Social-Aware Incentive Mechanisms for D2D Resource Sharing in IIoT

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***Abstract*—The industrial Internet of Things (IIoT), as one of the indispensable paradigms of the future network, challenges existing computing network architectures by supporting computational-intensive applications. In the IIoT, resource-rich industrial devices may share idle computing resource to lightweight nodes through device-to-device (D2D) technology, whereas such resource sharing is under social and locality constraints. When industrial devices are carried by human or installed on manned machines, resource sharing more likely occurs among social-trustworthy and locality-adjacent devices. In this article, we propose two social-aware incentive mechanisms for D2D resource sharing in the IIoT, namely one-hop-based social-aware incentive mechanism (OSIM) and relay-based social-aware incentive mechanism (RSIM). In the OSIM, resource-constrained devices bid for offloading tasks using a Vickrey–Clarke–Groves auction, while the RSIM relaxes the locality constraint to two hops to achieve a higher resource utilization ratio. Extensive simulation results show that the performance of the proposed mechanisms can significantly improve the system efficiency while maintaining truthfulness.**

***Index Terms*—Device-to-device (D2D), incentive mechanism, industrial Internet of Things (IIoT), resource sharing, social relationship.**

I. Introduction

THE INDUSTRIAL Internet of Things (IIoT), as the application of the Internet of Things in industrial scenarios, has undergone tremendous changes in the past few years. With the constant emergence of a large number of IIoT mobile devices (MDs), such as industrial monitors, industrial robots, and industrial sensors, the huge amount of traffic generated by these MDs puts great pressure on the radio access network [1]. In addition, in the area of industrial automation control, closed-loop control and interlocking can only tolerate the delay that is on the order of milliseconds (10–100 ms) and transmission reliability higher than 99.99% [2], which challenges the existing network architectures.

Resource sharing among IIoT MDs provides a new perspective to solve the aforementioned issues [3]–[5]. Note that IIoT MDs exhibit heterogeneity in terms of communication and computation capability, e.g., some MDs only have insufficient resource, while others have much idle resource [6]. When these IIoT MDs interconnect with each other via device-to-device (D2D) technology, resource-constrained MDs can offload their computational-intensive tasks directly to proximate resource-rich MDs, to achieve high quality of experience with high data rate, low latency, and high resource utilization rate [7].

Although D2D resource sharing has a bright application prospect in the IIoT, it also faces tricky challenges, such as incentives for profit-driven D2D pairs [8]. Specifically, for traffic offloading, service requesters (SRs, i.e., IIoT MDs that require task offloading) and the service providers (SPs, i.e., IIoT MDs that contribute resource) belong to different camps with the conflict of interest. Considering that IIoT MDs are energy and resource constrained, in the unprofitable case, SPs may be unwilling to provide their resources to SRs. The network economics, which manifests itself in the offloading of tasks, rewards SPs for their contribution, without compromising the property of incentive compatibility (i.e., truthfulness) [9], [10].

In IIoT D2D resource sharing, another factor that needs to be considered is the social awareness among industrial devices [11], [12]. A considerable part of IIoT devices is carried by human or installed on manned machines, which inevitably exhibit social relationship (such as friendship, kinship, and colleague relationship) and regularity in the process of communicating with each other through D2D links. On the other hand, even without the involvement of human beings, devices tend to share information with the trustworthy devices, which they have previously established access with, as establishing new access needs extra cost according to the widely used access control frameworks [13], [14]. The adoption of social awareness in IIoT resource sharing not only improves service quality, but also avoids unnecessary exposure to unreliable agents.

For resource sharing and task offloading between MDs, there have been some works on social awareness or network

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economics [15], [16]. The mobile data offloading issue is investigated in [17] from the perspective of social relationships. Specifically, the authors exploited the PageRank algorithm to model social relationships among mobile users, and a Vickrey–Clarke–Groves (VCG)-like incentive mechanism is developed to achieve the goal of efficient mobile data offloading. Wang *et al.* [18] utilized social ties in social networks to improve the resource-sharing efficiency and proposed a social-community-aware framework, in which users with strong social ties are grouped into the same community; a two-step coalition game was exploited to establish a coalition formulation for communities.

The existing works [15]–[18], although providing some insights into the resource sharing, did not jointly consider social awareness and proximate connectivity in the incentive design in multihop D2D resource sharing. Note that in the IIoT, resource sharing is more likely to occur among social-trustworthy MDs within proximate connectivity, and relaxing the locality constraints to multihop MDs could help fully utilize idle resources and achieve load balancing. Toward this goal, in this article, we explore the social-aware incentive scheme for D2D resource sharing in the IIoT with incentive-compatibility guaranteed. The contributions of this article are mainly threefold as follow.

1) First, we consider social awareness of IIoT devices, either manned or unmanned, in a D2D resource-sharing scenario, where resource-rich devices share their idle resource to nearby resource-constrained devices by exploiting the D2D technology. The social relationships between IIoT MDs are modeled as a weighted undirected graph in this scenario, to encourage resource sharing occur at trustworthy D2D links.
2) Second, the interaction between SPs and SRs is modeled as a market, where the resources of SPs are taken as commodities, and SPs and SRs are modeled as sellers and buyers, respectively. We propose two incentive mechanisms to improve the resource-sharing efficiency, namely one-hop-based social-aware incentive mechanism (OSIM) and relay-based social-aware incentive mechanism (RSIM). The OSIM using the VCG auction to offload takes to nearby resource-rich MDs under the one-hop constraint. The RSIM relaxes the locality constraint to two hops to achieve higher resource utilization ratio.
3) Finally, the effectiveness of the proposed incentive mechanisms is verified by simulation results. Extensive simulation results show that the performance of the proposed schemes can significantly improve the resource-sharing efficiency while maintaining truthfulness.

The rest of this article is organized as follows. We first discuss the related work in terms of social-aware resource sharing as well as D2D technology in Section II. Section III then describes our system model. In Section IV, we present two types of incentive mechanisms for task offloading. An evaluation regarding the proposed mechanisms is performed in Section V. Finally, Section VI concludes this article.

