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Advanced Service Search Model for Higher Network Navigation Using Small World Networks

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ABSTRACT Social Internet of Things (SIoT) is a new standard resulting from the integration of the Internet of Things (IoT) and social networking. IoT is a visionary, one-paradigm, whereas social networks are platforms where voluminous collaborations between humans exist. The SIoT is defined as a social network of objects that are not only smarter but also socially conscious. Fundamental requirements of both IoT and SIoT networks include efficient service search and the discovery of object mechanisms. Therefore, our paper proposes a simple model for social networks to discover the object or services by using a small-world network. Our proposed model comprised a set of objects, and where each object is looking for a service. The service search is initiated in different hops by an object using a service query message to the nearest object. If the requested object is identified immediately or at the first hop, a permanent link is established between the service requester and the service provider otherwise the search process is repeated until the service is discovered. In this study, we integrate the SIoT with the small world concept for the building of our model. Our proposed model guarantees that the object containing the information is in a bounded path length and is treatable owing to the structure of small-world networks. The process of search is efficient because it is initiated only when an object asks for another object or service. Our intention here is to increase the navigability of the network. We carefully performed numerical analyses for our model and presented the simulation results based on efficiencies such as average path length, clustering coefficient, service execution time, and the giant component. After conducting various experiments, we conclude that our proposed model is efficient and reflects the real network structures of small-world networks, therefore, it can be suitable for social networks.

INDEX TERMS Small-world network, Internet of Things, Social Internet of Things, service search.

I. INTRODUCTION

The Internet of Things (IoT) describes the network of physical objects. The most promising aspect of IoT is the ability to connect heterogeneous and homogeneous objects. Generally in IoT, billions of objects are connected over the Internet [1], [2]. These objects are equipped with sensors and actuators that observe the various aspects of human life to support services and applications [1], [3]. The objective of IoT framework is to provide services to users. According to a recent survey report, by 2025 connected devices across all technologies will reach 20.6 billion. It increases data size because a massive amount of data is flowing through IoT networks. This scenario introduces various new eras of research for the researchers to build new applications for domains such as e-health, supply chain management, and the management of industrial production plants, etc. However, IoT networks pose a challenge related to data management. Besides, the object discovery and the size of the searching space are the main and crucial challenges. The network traffic became very large due to the number of access devices and the number of queries received by search engines. The

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heterogeneity is the main concern where the IoT devices have different standards, deployment features, and also have various communication protocols [4]. Consequently, owing to a large number of objects, there is a need to develop a more flexible Internet infrastructure in the future. Besides, the object discovery and the size of the searching space are the main and crucial challenges. The network traffic became very large due to the number of access devices and the number of queries received by search engines. The heterogeneity is the main concern where the IoT devices have different standards, deployment features, and also have various communication protocols [4]. Currently, the human-object-interaction model is based on humans. In this model, the information is provided by objects but in near future, this model will quickly shift to the object-object interaction model. In this model, the object looks for others to provide various services for the assistance of humans and increasing the queries in the network. The scalability issue arises from the search for the right object for the service or the best path to the nodes in the network. In this scenario, there are several search methods have been proposed, i.e.; [5] and [6]. The common property between these two studies is that both search engines are mainly based on centralized systems. Therefore, they are not scalable both in terms of processing several queries or especially when many devices are connected. Similarly in [7], the authors discussed a novel topic-centric algorithm to cluster the results in a network. They highlighted the advantages of clustering a network for the processing of a query in the network. But this algorithm is not suitable for large dataset processing and the time to search a query, because it is very slow.

The IoT network is not scalable and hence the network navigability becomes more crucial. In general, the IoT devices will consume more energy and the use of services among each other, hence the network navigability is very limited to the selection of devices and the searching for suitable services. It becomes a challenge in this area. In general, the object discovery and the service composition both depend on the network navigability, which is considered a major issue especially when the network is very large and billions of connected devices [8]. Thus, there is a need to find alternative frameworks or derive new extensions from existing IoT to overcome the challenges and the issues in this direction.

A recent development in this direction is the introduction of the Social internet of things (SIoT) [9]. The SIoT refers to the convergence of the Internet of Things and Social Networking paradigms for the creation of social networks in which things are nodes that establish social links as humans do. This phenome allows people and smart objects to interact within a social structure based on relationships [10]. Thus, we consider SIoT as a network in which each device can establish social relationships with others according to the rules set by the owners. Thus, it allows us to compose the services and information in a trusted fashion by levering the interactions among objects that are friends. This paradigm gives the IoT a structure that can offer network navigability for scalable and efficient discovery of services like that of human-centric social networks. The service search in SIoT is performed in a decentralized manner. It is efficient as compared to the traditional centralized search. The SIoT does not rely on web technologies; instead, it is a complete platform for social network services (SNS) which deals with objects rather than only dealing with humans. In SIoT the objects are social compared to traditional IoT objects. Hence, they can make new relations efficiently. Another benefit of the SIoT is the trustworthiness level. It is established depending upon whether or not objects are "friends" or not. This could increase or decrease the degree of interaction between them and also would enable humans to increase the security level of each object's relationship.

P2P networks allow us to search through the resource, such as for an object address, so the probability of connections to an object will be high [11]. Therefore, resource distribution is a common issue in these networks. To overcome this problem, a reasonable solution is to perform a search when it is required. In a homogeneous network, it is feasible, but in the case of a heterogeneous network, it becomes difficult. Thus, to solve this issue, the solution goes into a different perspective of thinking such as the SIoT.

