Adaptive Capacity Task Offloading in Multi-hop D2D-based Social Industrial IoT

Muhammad Ibrar, Lei Wang, Aamir Akbar, Mian Ahmad Jan, Venki Balasubramanian, Gabriel-Miro Muntean, Nadir Shah

***Abstract*—Traditional communication technologies such as cellular networks are facing problems to support high service quality when used for time-critical applications in an Industrial Internet-of-Things (IIoT) context, including real-time data transmission, route dependability, and scalability. To address these problems, device-to-device (D2D) communications based on social relationships can be used, which allow for task-offloading: resource-rich devices share unused computing resources with resource constraint devices. However, unbalanced task offloading in Social IIoT (SIIoT) might actually degrade the overall system performance, which is not desirable. In this paper, we propose an adaptive capacity task offloading solution for D2D-based social industrial IoT (ToSIIoT) which considers devices utilization ratio and strength of social relationships in order to improve resource utilization, increase QoS and achieve better task completion rate. The proposed approach consists of three aspects: social-aware relay selection in a multi-hop D2D communication context, choice of a resource-rich SIIoT device for task offloading, and adaptive redistribution of tasks. The paper proposes heuristic algorithms, as finding optimal solutions to the problems are NP-hard. Extensive experimental results show that the proposed ToSIIoT performs better than existing approaches in terms of utilization ratio, QoS violation, average execution delay, and task completion ratio.**

***Index Terms*—Industrial IoT (IIoT), social relationship, resource sharing, Device-to-Device (D2D), task-Offloading.**

I. Introduction

THe Internet of Things (IoT) is seen as a critical enabler for the development of the modern industry. The success of IoT technologiesis also due to the constant integration of numerous controllers and/or sensors in current industrial production processes, which has propelled the conventional industry to a new, smart level, known as Industrial IoT (IIoT) [1], [2]. Among others, the IIoT increases industrial efficiency while also reducing resource consumption and production costs. However, in IIoT, industrial sensors integrated into industrial robots and mobile devices create massive amounts of data, putting a burden on the radio access networks [3], [4]. The time-critical applications (i.e., interlocking, closed-loop control, and industrial automation control) can tolerate delay within a range of 10 to 100ms and require transmission reliability of about 99.99%. In an industrial network setup, achieving such levels of delay and transmission reliability are considered significant problems which need focusing on [5], [6].

To address these challenges, and therefore, satisfy the needs of time-critical applications, device-to-device (D2D) resource sharing across smart mobile devices in IIoT architecture opens up a novel research avenue [7]–[9]. D2D communications in IIoT can provide low transmission delays and high power efficiency. Moreover, D2D communications also reduce transmission overhead caused by centralized, traditional management and coordination [10]. Mobile devices are generally heterogeneous, in terms of computational and communication capabilities. Some IIoT devices, for example, have idle or excess resources, while others have insufficient resources to offer. The resource-constrained mobile devices can offload their computationally-intensive tasks directly to nearby resource-rich devices to achieve high resource utilization rates, low latencies, and high quality of experience levels [11].

Furthermore, to enhance the quality-of-service (QoS) in D2D resource sharing context and minimize the undesirable exposure of unreliable devices, the social-awareness factor among IIoT mobile devices can be considered [12], as shown in Fig. 1. The available resources in social IIoT (SIIoT) are shared using social relationships (e.g., conflict, friendship, and incentives for profit-driven) [13]. Since the processing power of devices is limited in an IIoT architecture with social D2D communication, only a limited number of tasks may be delegated to them for execution. Therefore, in this work, we also took into account the device utilization ratio as well as the strength of social ties in order to reduce the pressure put on resource provider SIIoT devices.

A. Motivation

The IIoT devices have a short transmission range. Therefore, D2D communications require multi-hop communication support to enhance the efficiency of the SIIoT architecture, particularly for time-critical task offloading (i.e., content sharing or idle resource sharing). However, SIIoT devices also have social attributes, which is crucial for resource sharing because some devices share their idle resources with other devices that have social tie with them. Consequently, in multi-hop social-aware D2D transmissions, the IIoT devices offload the time-critical

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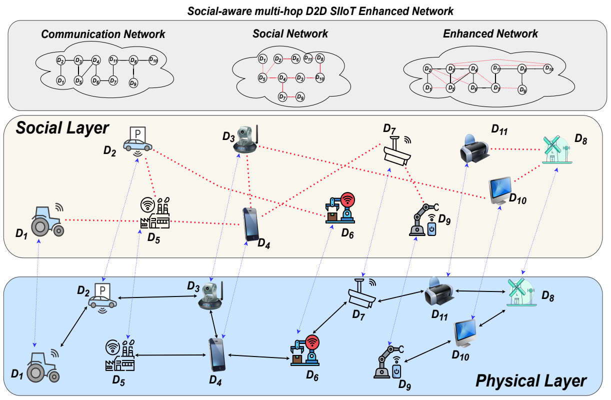

Fig. 1. System model of social-aware multi-hop D2D SIIoT architecture. In this figure, the lower part shows IIoT device connectivity at physical layer; the IIoT devices are connected via D2D communications. At the social layer, the devices are connected through social ties. The upper layer shows the social-aware multi-hop D2D enhanced network.

tasks instantly between devices without routing through the Base Station (BS) [14]. Researchers already studied social-aware single-hop D2D communications [15]–[18], but they ignored multi-hop D2D communications in a SIIoT architecture. Unlike existing work, this paper focuses on idle resource sharing in social-aware multi-hop D2D communications in SIIoT. Further, IIoT devices are heterogeneous in terms of computational and communication capabilities, and social ties enormously affect the unified communication between devices. Social-aware relay selection is critical because a device may or may not forward the packet based on a social tie. The main objective of this paper is to jointly consider the social tie and utilization ratio of resource providers, when offloading time-critical tasks.

