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A parameter centric service discovery framework for social digital twins in smart City

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In the contemporary digital era, the Internet of Things (IoT) and its applications have proliferated extensively, particularly within smart city environments, resulting in increased network traffic and raising the significance of efficient service discovery (SD) mechanisms. The social Internet of Things (SIoT) is an emerging paradigm that enables IoT devices to autonomously establish social relationships based on rules defined by their owners, thereby enhancing services through social relations. Things can interact with others; thus, the huge volume of traffic is increased. Each node or device could select an appropriate peer for the discovery of services, which is thus helpful for human beings. Although numerous service discovery and query processing models have been proposed in the recent literature. However, the existing state-of-the-art approaches often lack a comprehensive analysis of the parameters. Most traditional state-of-the-art models primarily focus on relationships or device similarity. Also neglecting the vital factors, for instance, query processing, efficiency, spatial-temporal dynamics, and service provisioning, etc. Thus, to solve this issue, this research proposes an exhaustive analysis of the main parameters needed to implement service discovery mechanisms for Social IoT and studies their relative importance based on a dataset of real objects. Based on the advanced parameters' selection, an efficient service discovery algorithm is proposed. The proposed model emphasizes efficiency by optimizing the service discovery through reduced social graph traversal (i.e., fewer hops), consideration of the service types, and integration of caching mechanisms. We have conducted a comprehensive analysis of key parameters essential for implementing an effective service discovery mechanism in SIoT, prioritizing based on their importance. Experimental validation demonstrates the superiority of the proposed over state-of-the-art models, confirming its efficacy, scalability.

Keywords Smart cities, Service discovery, Local navigability, Object discovery, Social internet of things (SloT), Digital twin, Internet of things

The Internet of Things (IoT) has transformed the interaction between digital systems and the physical environment, enabling billions of smart devices (In a smart city) to communicate, share data, and perform tasks autonomously. By facilitating seamless data exchange without direct human involvement. IoT has ushered in unprecedented levels of automation, efficiency, and intelligence in smart cities[1]. According to recent predictions by Cisco, the number of connected devices is expected to reach 125 billion by 2030, implying that each individual may own and maintain approximately 15 smart devices[2]. This explosive growth has dramatically increased network traffic and data volume, as massive information streams flow through interconnected IoT systems in smart cities.

A key challenge in this ecosystem is the discovery of specific services offered by IoT devices[3]. IoT deployments expand globally, efficient service discovery, management, and interaction with these devices have become increasingly complex. To address these challenges, researchers are increasingly leveraging and investigating Digital Twin (DT) technology[4].

A DT is a virtual representation of a physical device, replicating its components and dynamic behavior in real time[5]. More than just a mirror of a physical system, a DT is often equipped with predictive analytics to anticipate

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future states and performance characteristics. Service discovery (SD) becomes a critical mechanism within this framework, enabling the network to identify and connect to the appropriate DTs that offer the required service functionalities[6]. Implementing efficient service two primary challenges: (1) The large number of IoT devices results in a vast and complex search space, and (2) The volume of service queries directed at these devices generates significant network traffic. Together, these factors necessitate the development of intelligent, scalable strategies to manage service discovery and ensure efficient system performance.

Recently, the social Internet of Things (SIoT)[7] paradigm has emerged, integrating IoT with social networking concepts to form networks where smart objects establish social relationships and autonomously perform different tasks[3,8–10]. In SIoT, the objects interact and behave socially. These act as service providers and consumers within the network[11,12]. The introduction of social structures in the SIoT is inspired by Fiske's relational models theory, which characterizes human social relationships[13,14]. As proven in[15,16], the SIoT enables efficient discovery of short communication paths without requiring global network knowledge. Each node acts as a DT, and it is capable of autonomously forming social ties based on rules defined by its owner. This introduces the concept of DTs as prosumers. These entities provide and consume various services[5]. However, the challenging task is to implement this functionality for two reasons. First is the large number of IoT devices that produce a large search space, and secondly, the number of queries and the number of accesses to the devices. Both generate a large amount of network traffic.

The motivation of our research

The rapid proliferation of Internet of Things (IoT) and Digital Twin (DT) technologies has significantly increased the number of interconnected devices and systems. This growth, while promising, introduces new challenges in efficiently discovering and selecting the appropriate devices or services within these large networks. The SD process is a critical component of IoT and DT systems, as it enables the network to find and connect to relevant devices or DT that provide specific services. Given the nature of these networks, with devices continuously joining and leaving the network, traditional discovery mechanisms struggle to maintain efficiency and scalability.

In this context, Social IoT (SIoT) presents a promising solution by leveraging the social relationships between devices. By considering the social network of devices (i.e., how devices are connected and interact with one another), SIoT can facilitate more intelligent and context-aware service discovery. The motivation for this study is to propose a novel SD mechanism that utilizes SIoT principles, ensuring more efficient, reliable, and context-aware SD in large, dynamic IoT and DT networks. This mechanism aims to address the inherent challenges of traditional discovery techniques by incorporating social interactions and relationships into the decision-making process. Searching for services, device discovery is a key challenge in IoT and DT. It enables the network to look efficiently for an appropriate DT that provides the desired service. Thus, the primary motivation for this study is to propose an SD mechanism using SIoT.

Problem statement

The key challenge in IoT and DT systems is the efficient and scalable discovery of devices and services. As networks grow in size and complexity, traditional methods of SD, which often rely on centralized or exhaustive search algorithms, fail to scale effectively. These methods are often computationally expensive, slow, and not well-suited for dynamic environments where devices frequently join, leave, or change states. Furthermore, these approaches cannot leverage the inherent relationships and context between devices, which could significantly enhance the discovery process. In this study, we propose an SD mechanism within the context of Social IoT (SIoT) that can efficiently match services to devices, leveraging the social relationships between devices to optimize the discovery process. The underlying assumption in SIoT is that an object is more likely to discover relevant services through its social links. By navigating a social graph of trusted peers, SIoT improves scalability and finally improves the reliability of a network. However, to the best of our knowledge, the most recent literature still lacks parameters (which are suitable for the formation of friends and efficient navigation in a network). Thus, this research builds on this foundation by analyzing key parameters involved in SD with SIoT.

Briefly, our research addresses the shortcomings of recent state-of-the-art service discovery models, which often fail to specify the essential parameters for efficient network navigability by proposing a novel service discovery and provisioning mechanism to improve network navigability. Unlike prior state-of-the-art models, which rely on local or global navigability[16] and also lack efficient network navigability, and thus the selection of the next hop is a difficult task[17,18]. Our proposed framework combines both (Local and global) parameters' selection. Our propose framework is efficient in terms of service discovery and computation overhead. It is scalible and can be used in the development of smart cities.

Research contribution

Although state-of-the-art models presented in[19,20] yield acceptable results, However, they still lack crucial parameter selection and thus affect the service discovery in devices. In addition, most of the state-of-the-art methods focus on device relationships and similarity metrics, without exploring the parameter selection landscape. Furthermore, many studies, such as[21], emphasize only on query, often neglecting the core SD algorithm. In contrast, our proposed framework identifies and evaluates the most influential parameters and thus affects the SD in SIoT and improves the overall network navigability.