II. Related Work

The existing works on D2D traffic offloading and resource sharing try to find a tradeoff between energy consumption and delay [19], [20]. In order to reduce the energy consumption of help users while maximizing the amount of offloading traffic, Chen and Yang [21] proposed a user-centered caching strategy that controls the energy costs of users when transferring traffic. The proposed strategy optimizes the transmission power to minimize the help user's energy consumption, while optimizing the caching strategy to maximize the traffic offloading under the constraint of energy. In D2D networks, an important characteristic that most researchers value is the mobility of devices. Wang *et al.* [22] utilized the duration of user contact to characterize the impact of mobility on task offloading and caching. They designed an alternating renewal process to build the contact and the duration of the contact while using the data offloading ratio to measure the performance of the algorithm.

Incentives in the D2D network have also received great attentions to optimize network performance while maintaining the economic properties such as truthfulness. Gao *et al.* [23], [24] studied an incentive mechanism for truthful reporting in network optimization with local information in classic network utility maximization problems. They leveraged dual pricing in a user-centric problem and designed mechanisms to guarantee truthfulness under special cases. Zhang *et al.* [25] proposed to use contract-theoretic approach to provide incentives for D2D communications. They classify users' preferences toward D2D communication to several types, and necessary and sufficient conditions are derived to provide incentives for end users to participate D2D communications.

In order to integrate social relationship into the task offloading incentive framework, some researchers have turned their attention to social networks and auction theory for a suitable solution [16], [26]. To solve a series of problems caused by the explosive growth of mobile traffic, Wang *et al.* [27] exploited the D2D opportunistic sharing mechanism to offload mobile traffic by combining users' social interaction. In particular, they proposed a tag-assisted social-aware D2D sharing framework, in which content tags related to social relationships between users are fully considered to accelerate content dissemination and offloading. Yi *et al.* [28] studied the downlink cellular traffic offloading framework based on social-aware D2D content sharing and proactive caching, in which the user devices can select caching and sharing content according to its own preferences. In the meantime, in order to stimulate D2D communication between user devices, the authors proposed a pricing mechanism for rewarding user devices that contribute resource. To alleviate the congestion of cellular networks, Zhang *et al.* [29] utilized the social functions between users to assist the offloading of mobile data. In the process, they adopted a game-theoretical mechanism to resolve the conflict of interest between users who provide storage resource and content and users who need them. Detailed performance analysis demonstrates the effectiveness and feasibility of the mechanism.

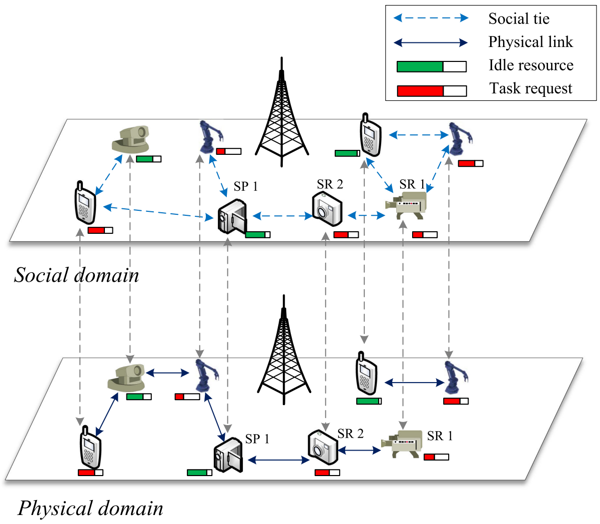

Fig. 1. System model. There are physical connections and social relationships between IIoT MDs. Physical links and social links do not always overlap completely.

It is noted that most existing works on D2D resource sharing do not explore how the social awareness domain and the locality connectivity domain interplay to incentivize trustworthy connections. In addition, the task offloading in the multihop scenario does not receive the attention it deserves in D2D communications. Toward this end, in this article, we jointly consider social relationships and incentive strategies and further study the task offloading in the multihop task offloading scenario.

III. System Model

In this section, we consider a resource-sharing scenario consisting of a BS, several SPs, and SRs, in which the physical domain and the social domain are jointly considered. As shown in Fig. 1, in the physical domain, physical links (i.e., D2D links) connect the MDs that physical locations are in close proximity. The task of an SR is directly offloaded to the corresponding SP through a D2D link underlying the cellular network. In the social domain, there are social relationships with different strength of social ties between IIoT MDs. Strong social ties ensure the traffic offloading to be established among trustworthy industrial devices, thus enhancing cooperative resource sharing. Therefore, when an SR tries to offload tasks to SPs through the D2D link, the SP with the strongest social tie with the SR should be preferentially selected, while taking into account link status, data rate, etc.

A. Channel Model

According to [28], as long as the distance between two devices is less than the threshold $d_{\max}$, a D2D link can be established between them. With the assistance of the BS, the channel assigned to each physical link is orthogonal to the channels of other D2D links. Therefore, the interference between any two D2D links can be eliminated. Assume that there are n IIoT MDs, including m SRs and k SPs, and $\mathcal{N} = \{1, 2, \ldots, n\}$, $\mathcal{M} = \{1, 2, \ldots, m\}$, and $\mathcal{K} = \{1, 2, \ldots, k\}$ represent the IIoT MD set, the SR set, and the SP set, respectively. For each D2D link $l_{i,j}$ $(i, j \in \mathcal{N})$, we denote $B_{i,j}$ as the bandwidth allocated to $l_{i,j}$, and $\mathbb{C}_{i,j}$ represents the set of transmitting devices of cellular links with the same signal frequency as $l_{i,j}$. The in-band interference between the D2D link $l_{i,j}$ and cellular links can be expressed as

$$I_{i,j} = \sum_{c \in \mathbb{C}_{i,j}} (P_c \cdot d_{c,j}^{-\alpha} \cdot |h_{c,j}|^2) \tag{1}$$

where P_c is the transmit power of the transmitting device c, and $d_{c,j}$ is the distance between c and receiving device j, while $h_{c,j}$ is the channel response from c to j. α is the path loss exponent greater than two.

In view of the abovementioned interference, the maximum data rate is given by

$$r_{i,j} = B_{i,j} \cdot \log_2 \left(1 + \frac{P_i \cdot d_{i,j}^{-\alpha} \cdot |h_{i,j}|^2}{I_{i,j} + |\sigma_j|^2}\right) \tag{2}$$

where P_i is the transmit power of SR i, and σ_j is the additive white Gaussian noise at SP j.