B. Contributions

This paper proposes an adaptive capacity task offloading solution for multi-hop D2D SIIoT that maximizes the utilization ratio of idle resources of resource provider devices and achieve load balancing. The proposed approach consists of three aspects: an innovative mechanism for social-aware relay selection in multi-hop D2D communications, a solution for resource-rich SIIoT device choice for task offloading, and a novel scheme for adaptive redistribution of tasks. In terms of the social-aware relay selection, the intended model ensures that the strength of the social tie between devices must be greater than some predefined threshold value as relay SIIoT devices should be willing to forward packets of trusted devices. Regarding the second aspect, we select the resource-rich device for task offloading while jointly considering the device utilization ratio and strength of social tie. Finally, we propose an adaptive task redistribution scheme to redistribute the tasks among IIoT devices in order to minimize the overloading problem of resource provider devices. In brief, the main contributions of this paper are as follows.

- This paper considers social industrial IoT devices in a multi-hop D2D resource sharing scheme, where devices share their idle or excess resources with resource-constrained devices by employing multi-hop D2D communication. To enable resource sharing of the trustworthy multi-hop D2D links, we modelled the communication system as a weighted undirected graph based on social ties between IIoT devices.
- A multi-hop D2D SIIoT architecture is considered, where IIoT devices offload computationally-intensive tasks to resource-rich devices, while also considering utilization ratio and strength of the social ties of these devices. To solve the trade-off problem between utilization ratio and strength of the social tie among IIoT devices in a polynomial time, we propose a heuristic task placement algorithm as the problem is NP-hard.
- An adaptive tasks redistribution algorithm is proposed to minimize the overloading issue of resource provider devices in the SIIoT architecture by focusing on utilization ratio and strength of the social tie among the devices.

The rest of the paper is organized as follows. Section II discusses related works and identifies their benefits and limitations. The proposed solution, including the related mathematical modeling, is introduced in Section III. Section IV discusses the experimental results to show the effectiveness of the proposed model in comparison with existing works. Finally, Section V concludes the paper and describes some potential future research directions.

II. Related Works

This section discusses some existing proposals related to D2D resource sharing based on social relationships relevant to the work presented in this paper.

In the recent past, social attributes-based communication has attracted unprecedented attention from academia and industry [19], [20]. In SIIoT, when smart mobile objects come in contact, they create social relationships/ties autonomously, without human intervention [21], [22]. The researchers have made several attempts and proposed various schemes for the SIIoT system. Table I describes some of the applications that can be developed based on the social features of smart mobile devices. The centralized and traditional IIoT architecture faces challenges in terms of delay and promoting computational-intensive applications. The resource-rich IIoT mobile devices can experience the unused computing resources with other resource constraints devices employing D2D technology and social awareness.

In order to integrate the social networking concepts for D2D task offloading in IIoT, some works have used auction theory for an optimal solution [8], [23]. In the social IIoT, mobile devices can share their resources based on locality and social trustworthiness. To handle these problems in indispensable IIoT architecture, Sun et al. [8] proposed two approaches for social IIoT D2D sharing, one hop-based social aware incentive mechanism (OSIM) and relay-based SIM (RSIM). In OSIM, the IIoT mobile device can offload the task to a nearby one-hop resource-rich device that employs the Vickrey-Clarke-Groves (VCG) auction. While in the RSIM, the IIoT mobile device uses a multihop approach for task offloading. Although the stated approach improves the performance of social IIoT D2D sharing, the authors do not examine the level of idle resources of the mobile devices while offloading the tasks.

The load balancing problem occurs due to the limited computed resources of the devices. Therefore, Zang et al. [24] use reinforcement learning to select the device for task offloading based on the social attribute perception. In the proposed model, the global module obtains the resource information from the devices and then uses social awareness and reinforcement learning in the selection process. To ensure the devices' truthfulness in D2D communication, Zhao et al. proposed a three-phase approach using social-aware data dissemination [17]. A large number of mobile devices also significantly affect D2D transmission. Accordingly, Wang et al. [25] practiced the D2D opportunistic sharing model to offload the tasks considering devices' social interaction. In the proposed model, the authors use tag-assisted social aware D2D content dissemination and offloading. Additionally, Yi et al. [26] focus on the D2D downlink traffic offloading in cellular networks based on social-aware. Based on user profile activity, it can share the content and cache the information in the devices. Furthermore, the proposed model also uses a pricing mechanism for the resource contributor devices.

Other studies [23], [27]–[29] also focus on multi-hop D2D resource sharing, but they did not jointly consider the social attributes and physical attributes. Note that multi-hop resource sharing occurs mainly among social-trustworthy and physically closed mobile devices in the social IIoT architecture. Multi-hop resource sharing maximizes the utilization ratio of idle resources of mobile devices in IIoT. To achieve this goal, in this paper, we proposed a multi-hop resource sharing solution in IIoT, considering jointly the social relationship level, i.e., CWOR, OOR, CLOR, and level of idle resources of IIoT mobile devices.

