Summary

Social peer-to-peer (P2P) networks are usually designed by reflecting a user's interest/behavior for structuring the underlying network. Human interest is affected by various factors such as age, locality and so on which changes after some time. The behavior when reflected in a network, results in peers moving within the network in order to connect the peer with peers of the same behavior/interest. Especially in community-based schemes when a peer leaves a community the data that a peer was sharing will not be accessible in the same community anymore. It has an effect on the performance of the network due to the inaccessibility of data and the unavailability of connections, which affect network robustness. We address this issue by considering Entities in data in the form of digital memories of a user and structuring network according to Entity-based communities. The simulation results for the proposed entity-based community are demonstrated, which shows the effect on network performance during varying network size and traffic.

KEYWORDS:
Peer-to-Peer (P2P) Networks, Memory for Life Systems, Online Social Networks, Social P2P Networks, Community-based P2P Networks, Human Digital Memories

1 | INTRODUCTION

A social peer-to-peer network is a developing research area which focuses on carrying an individual's social activities on top of peer-to-peer overlay networks[1,2,3]. The networks are aimed at providing data privacy, organizing network structure by reflecting individual's social network to achieve good network performance, improve searching techniques by following social behavior, security and so on[4,5]. Social peer-to-peer networks are more challenging than peer-to-peer networks because various features of the network are not only designed by keeping in mind network issues but also social priorities of its users about their relationships and data they share.

Social peer-to-peer networks are designed by reflecting human interest or behavior in the underlying network. As a result, communities of peers are formed having common interest. Since communities are a reflection of its natural existence in human social network and the fact that the social P2P network is organized in a meaningful way[6], the overall performance of the network is improved[7,8,9]. Similarly, network overhead is comparatively minimized which is created by connecting peers having no common reason or purpose to connect.

However, human interest is not constant and is changed by different factors, such as age, locality, work, etc. or a user himself keeps on changing his interest. In such a case, the underlying social P2P network by following the social network of the individual,

[0]**Abbreviations:** P2P, Peer-to-Peer; EBC, Entity-based Communities; IRF, interferon regulatory factor

will result in peers moving within the network by disconnecting from some peers and connecting to others. The behavior of peers i.e. moving within a network, which we have identified is a distinct behavior in social peer-to-peer networks, which to the best of our knowledge has not been mentioned before. However, the two similar behaviors to the mentioned are: peers churn and peers' mobility. This behavior is different than peers churn where peers go completely off the network [10,11]. It is also different than the mobility of peers where peers move from one location to another. In the problem we identified, peers keep their credentials and location and are not disconnected from the network, which makes it different and distinct than the two issues. Community-based schemes [12,13,14] e.g. Interest-Based Communities (IBCs) [15,16] are more affected by this behavior because any change in an individual's social network disconnects its peer from the whole community which makes the data inaccessible to all peers of that community.

As described earlier that human interest is affected by many factors, which any change in these factors results in a change of a human interest. So, change in the interest of a person, when reflected in a social P2P network results in leaving the community by the peer and joining another community of the new interest. But the data of the previous interest that was shared by the peer is still available on it because mostly people retain their data. However, the peer is not accessible anymore by the peers of the previous community. Therefore, the data will not be available anymore in the same community. The popular contents which are being stored by other peers might be available, but the unpopular contents which are shared only by the peer will not be accessible. Another possibility might be that since every person wants to be the owner of their data and may not allow other people to store them, which will result in the peer to be the only sharer of the data and hence by leaving the community the data will not be accessible. The network will be less robust due to the adhoc nature of peers and since peers will frequently be moving around will produce more network overhead.

People capture their data using various devices such as camera, mobile phones etc. which form their digital memories. A Memory for Life (M4L) system [17] is one of the grand challenges in UK which aims to capture, store, annotate, organize, analyze and share an individual's digital memories. By analyzing digital memories, an M4L system will identify various entities such as places, people, events etc. in digital memories and which will further be used to generate meaningful information about the individual life such as interests, schedule, habits and so on. These information will further help in improving life standard, generating healthy life routine, reminding medications, avoiding food causing allergies and many more. We have used the concept of entities in digital memories to formulate communities in a social P2P network in order to address the above mentioned problem.

This article addresses the issue by proposing a novel approach: Entity-based Communities (EBCs). Entity-based communities are created according to data that peers share. A peer joins those communities that have similar data, in the form of entities in data. The purpose of considering the actual data to form a community rather than reflecting the interest of a person in the network to form community is the dynamic nature of human interest, which has an effect on the performance of the social P2P network. Major contributions of this article include the following:

- To propose a technique that can overcome the problem of network inefficiency due to disconnection of peers emerges from the movement of peers from one community to another community, by forming communities based on the entities in digital memories of an individual rather than his interest.
- To reduce the number of frequent movement of peers from one community to some other community within a network and hence form a more stable network.
- To improve the efficiency of the network by producing a high rate of successful queries and lower network overhead and improve the scalability of the network.
- To comparatively analyze the proposed scheme for performance with existing approaches in terms of network traffic and size (scalability).

The rest of the paper is organized as Section 2 explains M4L system and assesses the suitability of various state-of-the-art technologies for sharing digital memories, the related work in Section 3 describes various social P2P networks that consider social networks for their connectivity. Section 4 explains the proposed solution which includes the idea of Entities in digital memories, a network of entities formed in digital memories, the relationship between entities that can exist in the form of a structure in digital memories and how the network of entities is reflected to organize peers into communities of entities to form Entity-based communities. Section 5 in this paper explains the simulation setup for simulating the proposed network. Section 6 shows the simulation results for entity-based communities and its comparison to existing social P2P network by considering query success rate, network overhead and number of hops queries traveled as comparison parameters. The work is concluded in Section 7 that also includes a description of the future work.

2 | BACKGROUND

People capture and store their memories in digital form using digital cameras, mobile phones, and various other devices. The increased amount of data being produced at an individual level requires to be properly organized in order to be easily retrieved and understood by the user. The Memory for Life (M4L)[17,18] challenge is an effort to capture, store, annotate, organize, analyze and share digital memories and generate meaningful information about a person's life, such as their interests, schedule, health and so on, in order to portray their personality. Gorden Bell inspired by the idea, originally proposed by Vannevar Bush in 1945 in the form of a machine called Memex[19], developed MyLifeBits[20]. The MyLifeBits software is able to store text, images, links, videos and other forms of data in a database and annotate it manually. Similarly, Total Recall[21], Haystack[22], EyeTap[23] and so on were also developed in order to capture, store, annotate and properly organize data.

The recent inspiration[18] for M4L systems was Forget-me-Not[24] and Memory Prosthesis[25] projects at Xerox EuroPARC, which were aimed to develop computer-aided human memory. A prototype of the M4L system is currently under research by Ismail et al.[26,27], described as Human Life Memory system. They captured various digital events of their lives, which are called "Serendipitous Moments". The data was annotated both manually and automatically and the information was stored in the form of metadata files. Various devices, such as GPS, digital camera, etc., were used to record useful information about the data at the time of capturing it. The data is then analyzed by software tools, such as face recognition, to recognize different objects, people, indoor or outdoor images, happy or sad moments, etc.

