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Efficient Service Discovery in Mobile Social Networks for Smart Cities

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Abstract Mobile social networks (MSNs) play an important role in the process of the development of smart cities. Citizens can interact and engage with services provided by MSNs. Smart city services enhance their quality of life. With the popularity of smart phones, mobile social activities have become an important component of citizens' daily life. People can post their social contents to their remote friends and can access shared information in the cycles of friends anytime and anywhere through their mobile devices. This human-centered social approach generates enormous amounts of social data that are distributed across various smart devices. Efficient service discovery from such cycles of friends is a fundamental challenge for MSNs. This paper proposes a friends' cycle service discovery (FCSD) model for searching social services in MSNs based on human sociological theories and social strategies. In the proposed FCSD network, intelligent network nodes with common social interests can self-organize to interact and form social cycles with other potential nodes, and further can co-operate autonomously to identify and discover useful services from cycles of friends and cycles of friends' friends. The proposed model has been simulated and evaluated in a decentralized mobile social environment with an evolving network. The experimental results show that the FCSD model exhibits better performance compared with relevant state-of-the-art services search methods.

Keywords Smart Cities · Smart Services · Mobile Social Networks · Self-Organization · Decentralization

1 Introduction

Smart cities are built by using advanced information and communication technologies (ICT), including smart hardware devices, mobile networks, and software applications [1]. Smart cities can utilize ICT to improve the operational efficacy of urban services, and better organize resources to provide services for their citizens [2–5]. In the process of the development of smart cities, the technologies of the internet of things (IoT) is widely applied to multi-areas of urban services, such as healthcare [3], vehicular communication [6], unmanned aerial vehicle [7] and so on. Furthermore, mobile networks are the important infrastructures of smart cities. People

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living in modern cities share own information and access authorized information of other devices using services supported by connected smart devices [8]. Mobile social activities have become part of people's daily life.

In MSNs, users are not only able to use existing online social networks (OSNs) via mobile devices, but also able to establish new social services facilitated through the powerful communication and sensing capabilities of smart devices [9]. MSNs allow people to communicate anywhere and anytime in the world without barriers. The convergence of social networks and smart devices provides supplements for users to actively participate in the generation and sharing of social resources based on device-to-device (D2D) communications [10]. For example, WeChat [11], a mobile messaging application that can be deployed in mobile phones, provides a service called "Moments" for users to post texts, documents, photos, and videos. The social contents shared through "Moments" can be easily accessed by users through their own smart phones. Today, users using MSNs are witnessed as a source of data generation at an enormous volume every day. Despite efficient routing strategies being put forward to handle such data generation [12, 13], it is still difficult for users to look and find valuable information from massive distributed social data.

MSNs deploy a decentralized scheme to design their infrastructure, where users have control over their data and can decide whether to store their data locally in their mobile devices or upload the data to a trusted server. The decentralized approaches often utilize unstructured Peer-to-Peer (P2P) architectures [14]. In the unstructured P2P architectures, peers establish connections among each other according to their needs without maintaining specific network structures. A range of research works [15–22] based on P2P architectures has been proposed to support the decentralized infrastructure OSNs (DOSNs) and MSNs.

Designing a novel decentralized network model to search for discover services in mobile social environments of cities is a significant challenge. The service is a general concept that is not restricted to well-defined web services, but many types of data, such as social text, photos, videos and so on. The service discovery should be the capability to locate social resources [21]. The network model should conform to people's social habits. Routing algorithm should be intelligent to make social computing to meet the requirements of service discovery in distributed environments. Intelligent nodes in the network can autonomously join and leave, and connect each other through the self-organizing method so that the query message can be forwarded adaptively.

To this end, this paper proposes a friends' cycle service discovery (FCSD) model to support social services discovery in mobile social networks for smart cities according to theories of social networks and values of cycles of friends. Important contributions of this article are summarized as follows:

1) A self-organizing decentralized model based on the P2P architecture is proposed according to human sociological theories. This model can intelligently exploit the information of cycles of friends of people to search for social services in mobile social networks via mimicking behavers of humans.
2) An efficient method based on probability is proposed to intelligently choose suitable search methods based on the knowledge level of a node. When the knowledge in the knowledge base of a given node is rated as low, the routing query algorithm selects the interest correlated search (C-Search) method to generate a higher probability of accurately searching relevant social services, otherwise, the normal search method (N-Search) is chosen.
3) An efficient method for evaluating the expected maximum number of social services from a neighbor node is designed, in order to help a new node to find its "good" neighbors for receiving queries during network evolution.
4) An algorithm for evaluating "expert" neighboring nodes is proposed to find "expert" neighboring nodes in a given interest area according to the information of cycles of friends of the corresponding node during the phase of self-adaptive query forwarding.
5) A software simulation platform is designed and developed to simulate and evaluate the proposed FCSD model against other compared models under various scenarios.

The rest of this article is organized as follows: Section 2 presents a review of the related work. The design of the proposed FCSD model and the routing algorithm are presented in Section 3 and the evaluation methodology is introduced in Section 4. The simulation results are discussed in Section 5 and Section 6 concludes this paper along with outlining our future research directions.

2 Related Work

2.1 The Relevant sociological Theories

Social networks usually experience a phenomenon called a small world, whereby two complete strangers without common experience may share mutual acquaintance and can be connected via a chain of no more than six intermediate acquaintances, which is a well-known idea termed as the "six degrees of separation" [23, 24]. Watts and Strogatz [25] analyzed the small-world phenomenon using a mathematical model, and concluded that the small-world networks can be highly clustered and have small characteristic path lengths. Persons belonging to multiple clusters at a given time can potentially create shortcuts between many other persons across multiple clusters. A person can theoretically link to anyone else using shortcuts, and resources can flow between different ends of the network [24].

Searchability is an important property in social networks. Watts et al. [26] presented a model to explain the searchability of social networks in terms of recognizable personal identities. This model can also be applied to resolve service discovery problems of mobile social networks in smart cities.

In social networks, people's relationships construct the flow of resources in a social environment and cover the sharing, delivery, or exchange of a wide variety of resources and information [27]. Both a stronger relationship and a weaker relationship can help people to seek information [28, 29]. The social network can be studied based on a socio-centric approach. The research goal is to identify groups of individuals engaged in similar activities and seeking similar information services [27].

An expert in social networks is generally considered someone who holds knowledge about given topics. His/her knowledge may have been acquired through training, research, and personal experience. Expert knowledge should comprise substantive information on a particular topic that is not widely known by others [30]. One of the most effective channels for disseminating information and knowledge of expertise within an organization is using his/her social network of collaborators, colleagues, and friends [31]. Xunzi [32], a Chinese Confucian Philosopher, emphasizes that the knowledge of people must be obtained from outside environments and the learning process must be sustainable. People, who are transformed by teachers and proper models and who accumulate culture and learning, can become experts.