III. Adaptive Capacity Task Offloading Solution for Multi-hop D2D Social IIoT

A. Problem Explanation

Resources sharing in multi-hop D2D-based social industrial IoT (SIIoT) is still in the infancy stage, and various researchers have focused on possible policies, techniques, and methods for establishing relationships among smart devices autonomously [21], [23], [30]–[32] and without any human intervention [33]. Although these studies have investigated the social ties to improve the resource sharing efficiency, they did not have considered the utilization ratio and strength of the social tie in a multi-hop D2D-based SIIoT. Suppose we have an IIoT architecture that has support for social-D2D resource sharing as shown in Figure 2. Assuming that there are some resource-rich IIoT devices (i.e., D_1, D_4, and D_{10}) and remaining resource-constrained devices. In the social layer, device D_6 has a social relationship with D_1 and D_{10}, but these devices are distant in the communication network (physical layer). Suppose, D_6 offload the task to D_2 based on strong a social tie and physical proximity [8], [22], [30]. It will create a burden on the D_2 because the utilization ratio (U) of D_2 is 80%. Consequently, it is complicated to provide desired end-to-end delay services. In contrast, if D_6 offloads the task to D_{10}, then it might receive a quick response from it because the utilization ratio (U) of D_{10} is only 20%. It would help to utilize resources efficiently and minimize the end-to-end delay at the social layer. Therefore, motivated by these facts, we intend to propose an adaptive capacity task offloading in multi-hop D2D SIIoT architecture by jointly holding the utilization ratio and social tie value.

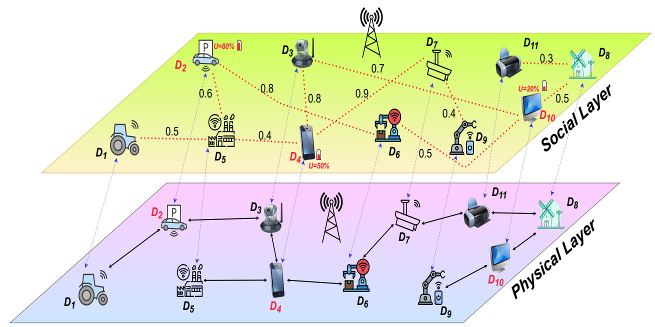

Fig. 2. System model of multi-hop D2D-based SIIoT architecture: In the physical layer, the IIoT devices are connected with D2D communication, whereas in the social layer, the devices are connected through social ties. In the social layer, the link value shows the strength of the social association between two devices. D_2, D_4, and D_{10} are resource-rich devices (aka, resource providers) which share their idle resource with the remaining IIoT devices (aka, resource requester).

B. Adaptive Capacity Task Offloading in Multi-hop D2D Social IIoT

The proposed method performs adaptive capacity task offloading in multi-hop D2D-based SIIoT. The system architecture consists of IIoT devices and a Base-Station (BS). The IIoT devices can act as both service requester (i.e., offloading tasks to others) and service providers (i.e., executing offloaded tasks). Furthermore, the mobile devices in SIIoT are heterogeneous and resource-constrained (i.e., limited computational power and storage), and they connect through D2D links in the physical layer. Moreover, the devices built a social network (logical connection) in the social layer, which is based on social relationships. After both physical and social connections are successfully created, mobile devices can offload their tasks based on the strength of the social ties using the D2D links. Strong social ties between service requester and service provider show trustworthiness; however, the proposed method also maximizes the utilization ratio of the devices in SIIoT.

1) Communication Model using D2D link: The D2D connection between mobile devices in IIoT is allowed to be created only if the distance is less than a pre-defined threshold. Suppose V represents a set of mobile devices of physical layer ($u, v \in V$), the connection is built only when $d_{v,u} < d_{max}$ is satisfied. Moreover, in D2D-based IIoT architecture, the BS can eliminate channel interference among mobile devices. The BS allocates the channel to each physical communication link is orthogonal to the channels of remaining D2D communication links [26]. Suppose a device u uses the same channel as the device v, mathematically, the channel interference $\mathbb{I}_{u,v}$ can be shown as follows.

TABLE I
TYPES OF SOCIAL RELATIONSHIPS

Name of Social Relationships	Explanation	Applications
Parental Object Relationship (POR)	relationships among similar smart objects	smart card reaching, smart printing
Social Object Relationship (SOR)	relationships create when objects come into contact	electronic toll collection, intersection collision warning, lane change assistance
Co-Work Object Relationship (CWOR)	relationships create when objects work together	tele-medicine, alarm system
Co-Location Object Relationship (CLOR)	relationships create when objects reside at the same place	smart parking, smart home, smart hospital, smart city
Ownership Object Relationship (OOR)	relationships create when objects belong to the same owner	smart transportation, smart energy management
Service Object Relationship (SerOR)	relationships create when objects fulfil the service request by coordinating the same service composition	smart navigator service, smart museum
Guest Object Relationship (GOR)	relationships create when a object spends time socially at friends place	smart shopping mall, smart bill payment, smart restaurant
Stranger Object Relationship (StraOR)	relationships create when a objects encounter the existence of each other in the public surroundings	smart marketing
Guardian Object Relationship (GuarOR)	relationships create when objects turn into a child in association the super objects	detour the traffic, early warning system
Sibling Object Relationship (SibOR)	relationships create when a objects belong to a family	smart stadium, crowd management, game statistics exchange

$$\mathbb{I}_{u,v} = \sum_{u \in V} P_v \cdot d_{u,v}^{-l} \cdot |R_{v,u}|^2 \tag{1a}$$

s.t.

$$P_v = min\left(\bar{P}_v, \quad \frac{k}{\max\limits_{BS}(\frac{|R_{v,u}|^2}{d_{u,v}^{-l}})}\right) \tag{1b}$$

$$\mathbb{I}_{u,v} = min\left(\frac{\bar{P}_v, \quad \frac{k}{\max\limits_{BS}(\frac{|R_{v,u}|^2}{d_{u,v}^{-l}})} \cdot (\frac{|R_{v,u}|^2}{d_{u,v}^{-l}})}{\sum_{u \in V} P_v \frac{|R_{v,u}|^2}{d_{u,v}^{-l})}}\right) \tag{1c}$$

In Eq. 1a, P_v shows the transmitting power of mobile device v, d signifies the distance between u and v, l shows the path loss, and R represents the channel response from v to u. Eq. 1b and Eq. 1c mitigate the interference by adopting power control strategy [34], and $\bar{P}_v$ shows the maximum transmit power, and k represents the interference power level at BS.