We are living in the world of networks where complex networks play an important role [12]. A complex network is a great area of interest and is derived from the theory of complexity science [13]. Moreover, the complexity science theory is rooted in graph theory, which is a relatively new area of research as it became a recognizable field and was given its name in 1980. There are many networks such as brain networks, sensor networks, and social networks that can be also represented as graphs. Usually, a graph is a combination of edges and vertices or points connected by lines. The philosophy of describing and solving a real problem by using a graph can be traced back to Euler's solution for the seven bridges problem [14]. The graph-based solutions are wildly applicable for real and social networks. Social networks follow the graph structure because they consist of objects and edges (as described earlier) where the edges are links, and the objects are the points that connect these links. The structure of social networks grows rapidly by the increasing of network links and can be changed over time [15]. Within networks, there are plenty of models to be considered. One of the most popular and simplest models is the small-world network, which was proposed by Watts and Strogatz [16] in 1998. It is a typical graph that starts from a ring-shaped network and the rewiring of each of its edges is performed based on probability [17]. The purpose of the small-world network is to find existing relationships in the real world or especially in a group of people.

In reality, the small-world phenomenon refers to the principle that all people are linked together by a short chain of acquaintances.

The small-world network [18] shows that the process of a service search in a large network does not affect the path length of any pair of objects in a certain condition. This is a very important property that solves the cost-related issues

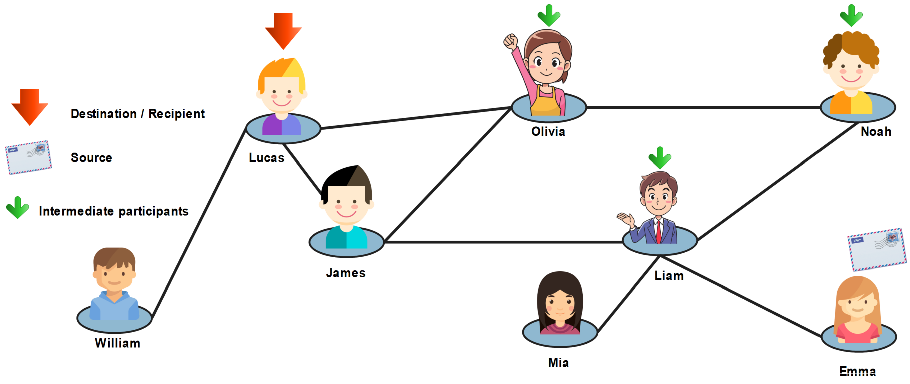

FIGURE 1. **An example of a small-world network.**

concerning the earlier issues in P2P networks. Additionally, the shortest path between any pair of objects is not sensitive to the network size [19]. For instance, six degrees of separation is the idea that everyone is linked by a chain that is, at most, six people long. For example, Figure 1 demonstrates the small-world phenomenon. In this example, a group of people in a social network is shown. Given two people, Emma and Lucas, there is a chain of other people such that Emma knows Liam, who knows Noah, who knows Olivia, who also knows Lucas. Suppose that Emma holds a letter and wants to forward this letter to Lucas (the target person). Under the six degrees of separation theory, she forwards it to a neighbor (e.g. Liam). The condition imposed on this network is that each participant can advance the letter only by forwarding it to a single acquaintance. Hence, Emma forwards it to Liam, Liam sends it to Noah, then Noah to Olivia, and finally, it reaches Lucas via Olivia. In this figure, we carefully observe that short paths (no more than six hops) always exist between all people. This is known as six degrees of separation. The degree of separation theory proves that the distance between two people in the world is very small as compared to the network size [20], [21]. However, even though the distance between the two objects is small, then it does not indicate the shortest path length. This graph property can only be seen when we analyze the complete graph [22]. Nevertheless, in some cases, this is not possible, as objects have limited knowledge of their neighbors, etc. Usually, social networks have the properties of knowledge sharing and dynamic division. Because of this feature, present-day social networks have become crucial channels for the transfer of knowledge [23]. Generally, a similar relationship between the receiver and the sender is affected by the network's structure in a knowledge-sharing network. In few studies, the analysis is being performed and based on micro-network interaction in the network subject along with other concerns regarding the macro behavior pattern of this subject. Hence, it is difficult to determine which network structure is better and which one is more appropriate for the growth of objects in the network [23].

Briefly, this research study is the integration of the Small world concept and the social IoT. For knowledge-based service search, we extended the Klinberg model and intelligent agent model. In our model, the information seeker searches for the service among neighbors in the network in a decentralized manner. Initially, the search procedure is initiated by using an object named information seeker, and then it looks for the service into the neighboring devices. Several neighbors exist among the information seeker and the information provider. Our model automatically identifies the short paths among neighbors based on centrality and distance. An active service search has been performed whenever it is requested. Our model uses together with the basic properties of small-world networks and the characteristics of SIoT.

A. PROBLEM DEFINITION AND MOTIVATION

The primary motivation of this study is to build a new service search model to overcome the service discovery issue in the IoT. Notably, IoT devices have limited memory and computational power. The discovery of short paths by using local information is suggested by J. Kleinberg [21] *et al.* They proved that a small-world network has a special structure i.e., a short path length and high clustering. Therefore, it helps in finding of service for an object in the network. We already know that decentralized search algorithms can find short paths with high probability. Additionally, Kleinberg *et al.* proved that only a unique model exists, in which the decentralized search became more effective. Hence, this key finding motivates us to do more research in this direction.

B. CONTRIBUTION

Our contributions to the research community are given below.

- This study proposes a decentralized knowledge-based search model using a small world for the discovery of objects that can provide a specific application based on SIoT.
- Our algorithm is completely based on local network properties of small-world networks, such as degree centrality and neighborhood degrees. An active search operation in the network has been performed whenever it is requested, hence the overall network navigability is

increased. Due to the existence of short paths in the network, the requested object is quickly accessed.
- After careful investigation, we find out that our proposed model is more efficient as compared to the prior state-of-the-art models.