It should be noted that if there is no direct D2D link between i and j, $r_{i,j}$ cannot be directly calculated by using (2). For example, in Fig. 1, there is no direct D2D link between SR 1 and SP 1. If SR 1 wants to offload task to SP 1, then other nodes are needed to act as relays. If SR 2 is selected as the relay node, the more reasonable formula for calculating the data rate between SR 1 and SP 1 should be $r_{\text{SR1,SP1}} = \min\{r_{\text{SR1,SR2}}, r_{\text{SR2,SP1}}\}$. We use $P_{i,j}$ to represent the relay path from i to j, and the corresponding data rate $r(P_{i,j})$ is given by

$$r(P_{i,j}) = \min\{r_{a,b} | (a, b) \in P_{i,j}\} \tag{3}$$

where (a, b) is the D2D link contained in $P_{i,j}$. If there is no relay path between i and j, then $r(P_{i,j}) = 0$. Since there may be more than one relay path from i to j, we will show how to select a path in Section III-C.

B. Social Model

In this article, we model the social relationship as a weighted undirected graph $\mathcal{G}(V, E, W)$, where $V = \mathcal{N}$ is the set of IIoT devices, and $E = \{e_{x,y} | x, y \in V\}$ stands for the set of social edges. E characterizes whether there is a social relationship between devices, i.e., if there is a social relationship between two devices, then connect them with one edge. In order to quantitatively analyze the closeness of social relationships, we assign a scalar value with a range of (0, 1] to each edge, i.e., the strength of social tie or weight.

Since $\mathcal{G}$ is an undirected graph, $W = \{w_{x,y} | x, y \in V\}$ is a symmetric matrix. For all $x, y \in V$, if there is no social relationship between x and y, $w_{x,y} = w_{y,x} = 0$. In addition, we assume that any IIoT device has a tie strength of 0 with itself, i.e., $w_{x,x} = 0, x \in V$.

There are many types of ways to calculate the strength of social ties [29]. In this article, we choose *Jaccard's coefficient* as a measure of the strength of social ties. If there is an edge $e_{x,y}$ between x and y, x and y are neighbors. We denote $\Gamma(x)$ and $\Gamma(y)$ as the set of neighbors of device x and y, respectively. Then, *Jaccard's coefficient* is defined as the ratio of the number of common neighbors for x and y to the total number of their neighbors, i.e.,

$$w_{x,y} = \frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|},\ x \neq y. \tag{4}$$

If $\Gamma(x) \cap \Gamma(y) = \emptyset$, $w_{x,y} = 0$, which means that there is no social relationship between x and y. Except that, the value of $w_{x,y}$ is distributed at (0, 1]. Therefore, *Jaccard's coefficient* is a very intuitive representation of the strength of the social tie between two IIoT MDs.

Note that enabling multihop resource sharing could further utilize the idle resource of industrial devices at a farther reach, leading to load balancing as well. However, *Jaccard's coefficient* is only applied in one-hop D2D pairs. That is, if there is no direct D2D link between x and y, $w_{x,y}$ cannot be directly calculated by using *Jaccard's coefficient*. For example, in Fig. 1, there is no direct D2D link between SR 1 and SP 1. If SR 1 wants to offload task to SP 1, then other nodes are needed as relay. If SR 2 is selected as the relay node, more reasonable way of calculating the strength of social tie between SR 1 and SP 1 should be $w_{\text{SR1,SR2}} \times w_{\text{SR2,SP2}}$. We use $P_{x,y}$ to represent the relay path from x to y, and the corresponding strength of social tie $w(P_{x,y})$ is the product of all the weights along the path, i.e.,

$$w(P_{x,y}) = \prod_{(a,b)\in P_{x,y}} w_{a,b} \tag{5}$$

where (a, b) is the D2D link contained in $P_{x,y}$. If there is no relay path between x and y, then $w(P_{x,y}) = 0$. This ensures that the D2D pairs that do not meet the locality constraints will not be selected in the auction. Since there may be more than one relay path from x to y, path planning also needs to be addressed (see Section III-C).

C. Auction Model

We model the interaction between SPs and SRs using the VCG auction, where the resource of SPs is traded as commodities, and SPs and SRs are treated as sellers and buyers, respectively. A VCG auction is a multi-item auction mechanism [17]. Each bidder in the auction submits the number of items required and the corresponding bid price they are willing to pay. All bidders' bids are sealed and cannot be revealed until the auction closes. The auctioneer selects winning buyers to sale items to them according to the principle of maximizing social welfare. Finally, every winner pays the items at a price lower than the corresponding bid.

We denote $\mathcal{W}$ as the set of winning buyers and $\mathcal{W}_j$ is the set of winning buyers that win SP j's resource. $\mathcal{W}_j$ needs to satisfy the following constraints.

1) The resource required by SRs is less than or equal to the capacity of the SP, i.e., $\sum_{i\in\mathcal{W}_j} r^i \leq R_j$, where r^i is the amount of resource that the SR i needs and R_j is the resource capacity of SP j.
2) There is a one-hop D2D link or a multihop D2D path between the SR i and the SP j following the locality constraints.
3) The residual lifetime of the one-hop D2D link or multihop D2D path is long enough for the completion of the requested task, which ensures that the transaction occurs at stable links.

Let $b_{i,j}$ be the bid from SR i to SP j, which represents the preference of SR i to offload resource to SP j. The preference accounts for the social ties between SR i and SP j and the link status. In this article, we consider the maximum data rate $r_{i,j}$ as link status [shown in (2)]. Generally speaking, the stronger the social tie and the greater the data rate can achieve, the higher task offloading efficiency will be.

If there is a direct D2D link between i and j, the bid can be expressed by the following formula:

$$b_{i,j} = \lambda_1 r_{i,j} + \lambda_2 w_{i,j} \tag{6}$$

where λ_1 and λ_2 are the weighting parameters, and $\lambda_1 + \lambda_2 = 1$. In order to correspond to the social relationship, the data rate used here is normalized. Unless otherwise specified, the data rate is normalized by default. If relaying is required from i to j, then given the parameters λ_1 and λ_2, we select the path with the highest value of $\lambda_1 r(P_{i,j}) + \lambda_2 w(P_{i,j})$ as the offloading path, and the corresponding bid is

$$b_{i,j} = \max\{\lambda_1 r(P_{i,j}) + \lambda_2 w(P_{i,j}) | P_{i,j} \in \mathbb{S}_{i,j}\} \tag{7}$$

where $\mathbb{S}_{i,j}$ is the set of all the paths from i to j.

