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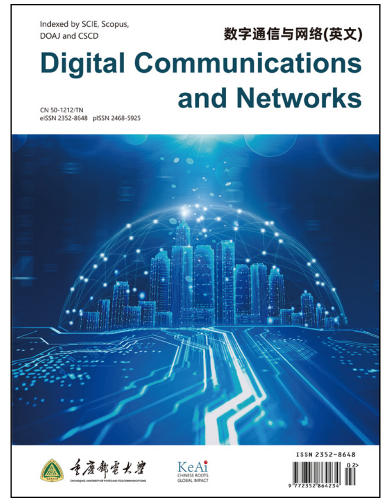

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Towards intelligent and trustworthy task assignments for 5G-enabled industrial communication systems

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Abstract

With the unprecedented prevalence of IIoT and 5G technology, various applications supported by industrial communication systems have generated exponentially increased processing tasks, which makes task assignment inefficient due to insufficient workers. In this paper, an Intelligent and Trustworthy task assignment method based on Trust and Social relations (ITTS) is proposed for scenarios with many tasks and few workers. Specifically, ITTS first makes initial assignments based on trust and social influences, thereby transforming the complex large-scale industrial task assignment of the platform into the small-scale task assignment for each worker. Then, an intelligent Q-decision mechanism based on workers' social relation is proposed, which adopts the first-exploration-then-utilization principle to allocate tasks. Only when a worker cannot cope with the assigned tasks, it initiates dynamic worker recruitment, thus effectively solving the worker shortage problem as well as the cold start issue. More importantly, we consider trust and security issues, and evaluate the trust and social circles of workers by accumulating task feedback, to provide the platform a reference for worker recruitment, thereby creating a high-quality worker pool. Finally, extensive simulations demonstrate ITTS outperforms two benchmark methods by increasing task completion rates by 56.49%-61.53% and profit by 42.34%-47.19%.

KEYWORDS:
Industrial internet of things, Insufficient workers, Trust evaluation, Social relation, Task assignment

1. Introduction

The Industrial Internet of Things (IIoT) is also known as Industry 4.0, which realizes the interconnection between machines and humans [1, 2, 3]. Enabled by the unprecedented prevalence of IIoT and communication technology, various robots, machines, and mobile devices are integrated [4, 5], to creates countless business opportunities for industrial communication systems by improving connectivity, scalability, productivity, and economic growth [6, 7, 8, 9]. The 5G network is regarded an evolutionary generation for providing enhanced Mobile Broad Bandwidth (eMBB), massive Machine-Type Communication (mMTC), and Ultra-Reliable and Low Latency Communication (URLLC) [10, 11, 12]. Therefore, with the empowerment of 5G and beyond 5G technologies, industrial communication systems are surely moving towards digitization, networking, automation, and intelligence [9, 13]. Along with this trend, the scale of IIoT devices and data in industrial systems is

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increasing explosively. According to CISCO's global cloud index report, IoT-based applications are projected at a 2.7-fold growth by 2020 [2, 14], and these devices will rise to 38.6 billion by 2025 [15]. This results in a tenfold increase in the data volume in industrial environments. The growth generates hundreds of billions of data processing tasks, which require efficient and fast task execution to meet the requirements of applications.

Task assignments are effective means to provide end users with better Quality of Experience (QoE) by effectively exploiting the computational capacities of massive IIoT devices [10, 16]. In general, there are three roles in task assignments, which are requesters, the platform, and workers (e.g., robots, vehicles, and machines) [17]. First, a requester publishes tasks through the platform, and then workers voluntarily participate in tasks and return results to the platform in exchange for rewards. In such a collaborative way, complex tasks are accomplished efficiently and conveniently by leveraging the computing power of workers.

Although many assignment methods are proposed, most of them consider task assignments in Fewer Tasks More Workers (FTMW) scenarios, which assumes the number of workers is sufficient [18, 19, 20]. However, it is not always true the platform has sufficient workers [17, 21, 22]. For example, a newly developed industrial system may face the cold-start issue. What's more, with the expansion of the system scale, the number of tasks increases linearly, it is very highly for the system to face worker shortage. As a result, task assignments in More Tasks Fewer Workers (MTFW) scenarios has become the research focus in recent years.