The benefit of this research proposal is to provide better object navigability and efficient search operation in a network. In our proposed network, the efficient service mechanism is performed by finding a target object that is located under the restricted path length. Whenever a search query is made by the object, it can be collected by looking around others in the network [24]. This navigable knowledge-sharing model is good for online social networks (ONS). The search procedure is calmly completed without affecting the overall performance of the network.

C. ORGANIZATION OF THE PAPER

This paper is organized as follows. Section 2 presents the literature review of this study. In this section, we discussed the basic concept of SIoT and the process of service search in IoT. Additionally, discussed the most recent studies along with limitations and advantages. In Section 3 we presented our proposed model along with real scenarios. Section.4 offers the analysis and the visualization of our proposed model. We have presented the experimental results in this section. Finally, Section 5, concludes with a summary of this study.

II. LITERATURE REVIEW

In this section, we discussed various studies related to the service search in the IoT. We divided this section into two sub-sections. In the first section, we discuss various studies related to service search in IoT. Then we discuss a distributed referenced scenario and explained the procedure of service search.

A. THE CONCEPT OF SIoT AND SERVICE SEARCH

The Social Internet of Things (SIoT) refers to the convergence of the Internet of Things and Social Networking paradigms for the creation of social networks in which things are nodes that establish social links as humans do. This phenome allows people and smart objects to interact within a social structure based on relationships. Thus, we consider SIoT as a network in which each device can establish social relationships with others according to the rules set by the owners. The SIoT is introduced to overcome the problems in IoT. Efficient service discovery is made possible in the SIoT due to its network navigability. Before going into the details, we first discuss the service search procedure in the IoT. It is a two-step procedure in IoT. In the first step the sensing is performed, and in the second step, the operation of data retrieval from other devices [25]. In the sensing process, the information seeker search for neighbors. Initially, the search procedure is initiated by using an object named information seeker, and then it looks into the neighboring devices. There are several neighbors among the information seeker and the information provider. We do not know the number of hops between them. Hence, owing to the number of devices, it is difficult to connect both objects, which creates several links [25]. The information seeker can store the routing information for neighbors. Owing to its limited storage capability, it is difficult to store all the information inside an information seeker. Additionally, instead of using global information, local information is a good solution. Therefore, in this proposal, we are not interested in keeping all the neighbors informed because we are only interested in the locals. The core objective of our research proposal is to keep the locals informed and launch the search information process whenever it is necessary.

B. THE SMALL-WORLD NETWORK AND THE CONCEPT OF NETWORK NAVIGABILITY

A network is the set of items which are named as vertices, and the connection are known as edges. The example includes word wide web, social network, etc. Network navigability has been discussed in prior studies [26]. The ''six degrees of separation'' theory was proposed by Milgram *et al.* in [27]. This theory suggests that if we select one person randomly from a group of six people, then it might be possible that they know another randomly chosen person. The six degrees separation philosophy is very common and known all over the world. However, two questions are not answered in this experiment. What is the structure of social networks? And what type of mechanism do people use for the one route to finding a target? To find the answers to these questions, we reviewed various studies. The literature review is given below.

The small-world model is a type of network in which an attempt is made to find the relationships in humans, ecosystems, information networks, etc. The small-world network is one of the simplest models proposed by Watts and Strogatz (WS) in 1998 [16]. It is a typical graph that starts from a ring-shaped network, and the rewiring of each edge is performed based on probability [17]. The purpose of the small-world network is to find relationships in the real world or especially in a group of people. The structure of small-world networks is based on the identification of short paths that co-exist between objects. There are various examples of small-world networks such as; food webs, cultural networks, sports networks and social influence networks.

Newman and Watts [28] proposed a modified small-world network where random rewiring by adding random edges to a network is performed.

Highly motivated by Watts and Strogatz lattice ring model, J. Kleinberg's proposed a new model in [21]. They describe a decentralized algorithm that attempts to locally route a message from the source object to the target object. This procedure is performed by visiting only local neighbors. This model is the combination of a regular and random graph. In this network, the objects are arranged in a $a \times a$ grid. All objects in the network connected by using short-range and long-range contacts. In this grid, each object has links to every object at lattice distance p. p is used for the short-range neighbors and the q is used for the long-range links. This model demonstrates that it is possible to construct a navigable network with the structure of a small world. The proposed structure is very appropriate for distributed networks.

The problem in the Kleinberg model is that when one column or row fails, the lattice is divided into a row of isolated networks. Subsequently, the following question appears: How does the Kleinberg model behave in these situations? Another disadvantage of this model is; It is not fully understood how the arbitrary distribution of shortcuts dictates might arise in practice. The Kleinberg model was successfully used for the P2P systems—but how does it relate to the real network? Furthermore, Kleinberg's model failed to show the navigability of objects. Another difficulty of this proposal is that every interaction requires an expensive message exchange process, which means that a lot of messages are generated during this process.

Recently, Z. Pengfei *et al.* in [19], discussed an agent management system (AMS) search procedure for the finding of agents in a small-world network. They modified the existing Kleinberg model for the agent search. The steps of the search mechanism are given below.

At first, the agent registers themselves in the system. After registering, the agent asks for the neighbors for a service. Therefore, an active search is made now. Due to the structure of a small-world network, it guarantees that an object contains the information under a bounded path length. The issue with this algorithm is that the size of the lattice is fixed. The main drawback of this proposal is that every interaction requires an expensive exchange of messages it means that a lot of messages have been saved during the registration process over the system.