When SR i achieves the resource of SP j, it needs to pay the corresponding price to SP j. Let p_i be the price that SR i has to pay, and the utility of SR i is

$$u_i = b_{i,j} - p_i. \tag{8}$$

Note that if $i \notin \mathcal{W}$, u_i will be zero, which means that SR i fails to bid.

A common goal of designing auctions is to maximize *social welfare*, which is defined as the aggregate user utility of all agents in the system with respect to the service provided by the system. In the distributed D2D network, social welfare could nicely measure the total interests of users. The objective of the proposed resource-sharing scheme for the IIoT is to determine the set of winning buyers to maximize the social welfare, under the constraints of the affordable resource at SPs, i.e.,

$$\begin{cases} \max & \sum_{i\in\mathcal{M}} u_i \\ \text{s.t.} & \sum\limits_{i\in\mathcal{W}_j} r^i \leq R^j \quad \forall j \in \mathcal{K}\cdot \end{cases} \tag{9}$$

Solving the above optimization problem is NP-hard, as it can be reduced to a packing problem [30]. In order to efficiently solve the problem and allocate resource among industrial devices, we design two auction mechanisms. The purpose of considering social weights in auction is to select social-trustworthy D2D pairs during the winner selection phase in auction. Typically, auction consists of two phases, i.e., winner selection and pricing determination. In the winner selection phase, the appropriate set of SRs is selected for each SP to share its resource, during which social weights need to be considered to enable the resource sharing more likely to happen among social-trustworthy users. In the pricing stage, the dynamic pricing scheme is determined to guarantee the truthfulness of industrial devices.

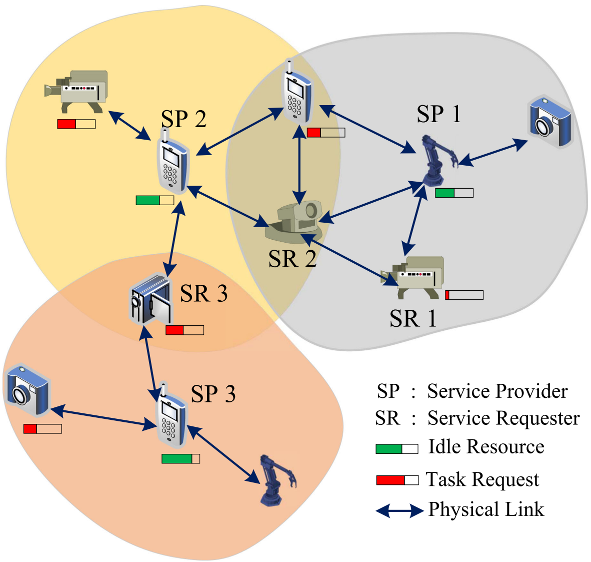

Fig. 2. Overlapped physical communities of SPs. MDs with close proximity can form a physical community, and each SP is a community center. For the MD covered by multiple communities, it has priority to participate in the auction of resources with large amount. For example, for SR 3, it has priority to participate in the resource auction of SP 3, and if it becomes the winner of SP 3, it will not participate in the resource auction of SP 2.

Algorithm 1: Social-aware Bid Matrix Calculation (SBMC).

Input: **the set of IIoT devices:** $\mathcal{V} = \{1, ..., n\}$**;**
Output: **the social weight matrix** w**, and the date rate matrix** r;
for $i = 1$ **to** n **do**
  for $j = 1$ **to** n **do**
    Calculate the social weight $w_{i,j}$ **according Eqn. (4).**
    $w_{i,j} = \frac{|\Gamma(i) \cap \Gamma(j)|}{|\Gamma(i) \cup \Gamma(j)|}, i \neq j$;
    Calculate the data rate $r_{i,j}$ **according Eqn. (2).**
    $r_{i,j} = B_{i,j} \cdot \log_2(1 + \frac{P_i \cdot d_{i,j}^{-\alpha} \cdot |h_{i,j}|^2}{I_{i,j} + |\sigma_j|^2})$;
  end
end
return w,r;

Algorithm 2: Social-aware Winner Selection and Pricing (SWSP).

Input: **the set of service providers** $\mathcal{K} = \{1, ..., k\}$**, the bid matrix** $\mathcal{B}$;
Output: **the winner set** $\mathcal{W}$**, and the price set** $\mathcal{P}$;
Order the SPs according to the amount of resource: $\mathcal{K}' = \{s_1, s_2, ..., s_k\}$;
for $j = s_1$ **to** s_k **do**
  Extract bid information: $\mathbb{B}_j = \{b_{i,j} | i \in \mathbb{N}_j\}$;
  Extract resource information: $\mathbb{R}_j = \{r^i | i \in \mathbb{N}_j\}$;
  Calculate optimal combination of winners for SP j **using the 0-1 knapsack algorithm:**
  $\mathcal{W}_j = Knapsack(\mathbb{B}_j, \mathbb{R}_j, R_j)$;
  Social welfare: $\mathcal{S}_{\mathbb{N}_j} = \sum_{i \in \mathcal{W}_j} b_{i,j}$;
  $\mathcal{W} \leftarrow \mathcal{W} \cup \mathcal{W}_j$;
  for *enumerate the element* $i \in \mathcal{W}_j$ **do**
    Calculate the price that i has to pay: $p_i = \mathcal{S}_{\mathbb{N}_j \setminus i} - (\mathcal{S}_{\mathbb{N}_j} - b_{i,j})$;
    $\mathcal{P} \leftarrow \mathcal{P} \cup p_i$;
  end
end
return $\mathcal{W}, \mathcal{P}$;

IV. Incentive Framework for Task Offloading in the IIoT

In this section, we propose two social-aware incentive mechanisms to solve the task offloading problem, i.e., OSIM and RSIM. Before the auction, we divided the IIoT MDs into different physical communities according to the physical proximity. As shown in Fig. 2, each SP and its directly connected SRs form a physical community, and the SP is the community center. The auction process will be conducted separately in each community.