Based on these insights, we design an efficient SD framework by incorporating local and global network navigability to enhance the service provisioning. This framework enables next-hop object discovery efficiently. In addition, identify the optimal paths to the requested services. Due to its distributed nature, our proposed model allows rapid and scalable service access, demonstrating higher network navigability. The results achieved based on hop discovery and service discovery demonstrate the superiority of our proposed approach over state-of-the-art models, confirming their applicability in real-world environments.

The remainder of this paper is structured as follows: State-of-the-art section reviews the most recent related work in this area. we have presented a reference scenario in proposed solution section.. In this section, we have explained our proposed framework. we have performed severalexperiments to check the efficiency of the proposed framework. This section presentsa deatiled analysis. Finally, the conclsuion section concludes our paper and outlines the potential directions for future research.

State of the Art in service discovery (SD)

SD remains a critical challenge in IoT networks[22]. The SIoT paradigm aims to integrate IoT devices seamlessly while alleviating the complexity associated with network navigation. However, the increasing number of interconnected devices and the dynamic exchange of services present significant difficulties, particularly in heterogeneous environments involving diverse users and devices.

In conventional social networks, certain entities facilitate rapidly identifying requested services. Similarly, in the SloT context, particular objects assist users in efficiently locating desired services. Despite its importance, limited research has addressed this specific challenge. For example, Nitti et al.[3] explored the SD in IoT environments, proposing a model that each object can autonomously establish social relationships with others based on owner-defined rules. Authors introduced a decentralized algorithm designed for object discovery, enabling the identification of nodes capable of providing specific application services with a social IoT framework. The proposed algorithm selects the next-hop object based on two primary criteria: degree centrality and object similarity.

Degree centrality refers to the number of direct links connected to a node at the same time. Object similarity is an external attribute of the SIoT. It measures how closely an object aligns with the query's requirements[21]. In this direction, Amin et al. in[23] proposed an algorithm to enhance network navigability in SIoT using local network metrics. Similarly, Rehman et al. in[24] addressed the problem of locating object service nodes within a network. They introduced a two-step, query-based search mechanism using smart social agents (SSAs) to reduce human intervention using small-world structures. In the first step, a service request is initiated by querying neighboring nodes. The algorithm's performance was evaluated using average degree, clustering coefficient, and average path length metrics. However, the study did not account for time and space complexity in query processing.

Mei et al. in[25] developed a query-generation model based on the Poisson distribution to compute the frequency of independent terms, enabling more efficient information retrieval. Ramachandran et al.[26] tackled the problem of sensor-based query interpretation by introducing a clustering mechanism, as sensors cannot inherently process complex human queries. User queries, typically in natural language, are parsed and stored in a priority-based table. The proposed system then identifies the relevant sensor by comparing transformed query bits with sensor identifiers. Xia et al. in[27] proposed a decentralized, semantic-aware social service discovery framework for SIoT, utilizing fuzzy logic to calculate the correlation degree for device ranking to enhance discovery performance. This method enables fast, scalable service discovery by selecting a prioritized subset of neighboring devices. However, their work did not address privacy and security. Fu et al.[27] introduced an IoT search engine concept, positioning it as an intermediary between IoT devices and social networks. This model, comprising a search engine, a user, and objects, facilitates the discovery of smart devices. Its performance was assessed through metrics such as degree distribution and network density. Marche et al. in[28] proposed a query generation model using real-world IoT datasets. It is used to stimulate how objects generate queries in response to application requests. Each application deployed on IoT devices seeks relevant information or services by querying potential service providers. Efficient objects or information discovery(ID) in such environments relies on two key factors: (1) the structure of a social network and (2) the type of information or service request, which typically governs interactions in the SloT[29]. Building on these considerations, the authors designed a query generation model (QGN) and analyzed object behavior in generating service and information requests through peers. They had constructed a dataset derived from real IoT devices. These devices, which include static and mobile units, are predominantly public. The proposed model enables the generation of application queries from any object in the network. The authors evaluated the model using network navigability metrics, analyzing degree distributions across various relationship types, including object–object relationships (OOR), colocation–object relationships (C-LOR), and parental-object relationships (POR)[30]. However, this model has two major limitations: It relies solely on global network navigability and does not incorporate a dedicated service search mechanism. Moreover, temporal and spatial factors affecting query processing are not addressed. Hamrouni et al. in[31] introduced a novel approach to service discovery in large-scale SIoT networks by leveraging Graph Neural Networks (GNNs). Their method utilizes the social relationships between IoT devices to reduce the search space during service lookups, enhancing efficiency in dynamic and heterogeneous environments. The authors proposed a resource allocation model that integrates both the structural and attribute information of the SIoT graph, facilitating clustering and subsequent service identification. Through simulations on a real-world dataset, their approach demonstrated significant improvements in scalability and performance over traditional service discovery methods. M. S. D et al. in[32], proposes a model that incorporates semantic rules to enhance service discovery in SIoT, particularly in the context of health applications. The study evaluates various machine learning classifiers, including Decision Tree, Naive Bayes, K-nearest Neighbors, and Artificial Neural Networks (ANN), using different dataset ratios (60:40, 70:30, 80:20, and 90:10). The simulation results demonstrate that the ANN classifier outperforms the other algorithms, achieving an accuracy of 100%, compared to 99% for Naive Bayes, and 100% for Decision Tree and K-nearest Neighbors. This work highlights the effectiveness of machine learning models in improving service discovery in SIoT, offering valuable insights into the potential of semantic rules and machine learning in optimizing IoT services. Khanfor et al. in[33] presented an automated service discovery framework for SloT, targeting mobile crowdsourcing task requests. Using two community detection algorithms, they propose a model that identifies a small subset of devices from a large-scale IoT network[34]. A natural language processing (NLP) module extracts the key service-related information, including type and location, to process textual crowdsourcing requests. This automation significantly reduces service discovery time while improving task assignment efficiency. SD et al. in[35] have proposed the development of a SIoT simulator. This simulator combines basic network simulator functionalities with advanced AI-based traffic analytics and visualization capabilities. It serves as middleware, facilitating communication between hardware and software interfaces. The middleware provides a configuration environment for various tasks, including object selection, navigation, service provisioning, object profiling, service and application recommendations, and user behavior predictions. Simulation experiments demonstrate the ease of use and scope of this simulation framework, emphasizing its potential for future SIoT research and development. Aljubairy in[36] proposes a comprehensive framework for SIoT service discovery, which includes three phases: (i) collecting information about IoT objects, (ii) constructing a social structure among these objects, and (iii) developing an end-to-end service discovery model utilizing the language representation model BERT. The proposed framework leverages state-of-the-art deep learning techniques to establish a social network among IoT objects, facilitating more efficient and intelligent service discovery. Extensive experiments conducted on real-world SIoT datasets demonstrate the feasibility and effectiveness of this approach, showcasing the potential of deep learning for optimizing service discovery in SIoT environments. Gulzar et al. in[37] presented a survey on IoT, SIoT, artificial intelligence (AI), and personalized internet of things (PIoT). The widespread adoption of the Internet of Things (IoT) has led to the emergence of Personal IoT (PIoT), a domain that focuses on devices, sensors, storage, and computing for personal use and surrounding environments. PIoT offers users high levels of personalization, automation, and convenience, with its increasing integration into everyday life. This proliferation has extended into a broader societal context, resulting in the Social Internet of Things (SIoT), where PIoT devices are interconnected to form social relationships. The convergence of PIoT and SIoT has highlighted the need for autonomous learning and comprehension of both the physical and social environments. Current research in PIoT focuses on enabling seamless communication among devices and striking a balance between sensing, observing, and perceiving the extended environment, thereby facilitating information exchange. Additionally, the virtualization of independent learning in the social environment has given rise to Artificial Social Intelligence (ASI) within PIoT systems. Despite the advancements, autonomous data communication between nodes in a social setup presents significant challenges in resource management. This paper offers a comprehensive review of the evolving domains of PIoT, SIoT, and ASI, presenting modeling insights and a case study exploring the role of PIoT in post-COVID scenarios. The study provides a deeper understanding of PIoT's complexities and lays the groundwork for future developments in this transformative field. Karras et al. in[38] try to address the challenges in Edge AI. According to the authors, these two paradigms have emerged as an innovative solution, integrating artificial intelligence directly at the data sources, such as sensors and cameras, ensuring real-time analytics and decision-making. This approach enables more responsive and tailored actions, reducing latency and optimizing resources.