The M4L system aims to share an individual's digital memories not only that people share their digital memories but also due to the nature of M4L system to generate meaningful information about a person's life. For this purpose, the M4L system also needs to search and collect digital memories from other people in order to generate, as much as possible, a complete report about the person. We have previously mentioned the challenges for sharing M4L system[5] which include developing an underlying network structure, providing data privacy, an individual's control over his data and a searching technique. Further, sharing human digital memories of M4L systems were investigated by explaining the sharing according to different technologies. Web-based online social networks (WBOSNs) such as Facebook[28,11] have various issues e.g. the data privacy issues[29,30] and single point of failure and so on.

Some of the problems in WBOSNs are overcome by P2P networks[31]. Since due to no central unit that controls each and every operation in the network, data privacy issues due to single authority that collects personal information and central point of failure are minimized. Unstructured P2P network[32,33,34] has no predefined structure or rules for the structuring the network Each peer has equal responsibility in routing messages and providing services. Peers' search data within the network based on the information given by neighbors or neighbor's neighbors, and so on (e.g. Gnutella v4). Random walk and Flooding are the most used searching techniques in unstructured networks[35]. Unstructured networks are less scalable, produce high network overhead and have lower search precision during searching data by directing queries to irrelevant peers[36,37]. Though techniques such as[38] use ant-colony optimization techniques to improve the efficiency of unstructured networks comparatively. Other P2P networks include Chord which is a structured network[39], BitTorrent a centralized P2P network[40].

P2P network has many application. Traditionally, P2P network has been used for file sharing applications[41]. However, it has many applications in other research areas as well. SPIDER P2P overlay networks[42] has been used for enhancing security of smart cities in Internet of Things using data fusion technique[43]. Similarly, it has applications in Mobile Ad-hoc Networks[44], Mobile P2P networks[45], Wireless Sensor Networks[46], Internet of Everything[47] and so on. Various P2P approaches have been developed by getting inspiration from natural phenomenon e.g. SPIDER: a bio-inspired approach[42], Ant-colony[48] and Inverted Ant-colony[49], Swarm-Intelligence inspired algorithms such as Bee Algorithm[50] and so on. These approaches have improved the efficiency such as routing, searching etc. of P2P networks. However, to carry social activities on top of P2P networks requires social information of an individual, which the above mentioned schemes lacks, and hence Social P2P networks were introduced[51].

3 | RELATED WORK

Generally, P2P networks in its current form lack social information for sharing data; therefore, a social P2P network is an appropriate choice for sharing HLDMs. Social P2P networks reflect social features in the P2P network in the form of a user's personal likes and dislikes, social trust, friends, and family relationships and so on[52].

Maze[53] is a centralized social P2P network where a server is responsible for most of the activities in the network such as security etc. The network cannot run without the server for longer and hence creating a single point of failure. MyNet[54] is another social P2P network which mostly focuses more on personal social networking. Turtle F2F (Friend-to-Friend)[55,56] can be categorized as a special purpose social P2P network which deals with sharing sensitive information through a trusted friend-to-friend connection. A peer can join only through a trusted link, authenticated by an existing Turtle friend. Once the peer is connected, the link is then encrypted between the two parties. Contents are shared anonymously for protecting the privacy of sender and receiver, but since the connectivity is through a trusted and encrypted friend-to-friend connection so it helps in avoiding any snooping or censorship issues by/against abuse of a government or corporation. Sharing that information through Turtle F2F P2P network which does not require any attention such as publicly available data, will create unnecessary security and processing overhead on peers.

Pouwelse et al.[7] designed a P2P system named Tribler[57] and assumed social concepts in their model to improve the usability and performance of BitTorrent P2P network. A mobile device based approach has also been developed for streaming videos named Tribler Mobile[57]. Social concepts considered are; friendship, trust, and communities of similar interest. Instead of direct content discovery, the search is based on approaching the communities having similar interests. Peers are provided more services if a peer has good reputation value. The reputation value is calculated according to the data shared by data downloaded. The more data shared by a peer will have higher reputation value and vice versa. This approach promotes sharing popular contents because unpopular contents are not being downloaded and hence reduces the uploading amount of the peer even if the peer is sharing the unpopular data for a longer time than the popular data. In online social networks, unpopular contents have the same importance as popular contents because some digital memories might not be much popular but still important for someone.

PeerSon[9] is a structured P2P network which has been proposed as a social P2P network. Structured P2P networks follow a strict network structure which brings extra administrative work for maintaining the network structure. As the M4L system produces very rich information about human digital memories where structured P2P networks are inefficient during handling such information. Also, handling data represented in different forms but having same meaning results in misinterpreting data which therefore makes Peers inappropriate for sharing human digital memories.

Community-based P2P approaches are very popular to support P2P networks[58,59,60] as well as social P2P networks[14,59,61]. In such communities, peers of similar interests are grouped together to form Interest-based communities (IBC)[13,15]. To find contents in the network, queries are sent according to their social links within those communities that match the behavior of the query. A major issue with IBCs is that sharing data is based on the interests of a host which by changing a host's interest, results in disconnecting the host from the community and hence results in inaccessibility of data. Furthermore, if the size of a community grows, it becomes on itself a sub-network and affects the scalability of the network. This approach provides no further procedure to connect peers based on further similarity within a community.

4 | PROPOSED SOLUTION

In this section, the proposed solution has been discussed in detail, where part A explains the concept of entities and network formed by entities. Part B explains that how entities are connected via digital memories called Inter-Entity association and part C discusses how Inter-Entity association has been used to form our proposed P2P network.

4.1 | Entities and network of entities

An entity can be considered to be anything which has its own digital memories captured or stored by itself or can form part of the digital memories of others. Entities present within a set of memories can be identified by various tools such as a memory for life system[27]. A memory for life system can analyze and annotate data, and detect entities which exist as part of it. For example, indoor or outdoor images, people, places, objects in an image and so on might all be considered as entities. Information about entities is often stored in the form of metadata which can further be used to organize the original data.

People capture and store their data in the form of digital memories and share them. The digital memories contain more information that is either not noticed by a user or it is difficult to mark the details in a computer environment. One of the aims of the memory for life system is to analyze a user's data and identify the details of that data. We refer to each distinctly identified part of a digital memory as an entity. So an entity can be defined as an object, place, person, event, idea, etc., which has its own digital memories or can form part of the digital memories of others. For example, a person is an entity who captures and stores his memories about various events in his life, the places he visited, and the people he met and so on. On the other hand, places, interests, friends, family members, etc., in digital memories of the person also represent Entities, but only as a part of his digital memories. Hence, according to the definition, a pen, the Eiffel Tower, a country, Tom, New Year's Eve, a conference, etc., are all Entities. Digital memory is composed of a single entity or a combination of more than one entity.

Entities in the real world are connected according to a correlation with each other. For example, people, who are entities, have friends and family, which therefore makes a connection among them. People and places, where both are entities, have a correlation that people visit different places. Other examples may include studying in school, college and university and people belonging to a country, city, etc. The correlation exists in our system in the form of captured digital memories where a digital memory encapsulates other entities as part of it, so a digital memory connects entities.