Amin *et al.* in [25], proposes an advanced algorithm for higher network navigation for the SIoT. In this study, they address the problem of link selection in SIoT. They have considered a small network, where people are the actors of that network. In this network, one person is a service seeker and the other is a service provider. A new link between the service seeker and the service provider is created or removed by using certain rules [25]. They have introduced a threshold to restrict the number of friends of an object. There are two main problems associated with this approach, the first is the fixed number of friends, and the second is the level of trust. Milano et al in [10] discussed a model to increase network navigability using game theory. In this model, they have discussed the problem of selecting the right friends in a network. To do this, an efficient service search for the selection of the right friends is performed. The short paths are very helpful to increase the overall network navigability in the network. They extended their previous work and also introduced the shape value of objects using game theory. They had restricted the number of friends per node. Their model helps to get higher network navigability. The problem with this approach is they used a certain threshold. If the number of connections is larger than it cannot be handled.

Briefly, the search for service in IoT is a major challenge. Table 1 provides a comparison of different network models. In this table, the description of the model along with the advantages and the disadvantages has been discussed.

C. THE CHARACTERISTICS OF SMALL WORLD

In the original model, the small-world effect was illustrated by comparing the clustering coefficient (CC) to the average shortest path length of networks. On the other hand, the random networks due to short path lengths, possess low clustering. However, the regular networks are highly clustered, while objects are, on average and quite distant from one another. The Watts–Strogatz (WS) model provides the structural insight between the clustering and the small world. It captures the structure of real networks and has high clustering for real networks, but it does not lead to the correct degree distribution and does not provide the navigability feature. Therefore, what mechanism do people use to navigate networks and find the object in the network?

In this study, we are going to present a unique network navigability solution for the objects. However, before going into the details of navigability we will first discuss the important properties of the small-world network.

There are three important metrics or properties of a small world network, i.e., degree distribution, path length, and the clustering coefficient. In this section, we will explain all these parameters in detail.

1) OBJECT DEGREES

The degrees of an object demonstrate how many neighbors are attached to it. Furthermore, the average degree is measured by taking the ratio of the degree of an individual object to the total number of objects in the network.

$$Pdeg\,(v) = k \tag{1}$$

where $deg\,(v)$ denotes the degree of (v) is equal to k.

The degree in social networks is very interesting for several reasons:

- In a social network, the ones who have connections to many others might have more influence, more access to information, or more prestige than those who have fewer connections.
- The degree is the immediate risk of a node catching whatever is flowing through the network (such as a virus, or some information).

2) PATH LENGTH

The path length is used to find the size of a network. It defines the average distance between two vertices or nodes [29]. The average path length L is calculated based on Equation (2).

$$L = \begin{bmatrix} N \\ 2 \end{bmatrix}^{-1} \sum_{i \neq j} l_{ij} \tag{2}$$

TABLE 1. Summary of current network models in service discovery.

Models	Description	Advantages	Disadvantages
Guan et. Al., [17], 2016.	Real Instant messaging chat network has been proposed.	• This instant messaging chat network is efficient as compared to the state of the art models.	• Lack of validation along with state of the art conceptual models.
Pengfei et. Al., [19], 2016.	The agent's search model has been proposed by using small world.	• The search process is efficient and the network is Fault tolerance.	• The lattice size is fixed. • The cost of message exchange is high.
Milano et. Al., [10], 2016.	The friendship selection model has been proposed using game theory approach.	• The higher network navigability has been achieved due to shape value based algorithm.	• The fixed number of friends and the threshold is a problem.
Amin et. Al., [25], 2019.	The friend's selection model has been proposed.	• The network is highly navigable and the service discovery time is very fast.	• There is no security or privacy criteria proposed in this framework. • The fixed number of friends are the bottleneck of this paper

where N represents the total number of vertices; l_{ij} is the distance between i and j vertices; and N is the possible number of pair vertices.

3) CLUSTERING COEFFICIENT

C lustering is the measure of how close the neighbors of a node are to being a clique, i.e. a complete graph [30]. The network average clustering coefficient for vertices $i = 1 \ldots..n$ is given by the fraction of objects. The clustering coefficient is calculated as blow.

$$C_{local(n)} = \frac{2E_n}{k_n * (k_n - 1)} \tag{3}$$

where k_n is the number of neighbors of the node n and E_n is the number of edges among the neighbors.

The clustering in a graph may be high or low. The high clustering value indicates that a vertex neighbor has a lot of connections. Conversely, if we have a few connections, then it represents low clustering.

4) GIANT COMPONENT

It represents many connected objects in the network. If the network has a large giant component, it means that the network is highly navigable. This is because, through the highly connected objects, the designation object can be discovered more easily. In this proposal, we provide a unique solution to solve this issue. We will discuss the proposed model in the next section.

III. PROPOSED MODEL

A. PROBLEM DEFINITION

Figure.2 presents the illustration of connected people holding objects in a social network. In this scenario, each person holds an object; each object is connected to the other objects in the network. Suppose Benjamin holding a personal computer and looking for a printer inside of that network. The printer is held by Emma. Then, to provide the requested service to the requester a service search process is required. The service requester can access the service by using different hops. For simplicity, we have converted it into a graph.

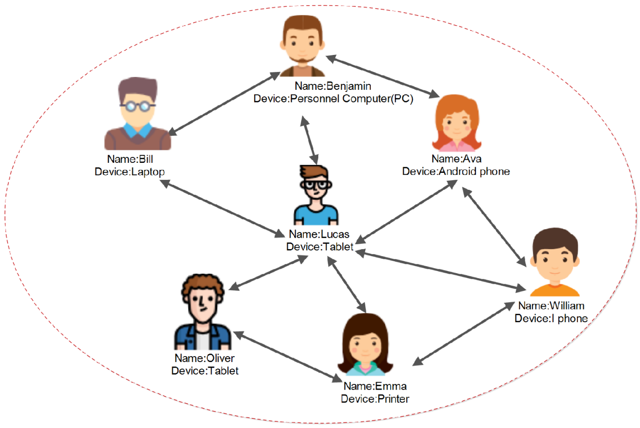

FIGURE 2. Sketch of the connected people holding objects.