The literature highlights the unique characteristics and applications of Edge AI in the context of IoT. Notably, the interaction between Edge AI and large-scale IoT domains is explored, emphasizing the combined potential of these technologies. A comparative study within big data infrastructures contrasts the performance of Edge AI and cloud-based AI, examining critical factors such as processing speeds, optimization techniques, and key metrics. Despite its advantages, Edge AI has inherent limitations, including resource constraints and scalability challenges, which are also discussed in the literature. Overall, Edge AI offers substantial improvements in operational efficiency, data privacy, and bandwidth utilization, making it a promising solution for the growing IoT ecosystem. As IoT continues to expand, the strategic deployment of Edge AI is expected to play a crucial role in enabling smart, real-time data utilization. Dong et al. in[39] presented collaborative edge computing for SIoT. According to the authors, the paradigm of the IoT has garnered significant attention across both academia and industry over the past decades. Recently, the integration of IoT with social networks, known as the Social Internet of Things (SIoT), has been proposed to foster further development and enhance IoT capabilities. This article explores the applications, solutions, and challenges associated with SIoT, particularly in the context of collaborative edge computing. Collaborative edge computing leverages the strengths of both mobile edge computing and the social relationships among SIoT users to improve the overall efficiency and performance of IoT systems. The article first highlights key applications within SIoT, including collaborative offloading, caching, and streaming data processing. It then discusses several representative social-aware solutions such as auction mechanisms, coalition game theory, and federated learning, which are integral to optimizing SIoT operations. Furthermore, the authors identify several research challenges that remain to be addressed in the development of secure, robust, and intelligent SIoT frameworks. The main contributions of this work include: (1) a specification of the role of social ties in traditional IoT applications and their influence on individual device selection, (2) an explanation of why the three presented approaches—auction, coalition game, and federated learning—are suitable for SIoT, and (3) a discussion of the challenges that could guide future research in SIoT systems, aiming for more secure and efficient frameworks.

Although state-of-the-art approaches yield satisfactory results, none offer a comprehensive analysis of the parameters and discovery involved in SIoT. Most focus solely on the importance of relationships and node/service similarity, while neglecting the underlying discovery algorithms. To address this gap, we propose a service discovery framework that leverages key parameters, details of which are presented in the following sections.

Proposed solution

This section presents our proposed framework for SIoT systems, supported by an example scenario. The complete service discovery (SD) process is structured into three parts: (1) an overview of social service discovery (SDTS) and network modeling, (2) the SD process, and (3) the framework for service provisioning.

Reference scenario

The proposed service discovery framework enables the entities to identify services and discover the networks of "friends" through social relationships. This approach follows a layered model consisting of four distinct layers:

Perception layer This bottom layer includes real-world physical objects such as temperature sensors and other environmental data sources. Its primary role is to sense physical conditions and transmit data to the higher layers.

Virtualization layer This layer contains social virtual objects (SVOs), digital representations of physical entities enhanced with social capabilities. These objects describe the entities' characteristics and the services they can offer.

Aggregation layer The aggregation layer is composed of micro engines (MEs), which are central processing entities. Each ME can comprise one or more social virtual objects (SVOs) or other MEs, forming a composite structure. This layer collects and processes data from the virtualization layer and transmits it to the application layer.

Application layer This layer is partially deployed on devices and primarily hosted in the cloud. It supports the deployment and execution of an application using one or more MEs. Various SDTS may reside at this level to provide or host services.

The SD process is initiated when a user submits a query (as illustrated in Fig. 1). This query is processed by the SDT component of the device, which activates the discovery mechanism. For each service the application requires, the system must identify the best available service node or "hop." Selecting a suitable peer or friend to fulfill the service request involves several mechanisms, which constitute the core contribution of this paper. Notably, following hop selection uses only local information, without requiring global network knowledge. The details of the SD and provisioning framework are elaborated on in the following section.

Social service discovery (SDTs) and network modeling

This section presents the modeling of the proposed framework. In the SIoT, SDTs are represented as $\boldsymbol{N}$ as nodes, denoted by the set $\boldsymbol{N} = \{\boldsymbol{n}_1, \ldots, \boldsymbol{n}_i, \ldots \boldsymbol{n}_I\}$ Where $\boldsymbol{I}$ is the total number of SDTs and $\boldsymbol{n}_i$ Denotes a generic SDT. The social network among these SDTs is modeled using an undirected graph $\boldsymbol{G} = \{\boldsymbol{N}, \boldsymbol{\epsilon}\}$ where $\boldsymbol{\epsilon} \cup \{\boldsymbol{N} * \boldsymbol{N}\}$ denotes the set of edges, and each edge represents a social relationship between a pair of SDTs. The set of friends associated with a generic SDT is defined as $\boldsymbol{F}_i = \{\mathbf{ni} \in \mathbf{N} : \boldsymbol{n}_i, \boldsymbol{n}_j \in \partial\}$, indicating all nodes directly connected to $\boldsymbol{n}_i$. Each SDT is capable of installing and executing applications. Thus, effectively allowing it to provide specific services.