Barabasi and Albert [33] found that large networks can self-organize into a scale-free state. The probability $p(x)$ that a node connects to x other nodes is indirectly proportional to the power of a constant $\gamma : p(x) \propto x^{-\gamma}$. Similar phenomenon has been observed in other networks, such as P2P networks, social networks and so on. These networks are called as scale-free networks or power-law networks.

2.2 The Relevant Models

There are existing distributed and decentralized models which can be used to provide services for searching for resources in decentralized environments such as DOSNs, MSNs, and WSNs.

The Random Breadth-First-Search (RBFS) [15] is a method of searching for resources in decentralized environments. In the RBFS network, a node randomly selects its neighboring nodes to forward query messages, and the number of neighboring nodes selected in each hop is a fixed number. The query message is randomly forwarded until TTL (Time-to-Live) reaches 0. The node in the RBFS network has no knowledge base and cannot learn knowledge from the previous search process, which has a significant impact on the performance of the network.

The RSP2PS [18] model makes use of the characteristic of the power-law to search for requested social resources. The routing algorithm selects neighboring nodes by evaluating the expected quantity of social resources in each hop. The query message is forwarded to n neighboring nodes with a large expected number of resources. The performance of RSP2PS is better than that of RBFS. However, the nodes of RSP2PS have no knowledge base, which can affect the efficiency of the routing algorithm.

The NeuroGrid [34] model creates a knowledge base for each node, which facilitates nodes with the ability to acquire knowledge. When receiving feedback messages from a target node, the source node stores the feedback information to its local knowledge base to make decisions during future searches. In order to limit the network overloads, the NeuroGrid model sets a range of nodes to be forwarded between the minimum number M and the maximum number N. Two phases are used to select the nodes to be forwarded. In the first phase, the neighboring nodes that are directly related to the requested topic in the local knowledge base are selected as nodes to be forwarded, with the number not exceeding the top bound M. If the number of selected nodes is less than the lower bound N, the remaining nodes are randomly selected from the connected pool of nodes. The search performance of NeuroGrid is generally claimed to be better than that of RSP2PS and RBFS.

The ESLP method [35] employs human social theories to design its model structure and the search algorithm. The nodes in the network are considered as the humans in social network and the links among nodes are regarded as their social relationships. The process that a social node searches for social resources uses the property of self-organization similar to social activities of humans. Each node of ESLP has a knowledge index to collect knowledge. However, unlike the forwarding mechanism of NeuroGrid, ESLP not only considers direct resources related to the search topic but also takes into consideration the correlated resources associated with interest areas of the requested topic. Three phases are designed to determine nodes to be forwarded. The neighbors directly related to the search topic are selected from the knowledge index of a node in the first phase. If the number of neighbors selected is less than the top bound M, the algorithm moves to the second phase, where the neighbors relevant to the interest area of the search topic are selected. The number of selected nodes in the first and second phases is maintained less than the lower bound N, the rest of the nodes are randomly selected from the connected pool of nodes. In comparison with NeuroGrid, the ESLP model exhibits a higher efficiency. Liu et al. [36] further improved the ESLP model to propose the SESD model in order to support a multi-topics service search.

In social networks, people can not only remember the important social events during a long-term period but can also easily forget some ordinary things. The IASLP [22] model relies on this phenomenon to design its node's knowledge base and routing algorithm. The knowledge base of a node is composed of an interest index that is related to sharing the interest of the corresponding node, along with a knowledge index that is relevant to search interest. The knowledge related to its long-term sharing interest is maintained in the interest index and the one relevant to the short-term search interest is stored in the knowledge index. The interest index groups nodes with similar social resources and common interest into a social resource sharing community. The knowledge index facilitates nodes to form a temporarily learning group. People often retrieve contents associated with their sharing interest area in many search processes, which makes the IASLP model have an advantage when compared with the aforementioned methods during the search process.

The CORDIAL [37] is a social and opportunistic algorithm that exploits the mobile behavior of humans and their community membership in MSNs. One member looks for services by advertising queries to other members within the common community. However, the mechanism of service discovery will generate large network overheads. The authors in [38] proposed a multistage detection framework based on deep learning to detect suspicious messages in MSNs. The framework uses edge computing to improves the utilization rate of computing resources. The mobile terminals detect messages and send results to the servers to reduce the servers' computing overhead. The RMER [39] is an event data collection approach in the WSNs. This approach aggregates data by more nodes distributed in non-hotspot regions and sends these data to the Sink by converging multiple-path routes into a one-path route. The approach increases network lifetime and event detection reliability. The FCSS [40] utilizes fog computing to shift resources from remote servers to the network edge. This method provides low-latency for security service filtering.

The aforementioned approaches achieve better performance on service and resource discovery, however, these methods also have some flaws. Although the ESLP, SESD, and IASLP exploit some sociological theories to improve the performance and have achieved better results compared to RBFS, RS2PS, and NeuroGrid, the design of these models has not been fully considered to exploit the value of cycles of friends. According to the small-world theory [23], friends of a friend may be friends. Furthermore, during the network initiation stage, the level of knowledge comprised in the nodes is usually zero, and so the performance of the network is usually lower. To this end, this paper exploits the concept of cycles of friends of people to design an efficient network model to promote the efficiency of routing algorithms.

3 FCSD Model

Human society is a self-organizing autonomous system in nature, in which people establish social contacts to form social ties. Each person in this system is either an independent individual or a messenger of information. When moving from one place to another place, a person can quickly adapt to new living and studying environments. In human society, well-connected people may have lots of social resources and could offer others with various beneficial support. A decentralized network in mobile social environments is very similar to human society. The nodes are regarded as persons and the links among nodes can be viewed as social ties among persons. Each node can act not only as a message receiver but also as a message forwarder. Nodes with a rich set of knowledge can benefit other potential nodes. These characters of human society can be taken into consideration when designing a decentralized network model for mobile social environments in smart cities. The design of our proposed network model and routing algorithm are derived from sociological theories.

3.1 Model Design

The structure of the FCSD network model is shown in Fig. 1. The Mobile Social Node consists of Local Social Services including texts, documents, pictures, videos, etc., Local Social Service Index, Local Interest Vector, Knowledge Base (KB), and routing components. The relationships among the nodes are established through social relation links. Each social user is mapped by its corresponding node. Social users search for social services through their nodes. User's social resources in local social services repository are mapped by the Local Social Service Index. The Local Social Service Index is composed of a service identifier that can be uniquely associated with a service and a set of keywords that can characterize the content of that corresponding service. The Local Interest Vector is constructed with keywords in the Local Social Service Index. A query is handled by routing components and propagated by social relation links. When a social user starts to search service, the node mapped by the user generates a query related to this service and searches the local KB to find target neighbors. The query message is sent to these neighboring nodes through social relation links. Receivers look for their own neighbors from their KB to forward the query message. Services matching the search topic will be sent to the start node along with social relation links by the target nodes.