A. One-Hop-Based Social-Aware Incentive Mechanism

The OSIM mechanism consists of two stages: *winner selection* and *price determination*.

In the stage of *winner selection*, the SP with the largest amount of resource will be selected first. When the resource auction of an SP starts, all buyers with direct D2D links to the SP submit their bids to compete for the SP resource. The auctioneer selects winners based on each buyer's bid and corresponding resource demand to maximize social welfare. The winner selection process can be equivalent to a *Knapsack Problem*, in which the seller's resource amount represents the maximum weight that the knapsack can bear, the buyer's resource demand represents the weight of the item, and the buyer's bid represents the corresponding value of the item. Therefore, our problem can be solved with the *Knapsack Algorithm* based on dynamic programming [31]. Under the constraints of limited resource, the *Knapsack Algorithm* can calculate the optimal combination of winners for each physical community to achieve the maximum social welfare. It should be noted that if an SR has already offloaded its own tasks from another seller, the SR can no longer be called a buyer and does not participate in the auction. For example, in Fig. 2, the resource amount of SP 3 is larger than that of SP 2, and therefore, the resource of SP 3 is auctioned first. SR 3 is the common neighbor of SP 3 and SP 2, and if the tasks of SR 3 have been offloaded to SP 3, then SR 3 will no longer participate in the resource auction of SP 2. After the first stage as described in Algorithm 1, we can get the optimal combination of winners, i.e., $\mathcal{W}_j$, and corresponding social welfare $\mathcal{S}_{\mathbb{N}_j} = \sum_{i \in \mathcal{W}_j} b_{i,j}$, where $\mathbb{N}_j$ is the set of all SRs belonging to the SP j physical community.

As shown in Algorithm 2, in the stage of *price determination*, the price each winner pays is the marginal harm to the other buyers. Assume that SR i ($i \in \mathbb{N}_j$) is absent from the resource

Algorithm 3: One Hop Based Social-aware Incentive Mechanism (OSIM).

Input: **the set of IIoT devices** $\mathcal{V} = \{1, ..., n\}$**, the set of service requesters** $\mathcal{M} = \{1, ..., m\}$**, and the set of service providers** $\mathcal{K} = \{1, ..., k\}$**;**
Output: **the winner set** $\mathcal{W}$**, and the price set** $\mathcal{P}$;

w, r = SBMC ($\mathcal{V}$);
for $j = 1$ **to** k **do**
  for $i = 1$ **to** m **do**
    if $i \in \mathbb{N}_j$ *(the physical community of j)* **then**
      $b_{i,j} = \lambda_1 w_{i,j} + \lambda_2 r_{i,j}$, $\lambda_1 + \lambda_2 = 1$;
    end
  end
end
$\mathcal{W}$, $\mathcal{P}$ = SWSP ($\mathcal{K}$);

auction of SP j, then after the first stage, the social welfare we get is $\mathcal{S}_{\mathbb{N}_j \setminus i}$. Therefore, the final price that the SR i has to pay can be formulated as

$$p_i = \mathcal{S}_{\mathbb{N}_j \setminus i} - (\mathcal{S}_{\mathbb{N}_j} - b_{i,j}). \tag{10}$$

The prices of all the winners form the price set $\mathcal{P}$. Since $\mathcal{W}_j$ is the optimal combination, if i is absent from the auction, there must be $\mathcal{S}_{\mathbb{N}_j} \geq \mathcal{S}_{\mathbb{N}_j \setminus i} \geq \mathcal{S}_{\mathbb{N}_j} - b_{i,j}$. If $\mathcal{S}_{\mathbb{N}_j} = \mathcal{S}_{\mathbb{N}_j \setminus i}$, then $p_i = b_{i,j}$. Otherwise, $p_i < b_{i,j}$. In other words, $u_i \geq 0$, and the OSIM is thus individually rational. The specific algorithm is shown in Algorithm 3.

B. Relay-Based Social-Aware Incentive Mechanism

In order to further improve the resource utilization, we extend the scope of tasking offloading to other indirect SPs through relay devices. Offloading tasks to an indirectly connected SP through relay nodes not only consume channel resource and energy of the relay devices, but the selection of the relay path is an NP-hard problem. Therefore, RSIM only considers the case of two hops, that is, only one relay device is selected during the task offloading. It is easy to prove that in the case of two hops, the time complexity of relay path selection is $\mathcal{O}(mk)$.

The RSIM contains three stages: *relay path selection*, *winner selection*, and *price determination*. In the stage of *relay path selection*, since we only consider the path selection under the two-hop constraint, the problem of path selection degenerates into the choice of a single relay node. Therefore, if relaying is required from SR i to SP j, the selection rule of the relay path is to select a relay node t so that the SR i has the largest bid for SP j through the path. According to (3), (5), and (7), we can derive the final expression of the bid of SR i to SP j

$$b_{i,j} = \max\{\lambda_1(w_{i,t} \cdot w_{t,j}) + \lambda_2(\min\{r_{i,t}, r_{t,j}\})\}. \tag{11}$$

In the stage of *winner selection*, the auctioneer needs to consider how to allocate the SP's resource based on the bids and resource demand information provided by the SRs to maximize social welfare. It should be noted that at this time, the physical community of each SP will expand to the range of two hops. For example, in Fig. 2, SR 1 can be connected to SP 2 through relay

Algorithm 4: Relay-based Social-aware Incentive Mechanism (RSIM).