As prosumers, SDTs can both offer and request services within the network. Figure 2 illustrates an example in which SDT. $\boldsymbol{n}_i$ is requesting a specific service $\boldsymbol{S}_h$. The proposed service discovery mechanism returns a potential provider. $\boldsymbol{n}_j$ Capable of fulfilling this request. Multiple SDTs may simultaneously request the same service or experience varying and evolving service requirements. As shown in Fig. 2, the graph consists of nodes $\boldsymbol{N} = \{\boldsymbol{n}_1, \ldots \ldots \ldots \boldsymbol{n}_9\}$. Each SDT can offer one or more services. In the diagram, SDT $\boldsymbol{n}_1$ It is marked in red, indicating that it is currently seeking service. $\boldsymbol{S}_7$ (Highlighted within a white cloud). The candidate providers for this service are SDTs $\boldsymbol{n}_5$ and $\boldsymbol{n}_{6,}$. In this scenario, SDTs $\boldsymbol{n}_4$ **He is** a friend of $\boldsymbol{n}_1$ With the highest degree. It is initially selected to forward the service query. Although, $\boldsymbol{n}_5$ and $\boldsymbol{n}_6$ share the same degree, the mechanism intelligently routes the request through the social network to optimize service discovery. Our proposed service discovery and provisioning mechanism is designed to enable SDTs to identify suitable service

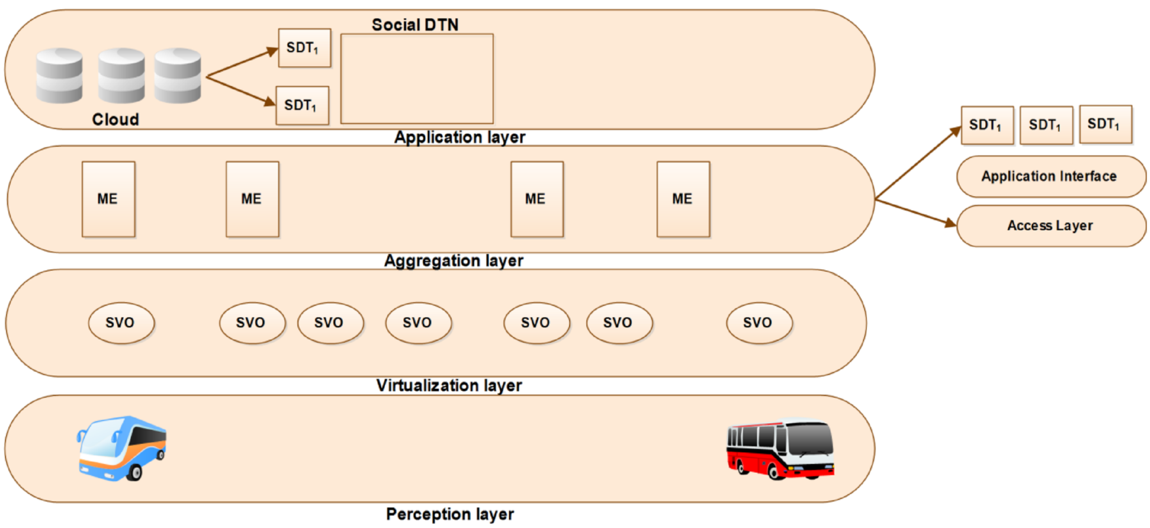

Fig. 1. Reference SIoT Architecture.

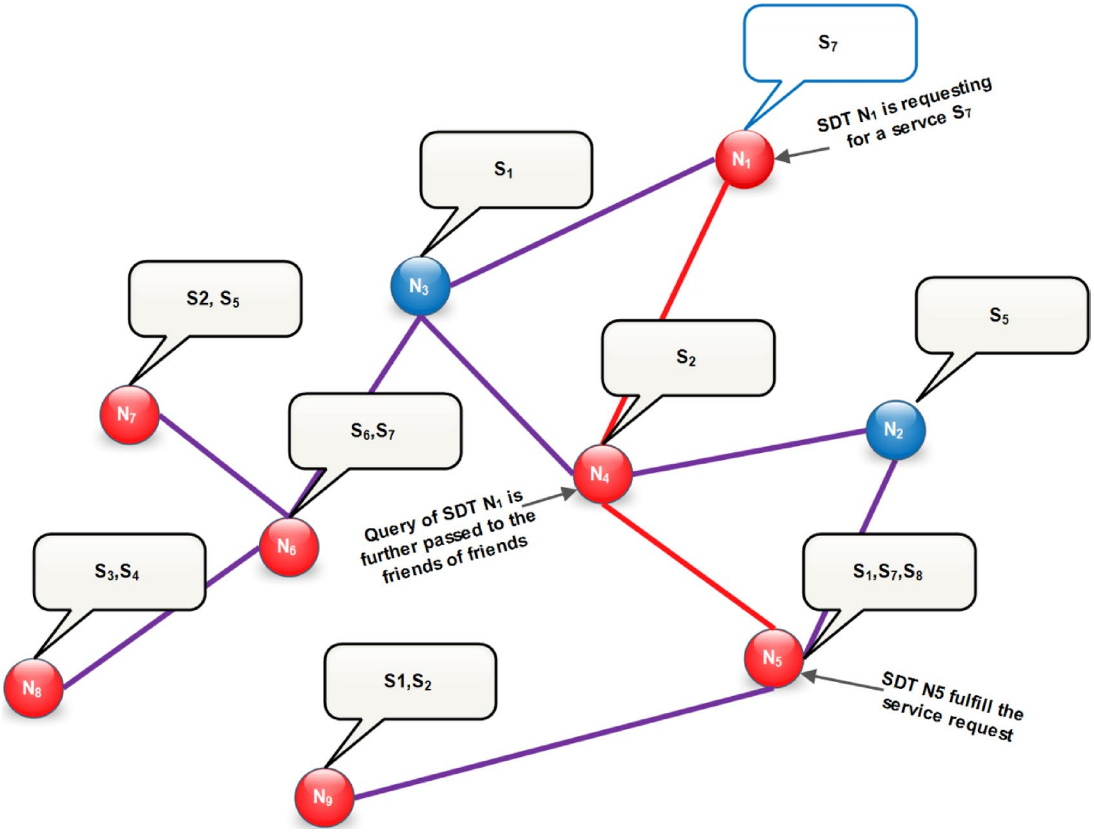

Fig. 2. SDT Friend Selection Scenario.

providers efficiently by leveraging social relationships and customized routing metrics. The proposed framework and the algorithm are given below.

Service discovery and provisioning framework

Figure 3 illustrates the proposed service discovery and provisioning framework. Upon receiving a new query at an object $\boldsymbol{N}_1$, an application $\boldsymbol{A} = \{\boldsymbol{a}_1, \boldsymbol{a}_2, \dots\ \boldsymbol{a}_\mathbf{n}\}$ is assigned to process the request. This query is decomposed into a set of services $\{\boldsymbol{s}_1, \boldsymbol{s}_2, \dots\ \boldsymbol{s}_{\boldsymbol{n}}\}$, which are fulfilled by various objects within the network. The dataset is derived from SIoT queries, which are modeled as a graph structure. The following hop selection process is divided into discovery and global analysis. During the global analysis, each node evaluates its neighbors (friends) to determine the optimal next hop. The graph structure represents a generic SIoT graph G, where I = 9, and each object is defined as a tuple: $\sqsupset = \{\mathrm{n}_i,\ m_{xyz}\}$. This graph-based component communicates with the shortest path analysis unit, which begins by generating a dataset from SIoT queries and identifying the shortest paths within the graph, as shown in Fig. 3.

A specific node is then selected to initiate the discovery process, which is triggered whenever an SDT requires a particular service. The node assesses various local discovery metrics for all neighboring nodes, such as degree centrality, relationship strength, and other relevant factors. Based on these parameters, the node selects the next hop with the highest probability of resolving the query. The selection of the next hop is based on a set of defined parameters given below.