The method in the IASLP model is adopted to design the KB of the proposed FCSD model.

Theory strategy1: Strong relationships constructed by close friends in social networks can facilitate greater knowledge exchange and can facilitate a knowledge seeker to use newly acquired knowledge [28]. Weak relationships provide people with access to information and resources beyond those available in their own social circles [29].

Theory strategy2: In social networks, most people's friendship circles are highly clustered and can be linked by persons who are members of multiple clusters [24].

Similarly, in the FCSD network, the KB collecting knowledge is composed of a long-term knowledge base (LKB) and a short-term knowledge base (SKB). The social services in the local service repository are associated with the node's long-term interest. During the process of searching social services, knowledge entries related to the node's long-term interest are stored in the local LKB. The node then establishes strong relationships with its neighboring nodes (friends) in the LKB. Knowledge entries within the short-term interest are collected in the SKB. The node then creates weak relationships with its neighbors in the SKB. Nodes in SKB forms multiple learning groups. The member with more learning groups can build shortcuts among groups. An ordinary node in a group can establish a connection with a member in another group in a short-path by shortcuts, which can make the corresponding ordinary node to acquire new knowledge.

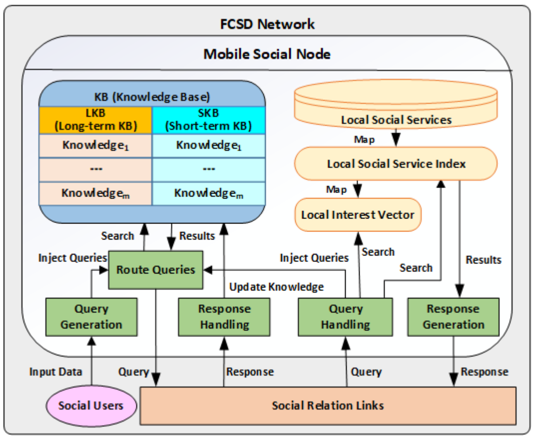


Fig. 1 The structure of FCSD network model

Theory strategy 3: The characteristic feature of social life is that activities of certain persons provide gratifications for other persons [41]. In the IASLP model, the KB only focuses on direct neighbors. Actually, the cycles of friends of a neighbor may have many resources and can be of use during the search process. Unlike the knowledge structure in the KB of IASLP, our proposed FCSD model considers both the information of a node's neighbors and that of the neighbors of the node's neighbors, when designing the knowledge structure.

In Fig.2, each knowledge entry in the KB of the proposed FCSD model consists of a keyword and a node pack vector associated with this keyword. Each entry in this vector is composed of a neighbor node related to the topic keyword, the number of neighbor's services x, and the number of services of neighbor's neighbors y. Taking into consideration the ability of neighbor's forwarding query, the number y is a mean value that can be calculated based on the number of services picked up by some of its neighbor's neighbors.

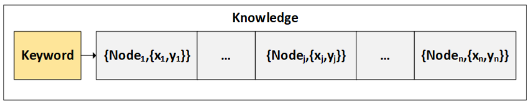


Fig. 2 The structure of knowledge in the KB (LKB and SKB)

3.2 RSP2PS-1

Theory strategy 4: In social networks, a "good" actor with good information sources and excellent information outlets can regulate information flow from one set of actors to other sets of actors [27]. Similar to social networks, in the FCSD networks, a "good" node knowing a good forwarding path can help other nodes to achieve more services.

The proposed FCSD model adopts the method of finding a "good" neighbor used in RSP2PS [18] model and further improves this method to present an RSP2PS-1 method in order to enhance the search efficiency. In the RSP2PS network model, the weight of the excepted number of files in each hop is equal to 1. Actually, in the process of searching for resources, the one-hop neighbor is usually close to the source node and has a great influence on the search result. The influence decreases with an increasing number of hops away from the source node. Thus, the FCSD model uses a method of weight reduction when the hop count increases in order to improve performance.

In the FCSD network, a query message should be sent to a "good" neighbor with more requested services, which helps to find more requested services with a high probability in the future hops. A goodness value G of a "good" neighbor is determined by the following formula:

$$G = w_1 * f_1 + \sum_{i=2}^{TTL} (w_i * E(f_i)) \tag{1}$$

where f_1 is the number of shared services in the one-hop neighbor, $E[f_i]$ is the expected number of services in the ith hop that can be estimated using the method in the RSP2PS network, and the weight w_i is assigned by the formula (2):

$$w_i = \begin{cases} \frac{1}{2^i}, & 1 \le i \le TTL - 1 \\ \frac{1}{2^{i-1}}, & i = TTL \end{cases} \tag{2}$$

where $\sum_{i=1}^{TTL} w_i = 1$, the weight of the expected files in the one-hop neighbor is 0.5, and a two-hop neighbor is 0.25, and so on. The weight of the expected number of files in nodes found in the last two hops is the same.

At the beginning of simulation of the FCSD network, there are no knowledge entries in the KB of many nodes, the routing query algorithm will search for neighbors with a larger value of G. These neighbors characterize a higher probability to find the requested services.

3.3 Routing Query Algorithm

Theory strategy 5: One of the properties of social networks is searchability. People can direct messages to a distant target person through social networks of acquaintances [26].

When a node generates a query, if the number of knowledge entries in its KB is equal to zero, this node will utilize RSP2PS-1 method to find a "good" neighbor and the query message will be forwarded to these "good" neighbors, otherwise, this node will search for neighbors from its local KB using the node selection algorithm and the query message will be forwarded to neighbors selected. The neighbors discard a duplicated message and continue to forward an unduplicated message to their corresponding neighbors until the TTL reaches 0.

3.3.1 Query Method Selection

Theory strategy 6: In social networks, a person who joins a new environment will try his/her best to obtain help from people in this environment. Similarly, in the FCSD network, a node without enough knowledge will actively learn from neighboring nodes.

FCSD network can search for services using two different methods. One is the normal search (N-Search) method that only looks for services directly related to the search topic. The other is the correlated search (C-Search) method, which not only looks for services directly related to the search topic but also retrieves services that are found to be correlating with the search topic. In the FCSD network, a node with little knowledge quickly absorbs knowledge in a large probability to execute the C-Search algorithm. Such nodes obtain more knowledge relevant to the search topics in a short period of time. With an increasing number of knowledge entries in the KB of a given node, the probability to run the N-Search algorithm will become higher and the speed of learning the knowledge for that corresponding node will slow down gradually. The probability of executing the search algorithm can be calculated using:

$$p(x) = \frac{\arctan(a * (L_{max} - x)/L_{max})}{\arctan(a)}, \quad (0 \le x \le L_{max}) \tag{3}$$

where $p(x)$ denotes the probability of selecting the search algorithm, such that $0 \le p(x) \le 1$, x is the number of knowledge entries comprised in the KB, arctan is an arctangent function, L_{max} is the maximum length of the knowledge base, and the parameter a denotes the curvature of the formula, such that $a > 0$.