Input: **the set of IIoT devices** $V = \{1, ..., n\}$**, the set of service requesters** $\mathcal{M} = \{1, ..., m\}$**, and the set of service providers** $\mathcal{K} = \{1, ..., k\}$**;**
Output: **the winner set** $\mathcal{W}$**, and the price set** $\mathcal{P}$;

w, r = SBMC ($\mathcal{V}$);
for $j = 1$ **to** k **do**
  for $i = 1$ **to** m **do**
    if $i \in \mathbb{N}_j$ *(the physical community of j)* **then**
      Find the relay node t**,** $s.t.$,
      $b_{i,j} = max\{\lambda_1(w_{i,t} \cdot w_{t,j}) + \lambda_2(min\{r_{i,t}, r_{t,j}\}\}, \lambda_1 + \lambda_2 = 1;$
    end
  end
end
$\mathcal{W}$, $\mathcal{P}$ = SWSP ($\mathcal{K}$);

node SR 2, and thus, SR 2 belongs to $\mathbb{N}_{\text{SP2}}$. In the RSIM, the *Knapsack Algorithm* is still used to obtain the optimal winner combination that maximizes social welfare. The seller's resource amount represents the maximum weight that the backpack can bear, the buyer's resource demand represents the weight of the item, and the buyer's bid represents the corresponding value of the item. As aforementioned, for a common SR, if the SR has already offloaded its own tasks from another SP, the SR does not participate in the auction. During the auction, we still follow the principle that sellers with the largest amount of resource give priority to sell their resource. Different from the RSIM, not only the SRs with the directly connected D2D link with the SP can bid for the SP's resource, but also the SRs connected to the SP through one relay node can participate in the auction. Therefore, for a specific SP, the corresponding number of buyers has expanded, while SRs also increase the corresponding selection space to improve the resource-sharing efficiency. After this stage, we can get the optimal combination of winners, i.e., $\mathcal{W}_j$, and corresponding social welfare $\mathcal{S}_{\mathbb{N}_j} = \sum_{i \in \mathcal{W}_j} b_{i,j}$.

In the stage of *price determination*, the price each winner pays is the marginal harm to the other buyers. If SR i wins the resource of SP j, according to (10), we can get the price p_i that SP i has to pay. Since $\mathcal{W}_j$ is the optimal combination, if i is absent from the auction, there must be $\mathcal{S}_{\mathbb{N}_j} \geq \mathcal{S}_{\mathbb{N}_j \setminus i} \geq \mathcal{S}_{\mathbb{N}_j} - b_{i,j}$. If $\mathcal{S}_{\mathbb{N}_j} = \mathcal{S}_{\mathbb{N}_j \setminus i}$, then $p_i = b_{i,j}$. Otherwise, $p_i < b_{i,j}$. In other words, $u_i \geq 0$, and the RSIM is thus individually rational. The specific algorithm is shown in Algorithm 4.

The main advantage of the proposed algorithm is to enable resource sharing among social-trustworthy multihop devices, thus improving the resource utilization of IIoT devices. The benefits of the proposed scheme are reflected in simulations in terms of social welfare, resource utilization ratio, and task offloading ratio.

C. Performance Analysis

Theorem 1: Both the proposed OSIM and RSIM satisfy truthfulness.

Proof: Assume that the true valuation of SR i for SP j's resource is $v_{i,j}$. For any SR $i \in S_{N_j}$, SR i is a winner, where S_{N_j} is the social welfare of SP j's optimal combination of winners. According to (10), $b_{i,j}$ is a part of S_{N_j}. $S_{N_j \setminus i}$ has nothing to do with $b_{i,j}$, where $S_{N_j \setminus i}$ is the social welfare of SP j's optimal combination of winners without SR i in SP j's winners. When the winner set does not change, the payment of SR i remains unchanged. If SR i raises the bid, SR i is still the winner. According to (8), when SR i intentionally reduces bid, the utility of SR i u_i decreases. When it drops to the critical value ($b_{i,j} < p_i$), the utility will be 0. If the SR intentionally raises the bid, the SR will still be the winner.

For any SR $i \notin S_{N_j}$, SR i is a loser. If SR i raises the bid until it becomes a winner, according to (10), S_{N_j} changes; it will lead to an SR ω become a loser ($b_{i,j} > b_{\omega,j} > p_j$). When SR i has no deceptive bids, its true valuation is lower than SR ω's bid ($v_{i,j} < b_{\omega,j}$). If SR i raises to the critical value and becomes a winner, the price that SR i has to pay will be p_j. According to (8), the utility of SR i is as follows: $u_i = v_{i,j} - p_j$. When $b_{i,j}$ goes up but still less than $b_{\omega,j}$, there are two conditions. When $v_{i,j}$ is greater than p_j ($b_{\omega,j} > v_{i,j} > p_j$), SR i's bid is the highest losing bid, i.e., $p_j = b_{i,j}$; therefore, $u_i = 0$. When $v_{i,j}$ is lower than p_j ($b_{\omega,j} > p_j > v_{i,j}$), the utility will be in deficit ($u_i < 0$). Whereas SR reduces bid, SR is still the loser. Therefore, the OSIM and the RSIM satisfy truthful for the SR.

It is the best strategy for IIoT MDs to submit bids based on their true valuation. For MDs, submitting deceptive bids may not only fail to win bids, but also reduce the utility.

Theorem 2: Both the proposed OSIM and RSIM are computational efficient, and the computational complexity of the OSIM and the RSIM are both $\mathcal{O}(cn^2)$.

Proof: For the OSIM, as shown in Algorithm 3. In line 1, the computational complexity is $\mathcal{O}(n^2)$. Similarly, from lines 2 to 8, the computational complexity is also $\mathcal{O}(n^2)$. In line 6 of Algorithm 2, the computational complexity of the *Knapsack Algorithm* based on dynamic programming is $\mathcal{O}(cn)$, where c is the capacity of the backpack, i.e., the computational capacity of the SP. The computational complexity of the loop from lines 1 to 13 of Algorithm 2 is $\mathcal{O}(cn^2)$, where c is the computational capacity of a certain SP, and n is the scale of the input of the algorithm. The computational complexity of Algorithm 1 is $\mathcal{O}(cn^2)$.

For the RSIM, as shown in Algorithm 4, in line 1, the computational complexity is $\mathcal{O}(n^2)$. According to (7), we determine the offloading path in line 5 through calculating the maximum value of $\lambda_1 r(P_{i,j}) + \lambda_2 w(P_{i,j})$, i.e., the bid of SR i for SP j's resource $b_{i,j}$. The SR that requires task offloading can be connected with the rest $(m-1)$ SRs at most, and the selected relay SR can be connected with k SPs at most. Therefore, in the worst case, if the value space of $b_{i,j}$ is km, where k is the number of the SP in the whole network and m is the number of the SR connected with the SP, the relay node SR can be determined by finding the maximum value from the value space. Then, the time complexity of the relay path is $\mathcal{O}(km)$. As mentioned earlier, from lines 1 to 13 of Algorithm 2, the *Knapsack Algorithm* based on dynamic programming is identically used to determine the winner set. In the worst case, the computational complexity of the entire loop is $\mathcal{O}(cn^2)$, where c is the computational capacity of a certain SP and n is the scale of the input of the algorithm. Identically, the computational complexity of Algorithm 4 is $\mathcal{O}(cn^2)$.