We have categorized the entities into two different groups: the first category contains those entities which can capture, store, maintain and are the owner of their digital memories, called Extant entities; while entities in the second category are those which either cannot capture, store or maintain their digital memories or do not own the digital memories that belong to them, called Virtual entities. Virtual entities exist as part of the digital memories of extant entities. For example, if a person visits a place, he captures his own digital memories that include him and the place. Another person, by visiting the same place, does similar things. These two people, who are entities, have connections to the place, which is also an entity, through their digital memories. The two people are extant entities because they capture their own digital memories but digital memories for the place, which cannot capture its digital memories, are being captured by them so the place is a virtual entity. However, it is also true that people capture and own digital memories about other people, who can also maintain their memories but still exist as part of their digital memories. For example, people like to capture digital memories about famous people and keep them as their own digital memories.

Entities are connected to each other through their captured digital memories. Two entities are in an Entity-entity association to each other when they are part of the same digital memory. Two distinct digital memories which have a common entity are associated with each other by the entity. We call this association a Memory association. A detailed example scenario has been given below to explain the idea of entities and network of entities.

Figure 1a shows Jane's digital memories, wherein (a) she has visited a place, in (b) she has memories of a country either she belonged to or visited, and in (c) she has captured some digital memories with friends. After being analyzed by memory for life system, entities found in Jane's above digital memories are given in Figure 1b, that includes her friends, the place she visited and the country she has data about.

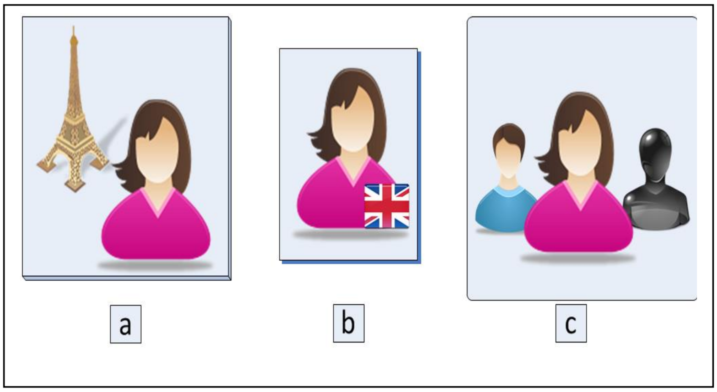
The entities found in Jane's digital memories are associated with her through her digital memories. This forms an entity-entity association between Jane and the other entities in her digital memories. It is shown in Figure 1c by a line drawn between them.

Now, Jane has a digital memory which includes the place that she visited. There is another digital memory of Lucy where she has also visited the same place. The two digital memories are associated with each other through the same place in them. This association is called a memory association, as shown in Figure 1d through a link between them.

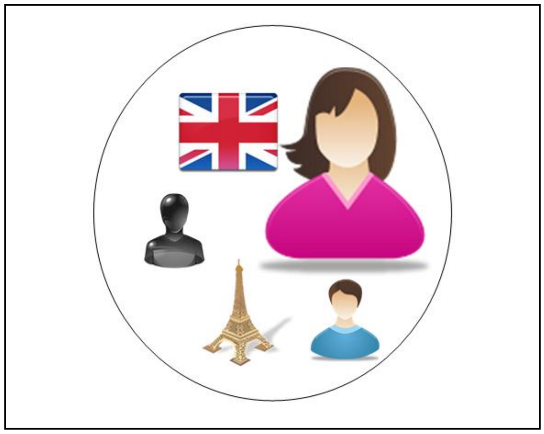
The place in Figure 1d is a common entity, so drawing an entity-entity association will result in Figure 2 where each entity is associated with its entity in the digital memory but at the same time the two entities - i.e. Jane and Lucy - which were not associated with each other are now indirectly associated through their digital memories.

To extend the idea further, suppose many people have captured their digital memories and the entities found in their digital memories are given in Figure 3a, where the person who captured and/or owns the digital memories is identified by the larger picture in the circle. Entities in each circle will form an entity-entity association as per Figure 1c. Then by applying their memory association, as shown in Figure 1d, and Fig 2, a network of entities is formed as shown in Figure 3b.

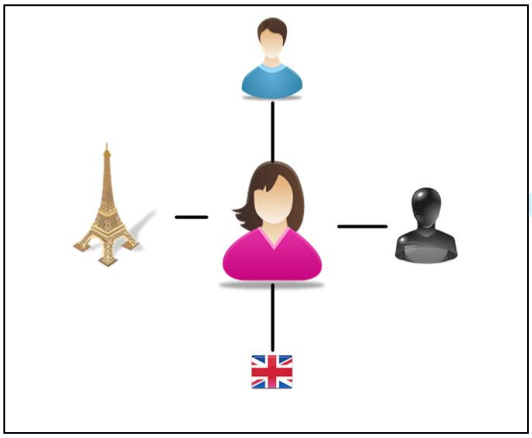
A network of entities exists logically through the association in people's digital memories. It will show how people are connected to other entities in their lives and how it can become a reason to socially connect to other people. For example, in our social lives people having a common interest quickly befriend each other. The concept of a network of entities will be used to structure our network to form entity-based communities.