1) PROBLEM REFERENCE SCENARIO

The network is modeled as an undirected and unweighted graph illustrated by G, and $G = (O, E)$ where V and E are vertices and edges, respectively. Each node in G denotes an element in the network, and each edge shows a link between pairs of objects. In the network N, $O = |o_i|$ denotes objects, and $m = |E|$ denotes edges. The adjacency matrix is $A = (aij)_{n*n}$; if object i and j are connected by links, then $aij = 1$; otherwise, $aij = 0$. The function $P_i = \{o_j \in O{:}o_i, o_j \in E\}$ be the neighborhood of the objects O, namely the objects that share a relation with O. Based on Figure.2, we first created a graph as shown in Figure.3. In this graph, the objects are numbered from 1 to 9. The links are the edges between these objects. To make it clearer we created Figure.4 named object discovery model. The service search is performed based on algorithm 1. The explanation details are given below. Suppose object u named service seeker is looking for a service and the service is located at object v. Therefore, the object u initiates

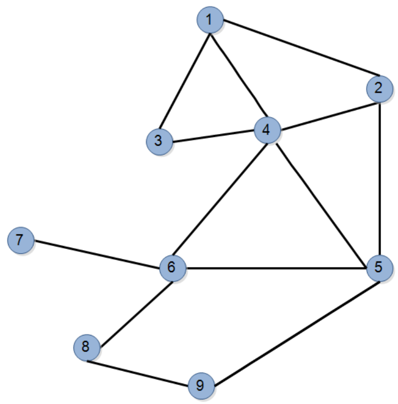

FIGURE 3. **Initial graph network.**

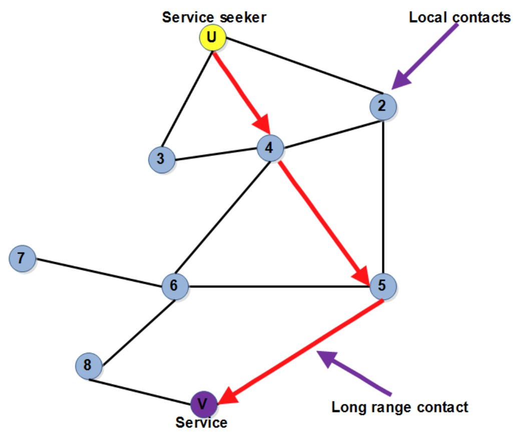

FIGURE 4. **Object discovery model.**

the service request. The distance between the objects in the network is computed by using the Manhattan distance equation (6). The first step in algorithm 1 is to find the next-hop neighbor based on the high degree of centrality, i.e., C_j. It results in the selection of object 4. As object 4 is not a service provider hence the service look-up procedure is repeated for the discovery of the service provider to other hops. The next step is to select the neighbor object based on minimum distance and centrality. So, object 5 is selected because it has a minimum distance. The service lookup procedure is initiated from object 5. Object 5 has a direct connection with a service provider. Finally, the object v is identified as a service provider. Thus, a long-range link is established between the service seeker and the service provider.

We extend the Kleinberg model and the current Intelligent model discussed in [19]. The next-hop neighbor in our proposed model is discovered based on a high degree of centrality. The degree centrality of object u is calculated based on equation (5) [9].

$$C_j = \frac{|P_j|}{max_{o_{i \in O}} |P_i|} \tag{4}$$

where $|P|$ is the cardinality of P. The range measure between [0,1]. We normalize it for the maximum number of friends of

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Algorithm 1 Service Search Model

Input: Send a Search request.
Output: Friendship circle.
Start ()
Step 1)
{Object u initiates the search request}
{Calculate the Manhattan distance for each object in the network}
{Compute degree centrality C_j for each object in the network}
If {Next hop neighbor has high centrality}
{Select as a next hop object}
Else {Go to Step 1.}
Step 2)
{Initiate the lookup procedure from selected object}
{Select the neighbor object having minimum distance}
If {Neighbor object has a direct link with object , then make a link between object u and object v}
Else {Repeat Step 2}
If {Target object v is found in this model, establishes a path to the object u}
Else {The process continues until the required object is found}
End ()

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an object. We use this property to compute the central objects and only using the local knowledge. The distance between objects for each hop is calculated and is denoted by variables p and q. Where p demonstrates the short-range neighbors and q for the long-range objects. The 2^{nd} hop links are considered as long-range links at lattice distance d. d Is the probability, $p(u, v) - \alpha$, where $p(u, v)$ is the distance between the grid objects u and v is the number of edges between two objects (Manhattan distance). The parameter α used to calibrate the network randomness. In our scenario $p = 1$, $q = 2$, and $\alpha \in [0, 2.5]$. Also, α is used to control the long-range links that are co-related with the geometry of the underlying structure. The Manhattan distance is the measurement of the distance of two neighbors u and v.

$$d = \sum_i |u_i - v_i| \tag{5}$$

For a universal constant, $p \geq 1$, the object (u) has a directed edge to every other object within a lattice distance p. These edges show local contacts for the object (u). For two universal constants $q \geq 0$ and $r \geq 0$, added an edge from an object (u) to another random 'object' with the probability $[d(u, v)]^{-r}$.This edge represents long-range contact.