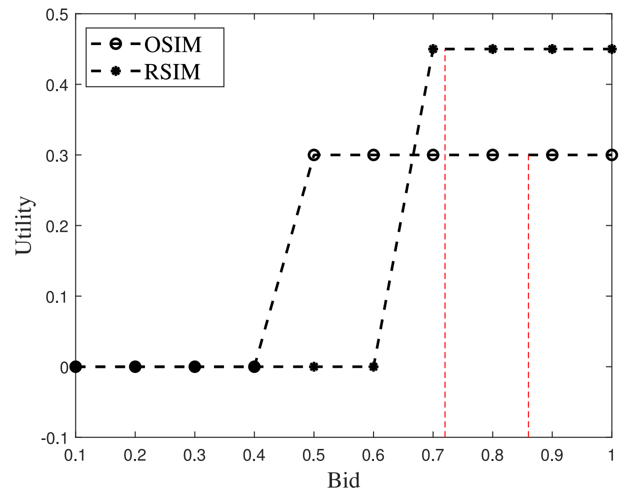

Fig. 3. Both the OSIM and the RSIM are truthful, in which the SR cannot receive additional revenue by submitting an untruthful bid.

V. Performance Evaluation

A. Simulation Settings

In this section, we evaluate the performance of the proposed mechanisms through simulations. We assume that 50 MDs are uniformly distributed in a 50 $\times$ 50 m area, while the BS is at the center of the area. The maximum distance between devices that can establish direct D2D links is $d_{\max} = 30$ m. All MDs have a transmit power of 100 mW. The carrier bandwidth is set to 1 MHz, and the noise variance is set to 6×10^{-10} mW. The path loss exponent $\alpha = 4$. The task size of each SR and the resource capacity of each SP are evenly distributed in [1, 4] and [4, 10] respectively. λ_1 and λ_2 are set to 0.5. The Kumpula model is used to construct the social relationships among the 50 MDs. In order to visualize the impact of social relationships on the performance of the proposed mechanisms, we have two counterparts to compare with the OSIM and the RSIM, respectively. A D2D resource-sharing scheme that uses the VCG auction but does not consider social awareness is used as a comparison scheme, called OSIW [18]. Since there is no suitable relay-based incentive mechanism, we make changes based on the proposed RSIM without social awareness as a comparison scheme, called RSIW. Other parameters are described separately if used in the following statement.

B. Truthfulness

To verify the truthfulness of the OSIM and the RSIM, we randomly select an SR to check how its utility changes at different bids. As shown in Fig. 3, in the OSIM mechanism, the SR's true valuation of the SP's service is 0.86, and in the RSIM mechanism, the SR's true valuation of the SP's service is 0.72. When the SR submits a bid that is lower than its true

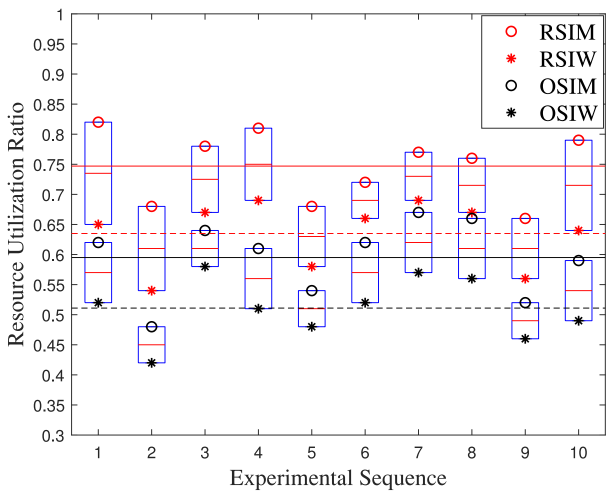

Fig. 4. Resource utilization ratio of ten experimental sequences and the average resource utilization ratio of four schemes.

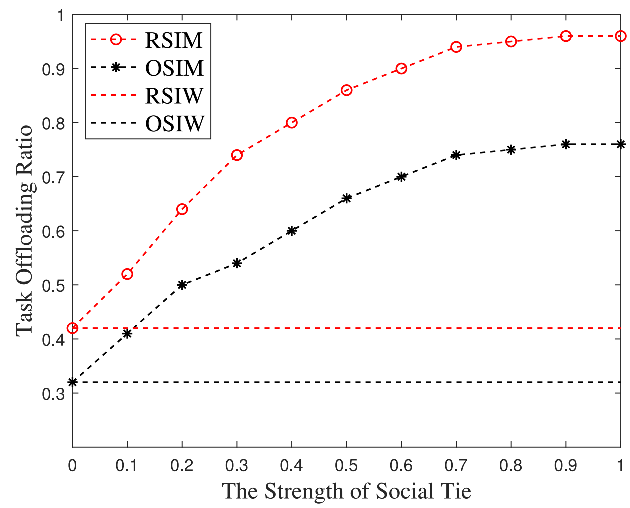

Fig. 5. Relationship between the strength of social tie and task offloading ratio.

valuation, its utility is zero, which means that it is a loser in the auction and cannot win the service of the SP. When it submits a higher bid than its true valuation, the utility is a constant and does not exceed the utility it receives when submitting the true valuation as the bid. This indicates that an MD cannot achieve a higher utility when it fails to report its true valuation of the task. Thus, the property of incentive compatibility, i.e., truthfulness, is guaranteed.

C. Resource Utilization Ratio and Task Offloading Ratio

Fig. 4 depicts the resource utilization ratio of SPs in ten experiments. We randomly regenerate new simulation parameters before each experiment. And the resource utilization ratio is recorded after each experiment. The resource utilization ratio refers to the ratio of the amount of resource utilized by the SRs to the amount of the original idle resource. In the box plot of Fig. 4, each box indicates that the resource utilization ratio of the RSIM is always greater than that of the RSIW or the resource utilization ratio of the OSIM is always greater than that of the OSIW in each experiment. Since social relationship is not taken into account, the average resource utilization ratio of the RSIW (approximately 0.64) is less than that of the RSIM (approximately 0.75), and the OSIW (approximately 0.52) is less than the OSIM (approximately 0.59). Besides the computational capabilities of SPs, the resource utilization ratio is also reflected by the D2D communication characteristics, as those one-hop D2D pairs and multihop D2D paths with instable channel link and poor channel status will not be selected according to the proposed schemes.