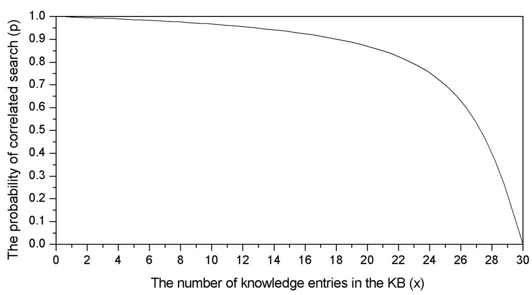


Fig. 3 The probability of choosing the search method (a=10, Lmax=30)

Fig. 3 shows that the probability p to execute the C-Search algorithm is changing with the number of knowledge entries x ($a = 10, L_{max} = 30$). When x is smaller, the node characterizes lack of knowledge and executes the C-Search algorithm in a higher probability to rapidly acquire knowledge. Until the number x reaches 18, the C-Search algorithm remains to run with 90% probability. Then the probability to execute the C-Search algorithm starts to decline and the probability to execute N-Search algorithm increases. Now, the node begins to absorb knowledge slowly.

3.3.2 Query Response

When receiving a query message generated by the source node, a receiver decides the search method depending on the received query message. If the N-Search method is used, the target node will search services in its local social services depository according to the search topic and further sends the results to the source node. If the C-Search method is used, the receiver will use the keywords in the search interest vector to scan the local social services depository to find services and returns the result to the source node. The result includes information such as the receiver, search topic and the corresponding number of services, and interest topics correlated to the search topic and their number of services respectively. Considering the network overheads, the length of the feedback message should be minimized. But it is ideal to select all the directly matching topics. The correlated topics associated with more services should also be selected and the number of the correlated topics k should not be greater than the maximum number $K_{max}(0 \leq k \leq K_{max})$.

The receiver sends not only its data but also some of its “rich” neighbor’s data. “Rich” neighbors are those encompassing more services than other neighbors in the KB of the receiver. It is assumed that the number of “rich” neighbors is n, which should never exceed D_{max} (the maximum number of nodes to be forwarded, as shown in the “routing forwarding algorithm”). The mean value y of n neighbor’s services should be included in the feedback message of the receiver, which can be calculated using the following formula:

$$y = \begin{cases} 0, & n = 0 \\ \frac{1}{n}\sum_{i=1}^{n} m_i, & 0 < n \leq D_{max} \end{cases} \tag{4}$$

where m_i denotes the number of services matching the search topic of the neighbor $node_i$. The structure of the topic pack in the feedback message is a composite comprising the following: {receiver, {topic keyword, {local services number x, the preferential neighbors’ services mean number y}, topic type t}}. The $t = 1$ implies that the respective topic keyword is a directly matching topic, and $t = 0$ implies that the respective topic is a correlated topic.

3.3.3 Knowledge Updating

Theory strategy 7: The knowledge of people is obtained from outside environments, and the process of acquiring and accumulating knowledge is sustainable [32].

Theory strategy 8: In social networks, some events associated with people fade from their memory in time [42]. Information learned repeatedly can be encoded into a person’s memory and can be correctly recalled [43].

In the FCSD network, the knowledge in the KB is dynamically updated during the social evolution process. The LRU (Least Recently Used) algorithm is used to update the knowledge in the KB. The knowledge related to nodes’ short-term interest in the SKB is updated in a short-time. The knowledge relevant to nodes’ long-term interest in the LKB stays relatively stable for a long time.

Upon receiving a feedback message from a target node, the source node reads the topic data from the received message to update its local KB using the LRU algorithm. The knowledge from a target node that has the same interest area as the source node will be updated into the local LKB, otherwise updated into the local SKB. The recent and newly generated topic knowledge should be inserted into the top of the LKB or SKB. If the number of knowledge entries reaches the maximum capacity of the LKB or SKB, the knowledge entry at the bottom should be removed. The node pack vector associated with each topic in the KB should also be updated using the LRU algorithm. The recently visited node should be added to the front of the node pack vector and the tail node pack should be removed when this vector is full.

3.3.4 An Example for Knowledge Updating

Suppose that node A is searching for services about "Java" programming language in the FCSD network, as shown in Fig. 4. Due to its empty KB, node A searches services about "Java" with interest area "programming languages" using the C-Search algorithm, as shown in Fig. 5. In Fig. 5, node B receives an unduplicated query message from node A. Node B then searches its local services and local KB, and sends the result to node A. Suppose that the maximum number K_{max} of correlated topics needed to be returned is 2 ($K_{max} = 2$) and the maximum number forwarding degree is 2 ($D_{max} = 2$). Then, the directly matching services to the topic "Java" (5 services) is selected. The correlated topics "Python" (4 services) and "C#" (3 services) are also selected as feedback topics. In the LKB of node B, neighbor nodes D, E, and F have services "Java" and "C#". As for the topic "Java", nodes E and F are the preferred neighbors for node B, as they comprise more services relevant to "Java" (E: 3 services, F: 3 services, D: 1 services). According to formula (4), the service's mean number y for the preferential neighbors of node B is 3 ($y = (3 + 3)/2 = 3$) for the topic "Java". Similarly, for the topic "C#", nodes D and E are the preferential neighbors for node B, and $y = (2 + 2)/2 = 2$. Then in the feedback message, topic pack composes as "{B, {{Java, {5, 3}, 1}, {Python, {4, 0}, 0}, {C#, {3, 2}, 0}}}".

When receiving the feedback message from node B, node A creates the direct matching topic knowledge $\{$Java $\rightarrow$ $\{$B, $\{5, 3\}\}\}$ to be inserted onto the top of LBK due to the common interest between nodes A and B. The correlated topic knowledge $\{$Python $\rightarrow$ $\{$B, $\{4, 0\}\}\}$ and $\{$C# $\rightarrow$ $\{3, 2\}\}$ are arranged after A in sequence, as shown in Fig. 5.