Here, we take the typical MTFW framework as an example shown in Fig. 1. As can be seen, the previous methods adopt a fixed Publish-Propagate-Recruit-Assign model. Recruitment of workers must be carried out before task assignments, and both of them are completed by the platform. Therefore, the previous methods have the following problems: First, the platform did not evaluate the reliability of expatriate workers in their social circles before recruiting them. Some expatriate workers with low quality or even maliciousness may be selected as official workers. Once they accept tasks, this will seriously affect task quality and data. Second, the previous worker recruitment mechanism cannot adapt to variable task requirements, which is not intelligent. Take the urban transportation system as an example, and the task request volume during the morning and evening peak hours may be tens or even hundreds of times higher. In summary, When the scale of the worker pool is too small, this requires to recruit workers regularly. On the contrary, if the scale of the worker pool is too large, many workers have no tasks to execute, resulting in idle manpower. Third, the previous methods adopt a centralized model, where the platform undertakes all worker recruitment and task assignments. As the scale of industrial communication systems explodes, the power of the platform cannot handle the huge workload well.

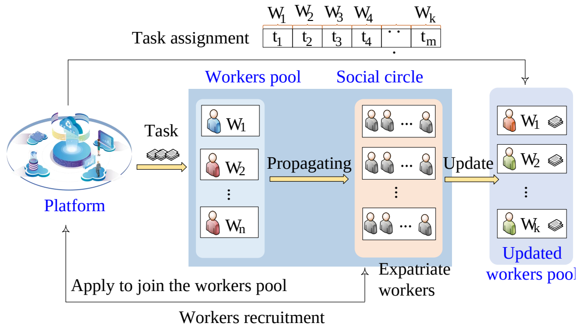

Fig. 1. Task assignments of traditional methods.

To address the above issues, an Intelligent and Trustworthy task assignment method based on Trust and Social relations (ITTS) is proposed for the industrial system. In ITTS, the worker recruitment and task assignments of the platform is transferred to workers with trust and social relation considerations. Specifically, our contributions are as follows:

- For the task assignment in MTFW systems, an intelligent and trustworthy task assignment method called ITTS is proposed. ITTS first performs initial assignments based on trust and social influences, thereby decomposing the complex large-scale task assignment by the platform into small-scale task assignments for each worker. Then, the first-exploration-then-utilization principle is adopted to initiate the dynamic on-demand task assignment by leveraging workers' social circles. Finally, the trust of workers is updated by accumulating task feedback and the worker pool is expanded based on the trust. Overall, different from previous methods, ITTS adopts a distributed and flexible task assignments, fully considers the social and trust relations, and thus having high efficiency and security performance.

- An intelligent Q-decision mechanism based on the workers' social circles is proposed. When a worker cannot cope with the assigned tasks, its social relation is leveraged to recruit expatriate workers for task completion, thus solving the worker shortage problem as well as the cold start issue. Specifically, workers in social circles are randomly selected with probability ε in the initial stage. Then as experience increases, the Q-decision incorporates trust, profits, and social influences to build a feedback matrix and assign tasks to expatriate workers with the largest value in the matrix, thereby enhancing task quality.

- A trust framework based on the performance of workers and social circles is established. Different from previous methods, the trust of workers is updated by accumulating success and failure records to provide with the platform a reference for recruiting workers, thus helping the system to create a high-quality worker pool. Extensive simulation results demonstrate that ITTS outperforms baseline methods by increasing task completion rates by 56.49%-61.53% and profit by 42.34%-47.19%.

The rest of this paper is organized as follows. Section 2 introduces related work. The system model and problem statement are presented in Section 3. In Section 4, we propose the ITTS method. Then, Section 5 provides performance analyses. Finally, conclusions are given in Section 6.

2. Related work

Empowered by IIoT and 5G communication technologies, future heterogeneous services and applications, such as Extended Reality (XR), holographic telepresence, robotics, and Brain-Computer Interfaces (BCI) generate exponentially growing industrial tasks [23, 24, 25]. The completion of these tasks requires effectively exploiting the computational capacities of workers (i.e., IIoT devices) [26, 27]. Therefore, as a crucial part of the four-stage life cycle (i.e., task creation, task assignment, task execution, and data integration [28, 29], task assignments are inevitably play an important role in supporting various services and applications. In the previous methods, task assignments are divided into pull mode and push mode according to the responsibilities undertaken by the platform [30, 31, 32]. In the pull mode, the platform publishes tasks, and then workers proactively decide which tasks to undertaken. It is obvious that this pattern makes it difficult to achieve optimal allocation as workers select tasks based on their own preferences. In the push mode, the platform determines the tasks undertaken by each worker according to the overall goal. In this paper, we consider the task assignment based on the push mode, and further divide the task assignment into two scenarios according to the quantitative relationship between workers and tasks, that is, the task assignments for FTMW scenario and task assignments for MTFW scenario [21, 33, 32].