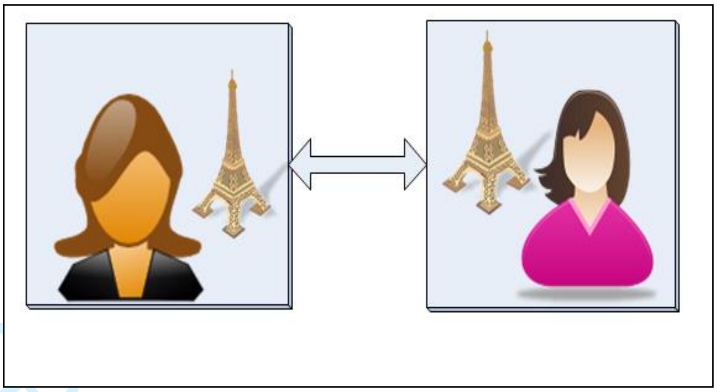
(a) Digital memories of the entity



(b) Entities in digital memories of the entity



(c) Entity-entity association



(d) Memory association

FIGURE 1 Entities in digital memories and their relation to other entities

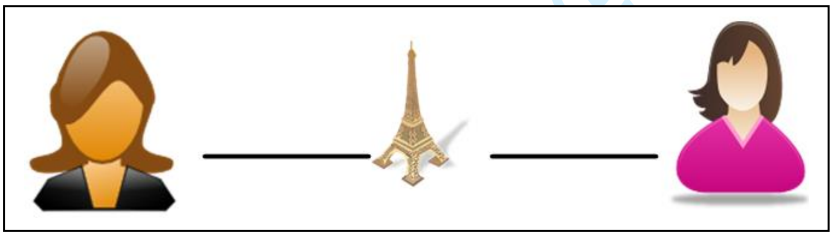
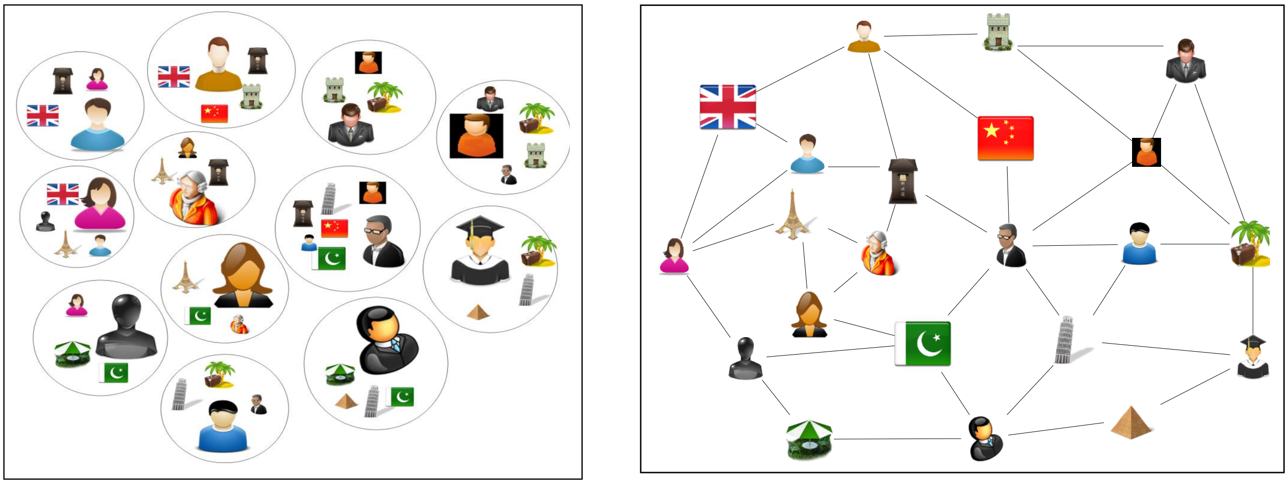


FIGURE 2 Entity-entity association from memory association

4.2 | Inter-entity Association

There are some entities in the real world that are formed by the combination of other entities such that by removing one or some of them the resulted entity will not remain the same. The entity formed is called an aggregate entity while the elements that form the aggregate entity are called component entities. The component entities may also have their own digital memories and might also exist as autonomous entities, but some of their digital memories form part of the aggregate entity. For example, a university might be an entity, yet it would be formed from the combination of staff, students, administration, buildings and so on. The university forms an aggregate entity while students, staffs, etc. are its components entities. If there are no students or staffs,



(a) Entities in digital memories

(b) A network of entities

FIGURE 3 Entities in digital memories and their network

then it cannot be called a university which, therefore, makes it an aggregate entity. Therefore, entity-within-entity relationships also exist which we call inter-entity associations.

An inter-entity association may exist for every entity within the universe either as an aggregate entity or as a component entity. For example, the universe has galaxies; Galaxies have stars; Stars have planets and Earth is a planet which has continents, countries, cities, people and so on. To establish such an organized system at such a large scale that comprises every entity within the universe and their association with each other, to the best of our knowledge does not exist. Entity-based communities are formed according to the network of entities in which entities connected to each other may or may not have Inter-entity association. A network of entities is formed by their association according to their existence as a part of digital memories, while in an inter-entity association the association of an entity defines the existence of the entity. As there is no global criterion to categorize entities and then connect the entities according to it, therefore, first of all, an extensive study is required to understand Inter-entity association and to establish a system comprising of every entity within the universe and then to develop and evaluate a network structure based upon the system

4.3 | Structuring the network according to network of entities

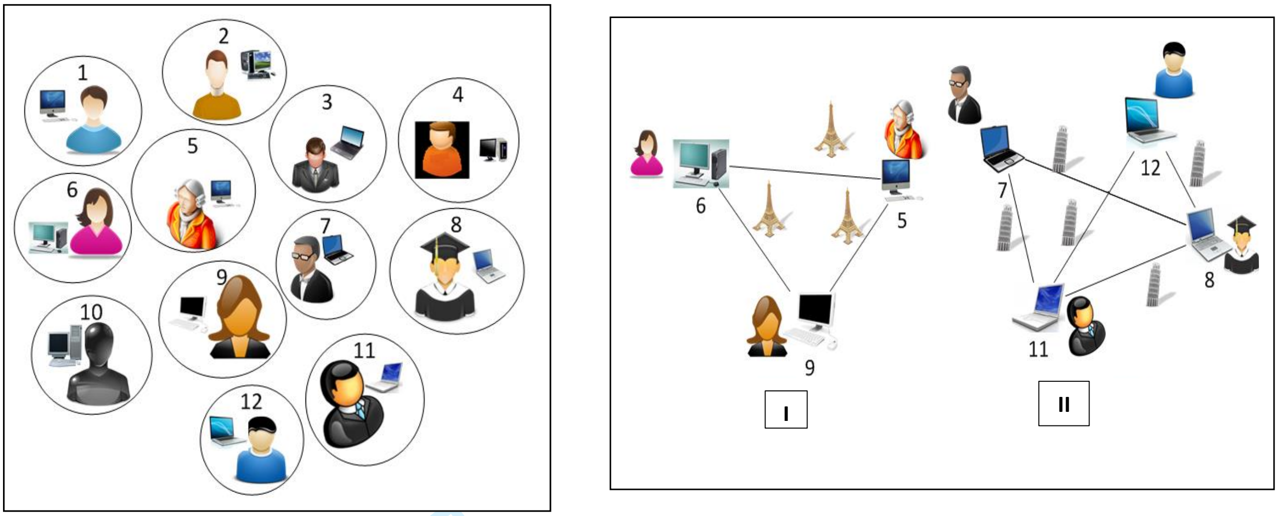
This section explains entity based communities and how they are formed from networks of entities.

4.3.1 | Entity based communities

In entity-based peer-to-peer communities, those peers that are store and share data which belong to an entity are grouped together to form a community. In other words, Peers connect to those peers that have similar digital memories of an entity, forming a community. As mentioned earlier, some entities - called extant entities - can capture, store, maintain and own digital memories while virtual entities cannot. The digital memories of extant entities are shared by their own peers and the digital memories of virtual entities will be shared by peers of extant entities.

We have assumed that only humans as extant entities are able to maintain their digital memories. Therefore, all their digital memories will be stored and shared by their peer. This is shown by Figure 4a adapting the form similar to given in Figure 4b, where each person has their own peer and will store their digital memories. However, in reality, maintaining and sharing digital memories through a device is not only limited to humans, because it is also possible that digital memories of a historical place are being maintained by the staff of that place.