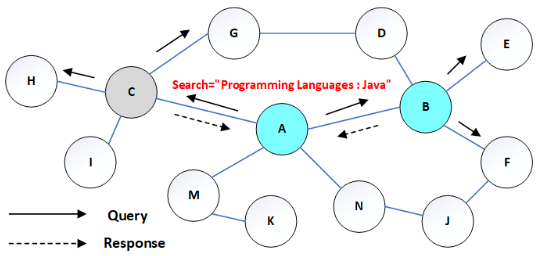


Fig. 4 Node A searches services about "Java" with interest area "Programming Languages"

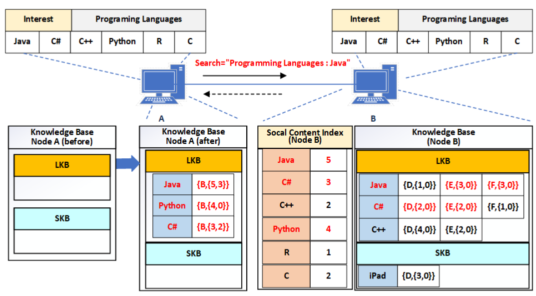


Fig. 5 Node A updates knowledge using a feedback message from Node B

3.4 Routing Forwarding Algorithm

In the FCSD network, when a receiver forwards a query message, the routing forwarding algorithm chooses the neighbors of the receiver from the receiver's local KB as nodes to be forwarded. The number of nodes to be forwarded is adaptively adjusted according to the dynamic strategies of node selection.

3.4.1 Adaptive Forwarding

Similar to the strategy of forwarding query messages in SESD and IASLP networks, the proposed FCSD network also uses an adaptive method to forward query messages. The number of nodes to be forwarded in each hop is adaptively adjusted between the minimum number (D_{min}) and the maximum number (D_{max}). This method is effective in balancing the trade-off between the search performance and the network overheads. The aforementioned adaptively adjustable procedure is dependent on the correlation degree of the selected nodes associated with the search topic. Both the SESD and IASLP networks select a node to be forwarded according to the node's cut-off criteria D calculated by its own correlation degree. The SESD network uses the number of direct and correlated topics in the knowledge index to calculate D of a given node. The IASLP obtains D by counting the number of resources matching the search topic of the neighbor nodes. Unlike the methods used in the SESD and IASLP networks, the FCSD network calculates D using either the number of services of neighbors or the number of services of neighbors' friends to adaptively select better nodes as nodes to be forwarded.

3.4.2 Node Selection

The procedure of node selection includes three phases such as searching for the nodes directly related to the search topic, searching for the nodes correlated to the search topic, and searching for random nodes.

In the first phase, the routing forwarding algorithm searches for nodes directly associated with the search topic from their local LKB or SKB. If the interest area of the search topic is found to be the same as that of the receiver node, the algorithm searches for nodes from the LKB of the receiver node, since the likelihood of finding requested services is higher in the common interest community. When the number of selected nodes from the LKB is less than D_{max}, the algorithm searches for nodes from the SKB. If the interest of the search topic is different from that of the receiver, the algorithm directly searches for nodes from the SKB, not from the LKB. At most D_{max} nodes can be selected as nodes to be forwarded. When the number of neighbors directly associated with the search topic is greater than D_{max}, the priority of neighbor nodes is calculated using formula (5).

$$z = x + \rho * y, \qquad \rho \in \{0, 1\} \tag{5}$$

where x is the number of services associated with the search topic in a given neighbor, y is the mean of services related to the search topic of preferential friends of the neighbor and y can be calculated via formula (4). In formula (5), the coefficient ρ denotes whether y should be used or not. If $TTL = 1$, then $\rho = 0$. When the query message reaches the penultimate hop ($TTL = 1$), the algorithm considers the number of neighbor's services. When $TTL > 1, \rho = 1$. The algorithm considers the number of neighbor's services and the number of their friends' services. The value z denotes the richness of services in a given node. Thus, the query message should initially be forwarded to the neighbor with a large z value. If the number of selected nodes is less than D_{max} in the first phase, the routing forwarding algorithm moves to the second phase.

Theory strategy 9: In social networks, an expert in a particular field is almost certainly unable to write down all he knows about the topic. Thus, searching for a piece of knowledge becomes a matter of searching this field for an expert on the topic, together with a chain of personal referrals directed from the searcher to the expert [31].

In the second phase, the routing forwarding algorithm searches for correlated neighbors from the LKB and SKB of the respective node. The local KB may contain relevant topics that are related to the interest area of the search topic. The node and neighbors associated with these topics should belong to a common community. A given node may find its required services with the help of its neighbors comprising rich knowledge. If a neighbor contains more correlated topics, more services associated with these topics, and more services of its friends, this neighbor can be regarded as an expert in the interest area related to the search topic. Thus, an expert should preferably be selected as a node to be forwarded.

Assume that the number of correlated topics of a neighbor in the KB is k. Then the sum of z value of these topics is $s = \sum_{j=1}^{k} z_j$, where each z_j can be calculated using formula (5). Further assume that the number of neighbors associated with the correlated topic is l, then the number k of the correlated topic of each neighbor can be assigned with a weight factor w ($w \in \{w_i | i = 1, 2, \ldots, l\}$). Then, w_i can be calculated using:

$$w_i = \frac{s_i}{\sum_{i=1}^{l} s_i}, \qquad i = 1, 2, \ldots, l \tag{6}$$

where $0 < w_i \leq 1, \sum_{i=1}^{l} w_i = 1$. The correlation degree of the $neighbor_i$ could be calculated using:

$$C_i = \frac{w_i * k_i}{\sum_{i=1}^{l}(w_i * k_i)}, i = 1, 2, \ldots l \tag{7}$$

The cut-off criteria D differs for each neighbor in the second phase between D_{min} and D_{max}, which can be determined by the correlation degree of the corresponding neighbor. The routing forwarding algorithm calculates the cut-off D_i of the $neighbor_i$ using:

$$D_i = Round(C_i * (D_{max} - D_{min}) + D_{min}) \tag{8}$$

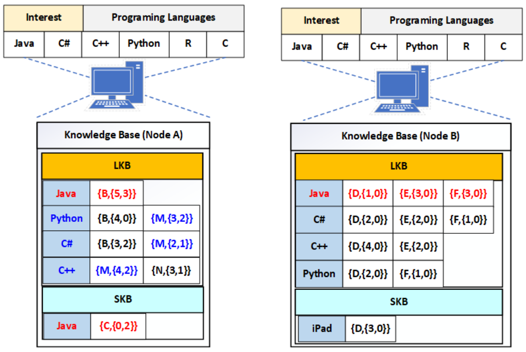
where $i = 1, 2, \ldots, l$, the function $Round(x)$ returns a closest integer to a given x. When the correlation degree is low ($C \to 0$), the probability of finding the requested services matching the search topic from the neighbor is also low ($D \to D_{min}$). In contrast, when the correlation degree is high ($C \to 1$), the likelihood of finding the requested services is also high ($D \to D_{min}$).

The neighbors associated with the interest area of the search topics are sorted in a list with the cut-off D that descends. The algorithm selects a neighbor from the list each time to check whether the neighbor could be selected as a node to be forwarded or not. Only when the cut-off D of the neighbor is greater than the number of selected nodes $n(D > n)$, the corresponding neighbor is selected as a node to be forwarded. For an increasing n and reducing cut-off value, the process of selecting nodes will stop when $n = D$.