Based on the interference model mentioned above, the proposed model can mathematically compute the maximum data rate as follows.

$$\lambda_{v,u} = (1 - z_k)\mathbb{B}_{v,u} \cdot log_2\left(1 + \frac{P_v \cdot d_{u,v}^{-l} \cdot |R_{v,u}|^2}{\mathbb{I}_{u,v} + |\sigma_u|^2}\right) + z_k\left((min\left\{\lambda_{i,j} | (i,j) \in \mathbb{P}(v,u)\right\}\right) \tag{2}$$

We define the binary variable z_k to represent whether there is a direct D2D link between the two IIoT mobile devices (i.e., service requester v and service provider u). The value of $z_k = 0$, if there is direct D2D link between v and u, otherwise $z_k = 1$. If there is no direct D2D link between v and u, then the other mobile devices act as relay devices in the task offloading process. In Eq. 2, $\mathbb{P}(v,u)$ represents the relay path from service requester v and service provider u, where (i,j) is the D2D link in $\mathbb{P}(v,u)$. Additionally, $\mathbb{B}_{v,u}$ is the bandwidth, P_v shows the transmitting power of a mobile device v, and the additive white Gaussian noise at mobile device u is σ_v.

2) *Social Graph Model:* Let us consider a SIIoT architecture, where mobile devices create a undirected graph based on social ties, $G^s = (V^s, E^s)$, where V^s signifies a set of SIIoT devices and E^s is the set of social links. We believe that each SIIoT device $v \in V^s$ has limited computing capability, and SIIoT devices are heterogeneous in nature. Additionally, a link $e \in E^s$ exist between two SIIoT devices with positive value (i.e., $W_e = (0,1]$) if there is a social tie, such as SOR, CLOR, POR, and CWOR. Table-1 presents the remaining symbols used in this paper.

TABLE II
SUMMARY OF SYMBOLS

Symbols	Explanation
G^s	network graph
V^s	set of SIIoT devices in network, $v \in V^s$
E^s	set of links, $e_i(v,u)$, $e_i \in E^s$
τ	set of computing tasks, $t \in \tau$
C_v^{max}	maximum capacity of SIoT device
C_v^{util}	utilize capacity of SIoT device
W_e	weight of a link based on social tie

3) *Graph Formation and Social-aware Relay Selection:* In SIIoT architecture, mobile devices communicate with multi-hop manner due to limited transmission range and creates a communication graph G(V, E) at physical layer. Additionally, all IIoT devices independently utilize social relationships at social layer. The strength of social tie (W$_e$) depends upon the relationship (i.e., SOR, CLOR, POR, and CWOR). Algo-

rithm 1 shows graph formation which constructs G(V, E) and G^s = (V^s, E^s (lines 1 to 7).

Algorithm 1: Graph Formation and Social-aware Relay Selection Algorithm

Input: Set of SIIoT devices (V)
Result: $G(V, E)$, $G^s = (V^s, E^s)$, Social-aware Relay Selection

1 **while** $u \in V$ **do**
2   **if** *d(u, v) in Comm_Range* **then**
3   G.add_edge(u, v)
4   **if** $W_e \geq W_e^{th}$ **then**
5   G^s.add_social_edge(u, v)
6   **end**
7   **end**
8 **end**
9 **while** $u \neq v$ **do**
10   compute transmission power // `Eq. 1b`
11   **for** *neighbors of IIoT device* $u \in V$ **do**
12   compute power and social tie // `Eq. 3, Eq. 4, Eq. 5`
13   **end**
14   **if** *No neighbors of IIoT device* $u \in V$ **then**
15   cellular communication between u and v via BS
16   **end**
17 **end**

After graph formation, the proposed ToSIIoT model selects a candidate from path between a resource requester device (u) and resource provider device (v). Suppose, $\mathbb{P}(u, v) = \{u, u_1, u_2, u_3, ..., u_n, v\}$, where u signify the source device and v is destination. The main goal of relay selection in the intended model is to ensure that the strength of the social tie between devices must be greater than some predefined threshold value as a relay SIIoT device is willing to forward the packet of trusted devices. Additionally, we also focus on minimizing the power consumption of the SIIoT devices. The designated path must satisfy the subsequent provisions:

$$\min_{P_u} \max_{W_e} \sum_{u \in V} \sum_{e^s \in E^s} P_u W_e \tag{3}$$

$$s.t. \quad W_e \geq W_e^{th}, e^s \in V^s \tag{4}$$

$$P_{min}^t \leq P_u^t \leq P_{max}^t \tag{5}$$

where W_e^{th} shows the minimum threshold value of the social tie while selecting a relay device in a path. Algorithm 1 computes the candidate path from a source to destination device (lines 9 to 16).