Degree centrality $\mathbf{D_i}$This metric reflects the number of connections associated with an SDT. As a critical parameter in social networks, the degree of centrality conveys the level of connectivity. More centralities indicate a greater likelihood of successfully resolving queries and locating services. This parameter is utilized in our model to select both the requester and neighboring nodes. It is one of the key factors considered in determining the next hop. The degree centrality is selected based on the equation below.

$$\boldsymbol{C}_{\boldsymbol{j}} = \frac{|\boldsymbol{F}_{\boldsymbol{j}}|}{\boldsymbol{max}_{\boldsymbol{oi}} \in\ \boldsymbol{O}\,|\boldsymbol{F}_{\boldsymbol{i}}|} \tag{1}$$

Where $|\boldsymbol{F}_{\boldsymbol{j}}|$is the cardinality of $\boldsymbol{F}$. We keep this measure within the range [0,1]. We normalize it for the maximum number of friends of an object[3].

Relationship Factor $\mathbf{D_i}$This internal parameter captures a distinctive feature of SIoT, representing the strength of the relationship between two nodes $\boldsymbol{n}_{\boldsymbol{i}}$ and $\boldsymbol{n}_{\boldsymbol{j}}$. It supports efficient network navigability, particularly in scenarios involving distant services; PoR. Additionally, it assists in service discovery for objects like CLOR or CWOR.

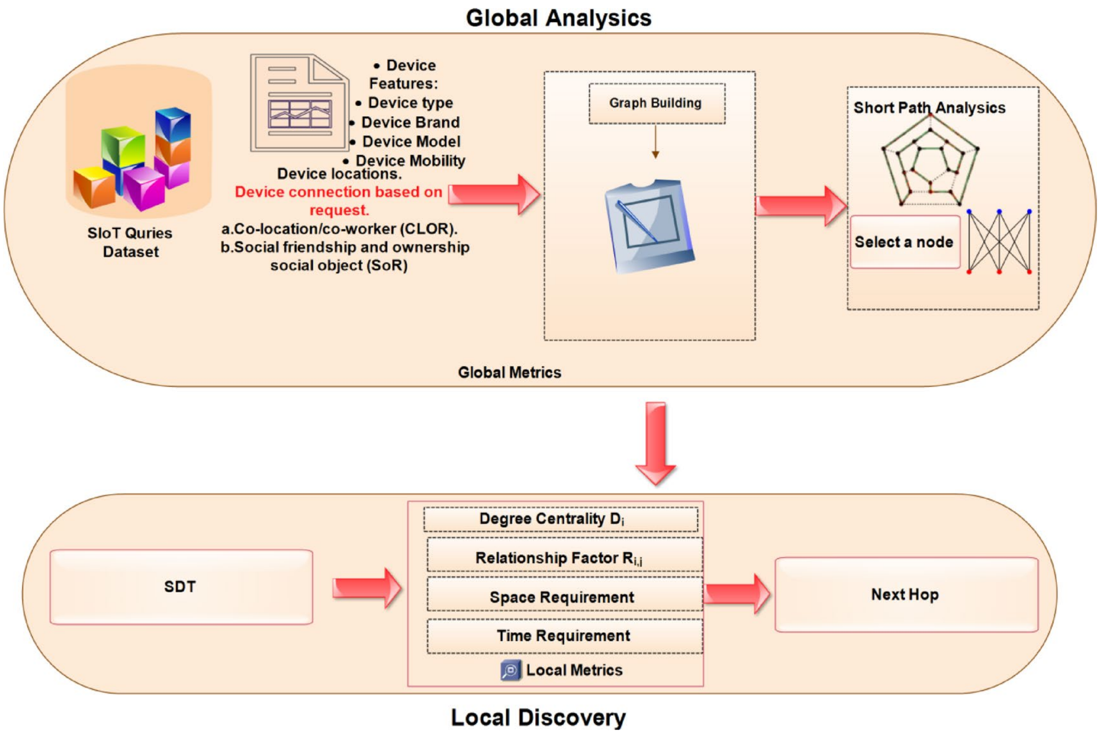

Fig. 3. Service discovery and provisioning framework.

Input: Send a Search request Q
Output: Select SDT

Start ()
Step 1) {For each service request S_i in Q}
{For each neighboring SDT $\mathbf{n_j}$ in F_i}
Calculate $\mathbf{D_i}$, $\boldsymbol{L_j}$, $\boldsymbol{T_j}$, $\mathbf{S_{ij}}$ and $\boldsymbol{A_{ij}}$

Step 2) For each $\mathbf{n_j}$ in F_i, compute Score ($\mathbf{n_j}$):
$$\textbf{Score}\ (\mathbf{n_j}) = \alpha_1.C_j + \alpha_2.\mathbf{D_i}\ (\mathbf{n_j},\mathbf{n_j}) + \alpha_3.\boldsymbol{L_j} + \alpha_4.\boldsymbol{T_j} + \alpha_5.\mathbf{S_{ij}} + \alpha_6.\ \boldsymbol{A_{ij}}$$

Step 3) Select $\mathbf{n_j} = argmaxScore(\mathbf{n_j})$. (node with highest score)

Step 4) If $\mathbf{n_j}$ cannot fulfill the service, forward the query to the next hop

Step 5) Return $\mathbf{n_j}$ that successfully fulfills the service
End ()

Algorithm. ServiceDiscoveryProcess

$$\mathbf{Di}\,(\mathbf{n_i}, \mathbf{n_j}) = \mathbf{f}\ (\mathbf{R_{ij}}, \mathbf{C_{ij}}, \mathbf{T_{ij}},\ \mathbf{S_{ij}}) \tag{2}$$

Where $\mathbf{Di}\,(\mathbf{n_i}, \mathbf{n_j})$ **is the relationfactor from node $\mathbf{n_i}$ to $\mathbf{n_j}$**

$\mathbf{R_{ij}}$ **is the relationship intensity between $\mathbf{n_i}, \mathbf{n_j}$**

$\mathbf{C_{ij}}$ **Is the contextual similarity among nodes**

$\mathbf{T_{ij}}$ **icapture the temporal recency of interactions.**

$\mathbf{S_{ij}}$ **it is the service similarity**

.

Spatial requirement $\mathbf{L_j}$: This parameter enables requester SDTs to route queries toward the desired physical location within the network. For each friend node $\boldsymbol{n_j}$ It is calculated as the Euclidean distance between the node's position and the target location specified in the query. It is a binary parameter: assigned a value of 1 for friend nodes that contribute data and 0 for SDTs that do not.

$$\boldsymbol{L_j} = \begin{cases} 1, \; if \; \mathbf{n_j} \; contribute \; data \\ 0, \; otherwise \end{cases} \quad (3)$$

Time requirement $\mathbf{T_j}$ The time requirement specified in the query is represented by this parameter. Nodes that frequently generate information have a higher probability of offering the requested service. $\boldsymbol{T_j}$ Thus, it reflects the time-frequency with which a given SDT generates data relevant to the query.

$$\boldsymbol{T_j} = \frac{\boldsymbol{f_j}}{\boldsymbol{f_{max}}} \quad (4)$$

Were the

$$\mathbf{f_j \; is \; the \; freuancy \; of \; data \; generation \; by \; node \; n_j \; relevant \; to \; the \; query}.$$

$$\mathbf{f_{max} \; is \; the \; maximum \; frequancy \; among \; all \; nodes}$$

.