When the second phase of selecting nodes is completed ($n \geq D$), and there are still not enough selected nodes ($n < D_{min}$), the routing forwarding algorithm randomly picks up nodes from the connection nodes irrelevant of interest area of the search topic, until the number of selected nodes reaches $D_{min}(n = D_{min})$.

3.4.3 An Example for Choosing Node to Be Forwarded

Figure 6 illustrates an example of the routing forwarding algorithm's node selection process. Suppose that $D_{min} = 2, D_{max} = 3$, and $TTL = 2$ for node A. In Fig. 6(a), node A forwards a query message with the topic "Java" associated with interest area "Programming Languages". Because of the fact that the interest area "Programming Languages" of node A is the same as that of the search topic, the routing forwarding algorithm first searches for direct knowledge from the local LKB of node A and obtains the knowledge entry $\{Java \to \{B, \{5, 3\}\}\}$. The algorithm calculates z of node B according to formula (5). Because the neighbor node B is not the last hop node ($TTL = 2$), $\rho = 1$, $z_B = x_B + \rho * y_B = 5 + 3 = 8$, node B is selected as a node to be forwarded. The number of the selected node n is set less than $D_{max}(n = 1, D_{max} = 3)$ and there is no other knowledge associated with the search topic in the LKB. Now, the algorithm continues to search for knowledge from the SKB of node A and obtains the knowledge entry $\{Java \to \{C, \{0, 2\}\}\}$. Then, the algorithm calculates the z value for node C ($z_C = x_C + \rho * y_C = 0 + 2 = 2$), and node C is selected as the node to be forwarded ($n = 1 + 1 = 2$). Because of $n < D_{max}(n = 2, D_{max} = 3)$ and there is no knowledge directly related to the search topic in the KB, the algorithm moves to the second phase to search for correlated knowledge associated with the interest area "Programing Languages". In the LKB of node A, node M and node N are found to be relevant to the search interest area. Node M comprises three different services about "Programing Languages" such as "Python", "C#" and "C++", and the sum of z for node M is 14 ($s_M = (3 + 2) + (2 + 1) + (4 + 2) = 14$). Node N comprises just a single service about "C++" related to "Programing Languages", and the sum of z for node N is 4 ($s_N = 3+1 = 4$). According to formula (7), the correlation degrees of node M and node N with the search topic are given separately as $C_M = \frac{14}{14+4} = \frac{7}{9}$ and $C_N = \frac{4}{14+4} = \frac{2}{9}$ respectively. Then the cut-off D_M and D_N are calculated using equation (8), as $D_M = C_M * (D_{max} - D_{min}) + D_{min} = \frac{7}{9} * (3 - 2) + 2 \approx 3$, and $D_N = C_N * (D_{max} - D_{min}) + D_{min} = 2/9 * (3 - 2) + 2 \approx 2$ respectively. The cut-off of node M is greater than either that of node N or the number of selected nodes n ($D_M = 3, D_N = 2, n = 2$). Thus, node M is firstly selected as the node to be forwarded. Then $n = 3$ eques to $D_{max}(D_{max} = 3)$ and the procedure of selecting the node is stopped. In this case, nodes B, C, and M are selected as the nodes to be forwarded.



(a) select nodes from A (b) select nodes from B

Fig. 6 An example for selecting nodes to be forwarded

In Fig. 6(b), node B forwards a query message that is received from the source node A. the routing algorithm obtains the knowledge list as $\{Java \rightarrow \{D, \{1,0\}\}, \{E, \{3,0\}\}, \{F, \{3,0\}\}\}$ from node B. Because nodes D, E, and F are the last hop nodes ($TTL = 0$), so that $\rho = 0$. Then $z_D = 1, z_E = 3$, and $z_F = 3$ is computed based on formula (5). Because nodes D, E, and F are directly related to the search topic "Java", all of these nodes are selected as the nodes to be forwarded. Due to the number of selected nodes reaches $D_{max}(n = 3, D_{max} = 3)$, the process of node selection completes.

4 Evaluation Methodology

4.1 Simulator Design

A simulator for the FCSD network is designed using Java programing language, as shown in Fig.7. This simulator consists of a Network Initialization Module and a Simulation Module. The simulating parameters are trained into the Network Initialization Module through the module interfaces. The FCSD network is initialized to generate the network elements, generate and distribute social services, and generate the network topology. Then, the Simulation Module uses simulation parameters to simulate the FCSD model and outputs the results.

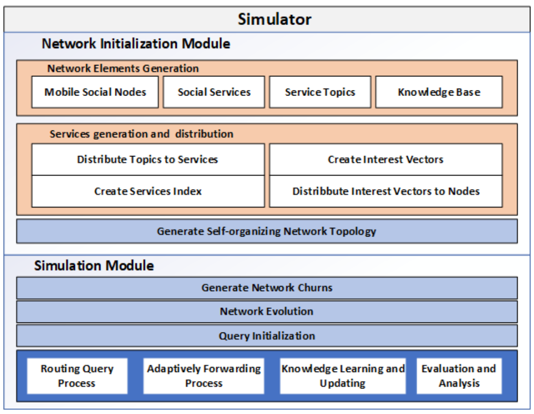


Fig. 7 The structure of the simulator

The simulation setting uses the following parameter settings: 1280 social topics, 10000 social services, 3 social topics per services, 40 interest areas, and 32 social topics per interest area (1280/40=32). These parameters are written in a configuration file. At the beginning of the simulation, the simulator reads the simulating parameters from the configuration file. The social topics and interest areas are extracted from the DMOZ dataset known as the Open Directory Project (ODP) [44]. The interest vector of each node is randomly related to an interest area. The simulator distributes services to nodes using a power-law [33] distribution with the exponent of $\gamma_1 = 1.5$. Each node shares at least one service to the network. Services in each node are relevant to its interest vector with a probability of 90%, and each service related to the node's interest vector contains at least one of the topics that are included in the interest vector. The value of adjusting coefficient a is equal to 10 ($a = 10$) in formula (3).

In order to observe and evaluate the effect of network evolutions, the simulator simulates a growing network. At the beginning of the simulation, the simulator sets up a small-size network with 100 nodes, in which the number of connections of nodes follows a power-law distribution with the exponent of $\gamma_2 = 1.5$. Each node connects to at least one node. In the first month, the simulator adds 30 nodes to the network every day, until the number of nodes in the network reaches 1000. Now, the network becomes a mature network with 1000 nodes and continues to run for one more month until the total number of simulating days reaches 60. If the number of nodes is n, the number of simulations each day is given by $n * 2$.