4) Selection of resource rich SIIoT device for task offloading: One of the proposed work's primary purposes is to distribute the tasks in SIIoT mobile devices and reduce the associated cost. We intend a cost function χ_v to offload the task to SIIoT device v while considering the SIIoT device's capacity and social tie value. Mathematically,

$$\chi_v = \Theta_v + \beta \frac{C_v^{util}}{C_v^{max}} + \alpha \frac{W_e}{W_e^{max}}, \tag{6}$$

where Θ_v confers the boolean parameter to indicate whether a new SIIoT device $v \in V^s$ is elected for the task offloading. In Eq. 6, the predefined constants β and α represent the relative importance of utilization of a SIIoT device and social tie, respectively and values of the constants are user-defined. Suppose if available capacity in a SIIoT device is very low, β should be relatively high as compared to α. In the proposed work, we assume $\beta = \alpha$. In the proposed work, we minimize the maximum utilization ratio of SIIoT device subject to the cost function. Mathematically,

$$\min_{t \in \tau} \max_{v} \sum_{t \in \tau} \sum_{v \in V^s} \tau_v^t \chi_v x_v^t \tag{7a}$$

$$s.t. \quad \sum_{v \in V^s} x_v^t = 1, \forall v \in V^s \tag{7b}$$

$$\sum_{t \in \tau} v_t \leq C_v^{max}, \forall v \in V^s \tag{7c}$$

The SIIoT devices offload the tasks; however, each task should be offloaded to only one SIIoT device. In other words, the tasks are unsplittable, as shown in Eq. 7b. Additionally, Eq.7c ensures that the total number of assigned tasks does not exceed the maximum capacity of any SIIoT device. Eq. 6 is optimization as well as an NP-hard problem because processing and complexity are involved in the computation of all possible combinations of the select SIIoT device. Therefore, we propose a heuristic algorithm to select SIIoT devices for task offloading based on utilization and social tie parameters. Mathematically, we can formulate the social tie between SIIoT devices u and v as follows:

$$sim(u, v) = \frac{\sum_{i=1}^{h} w_{1_i} * w_{2_i}}{\sqrt{\sum_{i=1}^{h} w_{1_i}^2} * \sqrt{\sum_{i=1}^{h} w_{2_i}^2}}, \tag{8}$$

where h shows the similarity indicator and w_{1_i} and w_{2_i} show the strength of the i^{th} social tie.

There is a trade-off between utilization ratio and strength of social tie. To minimize the trade-off and improve the network performance, we introduce a *network performance factor*, $\Re$. Additionally, we also compute an eligibility score, $\emptyset_v$, of a SIIoT device for task offloading. Mathematically,

$$\emptyset_v = \Re\left(sim(u, v)\right) - (1 - \Re) \frac{C_v^{util}}{C_v^{max}} \tag{9}$$

where $0 < \Re < 1$ is the desired weight based on strength of the social tie and utilization ratio of a SIIoT device. Eq. 9 ensures a trafe-off between social tie and utilization ratio. Algorithm 2 presents the proposed heuristic approach.

5) Adaptive redistribution of tasks in D2D SIIoT: To efficiently utilize the computing resource of mobile devices and accommodate more tasks in SIIoT architecture, this section proposes an adaptive scheme to redistribute the tasks among mobile devices, as shown in Algorithm 3. The proposed algorithm redistributed the tasks among the existing mobile devices, without exploring new devices (see lines 6-9). The main reason behind this is to utilize mobile devices with strong social ties and less utilization ratio. Therefore, the proposed

Algorithm 2: Task placement algorithm

```
Input: Set of SIIoT devices, Max. capacity of the
       SIIoT devices, Set of SIIoT devices with tasks,
       Set of utilized capacity C^util of SIIoT devices.
Result: min. the max. utilization of SIIoT devices
1 τ ← 1 // Number of tasks
2 while v ∈ V^s do
3     v ← max_score // Eq. 9
4     v ← τ offload
5     update utilization ratio C_v^util
6     τ ← τ ← +1
7 end
```

algorithm utilizes the mobile device until the utilization ratio reaches a predefined utilization threshold. If the utilization ratio of a mobile device is greater than the threshold value, then the proposed Algorithm 3 uses Eq. 9 (see Algorithm 2) for task offloading.

Algorithm 3: Adaptive redistribution of tasks

```
Input: Set of SIIoT devices, Max. capacity of the
       SIIoT devices, Set of SIIoT devices with tasks,
       Set of utilized capacity C^util of SIoT devices.
Result: redistribution of tasks
1  v^o ← overloaded SIIoT devices
2  τ ← tasks
3  γ // threshold value for utilization
4  v^o-flag ← 0 // overloaded threshold
5  for t ∈ τ do
6      for v ∈ V^s \ u do
7          if C_v^util ≤ γ and W_e > u then
8              offload t to v
9              remove t from u
10         end
11     end
12 end
13 if v^o-flag ← 1 then
14     for t ∈ τ do
15         using Algorithm 2 for tasks offloading (line
             3-5)
16     end
17 end
```

IV. Simulations Results

We use a simulation environment to validate the performance of the above proposed ToSIIoT model. We randomly distributed 100 SIoT mobile devices in 100×100 areas and placed a Base Station (BS). Moreover, we divide the mobile devices into two groups: 30% services providers and services requester are 70%. The resource capacity of each services provider is [5, 15] Mb, and offloading task size of each services requester is [1, 5] Mb evenly distributed. The mobile devices can make a D2D connection if the distance between devices is less than 15 m. Additionally, the transmitting power of each mobile device is 100 mW, bandwidth is 1 MHz, the value of path loss exponent l is set to 4, and noise variance is -174 dBm/Hz. In the simulation, we also vary the values of user-defined constants i.e., β and α, which represent the relative importance of utilization ratio and strength of the social tie, respectively.