$\mathbf{T_j} \in \; [0, 1]$ where values closer to 1 indicate higher temporal.

Service Similarity $\mathbf{S_{ij}}$ This matrix quantifies the similarity between the service requested in the query and the service of a neighboring node $\boldsymbol{n}_\mathbf{j}$ Can provide. It facilitates faster identification of suitable services, as nodes offering highly similar services are more likely to fulfill the request. Specifically, $\boldsymbol{S_{ij}}$ denotes the similarity between the service needed and the service offered by the node $\boldsymbol{n}_\mathbf{j}$. In this work, $\boldsymbol{S_j}$ It is assigned a value of 1 if the target node provides the desired service; otherwise, it is 0.

$$\mathbf{S_{ij}} = \begin{cases} 1, \; if \; \mathbf{n_j} \; provides \; requested \; servise \\ 0, \; otherwise \end{cases} \quad (5)$$

Application Similarity $\mathbf{A_{ij}}$ The metric evaluated whether a neighboring SDT can run an application similar to the one associated with the querying node. Application similarity can be enhanced through caching mechanisms, enabling quicker response times. $\boldsymbol{A_{ij}}$ represents the similarity between applications supported by nodes $\boldsymbol{n}_\mathbf{i}$ and $\boldsymbol{n}_\mathbf{j}$. If the target node supports the application, $\boldsymbol{A_{ij}}$ It is set to 1; otherwise, it is 0.

$$\boldsymbol{A_{ij}} = \begin{cases} 1, \; if \; \mathbf{node \; n_j} \; Support \; the \; application \; associated \; with \; \mathbf{node \; n_i} \\ 0, \; otherwise \end{cases} \quad (6)$$

Where:

I show the corresponding node to the querying node

J corresponds to the neighbor node.

The overall service discovery process is shown in Algorithm 1. It is used to decide the next hop. The explanation of Algorithm 1 is given as follows. Our algorithm takes a user query Q, which consists of a set of service requirements $\{s1, s2, ..., sn\}$, along with the SDT Network N. It includes all nodes ($SDTs$) in the system. It also uses the friend network F, where each SDT n_1 has a list of neighboring SDTs F_i, and the Social Graph $G\; = (N, \in\,)$ Represent social relationships between SDTs. For each service request S_i, the proposed algorithm evaluates each neighboring $SDT \;\; n_J$ in F_i. The calculation is performed based on metrics including $\mathrm{D_i}$, L_j, T_j , $\mathrm{S_{ij}}$ and A_{ij}. In step 2, for each neighboring node n_j score is computed by combining the above metrics using predefined weights $\alpha_1, \alpha_2, \; \alpha_3 \ldots \; \alpha_n$.This score shows suitability of $\mathrm{n_j}$ in the fulfillment of a service request $\mathrm{Score} \; (\mathrm{n_j}) = \alpha_1.C_j + \alpha_2.\mathrm{D_i} \;\; (\mathrm{n_j}, \mathrm{n_j}) + \alpha_3.L_j + \alpha_4.T_j + \alpha_5.\mathrm{S_{ij}} + \alpha_6. \; A_{ij}$.In step 3, The algorithm selects the neighboring node $\mathrm{n_j}$ with the highest score, meaning it is the most suitable node to fulfill the service request. This selection is done by finding the node that maximizes the score. $\mathrm{n_j} = argmaxScore\,(\mathrm{n_j})$. In step 4 if the selected object $\mathrm{n_j}$ is not a service provider. The request query is forward to the neighbor. In step 5, If the selected object $\mathbf{n_j}$ hold a resource, it is considered as a service provider. Finally, a link is established between the service seeker and service provider.

Simulation, experiments, results, and discussion

In this section, we explain the details of experimentation of our proposed model and the state-of-the-art models. We have conducted our simulations using NetworkX. It is a widely used platform-independent Python library designed to create, manipulate, and analyze complex networks[17].

Datasets

We have used a real-world social IoT dataset. This dataset is publicly accessible to the research community. Figure 4 shows the key features of the dataset. This dataset comprises a wide range of IoT objects, such as smartwatches, smartphones, personal computers, and weather sensors, all located in Santander, Spain[28]. Table 1 highlights the primary features of the dataset. Each IoT device is represented by several attributes, including:

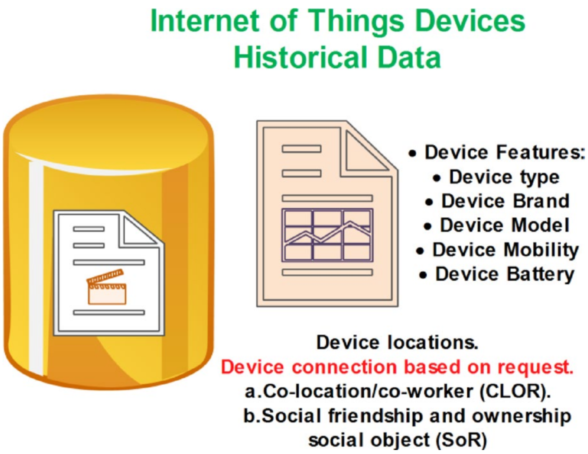

Fig. 4. The real social IoT dataset.

Data model	Description
Point of interest	Specific point location that a user may find useful or interesting
Environment and weather	Object responsible of the environmental and weather monitoring
Transportation	Buses, taxis and vehicles
Indicator	Digital signage to display the information
Garbage truck	Collection and transport of waste products
Streetlight	Streetlight to see the roads in the city
Parking	Location designed for parking
Alarms	Traffic monitoring or security supervisor

Table 1. Device type

- id_user: Identifies the user who owns the device.
- device_id: A unique identifier for the device.
- device_type: Specifies the type of device (e.g., smartphone, sensor).
- device_model: Indicates the model of the device. This real-world dataset simulates service discovery and application similarity in a realistic IoT environment.
- device_brand: field specifies the brand name of each device.

This entire dataset contains 16,216 IoT objects. It is noted that 1,616 are public and 14,600 are private. It includes two categories of devices: mobile and static. Mobile devices are associated with dynamic attributes such as timestamps, longitude, and latitude. In contrast, static devices maintain fixed geographical coordinates. The types of devices included are listed in Table 1. The dataset features an adjacency matrix representing SIoT relationships, along with several predefined parameters.