2.1. Task assignments for FTMW scenarios

In task assignments with sufficient workers, it is usually considered how to select the most suitable workers for performing tasks from a large worker pool. In [18], Zhao et al. propose a bilateral task assignment mechanism called iTAM. According to the number of required task participants, they propose a differentiated allocation strategy for the single-task participant selection problem and the multi-task participant selection problem. iTAM can find the closest one or more task participants based on the PCP and PMIN protocols. At the same time, the privacy of task participants and task requesters is also considered, and equality and range constraints are provided by utilizing the Paillier cryptosystem. In [19], Yadav et al. address heterogeneous task assignments within a given deadline and budget. The authors use a timeline-based weighted aggregation technique to score workers based on their profiles and past work experiences. And a two-stage approximation solution is proposed. In the first stage, a greedy 2-approximation algorithm for a single task is given. In the second stage, a local ratio-based algorithm is given. In IIoT services, task allocation usually depends on the collaborative consensus and similarity capabilities. In [20], Pedroso et al. propose a consensus-based collaborative task allocation mechanism CONTASKI for IIoT. It divides the network into groups according to similarities, then uses a distributed consensus strategy to make task decisions, and finally completes the maximum distribution and improves the quality of information. Similar to the problem studied by Pedroso, in [34], Hou et al. propose a hierarchical edge-end task allocation scheme with collaborative edge computing in IIoT networks, while an importance-aware task allocation strategy is designed for scheduling and processing dynamic and heterogeneous tasks. Assuming that a worker can undertake multiple tasks, and both workers and tasks have time constraints, we propose a two-stage multi-task assignment method based on discrete particle swarm optimization [29]. First, we redefine the encoding form of the task assignment particles, then find the optimal particle by continuously updating the particle position and velocity, and finally perform a correction operation on the particle to avoid falling into a local optimum. Different from previous methods, in [29] we also consider using workers' remaining time for second-stage task assignments to assist trust evaluations. Similar to the problem studied in [29], Zhao et al. [32] present a destination-aware task allocation to achieve the maximum assignment in spatial crowdsourcing. In this approach, workers have deadlines to reach the destinations when completing tasks, and therefore they employ tree-decomposition technology to divide workers into independent clusters, and propose a depth-first search algorithm with progressive bounds to prune non-promising assignments.

Obviously, task assignment methods for FTMW scenarios have limited availability in future networks where the number of tasks are growing dramatically.

2.2. Task assignments for MTFW scenarios

Different from the task assignments in the FTMW scenario, in the MTFW scenario, enough workers must be recruited before task allocation. Wang et al. [17] propose a dynamic incentive mechanism called SocialRecruiter, which leverages social networks to recruit sufficient workers. Based on the Susceptible

Infected Recovered (SIR) epidemic model, the initial workers propagate tasks in social networks and a multi-cycle-based reward update mechanism balances the relationship between task completion and worker recruitment. Gao et al. [35] model worker recruitment with unknown sensing quality as a combinatorial multiarmed bandit problem and propose an extended upper confidence bound based worker recruitment algorithm. In addition, they also extend the problem to situations where the cost of workers is unknown, with the purpose of maximizing the total weighted completion quality under a limited budget. In [36], Xiao et al. model the worker recruitment problem as a K armed combinatorial bandit problem, and adopt a reverse auction method to incentivize workers to participate and inhibit speculative behaviors. This reverse auction method is called CMABA, which can solve the multiple unknown worker recruitment problem in mobile crowdsensing. Based on CMABA, they also propose the ACMABA incentive mechanism to recruit workers through alternative recruitment and quality updates. In [33], Lu et al. propose a two-phase hybrid recruitment framework named HySelector, which embodies a trade-off between sensing costs and quality. HySelector includes the offline and online phases. In the offline phase, it introduces influence propagation in communication and social networks and propose an algorithm to recruit opportunistic workers to alleviate the cold start problem. In the online phase, a participatory worker recruitment algorithm based on sensing subareas clustering is proposed to reduce computational complexity.