To validate the performance of the proposed adaptive model, ToSIIoT, we compare the simulation results with existing works - social-aware incentive model (SIM) for IIoT [8] and 3-D social identifier structure (3D-SIS) [22].

A. ToSIIoT: Performance Parameters

This section discusses the performance parameters used to compare the proposed approach with state-of-the-art approaches called SIM and 3D-SIS. We consider the following parameters for the comparison and simulation.

1) Resource Utilization Ratio (percentage): In the simulation, we randomly divide the IIoT devices into two groups (i.e., service providers 30% and 70% services requester) to depict the service providers' resource utilization percentage. The resource utilization ratio (percentage) confers the balance of the service requester's utilized resources to the amount of the original unused resources.

2) Quality-of-Service (QoS) Violation (percentage): In the proposed model, we treated a task as QoS violated task when the algorithm violates at least one parameter like delay or task assigned to overload device or select social tie – is not satisfied.

3) Average Execution Delay: We compute the average execution delay of tasks in the proposed model with respect to the various number of resource services providers.

4) Task Completion Ratio: In the proposed model, task completion ratio can be define as the total number of generated tasks from the resource constraints IIoT devices and number of completed tasks in the resource rich IIoT devices.

B. ToSIIoT: Results and Discussion

This section shows the performance results obtained using the schemes – ToSIIoT (Proposed), 3D-SIS, and SIM – using different performance parameters.

1) Resource Utilization Ratio (percentage): The main objective of our proposed ToSIIoT scheme is to offload the task while jointly considering the idle resource of service provider and strength of social tie with services requester as mentioned in the Section III-B4. Additionally, ToSIIoT utilizes the idle resources of IIoT devices until the utilization ratio of a device reached the threshold level. It is noteworthy that the proposed adaptive redistribution algorithm (see Algorithm 3) uses the statistic of social tie and utilization of the idle resources of the IIoT devices, so that additional delay or burden on the service provider is avoided. Figure 3 shows the percentage of resource utilization ratio of 30% service providers with different approaches – ToSIIoT (Proposed), 3D-SIS, and SIM, in five various experiments. Box plots (i.e., box-and-whisker plots) are used to illustrate comparatively the experimental results. For each scenario, a box is drawn by connecting the lower quartile, median, and upper quartile. Finally, the

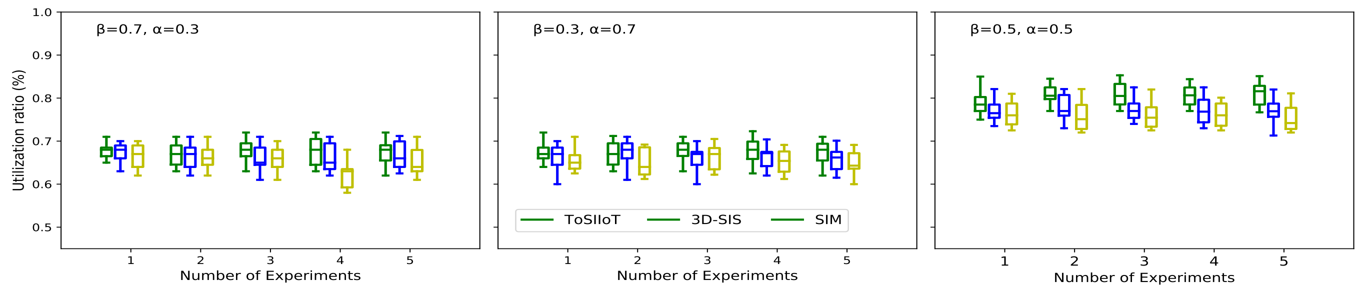

Fig. 3. The average utilization ratio of three models, i.e., ToSIIoT, 3D-SIS, and SIM, and number of experiments

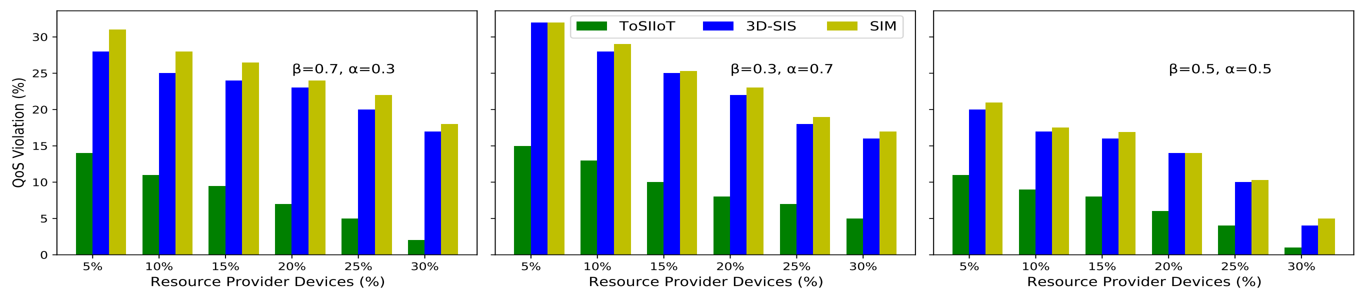

Fig. 4. The average QoS violation of three models, i.e., ToSIIoT, 3D-SIS, and SIM, and number of resource rich devices (%).