Hop discovery

This subsection evaluates the performance of our proposed framework based on the number of hops traversed in the social graph during query forwarding. The first results shown in Fig. 5 illustrate the impact on hop discovery. This graph shows a comparison of two different services, called an occasional service and a frequent service. The uncommon queries are that it is hard to find a network, and the frequently provided services are owned by several SDTs in a network. The comparison distinguishes between two service types: occasional services, commonly available across multiple SDTs in the network. We compare our proposed model against those proposed by Roopa et al.[18] and C. Marche et al.[20]. Figure 5 shows the result based on the type of service, either frequent service or occasional service. It is shown in Fig. 5 locating occasional services require more hops as compared to frequent ones. We have three different colors for this cart. We have used brown color for our proposal, yellow for C. Marche et al.[20] et al. and the blue color for Roopa et al.[18]. A reader can examine that for occasional service, our proposed framework requires a smaller number of hops. We have verified the same behavior using frequent service. Herein, we can see that our proposed framework needs a smaller number of hops as compared to the state-of-the-art models. To verify this behavior, we performed another experiment based on 'Requirements in "queries". Figure 6 presents a graph, the first is "run queries without requirements", and the second one is with "space and time requirements". Herein, we have used a query scenario, averaging around 20 hops for these models. We can see in the first result that the proposed framework performs better than others, but not so much. We perform another experiment. On the right-hand side in Figure. 6, we can see the space and time requirements result. When a query complexity increases, particularly with added spatial and

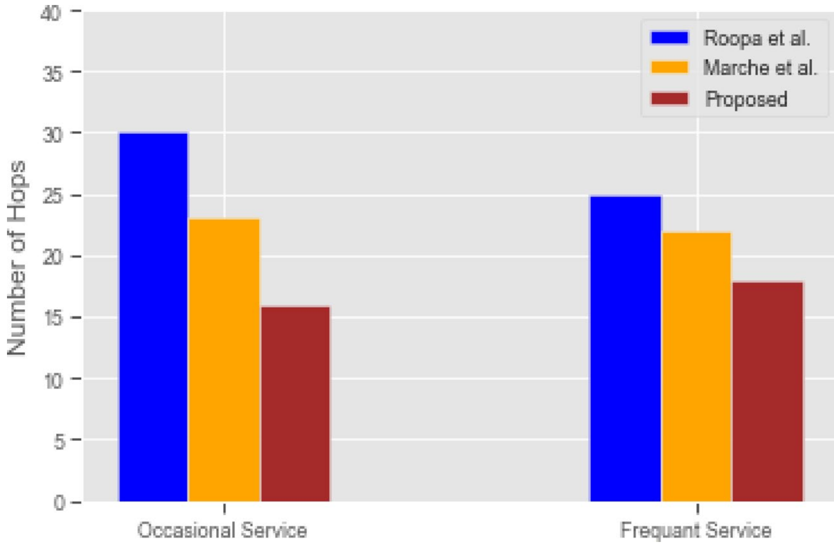

Fig. 5. Type of service.

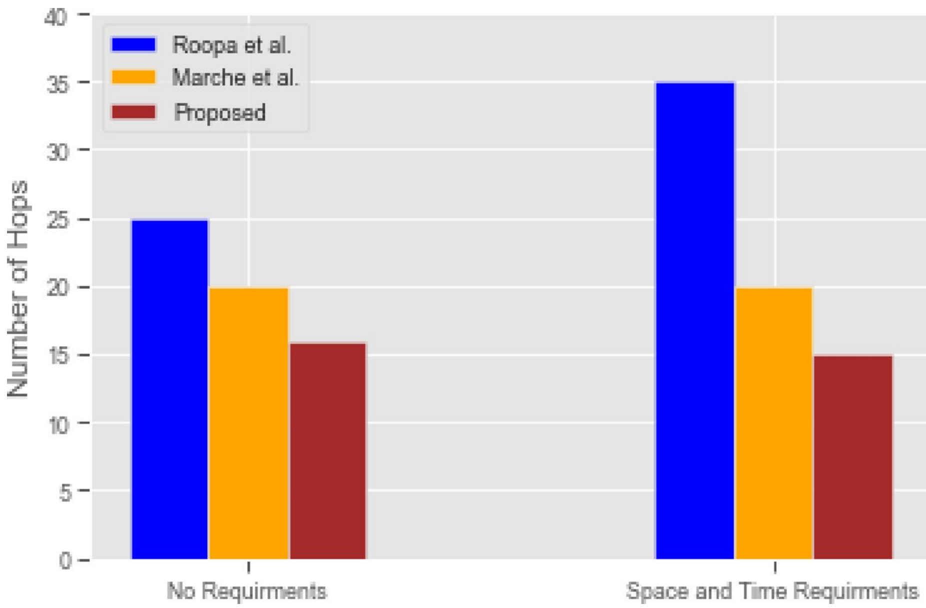

Fig. 6. Requirements in queries.

temporal constraints. Marche et al.[20] and Roopa et al.[18] do not perform well. However, our proposed framework performs well.

Service discovery using caching

This experiment evaluates how efficiently a node can resolve a query and locate the desired service using caching and without caching. The efficiency is measured with and without a caching mechanism. The x-axis shows the query, and the y-axis shows the number of hops in Fig. 7. These results indicate that integrating a caching mechanism significantly improves service discovery in SIoT. Specifically, the caching-supported framework reduces the average hop count. In this experiment, we can see that it is approximately 6 as compared to 20 hops (non-caching scenario). These results show the importance of caching as a critical strategy for hop routing in SIoT.

Service processing time and computation overhead

In this experiment, we examine the service processing time and the computation overhead of our proposed framework and the state-of-the-art models, for instance[40], . Figure 8 shows the query processing time and computation overhead. The X-axis shown in this figure represents the dataset size. The Y-axis corresponds to the

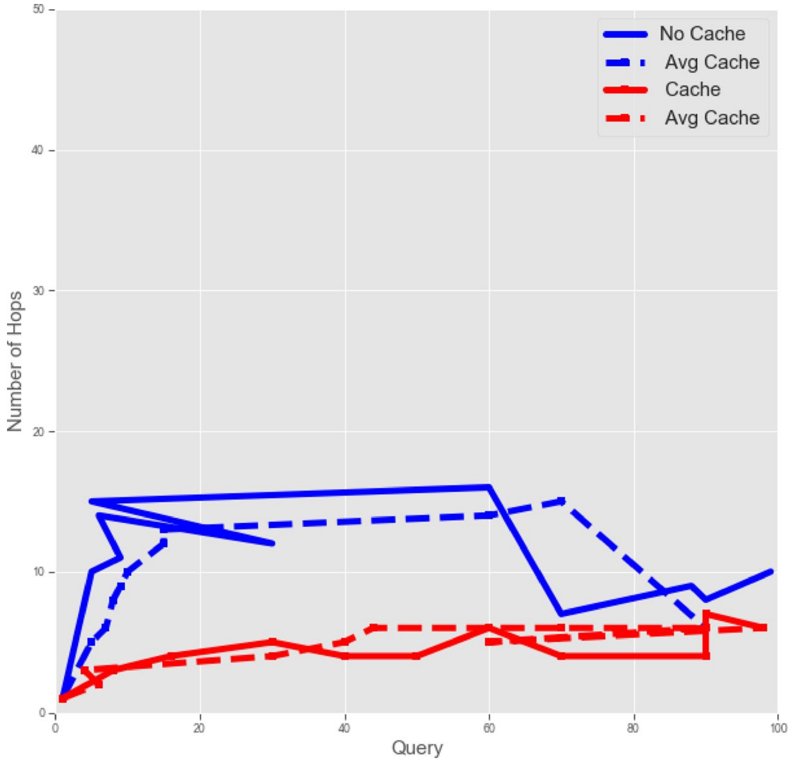

Fig. 7. Number of hops with and without caching.

processing time and is measured in milliseconds. In this figure, the red color indicates the proposed framework, and the green color indicates state of the art model[40]. We can see that as the dataset size increases, the same time processing time decreases. Initially, the processing time increases gradually but accelerates significantly as the data size grows. For larger datasets, the processing time is reduced considerably. Thus, it indicates the efficiency of the proposed framework as shown in red color. Additionally, the overall throughput is also analyzed in relation to the data size. It exhibits a direct correlation with the dataset size, which is consistent with the inherent characteristics of the proposed framework. The simulation result demonstrates that the proposed model performs well as compared to the state-of-the-art models.