D. Social Welfare

In order to evaluate the influence of social relationship on the success rate of task offloading, we randomly select an SR i for verification. We repeatedly perform the proposed mechanisms 100 times, and in each time, we fix the strength of the social tie between the SR i and SP j that is in the same community as the SR i (i.e., fixing the weight $w_{i,j}$), and then, we randomly generate other elements in the $\mathbb{W}$ matrix within the range (0,1] (it is worth emphasizing that in order to maintain the social topology, elements with a value of 0 will not be changed). In these 100 experiments, we record the number of times the SR i was successfully served (represented by s_i), and the success rate of task offloading of the SR i was defined as: $s_i/100$. By modifying the value of $w_{i,j}$ several times and then performing our simulation as described above, we can draw the curve shown in Fig. 5. From Fig. 5, we can see that as the strength of social tie increases, the success rate of task offloading also increases. When the strength of social tie is equal to 1, the success rate of task offloading does not reach 100%. That is because the proportion of social relationships in our setting is only 0.5 ($\lambda_2 = 0.5$). If the corresponding data rate $r_{i,j}$ is too small, it may not be able to offload the task to SP j. Since the RSIW and the OSIW do not consider the social relationship, their respective task offloading rates do not change. Meanwhile, with the RSIM, high offloading ratio could be achieved, as it is easier for the SR to find appropriate SPs. When intensive requests occur at the range of an SP, load balancing can be achieved as the load could be evenly assigned to SPs with relaxed locality constraints.

Fig. 6 depicts how the social welfare of the system varies with the number of SRs when the number of SPs is fixed (ten SPs). Horizontally, the more the number of SRs, the more the social welfare of the system is, but as the number of SRs increases, there is a limit to improvement. That is because the resource capacity of the SP is gradually exhausted. From a vertical perspective, for the RSIW mechanism and the OSIW mechanism, since social information is not taken into account, i.e., all weights are equal to zero, according to (6) and (7), their corresponding bids will be reduced. Therefore, compared with the RSIM and the OSIM, the RSIW and the OSIW are lower in social welfare, respectively. However, we can also see that regardless of whether or not social information is considered, higher social welfare can be obtained in the case of two hops, which indicates that the resource of

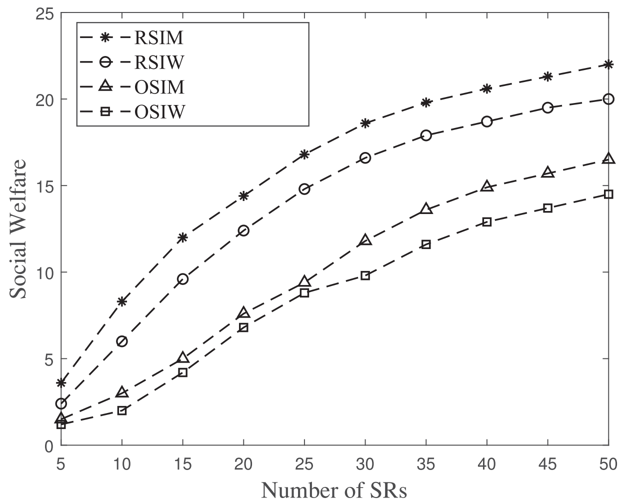

Fig. 6. Social welfare varies with the number of SRs.

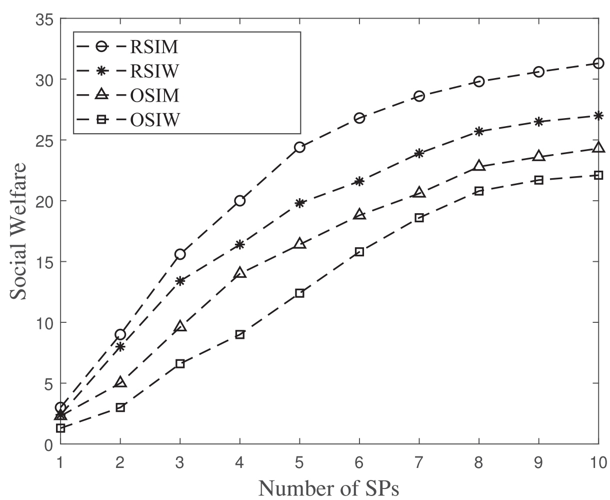

Fig. 7. Social welfare varies with the number of SPs.

SPs is more fully utilized through relaying, and more SRs are serviced.

In Fig. 7, when the number of buyers remains unchanged (30 SRs), the corresponding social welfare increases as the number of sellers increases. When the number of SRs increases with fixed number of SPs, the improvement of social welfare becomes slower. The maximum achievable social welfare is constrained by the resource capabilities of SPs. Actually, if the number of both SR and SP increases, the trend is similar, as the performance will be constrained by the bandwidth of D2D links. Similar to Fig. 6, in the vertical comparison, considering social information leads to more social welfare, and the performance of the two-hop mechanisms is always better than that of the one-hop mechanism.

VI. Conclusion

In this article, we proposed two social-aware incentive mechanisms to achieve efficient task offloading in the D2D network in the IIoT. We first considered resource sharing among one-hop neighbors and proposed an incentive mechanism to encouragingly establish trustworthy D2D pairs. In order to make fully use of the idle resources of SPs, we further relaxed the locality constraint to two hops and proposed an RSIM. Simulation results have shown that the proposed social-aware incentive mechanisms are feasible and effective for resource sharing in the IIoT with guaranteed economic properties, including truthfulness. In the future work, we will introduce more constraint variables, such as energy and signaling, to get closer to the real scene.

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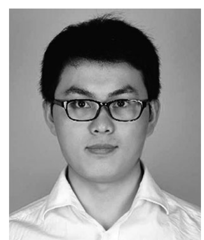

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