whiskers from the box show the lower and upper extremes of the scenario. Additionally, the middle line in a box depicts the mean value of the scenario. All the simulations are performed 10 times, and after each experiment ratio of resource utilization is recorded, giving credibility to the analysis of the proposed algorithms. In the simulation, we vary the values of the user-defined constants β and α. Box plots in Figure 3 represent that the proposed scheme, ToSIIoT, is capable of efficiently utilizing the idle resources of services providers compared to the existing works. It is mainly because the proposed ToSIIoT scheme attentively distributes the tasks among the service providers by jointly considering the utilization level of idle resources and strength of social tie. In the contrast, the 3D-SIS and SIM schemes do not consider the utilization level of idle resources of the IIoT devices; therefore, the percentage of utilization ratio is less compared to the proposed ToSIIoT model. Interestingly, if we give importance to the predefined constants (i.e., β and α), then it dramatically decreases the utilization ratio of the idle reassures. Consequently, from Figure 3, it is evident that the proposed ToSIIoT scheme yields an improved utilization level of the idle resources compared to the existing works – 3D-SIS and SIM. The percentage of resource utilization ratio is about 80% in the proposed ToSIIoT scheme, in 3D-SIS, the percentage of resource utilization ratio is almost 75%, and in SIM, the ratio is 72% (approximately).

2) *Quality-of-Service (QoS) Violation (percentage):* In this subsection, we confirm the efficacy of the intended ToSIIoT scheme in terms of Quality-of-Service (QoS) violation (percentage) with the existing works – 3D-SIS and SIM. Another objective of the proposed scheme is to minimize the overloaded problem in social-D2D IIoT. In social-D2D IIoT, the service requester offloads the tasks based on strength of social tie or physical distance with the service provider, which leads to the burden on the service provider and increase the delay. Consequently, we have some QoS-violated tasks that are offloaded to the service requiters in the social-D2D IIoT network. Figure 4 represents the percentage of QoS-violation with the various number of resource provider devices (%). In the simulation, we vary the percentage of resource provider devices and after each experiment ratio of QoS-violation is recorded. The results show that as the number of resource provider devices is increasing, the percentage of QoS violation is decreases in all schemes: ToSIIoT, 3D-SIS, and SIM. However, in the proposed scheme, the percentage of QoS violations is less than that recorded in the 3D-SIS and SIM. The reason is as follows. The proposed scheme utilizes the IIoT devices with strong social ties and less utilization ratio using an adaptive approach. From the results, we can notice that the proposed scheme is capable of fulfilling the QoS requirements of the service requester. In particular, the percentage of QoS-violation ratio in the proposed scheme is almost 9% and 12% less than compared to 3D-SIS and SIM, respectively.

3) *Average Execution Delay (seconds(s)):* In the proposed work, we examine the average execution delay (s) in the SIIoT architecture, as shown in Fig. 5. In the simulation, we varies the values of β and α and the percentage the resource provider SIIoT devices to compute the average execution delay. The results show that if we give more preference to utilization ratio β or social tie α, then it will increase the average delay. However, if we set the values of utilization ratio β and social tie α equal, then the model perform well, as shown in Fig. 5. From the results, we observe that there are more average execution delay in 3D-SIS and SIM than in our approach

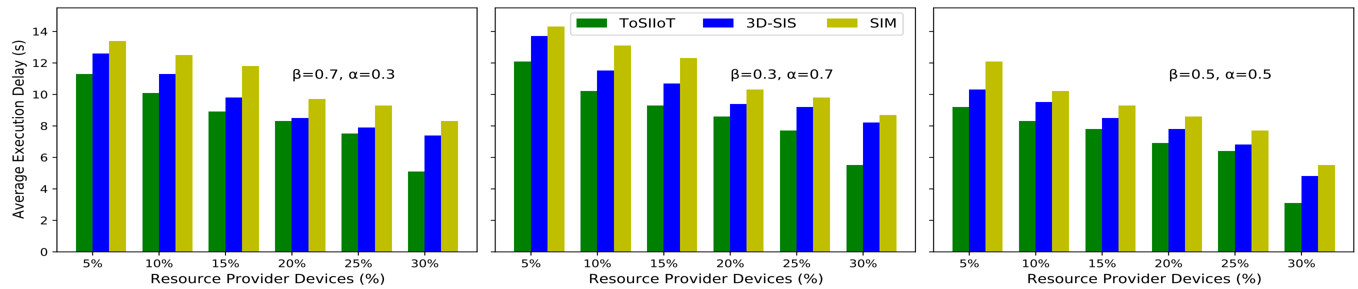

Fig. 5. Impact of resource services providers (%) on average execution delay in three models, i.e., ToSIIoT, 3D-SIS, and SIM.

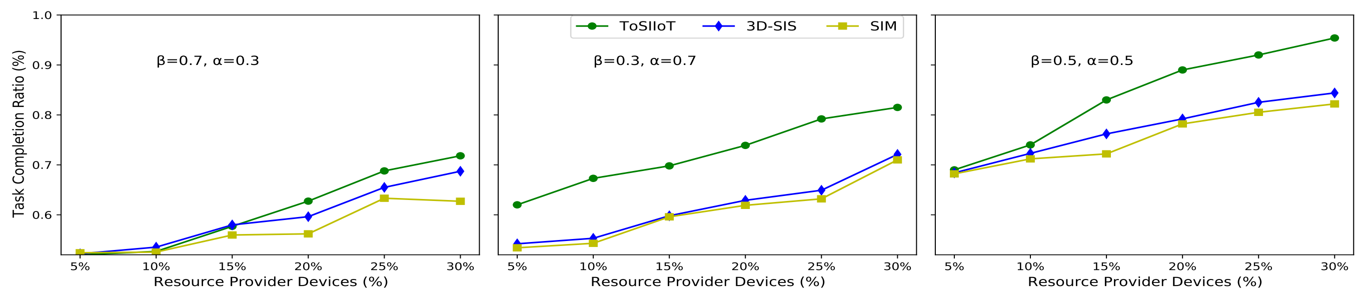

Fig. 6. Impact of resource services providers (%) on task completion ratio in three models, i.e., ToSIIoT, 3D-SIS, and SIM.