We have performed another experiment. In this experiment, we want to see the impact on service execution time and check the scalability of the proposed models as compared to the state-of-the-art models presented in[40]. In Fig. 9, we compare our proposed framework with the most recent model[40]. The x-axis shows the number of objects, and the y-axis shows the execution time measured in seconds. These results indicate how the number of objects grows based on elapsed time. We have used red color for our proposed framework and green color for the state-of-the-art model. We have tested both models for different iterations and concluded that the efficiency of our proposed framework increases in the intervals or passage of time intervals. In this graph, we see that the execution time of our proposed framework is shorter than the most recent state-of-the-art model[40]. This result proves that the proposed framework is more efficient because it requires less time to discover neighbor objects as compared to the state-of-the-art models[40]. It means that the proposed model is highly scalable as compared to state-of-the-art models.

Conclusion and future work
This study addresses the issue of object/ service discovery in the SIoT. In SIoT entities, known as SDTS, can establish social relationships and create a social network of friends. When an SDT receives a query, it first checks whether any of its friends can fulfill the request. If not, it selects the most suitable peer to forward the query. We have proposed a framework based on parameters for the next hop selection, prioritizing based on their importance. We performed extensive experiments, and the efficiency is measured in terms of query processing time and computation overhead, scalability, type of service, and caching. The efficient experimental results demonstrate that our propose framework outperforms as compared to state of the art models and thus enables faster and more autonomous service discovery. In this study, we did not consider the trust between the objects for next-hop selection. In addition, we rely on the SIoT standard dataset. In the future, we plan to incorporate the trust between objects and and verifying using very large datasets. We also consider the dynamic envoiroment.

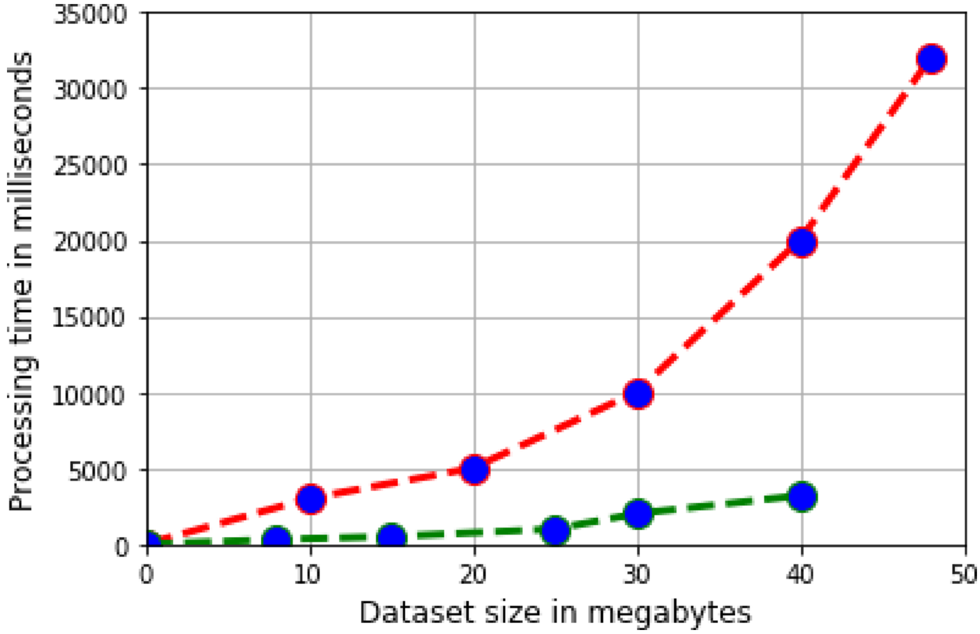

Fig. 8. Query processing time and computation overhead.

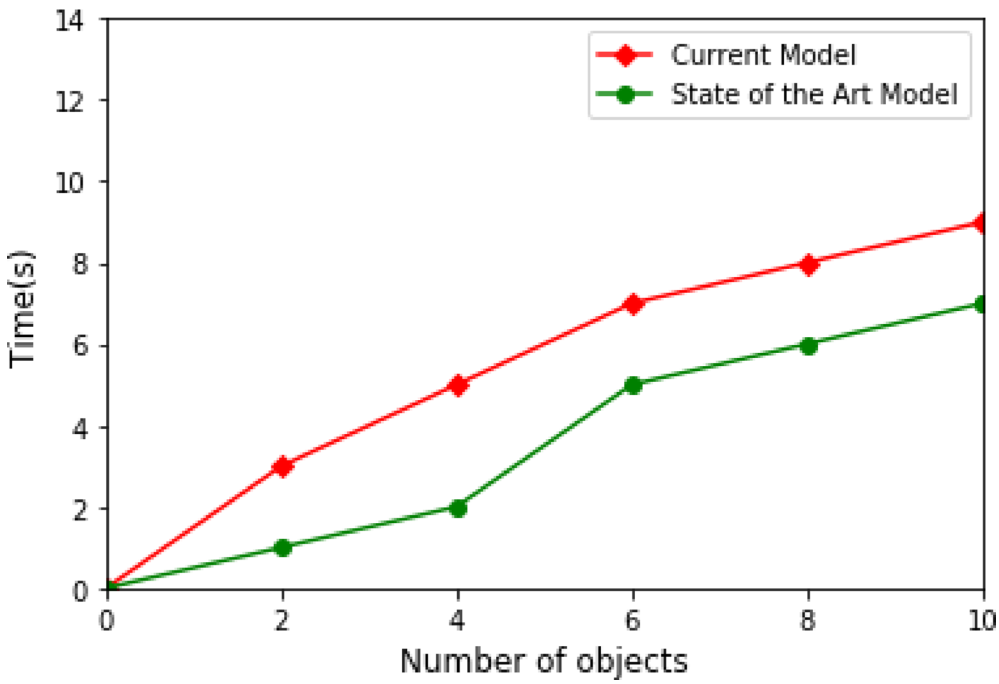

Fig. 9. Service discovery time and scalability.

Data availability

Data is provided within the manuscript.

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Author contributions
Farhan Amin .Salabat Khan. Gyu Sang Choi wrote the main manuscript text, and Muhammad Ali abid. Isabel de la Torre. Elisabeth Caro Montero. Irene Delgado prepared Figs. 1, 2 and 3. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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