In MTFW scenarios, task assignments start after workers are recruited. In [37], Abououf et al. propose a group-based multi-task worker selection method called GMWS. GMWS ensures quality of service and completion time for task assignments. First, it uses the k-medoids algorithm to cluster tasks based on geographic locations, then employs a genetic algorithm to match a group of workers to a cluster of tasks, and finally delegates workers to individual tasks within a tabu search algorithm. Like the above methods, most existing task assignments pay little attention to security, privacy, and trust issues. For the allocation of the carrier and computing resources in IIoT applications for smart manufacturing, Jeong et al. [38] propose a Vickrey–Clarke–Groves auction-based hierarchical trust computing algorithm. This algorithm can be used to solve two problems. One is the computing carrier resource issue between IIoT devices and gateways; the other is distributing CPU resources by the central processing controller. In [39], Tran et al. address hyperlocal space crowdsourcing, and distribute the task assignment problem in variants, such as budget-per-time-period vs. budget-per-campaign and binary-utility vs. distance-based-utility, and then solve these problems in the offline setting and propose online heuristics.

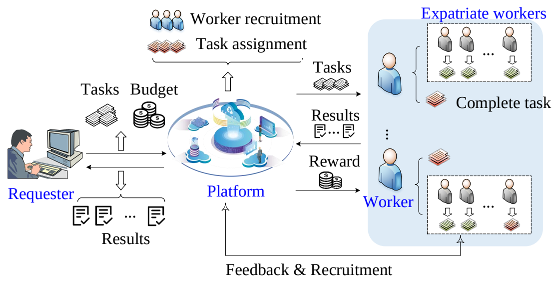

Fig. 2. Worker recruitment and task allocation.

As can be seen, the previous MTFW task assignments methods treat worker recruitment and task assignment as two separate issues. By expanding the worker pool through the recruitment mechanism, we convert the problem into the FTMW task assignment. Moreover, there are few studies that consider trust of workers or other participants. Therefore, in this article, a distributed task assignment method is proposed to flexibly initiates recruitment in MTFW scenarios based on social and trust relations.

3. System model and problem statement

3.1. System model

In this article, we consider task assignments in the MTFW scenario of industrial communication systems. As shown in Fig. 2, a typical framework contains task requester, the platform, and worker. The workers here refer to industrial equipment such as robots, machines, and lathes that complete various tasks. In task assignments, the requester publishes tasks, gives the platform a certain budget, and asks the platform to return processing results. The platform allocates tasks to appropriate workers to optimize the objectives (e.g., maximizing the assignment rate and profit or minimizing delay). Workers are employed by the platform to perform tasks in exchange for rewards. There is a cold start problem in the MTFW scenario [17, 21]. In the early stage, the platform could not find enough workers to take on all the tasks. Therefore, the platform must first recruit a sufficient number of workers. Assisted by social networks [40, 41, 42], the platform mobilizes workers to propagate the recruitment information, and workers invite some credible friends in their social circle to participate in tasks based on their relations. As an incentive, the workers who propagate the tasks will get rewards, the invited participants are called expatriate workers, and they also get reward after completing tasks. Finally, the platform adds some high-quality and credible expatriate workers into the local worker pool. Based on the diffusion of these social relations, the number of workers rapidly expand. When the number of workers reaches the required quantity, the platform starts task assignments.

When assigning tasks, we consider the following constraints:

1) We adopt the binary task allocation mode. Each task is independent and has a strict time constraint, which can only be assigned to one worker as a whole. Task results can be verified so that trust evaluations are achievable based on feedback.

2) Each worker constantly updates the status of the task processing queue and the task waiting queue. Due to the limited computing power and resources of workers, we stipulate that each worker can have at most one task in the processing queue, but there can be multiple tasks in the waiting queue.

3) To avoid conflicts and allow more workers to have the opportunity to obtain tasks, we stipulate that workers can no longer serve as expatriate workers, and an expatriate worker can only belong to one worker's social circle.

To explain the proposed ITTS more intuitively, we list the symbols involved in this paper in Table 1.

Table 1 Symbols and their descriptions.

Symbols	Descriptions
m	Number of tasks
n	Number of workers
$\mathbb{W}/W_i$	Set of workers/ the i-th worker
$\mathbb{EW}_k$	Set of expatriate workers of W_k
EW_k^i	The i-th expatriate worker in $\mathbb{EW}_k$
β_W	Reward paid by the platform to a worker
β_{EW}	Reward paid by the worker to an expatriate worker
$\mathcal{A}_{i,W_k}$	Status of assigning t_i to worker W_k
$\mathcal{A}_{i,W_k\to EW_k^j}$	Status of assigning t_i to expatriate worker EW_k^j
TR_{W_k}	Trust of W_k
N_{TASK}^k	Number of tasks assigned to W_k
$TR_{P\to W}$	Trust of a worker evaluated by the platform
$TR_{W\to EW}$	Trust of an expatriate worker evaluated by a worker
$TR_{P\to EW}$	Trust of an expatriate worker evaluated by the platform
PR_{W_k}	Profit of W_k
P_{EW_i}	Probability of EW_i being recruited as a worker