IV. PERFORMANCE ANALYSIS

In this section, we demonstrated the impact of our proposed algorithm. The SIoT is not completely deployed to date, so most of the experiments are performed in an IoT environment by using different tools. For instance, we have

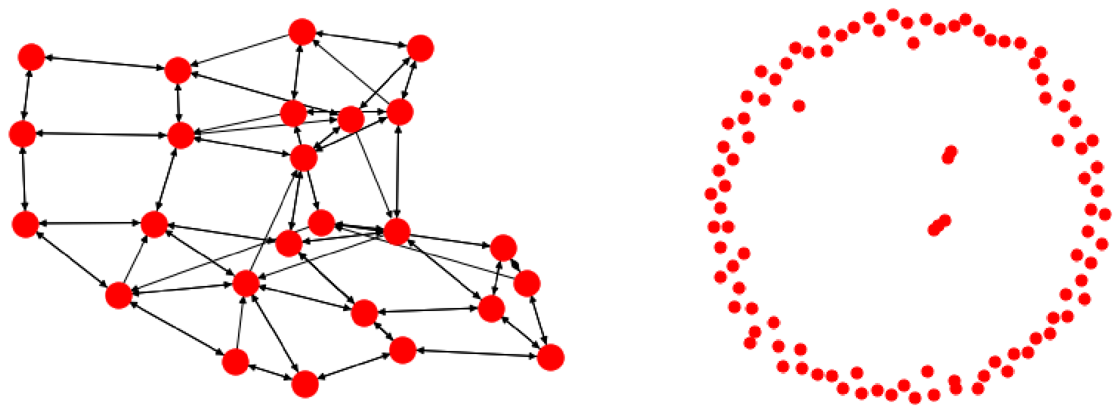


FIGURE 5. a) Navigable small world network b) 10*10 lattice construction.

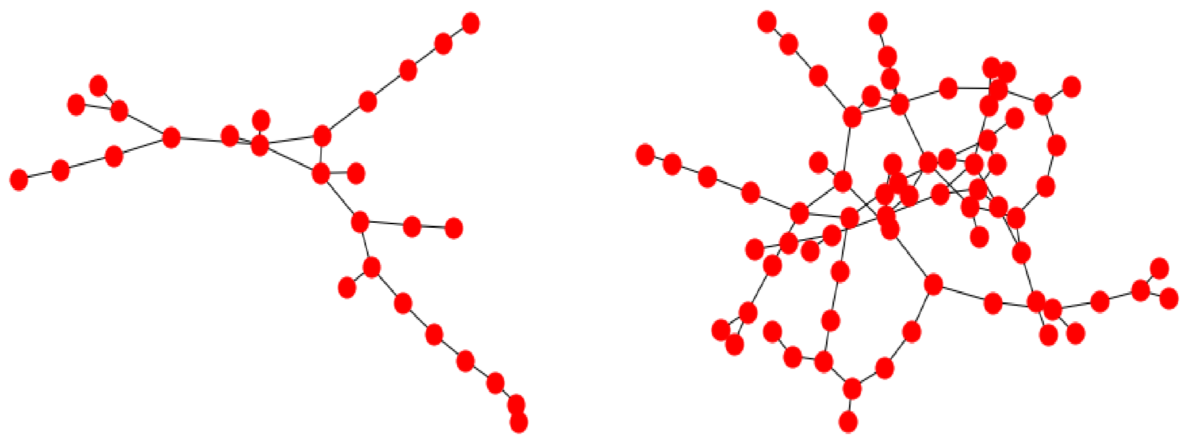


FIGURE 6. a) Giant component visualization using small number of objects b) Giant component visualization using large number of objects.

used Network X in this study[31]. Network X is one of the famous tools that is widely used for fetching unstructured information. Network X is an independent platform and used for the creation, manipulation, and identification of structures in complex networks [31]. We have divided, performance analysis section into two sections.

The first part presents the visualization and social network analysis (SNA) of the proposed model. The subsequent section demonstrates the efficiency of our proposed algorithm. We describe the efficiency of our proposed model in terms of execution time, path length, clustering coefficient, and the giant component.

A. VISUALIZATION OF THE PROPOSED MODEL

In this section, we visualize our proposed model using giant components, path length, and the clustering coefficient. The objective of this section is to clearly understand the behavior of our proposed model [6].

The first simulation result is illustrated in Figure.5 (a). In this figure, the deployment of an initial graph is displayed. Initially, we have deployed a small number of objects, if we increase the number of objects to 100 then, it results in getting a quite complex graph, and due to many links, and it is very hard to examine the structure of a network. For better visualization, we decided to remove the bidirectional links between these objects, which is more meaningful for the readers. It results in the illustration of Figure.5 (b). This figure indicates the result of 10×10 objects is in the form of a lattice. In this figure, the red dots indicate the objects in our proposed model, and the connection of these objects depends upon the certain value of probability.

Figure.6 a) demonstrates the giant component visualization of our proposed model. Initially, we deployed 100 objects shown in this figure. We have repeated it for 10 iterations. The giant component for this graph is 28. Figure.6 (b) shows the visualization of a giant component using many objects. It results in terms of getting a large giant component. The giant component for this experiment is 72.

Our key findings are, the giant component completely depends upon the number of objects, and if we have many objects then it results in terms of getting a large giant component. Usually, the giant component represents the group of

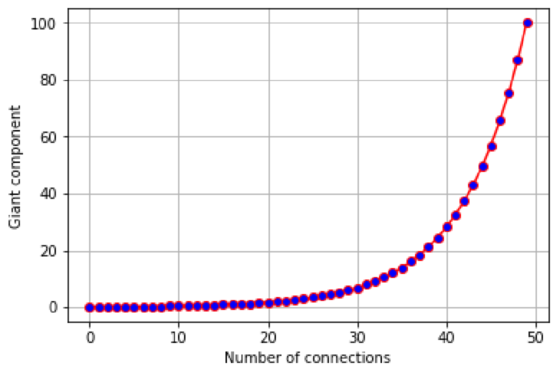


FIGURE 7. Giant component in proposed model.