An entity-based community is formed by connecting those peers whose digital memories contain the same entity. The connection between peers is a result of the memory association of their digital memories. For example, peers that are sharing digital memories about the Eiffel Tower will connect to those peers that are sharing similar digital memories. Figure 4b shows an



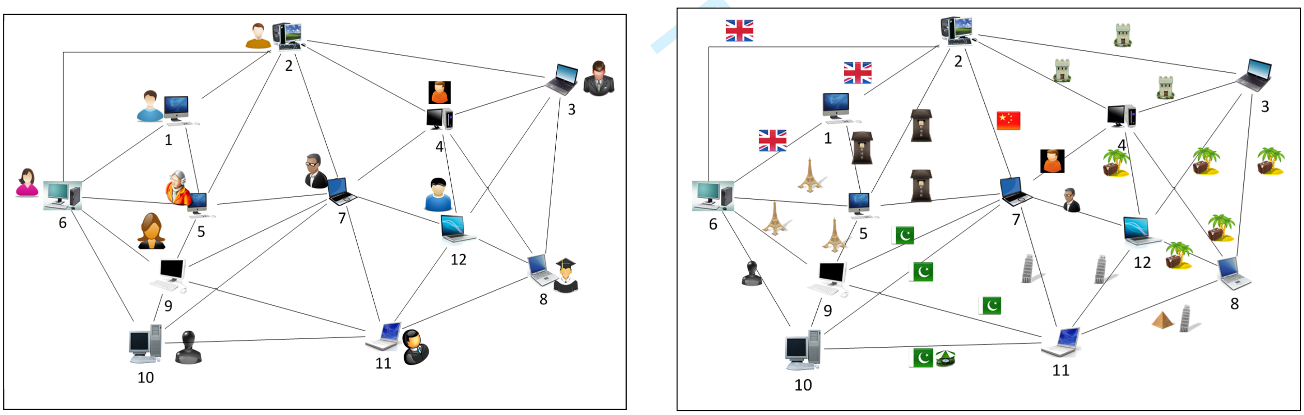
(a) Entities that can maintain and share their digital memories.

(b) (I) shows community of peers for Eiffel Tower; (II) is a community connecting peers based on the entity leaning tower of Pisa

FIGURE 4 Entities which can maintain and share their digital memories

example of the communities that can form for an entity: (I) in the figure contains peers 6, 5 and 9 which form a community for the Eiffel Tower, similarly (II) shows peers 7, 8, 11 and 12 forming a community for the Leaning Tower of Pisa.

Figure 5a shows the whole network connecting peers in all entity based communities formed according to the network of entities.



(a) (b)

FIGURE 5 (a) Connecting peers according to the network of entities. (b) Entities which can maintain and share their digital memories

The connectivity of peers is due to the memory association in their digital memories. When two peers connect with each other, the associated community information is stored with each link on its own side. However, if the same peers are connected to each other in multiple communities then the same link is used with multiple descriptions, one for each community. Figure 5b shows an example scenario where each link is labeled with the figure of the entity with which, due to its memory association, the connection is formed. Some links are labeled with two entities, such as the link between peers 10 and 11 or 11 and 8, which shows that these peers are connected to each other in the two communities through one link with a separate description of each entity.

4.3.2 | Entity participation in community

By considering actual data on a peer, for connecting it in a community, is to allow digital memories to be accessible by other peers even in the case that a person's interest changes. A peer connects according to entities in digital memories on it, but the person sharing the digital memories may or may not be interested in all entities in his captured digital memories. So he might not want to participate in all of the communities of entities. Therefore, forcing him to do so will be against his social choices.

Based on the choice of an individual's participation in various events of different communities, we have devised two types of entity-based communities, i.e. active participation communities and passive participation communities. The active participation will be the one where a user himself is interested in participating in various events of the community, while in passive participation a user's data will be accessible to other peers in a community but there will be no participation by the user in different events in the community. For example, when Alice was in school, which is an entity, she used to capture and store her digital memories of various events taken place at her school. But when she moved to college, she is now interested in various events taking place at her college which she captures and store as her digital memories. So, 'college' is her active participation community and 'school' is her passive participation community. Active participation communities will allow her to share digital memories that are of her active interest, whereas the passive participation community will allow her digital memories to be accessible by others that have the same interest. With this approach, as long as the same data is being shared it will somehow be accessible, but if a person does not want to share it then this approach cannot force him, due to his social rights.

5 | SIMULATION SETUP

Entity-based communities have been simulated through the simulator provided by Modarresi et al.[62]. This simulator has the facility to simulate community-based schemes and, therefore, is more relevant to our work, which is why we have chosen it to simulate and compare entity-based communities.

The following results demonstrate Entity-based Communities (EBC) and their comparison with existing Interest-Based Communities (IBC) and unstructured peer-to-peer network (Unet). Interest-based communities are well suited for our comparison: first due to their claim that their network supports online social networks; and second due to the community structure that both networks exhibit. An unstructured peer-to-peer network is a basic pure peer-to-peer network which will provide a good comparison with the peer-to-peer network.