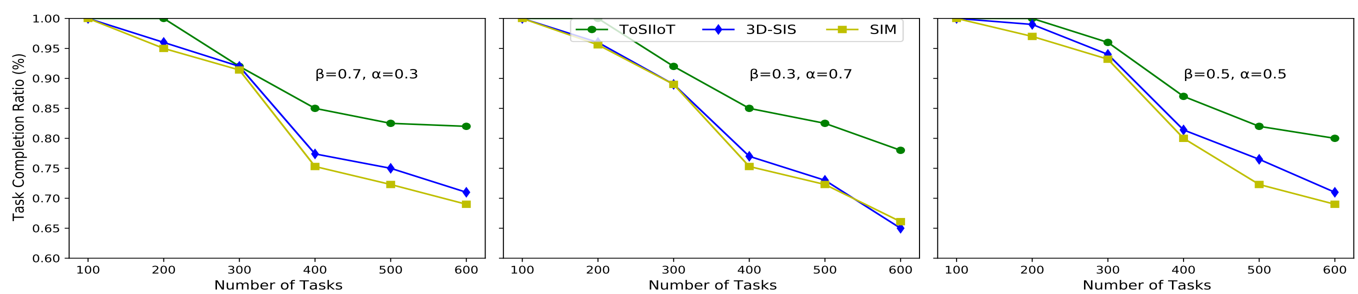

Fig. 7. Impact of number of tasks on task completion ratio number in three models, i.e., ToSIIoT, 3D-SIS, and SIM.

because 3D-SIS and SIM do not jointly consider the utilization ratio β and social tie α among the SIIoT devices during the task offloading process.

4) Task Completion Ratio: We investigate the performance of the propose ToSIIoT model with respect to a number of resource service providers (%) and compare them with the 3D-SIS and SIM. In the propose work, the task completion ratio is the number of completed tasks in resource service providers to the number of arrived tasks. In the simulation, we set the total of tasks is 500. In Fig. 6, as the number of resource service providers (%) is increasing, the task completion ratio is also increases in all approaches. However, in the proposed ToSIIoT, the task completion ratio is more than that of the 3D-SIS and SIM approaches. The main purpose of the proposed ToSIIoT model is to minimize the utilization ratio of resource rich SIIoT devices by jointly consider the utilization ratio β and social tie α during the task offloading process. Additionally, we also take into account the adaptive redistribution tasks in SIIoT architecture. Therefore, the results show that ToSIIoT performs better than 3D-SIS and SIM. In Fig. 7, as the number of tasks is increasing, the task completion ratio decreases in all approaches: ToSIIoT, 3D-SIS, and SIM. However, in the proposed approach, the task completion ratio is higher than that recorded in the 3D-SIS and SIM approaches.

In summary, it is manifest that the intended ToSIIoT scheme is capable of intensifying the social-D2D IIoT performance in terms of resource utilization ratio (percentage) and Quality-of-Service (QoS) Violation (percentage). Additionally, it is also observed that values of user-defined constants degraded the performance of the intended scheme. Nevertheless, it is always more trustworthy than the existing schemes.

V. Conclusion and Discussion

In this paper, we proposed an adaptive capacity task offloading scheme for multi-hop D2D communications in Social Industrial Internet of Things (SIIoT) to maximize the utilization ratio of idle or excess resources of the system and solve the trade-off problem between utilization ratio and strength of the social tie. The proposed approach consists of three aspects: social-aware relay device selection for D2D communications, selection of resource rich SIIoT devices for task offloading, and adaptive redistribution of tasks. First, increases resource sharing for trustworthy multi-hop D2D links, based on the strength of the social tie among the IIoT devices. Secondly, a heuristic algorithm finds the optimal device for task placement using device utilization level and social relationship value. Finally, the tasks are redistributed over social-D2D IIoT to accommodate more incoming tasks and minimize the response time. To show the efficacy of the proposed model, experimental results were presented. The results show that the proposed model can increase the utilization ratio of devices and efficiently minimize the QoS service violation compared to the existing works in multi-hop D2D SIIoT architecture.

Several schemes have been proposed for task offloading in IIoT while considering D2D communication and social networks concept. However, this paper proposed an adaptive scheme that can optimally compute the desired device for task offloading in a fast and scalable manner. In the future, we will further optimize our proposed scheme by following some potential directions 1) make the schemes more secure and reliable by focusing on the social link selection issue; 2) handle the mobility in the D2D communications-enhanced SIIoT architecture and target a high mobility scenario.

Acknowledgments

G.-M. Muntean would like to acknowledge the Science Foundation Ireland (SFI) support for the Insight SFI Centre for Data Analytics (grant number 12/RC/2289_P2). The work was supported by the "National Natural Science Foundation of China" grant no. 61902052, "National Key Research and Development Plan" grant no. 2017YFC0821003-2, "Science and Technology Major Industrial Project of Liaoning Province" grant no. 2020JH1/10100013, "Dalian Science and Technology Innovation Fund" grants no. 2019J11CY004 and 2020JJ26GX037, and "Fundamental Research Funds for the Central Universities" grants no. DUT20ZD210 and DUT20TD107.

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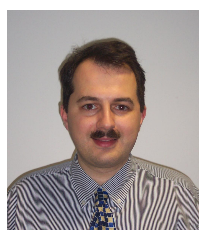

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