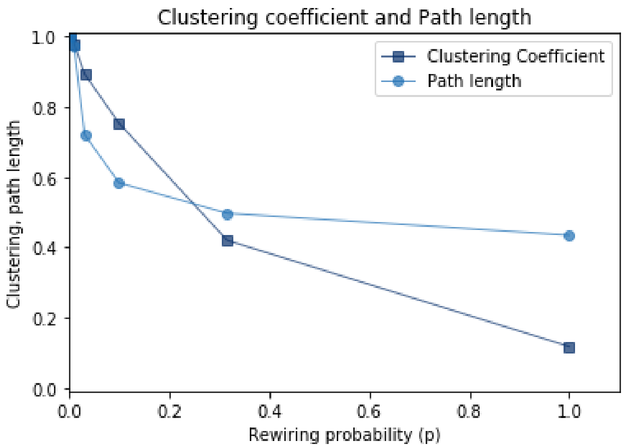


FIGURE 8. clustering coefficient and path length measurement in proposed model.

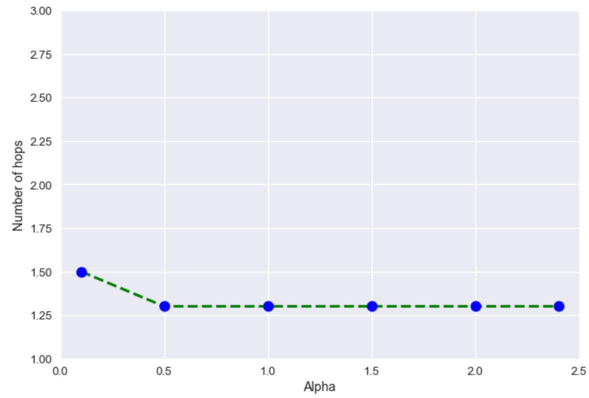


FIGURE 9. The alpha and the effetcts over network network navigability.

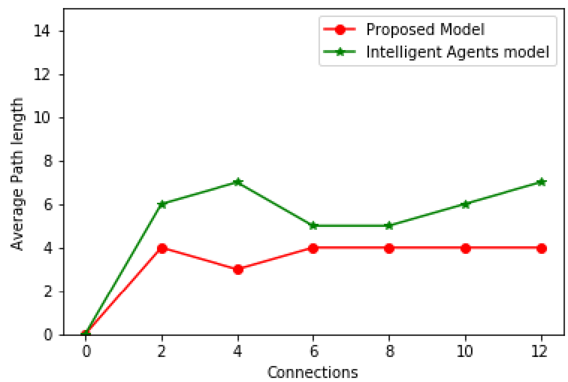


FIGURE 10. Average Path length comparison in proposed model.

objects in the network. The giant component will be increased by adding more objects to the network. The objective of this experiment is to observe the structure of the links and the objects during a certain time. We checked this effect using 10 iterations.

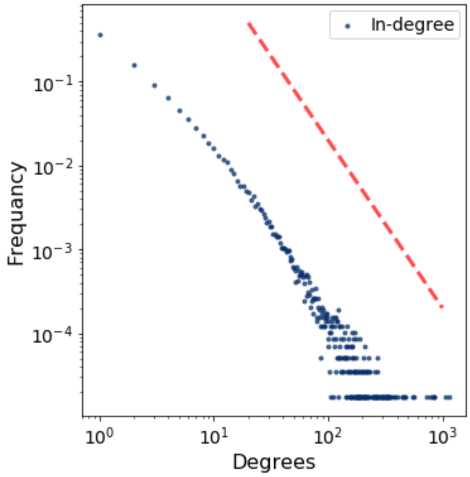
Figure.7 illustrates the existence of giant components in our proposed model. In this diagram, the x-axis demonstrates the number of connections and the y-axis demonstrates the giant component. We examine that by increasing the number of connections the giant component is increasing in this graph. For fewer connections, the giant component is small. By increasing the number of connections, the giant component is increasing. For maximum connections, we achieve higher giant components, such as 100%. The 100% giant component means that most objects in the network connection and hence our network is highly navigable.

The next step is to check whether the behavior of our model. To do that we need to draw a graph and compute the basic network measures.

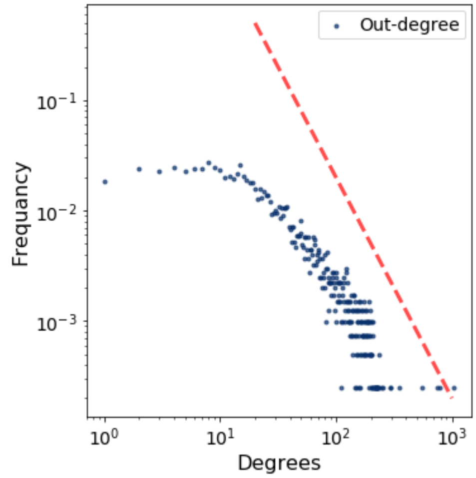
Figure. 8 shows the clustering coefficient and the path length measurement of our proposed model. In this figure, a graph containing the average path length L and the clustering coefficient C is displayed. In this graph, one could easily observe that initially C and L are both at the same level. But when the network grows, the behavior of the proposed network slightly changes. This result obeys the logarithmic distribution, as we predicted earlier. So, based on this result, we predict that our model behaves the same as like small-world network and the state-of-the-art model discussed in [19]. Also, our simulation graph completely obeys logarithmic distribution as we already predicted earlier. We observed few points in this regard which are given below.

The small-world clustering factor is slightly lower than our expectations, even though we expected that only 10% of the objects would be connected. But the interesting part of this result is, around 40% of the objects are in the form of a small-world network as we examined earlier in Figure.6 giant component visualization.

Figure.9 illustrates the effects of overall network navigability by using a different value of alpha α. In this figure, the x-axis demonstrates the α where $\alpha \in [0, 2.5]$. The y-axis demonstrates the number of hops needed to find a single service. This figure demonstrates the service is discovered in the first hop. It is possible because every object has at least a friend which can provide that service. we have observed a slight difference when increasing the value of α.



a) In-degree



b) Out-degree

FIGURE 11. Frequency distribution of a) In-degree b) Out-degree.