As there does not exist, to the best of our knowledge, a dataset produced by a memory for life system - although an effort has been initiated to develop a dataset for research activities[63] - or an online social network with properly analysed and annotated data where entities have been identified in data, the simulator helps in assuming this fact on behalf of the memory for life system. For this purpose, an input dataset has been used. Input datasets contain information about files (digital memories and their metadata) for entities in the form of RDF (Resource Description Framework) language[64]. The input dataset is produced according to the ACM classification[65], which is assumed to be the academic digital memories of a user. A sample is given below for a paper published by Haller with the title and publication date of the paper and the category to which it belongs in the ACM classification. This sample represents a file in the simulation.

```
<Publication rdf:about="dblp:persons/conf/sigmod/Haller10">
<title>The test data challenge for database-driven applications</title>
<PubDate>2010</PubDate>
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   Information_Systems/Database_Management"/>
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Before running the simulation, a network environment is set according to the static input parameters provided at the start of the simulation, stated above. When the simulation environment is set for each of the given schemes then the simulation starts. The simulation environment is set according to the below-given parameters.

5.1 | Simulation parameters

The environment to run the simulation is set according to the defined input parameters. The parameters are taken by the simulator at the start of the simulation. There are two types of parameters being set for simulation in order to measure the performance of the networks, namely static and dynamic input parameters. The static parameters are those which do not change during the whole simulation process. Their purpose is to set the environment for simulation. The purpose of dynamic parameters, which change during various experiments, is to test network efficiency. The static parameters and their values are:

- Neighbour distribution: this defines the number of neighbors that each peer has in the networks. For this simulation, the neighbor distribution is set to follow a power-law distribution with scale value greater than two. This is in line with the finding in[66] regarding the behavior of online social networks where only a few people have higher links than others. Since the connections cannot be limitless, therefore each peer is assigned an upper limit of connections.
- Files distribution: each peer has a certain number of files, which is determined by file distribution for the whole network. In this simulation, each peer can have a number of files ranging from five to 15. The probability of the number of files each peer has is linear.
- Total number of communities and the number of communities per peer: in this simulation, there are a total of seven communities and each peer is assigned as a member of three communities at a time.
- Searching technique: this parameter governs the way a search is propagated throughout the entire network. In this simulation, the flooding technique is used as the searching technique. The time-to-live value of each search query is set to three hops, which means that each query can travel up to a maximum number of three hops.
- Number of special peers: special peers are those that possess a significantly greater number of resources than most other peers. Examples of such peers are hubs and super peers. In this simulation, there are no special peers used.
- Network connectivity: in this simulation, the peers have bi-directional links between them.
- Total simulation time: in this simulation, it is set to 5,000 seconds.
- Simulation repeats. due to the random nature of how the files and simulation times are set, the performance of the networks can vary. Therefore, to provide a more statistically sound result the simulation is carried out 15 times for each setting.

In addition to the above static parameters, the simulation also uses two dynamic parameters. These parameters are the total number of peers in the network and the number of sent queries in the network, which, consequently, affects the network traffic.

This simulation is carried out to measure the performance of the networks under varying dynamic parameter values. In each experiment, one dynamic parameter is kept constant while changing the other value. The detailed description of each of the dynamic parameters is given as follows:

Number of peers:

the scalability of a network affects its performance. The network scalability is defined as the number of peers in the network. Therefore, by simulating the network with different numbers of peers, we can measure the effect of this on the performance of the network. The node densities range from 2,000 – 20,000 peers. The traffic in the network is generated according to the linear distribution given in Equation (1).

$$T_{n+1} = T_n + (b \pm m) \tag{1}$$

where T_n is the time of the last event to send a new query, T_{n+1} the time of the next event to be set, b is a base value for the average delay and m is a modifier. The base value represents the time interval between sending new queries in the network. The modifier value is used by the distribution function to vary the interval. The successful queries in the network and the level of overhead created were recorded while increasing the network size.

Query distribution:

it is understood that the performance of a network is also affected by how much traffic is generated in the network. Therefore, it is crucial that our measurement takes this into consideration. In this simulation, network traffic is adjusted by changing the number of queries sent in the network. The number of queries is randomly created using a linear probability distribution. The distribution function which is used to distribute the events and to send new queries in the network within the 5,000s time limit is as in Equation (2). The base b for the function takes the values 200s, 100s, 60s, 40s, 30s, 25s, 20s, and 15s and the modifier m takes the value 40s. The base value affects the amount of traffic in the network: the lower the base value the more events are created to send new queries, and the greater the network traffic and vice versa. We test the successful queries in the network and the amount of overhead created by changing network traffic. For these runs, the network size is set at a constant 5,000 peers.

5.2 | Dynamic interest

We have simulated entity based community (EBC) and compared it to the Interest-based community (IBC). Interest-based communities are formed according to human interest and those peers having similar data join together and form these communities. As explained earlier, the problem with IBCs is the dynamic nature of peer such that as soon the interest of a person changes, the peer leaves the community and disconnects from it which results in inaccessibility of data to other peers in the community. The simulation is carried out for two types of community structures i.e. entity based communities which form communities based on entities in digital memories and Interest-based communities based on the interest of a person. As EBCs are formed according to data shared by a peer, so as long as data is being shared by the person the peer will be a member of the same community. It comparatively results in a more static network which will form a more stable network. Interest-based communities have dynamic nature, which means that after a period of time, interests of some peers change and new interests are assigned. It results in the peer leaving the previous community and joining a new community of the new interest. To simulate the dynamic nature of interest, events are set within the simulation time limit at which X numbers of peers are selected randomly and their interests are randomly changed. Events are linearly distributed having a base value of 100 and modifier 40. The value of X numbers of peers is determined by the following Equation 2:

$$X = \frac{n}{E} \tag{2}$$

Where n is the total number of peers and E is the total number of events, which occur to change the interest of randomly selected peers.

X numbers of peers are selected at each event, so by the end of simulation approximately n numbers of peers will have the chance to be selected. For example, if there is a network of 100 peers and 10 events are set during the simulation time period, then at each event 10 peers will be selected and at the end of simulation 100 peers will have the chance to be selected. Due to using a random approach, it is also possible that a peer is selected more than one time in which case it is not guaranteed that every peer is selected at least once.

5.3 | Performance metrics

There are some metrics upon which the performance of the networks is measured, mainly for EBCs and IBCs.

5.3.1 | Query success rate

It determines the rate of successful queries. A successful query is the one which finds the requested contents in the search query before the query forwarding condition fails.

5.3.2 | Actually sent queries

When a peer is sending a newly initiated query, it selects neighbors from its neighbors' list and then sends its query to them. In some cases when a peer cannot find an appropriate neighbor(s) then it drops the query before it is sent. This is due to inappropriate connections when a peer loses neighbors or is searching for data of a community to which it does not belong anymore, due to moving from the community as a result of a change in interest. The rest of the newly created queries which are sent after finding appropriate neighbors are Actually sent queries. A high percentage of Actually sent queries shows that peers are connected in a more appropriate neighborhood and can easily find relevant peers.

5.3.3 | Network overhead

Network overhead is the surplus messages which are produced as a result of an undesirable but important operation. It is produced due to the dropped messages and dynamic behavior of the network. A query is dropped when the forwarding condition fails before data is found, a repetitive message is found, or an unrelated answer is received. The overhead due to the dynamic behavior is produced as a result of searching and joining new communities due to change in the interest of a peer.

5.3.4 | Average number of hops a query has traveled

It measures the number of hops a query travelled to produce a successful query. The values are averaged for all the experiments carried out to produce a single and more precise value.

6 | RESULTS AND COMPARISON

The following results demonstrate Entity based communities and their comparison with existing interest-based communities and Unstructured P2P networks (Unet). Interest-based communities suit well for our comparison; first due to their claim that their network supports online social networks and second due to community structure that both networks exhibit. An unstructured P2P network is a basic and pure P2P network which will provide a good comparison with the P2P network.

The density of a network can have a positive or negative effect on the performance of a network. Therefore, it is important that before running the simulation the network densities of each network should comparatively be equal so that the results can be compared impartially. To test performance, entity-based communities and interest-based communities with the same network density are equally initialized, whereas the network density of Unet has, comparatively, been kept lower only to take less time during each experiment - although it will be clear from the results that this has comparatively no effect on judging the performance of Unet.. Each network has the same structure at the start of the simulation when the simulation time is zero, but changes according to its own approach afterward. Figure 6 shows network density for each of the networks.

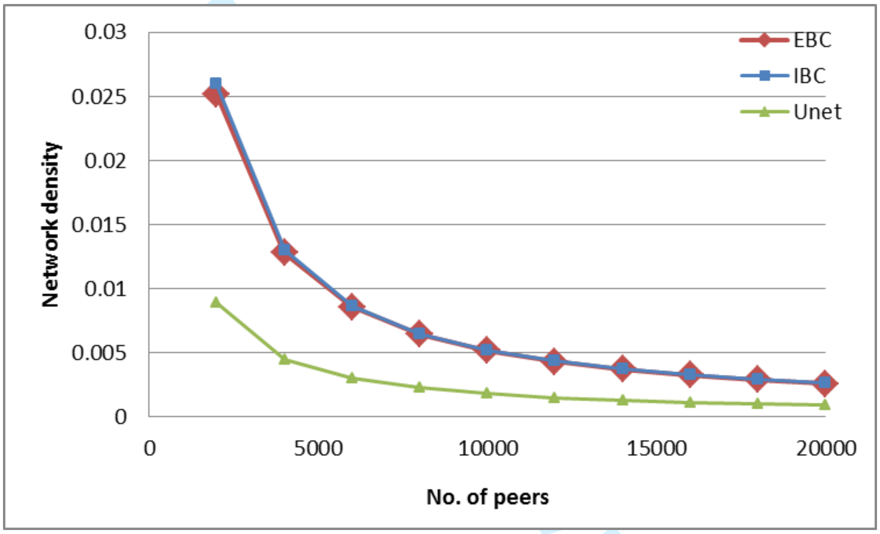
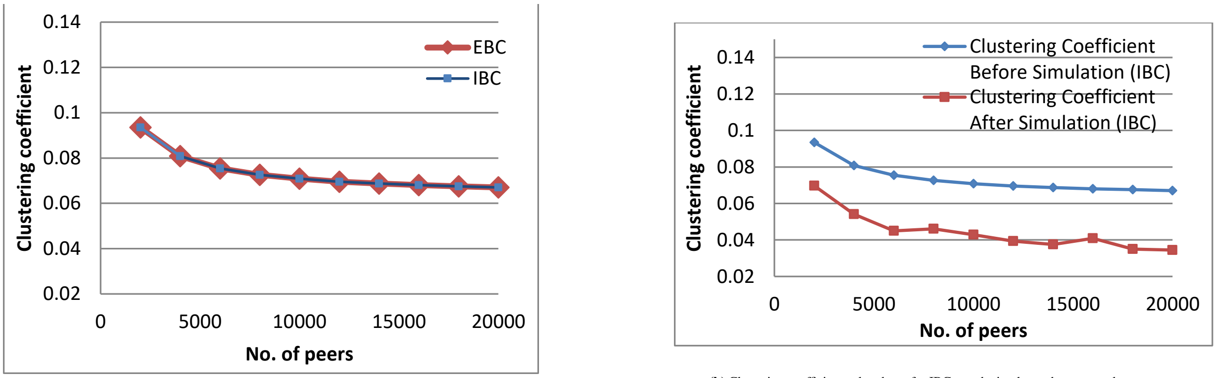


FIGURE 6 EBCs and IBCs have same network density

As mentioned earlier, people always want to keep and share their digital memories. Therefore, a network produced as a result of human life digital memories will have a more static nature as compared to interest-based communities where an individual's interest is affected by many factors and may change after some time. Based on this argument, entity-based communities have a static nature, while in IBCs peers move from one community to another according to their interests. There are two possibilities when a peer moves within a network. First, it may increase network efficiency by joining a new community and hence connecting new peers in the network. Second, it may degrade network efficiency by leaving a community; this is due to disconnecting peers and inaccessibility of data which was previously available in the same community.

The dynamic behavior of IBCs will also have an effect on the clustering coefficient value of the network. Clustering coefficient measures the connectedness among neighbors of a peer. The availability of such connections creates alternate routes in the network so that in the case of failure of a link an alternate route is available, thereby increasing network robustness. Clustering coefficient is measured between 1 and 0, and a value closer to 0 indicates a network of a random nature, which is less robust, and vice versa.

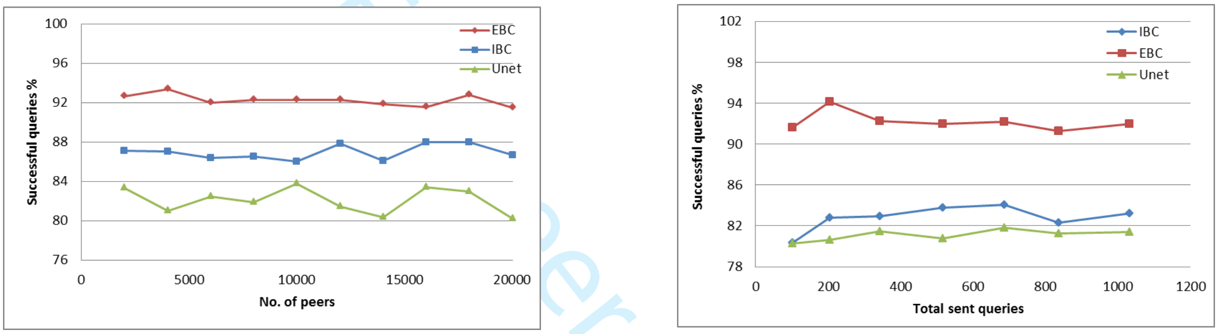
Figure 7a and Figure 7b compare the clustering coefficient value for the networks before the simulation was started and after the simulation was finished. In the Figure 7a, the calculated clustering coefficient value for both networks is the same. When the simulation is started and the peers started moving between different communities, due to the dynamic behavior of IBCs, it resulted in degrading the clustering coefficient value, as can be seen in the graph in Figure 7b. When a network is more static,



(a) Clustering coefficient value is the same for IBCs and EBCs before simulation

(b) Clustering coefficient value drops for IBCs producing less robust network structure

FIGURE 7 Clustering coefficient values and their impact on the robustness of network structure



(a) Rate of successful queries by change in network size, where EBCs have higher success rate

(b) Rate of successful queries by increasing network traffic

FIGURE 8 Rate of queries success and its behavior due to increase in network size and network traffic

each peer acquires a place known to its neighbors in the network and will create stable/known routes in the network. When peers move inside a network, the known routes are disconnected. The peer joining the new community may not acquire enough connections due to other peers in the community having the maximum number of connections. Also, the network follows power law distribution where a few peers have a higher number of connections. If a hub peer moves then the situation might be worse than if a normal peer moves because if the hub peer cannot connect to all the connections that it had in the previous community this will result in the loss of many connections. This loss in alternate routes reduces the clustering coefficient value and hence results in a less robust network as compared to our approach, shown in Figure 7b. Similar behavior can be observed in our society when people travel or go to new communities, as it usually takes time to make friends and become familiar.