The network is characterized by dynamic churn, such that nodes goes online and offline very often. During each simulation, an online node is selected randomly as a requesting node in order to forward a query with a topic. The topic is related to the interest area of the requesting node with a probability of $p = 0.9$, but sometimes relates to other interest area with a probability of P=0.1. Furthermore, the query is tagged by the interest identity of the requesting node and that of the topic, and $TTL(TTL = 4)$.

4.2 Performance Metrics

The following metrics are used to measure network performance.

- Recall. The ratio of the average number of successfully found services to the average number of all matched services in the network.
- The number of found services. The average number of services found successfully.
- The number of query messages. The average number of all query messages to be forwarded.
- The number of visited nodes. The average number of nodes that are visited per query.
- Recall per visited node. The ratio of the average recall to the average number of visited nodes.

5 Simulation Results

This section evaluates performance of the FCSD network against other studied networks under various scenarios.

5.1 The Benchmark Methods

The performance of the FCSD network is compared against five relevant methods including IASLP, SESD, NeuroGrid, RSP2PS-1, and RBFS. In the FCSD, IASLP, SESD, and NeuorGrid networks, the minimum and maximum number of neighbors used for forwarding query messages is set to 2 ($D_{min} = 2$) and 5 ($D_{max} = 5$) respectively. The size of the knowledge base is set to 50 in the FCSD, SESD, and NeuroGrid networks.

- FCSD: searches the network using N-Search and C-Search methods. In the feedback messages, the number of the correlated topics associated with the interest area of the search topic is set to 3 ($k = 3$) using C-Search.
- IASLP [22]: searches the network with interest queries. The value of the adjustment factor is set to 0.3 ($\alpha = 0.3$), which adjusts the curve of forwarding degrees of neighbors to which the queries are forwarded.
- SESD [36]: searches the network with the ordinary query or the active query method. The method of the query with a single-topic is similar to ESLP [40], and the threshold ratio of the active query is set to 0.8.
- NeuroGrid [34]: searches the network using the ordinary method only.
- RSP2PS-1: forwards queries to a neighbor with the largest expected number G of services and another neighbor with a larger number of connections.
- RBFS [15]: forwards queries to randomly chosen $D_{min}(D_{min} = 2)$ neighbors in each hop.

From Fig. 8 and Fig. 9, the FCSD network achieves a better performance than the other methods. On each day of the first month, the newly joining nodes in networks give rise to networks churn, so that the recall metric for all the methods are gradually decreasing, as shown in Fig. 9. When the networks become more mature in the second month, the recall of the FCSD, IASLP, SESD, and NeuroGrid networks is gradually increasing, by exploiting the knowledge in their respective knowledge bases. The SESD uses the active query method to learn knowledge that is correlated to the search topics, which gives the SESD method a higher probability to acquire more knowledge, so its recall is higher than that of the NeuroGrid, RSP2PS-1, or RBFS methods. The RSP2PS-1 and RBFS characterize no learning abilities because they have no knowledge bases. The NeuroGrid network only learns the knowledge that is directly related to the search topics. Thus, its search performance is not better than that of the SESD method. Unlike the SESD and NeuroGrid methods, each node in the IASLP network has an interest index that is used to collect knowledge relevant to its shared services. This ability facilitates this node and its neighbors in the local interest index to form a stable knowledge community. The knowledge communities associated with the interest areas of nodes can improve the search efficiency of IASLP.

The FCSD network encompasses an interest knowledge base similar to the interest index of IASLP. However, the structure of knowledge in the knowledge base of a node in the FCSD network is different from that of IASLP. The knowledge structure of IASLP only includes information of neighbors, but the knowledge structure of FCSD is composed of information of neighbors and that of friends of neighbors. The social cycles of neighbors and the social cycles of neighbors of neighbors help the FCSD network to improve its efficiency of searching services. Furthermore, the FCSD network exploits the information of cycles of friends in its local knowledge base to identify "expert" nodes to promote the search effect. Thus, the FCSD network can find more services, as shown in Fig.8, and achieves a higher recall, as shown in Fig. 9, than the other compared methods. During the first month, newly joining nodes in the FCSD network have not enough knowledge to help searching services. These newly joined nodes use the method of RSP2PS-1 to look for neighbors which have large expected number G of services and many connections to other nodes, which helps the FCSD network to achieve a better search effect in the initial phase of the network evolution, as shown in Fig. 9.

The method of searching for correlated topics relevant to the same interest area in the SESD and FCSD networks allows them to reach a greater number of nodes in the network, as shown in Fig. 10, but generates more query messages, as shown in Fig. 11, than other methods. However, their performance is not greatly affected, as shown in Fig. 12.

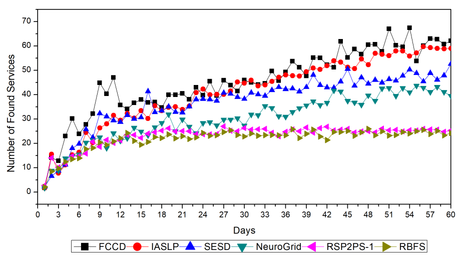


Fig. 8 The number of found services with different methods

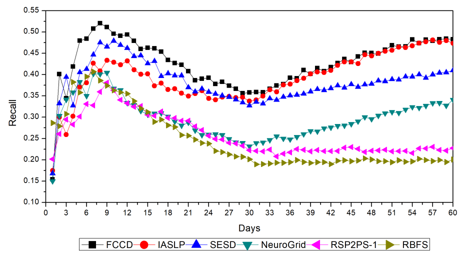


Fig. 9 Recall with different methods

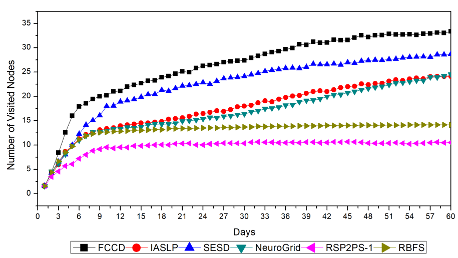


Fig. 10 The number of visited node with different methods

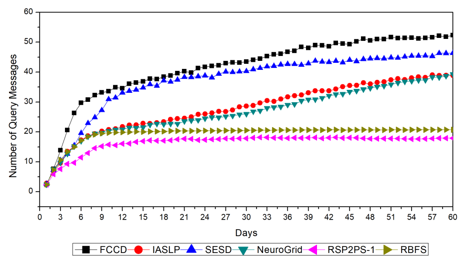


Fig. 11 The number of query messages with different methods

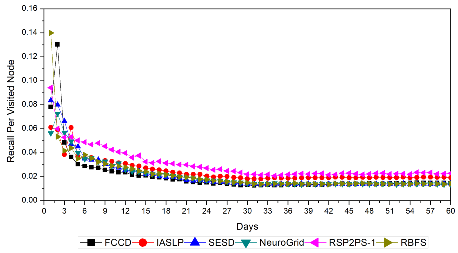


Fig. 12 The recall of per visited node with different methods

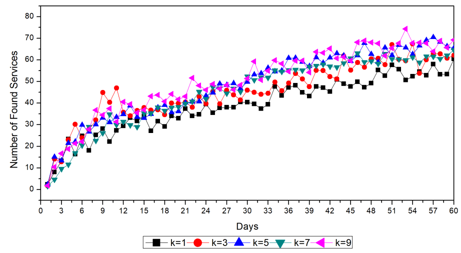


Fig. 13 The number of found services with different the number of correlated topics associated with same interest area in feedback message