We already know that in a two-dimensional plane, the objects are usually connected but they never form a triangle. Therefore, it makes a long link (as we are looking for that), and then it turns into the generation of transitional connection. Finally, the achieved C is higher.

Figure.10. demonstrates the simulation result of average path length in our proposed model and the Intelligent agents model discussed in [19]. It is computed based on equation 2. As our network model obeys power-law so, the appearance of the shortest path length is more frequent than the longest path. The X-axis represents the number of connections per node and the Y-axis is the average path length. We compared our proposed model with the intelligent agent model [19]. In this figure, we examine the average path length of our proposed model is lower as compared to the current Intelligent agent's model [19]. The shortest path is due to the occurrence of the triangle in the network. The maximum path length for our proposed model is 4.

Briefly, we concluded from these graphical results that the extended Kleinberg network and current intelligent model [19] are considered a small-world network. We can use it to create a navigable network and find the short paths among any pair of objects by using only local information.

B. THE SERVICE SEARCH

In this section, we discuss various results related to our proposed and state-of-the-art models. In our network, each object is connected to the number of objects.

In this regard, we assume:

- At first, our model is created, and later the structure of our network is not changed. It means that the topology of our network is fixed.
- Secondly, all objects in our proposed model implement the same assignment function.

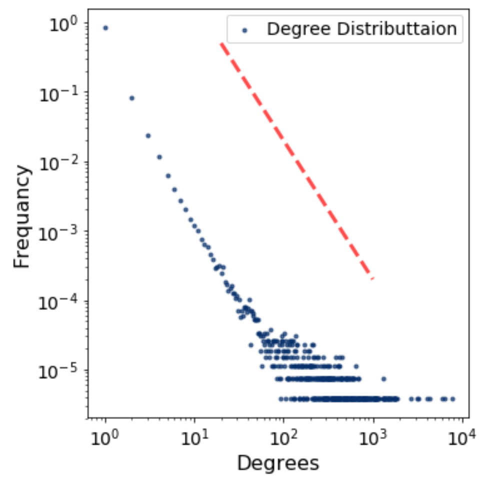


FIGURE 12. Degree distribution.

1) DEGREE DISTRIBUTION OF OUR MODEL

Figure.11 demonstrates the frequency distribution in-degree and out-degree of our proposed model. Generally, the frequency distribution shows the frequency of nodes in the network. For this purpose, we have plotted three graphs on a logarithmic scale. In this graph, the x-axis represents the frequency of nodes. The logarithmic scale is used to show a large range of values. In all three graphs, we have used the red color to indicate the power law. Also, the power-law explains the disputation of degrees 3.017 for in-degree, and out-degree is 3.01 and 3.084 for degree distribution. Figure.12 demonstrates degree distribution using the Facebook dataset. We generated these graphs primarily based on the parameters discussed in Table.2.In these graphs, we examine that our proposed model obeys logarithmic law.

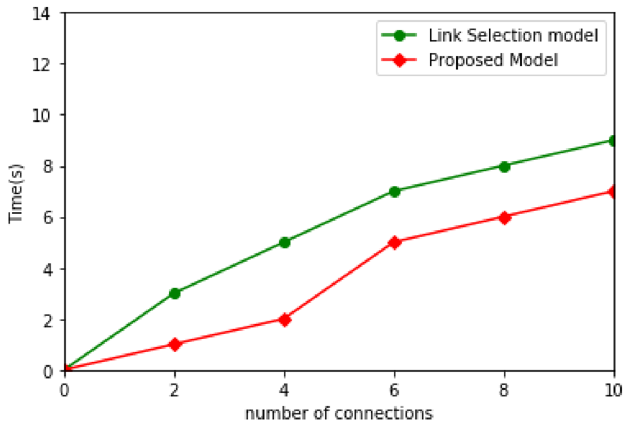


FIGURE 13. Service time comparsion.

TABLE 2. Parameters in this experiment.

Parameters	Dataset Facebook
Nodes	40399
Edges	88234
Average Degree	43.69
Average clustering coefficient	0.602
Average path length	3.8
Network Diameter	8
Giant Component	100%

2) SERVICE TIME

Usually, In-service search algorithms, the time required for the search process is very important [25]. In general, the execution time of an algorithm depends upon the number of objects and the hops to reach the destination object [25]. In Figure.13, we have compared our proposed model with the most recent link selection model discussed in [25]. In this figure, the x-axis demonstrates the number of connections or links and the y-axis demonstrates the execution time in seconds. This result reflects that the connections are growing by an elapsed time interval. We tested it for different iterations and obtained the result which shows the efficiency of our proposed algorithm with an increase of interval time. In this diagram we observe that the execution time of our proposed algorithm is quite shorter than the current link selection algorithm discussed in [25]. It means our proposed algorithm is more efficient because it requires less time to search the information in the network.

V. CONCLUSION

This paper has addressed the issue of service search and object discovery in social IoT networks. For efficient object discovery, we extended the Klingberg and intelligent agents model using distributed search model and applied it to a real social network dataset. By using simulation results we demonstrated that our proposed model is completely navigable it has short paths and the service search process more efficient. Also, we achieved the higher giant component and the short path length in the network. However, there is an open issue with our proposed model is level of trustworthiness between the objects. In this study, we did not discuss the trust-based neighbor discovery. So, In the future, we plan to build a query optimizer for social networks. That optimizer is installed over a server and hence performs a bridge between the devices and users. In that model, the trust-based service query is initiated by the service seeker. Also, we plan to improve the current study using other parameters such as Graph Laplace etc.

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