With the help of the results obtained from the simulation, we will now demonstrate the effect of the resultant network structure. The following figures will demonstrate the differences in performance of entity-based communities, interest-based communities and unstructured networks (Unet) due to the approach being used by each technique. The Unet is simulated in a static form where no peers move from one place in the network to another. The purpose is to provide a baseline for measuring the performance of interest-based communities and entity-based communities.

Figure 8a and Figure 8b show the rate of successful queries for entity-based communities, IBCs, and Unet during varying network size and network traffic. In Figure 8a, entity-based communities, during increasing network size, have a higher query success rate than interest-based communities by approximately 5% and Unet by approximately 10%, whereas interest-based communities have a higher success rate than Unet by an average of 4.8%. The success rate of entity-based communities, during increasing network traffic, is approximately 9% and 11% higher than interest-based communities and Unet respectively as shown in Figure 8b.

When a peer is sending a newly initiated query, it selects neighbors from its neighbors' list and then sends its query to them. In some cases when a peer cannot find an appropriate neighbor (s) then it drops the query before it is sent. This is due to

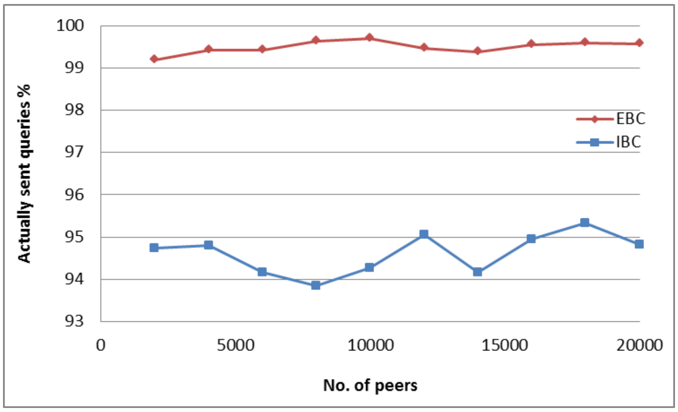
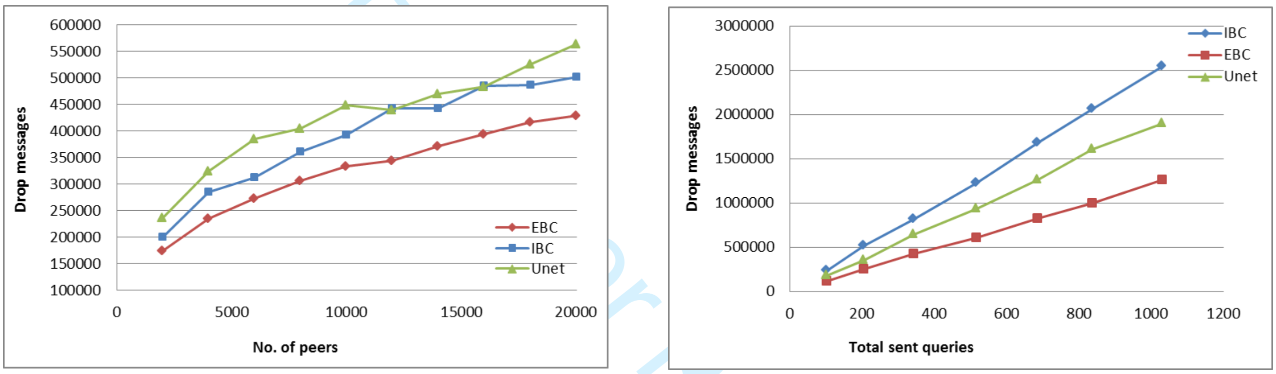


FIGURE 9 Queries sent by peers out of all queries that were supposed to be sent



(a) Network overhead (Drop messages) measured during increased in network size

(b) Network overhead (Drop messages) measured during increased in network traffic

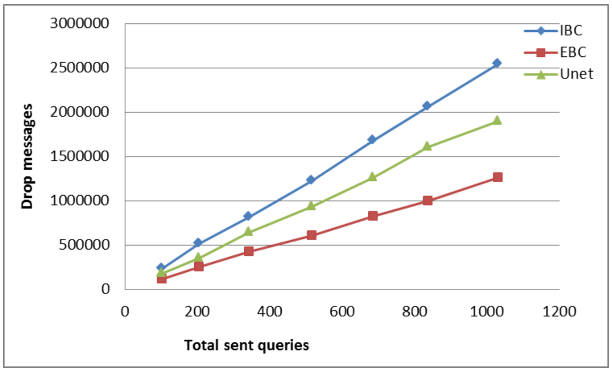
FIGURE 10 Network overhead measurement in terms of network size and increase in network traffic

inappropriate connections when a peer loses neighbors or is searching for data of a community to which it does not belong anymore, due to moving from the community as a result of a change in interest. The rest of the newly created queries which are sent after finding appropriate neighbors are Actually sent queries. A high percentage of Actually sent queries shows that peers are connected in a more appropriate neighborhood and can easily find relevant peers.

The graph in Figure 9 shows the 'actually sent queries' by peers. As we can see, interest-based communities have a lower rate of actually sent queries than entity-based communities due to the fact that peers move within communities and, therefore, some peers lose appropriate neighbors, either the peer that moved or because a peer has lost some connections due to the moved peer, and hence cannot find any suitable neighbor to forward a query to.

Unstructured networks have a higher network overhead, as can be seen in Figure 10a, due to the network structure where a query is sent to every peer even if there is no chance of finding data based on their similarity. Comparatively, interest-based communities have a lower network overhead because queries are sent only to those peers that have the chance either of holding data themselves or being connected to a peer holding data. The stable network structure of entity-based communities produces a lower network overhead.

The scenario for IBCs in Figure 10b is different, where IBCs have a higher network overhead. When an interest of a peer changes and it moves from the community then queries being sent by other peers for searching the specific data, that is stored on the moved peer, are finally dropped because the data is not available. The more such queries are sent, the more they are dropped. Due to this reason, IBCs produce a higher network overhead than Unet and entity-based communities. In this case too, entity-based communities have a lower network overhead.



(a) Number of hops taken by queries to find data (Successful queries) during increasing network size

(b) Number of hops taken by queries to find data (Successful queries) during increasing network traffic

FIGURE 11 The impact of number of hops in finding data in terms of network size and increasing network traffic

Figure 11a and Figure 11b shows the average number of hops for successful queries. In the figures, Unet takes a higher number of hops to find data successfully than entity-based communities and interest-based communities do, whereas entity-based communities and interest-based communities have a similar number of hops.

7 | CONCLUSION AND FUTURE WORK

A new research problem has been identified, that involves peers moving within a network. The problem is different than early mentioned peer churn in which peers leave and join a network leading to the peer being available or unavailable in the network. Another similar problem is peer's mobility from one location in the network to another where the peer is available in the network but due to the change in the interest makes the peers to move by connecting with new peers and disconnecting from previously known peers hence disconnecting known paths in network and thereby reducing network robustness. In this article an entity-based community have been structured according to digital memories of individuals which comparatively produce more static network structure than a network structured based on human interest. Entity based communities are formed by grouping communities with similar interests together. Rather than representing data by peer and finding peer to find data, in entity-based communities data itself is known in network by connecting peers sharing similar data. A peer becomes only a device to share data instead as an important unit of network. An M4L system has been used to identify entities in digital memories. The research is in very early stages; therefore, an entity cannot be defined precisely yet and it is not known that how each entity will uniquely be identified. The proposed method has been simulated to test the basic structure of the network. The network did not involve any special peers for communication in the network. As a future work the robustness of entity-based online social network may simulated by introducing a link failure algorithm and then measuring the performance of the network. In future, it may be investigated that whether the idea can be applied in online social networks keeping in mind their limited entity identification in digital memories such as using face and location recognition.

Every human in the world is believed to have access to every other human through their social acquaintance. The theory was tested by Stanley Milgram in 1967 and found six degree of separation. As Watts describe in his book[67] that technology has played important role in shrinking the physical distances among people The recent advances in online social network have even further allowed human to reduce the distance by getting acquaintance with people which is difficult in normal routine life[68]. We can clearly see from the results obtained by Ugander et al.[69] from crawling Facebook. The average path length found for the network was 4.7, which is less as compared to the value from the experiment of Stanley Milgram which was conducted at a small scale. We believe that human to human acquaintances have certain limits as can be seen by the power law behaviour of social networks where a least number of people have higher connectivity. On the other hand, acquaintance via an individual's digital memories contain many connections to many entities which connect him to many people. We believe that considering entities in human digital memories for acquaintance will be an interesting area to study to find the effect on the degree of separation.

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