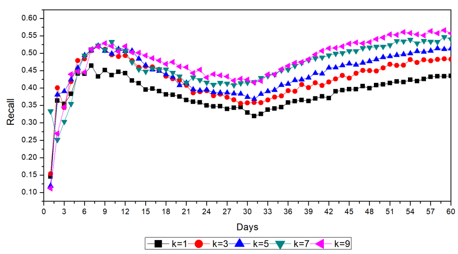


Fig. 14 The recall with different the number of correlated topics associated with same interest area in feedback message

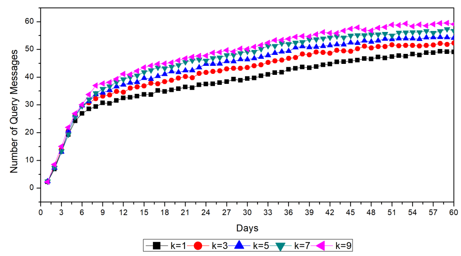


Fig. 15 The number of query messages with different the number of correlated topics associated with same interest area in feedback message

5.2 Effect of Number of Correlated Topics in the Feedback Message

In the FCSD network, when the number of knowledge entries in the local KB of a node is lower, this node uses the “C-Search” query method to search for services both matching a requested topic and relevant to the interest area of the requested topic. A receiver will respond to the source node through a feedback message including directly related topic information and k number of correlated topic information. The effect of k on the network performance is shown in Fig.13-15. The number of found services, recall and the number of query messages gradually grow with an increasing k value. The more the correlated topics to be responded, the faster the nodes learn the knowledge, and the nodes will find more services using their knowledge bases. However, the number of query messages will also increase and the size of the feedback message will eventually become larger, which will result in a heavy network overhead. So, the k value should be set to an appropriate number. In the FCSD network, k is equal to 3.

5.3 Effect of Shift of Interest Areas

In the FCSD network, some social nodes shift their interest areas to change sharing services for some reason. In order to observe and evaluate the performance of the network with these changes, 1% nodes, 5% nodes, and 10% nodes are selected randomly to shift their interest areas and change their sharing services respectively every day. The average recall declines and the average number of found documents decreases with the increment of the number of nodes shifting their interest areas. The results are shown in Fig. 16-17. When some nodes shift their interest areas, neighboring nodes associated with them also are affected and their knowledge will be outdated. Paths of messages forwarded by these neighbors become invalid, which gives rise to the decrement of the performance of the network. Although the recall of the FCSD network decreases with the increment of the number of nodes changing their interest areas, its performance is still better than that of the IASLP networks, the SESD network, and NeuroGrid network on the same conditions. On the last day of the second month (60 days), the recall of the FCSD network is witnessed at around 27%, however, the recall of the IASLP networks is witnessed at around 23%, the recall of the SESD network is witnessed at around 14%, and the recall of the NeuroGrid network is witnessed at around 11%, when 10% node in networks change their interest areas, as shown in Fig. 16. On this day, the number of found services of the FCSD network is witnessed at around 32, however, the number of found services of the IASLP network is witnessed at around 26, the number of found services of the SESD network is witnessed at around 18, and the number of found services of the NeuroGrid network is witnessed at around 14, under the aforementioned conditions, as shown in Fig. 17.

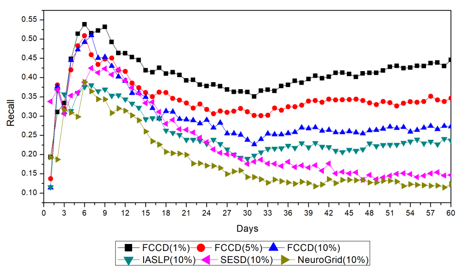


Fig. 16 Effect of the recall with the different ratio of the number of nodes which shift their interest areas to that of all nodes in networks

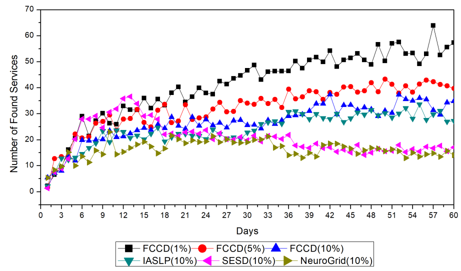


Fig. 17 Effect of the number of found services with the different ratio of the number of nodes which shift their interest areas to that of all nodes in networks

6 Conclusions

One of the key aims for smart cities is to provide citizens with an improved living environment and increase their overall quality of life [4]. Citizens are users of smart services. In MSNs for smart cities, people autonomously share social services with their friends through their smart phones on a daily base. Mobile social have become a part of our daily life, and significantly drives and facilities a great range of benefits to our work and learning strategies. However, it is difficult to find valuable social services from an abundant pool of social data that is distributed across various personal smart devices. This paper proposed the FCSD model for services discovery in MSNs based on human sociological theories.

In the proposed FCSD network, intelligent nodes similar to humans can self-organize to establish connections with each other, help each other, and autonomously form cycles of friends. Each node can acquire and accumulate knowledge from its cycles of friends to become intelligent. A new node can join the FCSD network to search for social services by contacting "good" neighbors that can predict "good" paths. The characteristics of the FCSD network can facilitate achieving better performance during network evolution. When a node has a lack of knowledge about its neighbors in its knowledge base, it can use the C-Search method to search for services with the interest area associated with the requested topic with a higher success probability. Otherwise, utilize the N-Search method to look for the service directly related to the requested topic with a higher success probability. In the FCSD network, there are "expert" nodes that have more knowledge and more categories of knowledge. Such "expert" nodes also have some valuable connections. Each node forwarding query can adaptively look for "expert" neighbors encompassing a "rich" set of knowledge from its knowledge base. The FCSD network is simulated and evaluated in a decentralized dynamic environment. The evaluation results show that our proposed method exhibits better performance and search efficiency compared with state-of-the-art methods.

As future work, we plan to consider to test and evaluate our model in a real decentralized mobile social environment. Furthermore, the knowledge graph as a new type of knowledge representation can effectively aid organizing services in MSNs. Using Artificial Intelligence (AI) algorithms to construct a services discovery model based on knowledge graphs in MSNs is another our research direction.

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