3.2. Problem statement

Suppose there are m tasks and n workers, the set of workers is denoted as $\mathbb{W} = \{W_1, W_2, ..., W_n\}$ and the set of tasks is denoted as $\mathbb{T} = \{t_1, t_2, ..., t_m\}$. For each worker W_k, the set of its expatriate workers is $\mathbb{EW}_k = \left\{EW_k^1, EW_k^2, ..., EW_k^z\right\}$. We adopt a static pricing strategy and the payment of each task is β_W, which is paid by the platform to the worker. If a task is completed by an expatriate worker, the expatriate worker can get a reward β_{EW}. We want to allocate as many tasks as possible to strive for greater productivity and profits. Therefore, the task allocation objective is:

$$Max \sum_{i=1}^{m}\sum_{k=1}^{n}\left(\mathcal{A}_{i,W_k} + \sum_{j=1}^{z}\mathcal{A}_{i,W_k\to EW_k^j}\right) \tag{1}$$

subject to:

$$\begin{cases} C1: \ \mathcal{A}_{i,W_k} \in \{0,1\}, \ \forall\, W_k \in \mathbb{W}, \ t_i \in \mathbb{T} \\ C2: \ \mathcal{A}_{i,W_k\to EW_k^j} \in \{0,1\}, \ \forall\, EW_k^j \in \mathbb{EW}_k, t_i \in \mathbb{T} \\ C3: \ \sum_{k=1}^{n}\left(\mathcal{A}_{i,W_k} + \sum_{j=1}^{z}\mathcal{A}_{i,W_k\to EW_k^j}\right) \le 1, \ t_i \in \mathbb{T} \\ C4: \ \mathfrak{D}_{t_i} \le \ t_{Max}^i, \ \forall\, \mathcal{A}_{i,W_k} = 1, \ \mathcal{A}_{i,W_k\to EW_k^j} = 1, t_i \in \mathbb{T} \end{cases}$$

In the above formulas, $\mathcal{A}_{i,W_k}$ represents the state of task assignments. If $\mathcal{A}_{i,W_k} = 1$, it means the platform assigns task t_i to worker W_k; otherwise $\mathcal{A}_{i,W_k} = 0$. Of course, W_k can assign the task again. If W_k assigns a task t_i to an expatriate worker EW_k^j, then $\mathcal{A}_{i,W_k\to EW_k^j} = 1$ and $\mathcal{A}_{i,W_k} = 0$. In Formula (1), constraints C1-C3 ensure a task can only be assigned to one worker or an expatriate worker at most. $\mathfrak{D}_{t_i}$ is the task allocation time of t_i, and t_{Max}^i is the time constraint of the task. Constraint C4 ensures that the task is successfully assigned within the time constraint.

4. Our proposed ITTS method

In MTFW environments, the task assignment process of traditional methods is shown in Fig. 1. The platform must recruit enough workers before assigning tasks and strictly follow the Publish-Propagate-Recruit-Assign process. Therefore, the previous methods are not flexible and effective. In this paper, we propose a novel ITTS method. Its framework is shown in Fig. 3, which includes the following steps:

1) The platform performs initial task allocation. The platform first assigns tasks to each worker according to the trust and social influences. Suppose trust of worker W_k is TR_{W_k}, and the number of expatriate workers in his/her social circle is $|\mathbb{EW}_k|$. Then, the number of tasks assigned to W_k is calculated as:

$$N_{TASK}^k = N_T \frac{\alpha TR_{W_k} + (1-\alpha)\frac{|\mathbb{EW}_k|}{\sum_{j=1}^{n}|\mathbb{EW}_j|}}{\sum_{i=1}^{n}\left(\alpha TR_{W_i} + (1-\alpha)\frac{|\mathbb{EW}_i|}{\sum_{j=1}^{n}|\mathbb{EW}_j|}\right)} \tag{2}$$

Here, N_T is the total number of tasks, α is the weight of trust and $\sum_{j=1}^{n}\left|\mathbb{EW}_j\right|$ is the total number of expatriate workers. Because the trust is quantified as a value between 0 and 1 [22, 42], we initially set $TR_{W_k} = 0.5$, meaning the probability of a worker being evaluated as trustworthy or malicious is the same. Formula (2) assigns initial tasks according to the trust and social influence. Workers with higher trust and more expatriate workers in the social circle are assigned more tasks.

2) Workers carry out their own internal task assignment. After obtaining multiple tasks from the platform, workers seek credible expatriate workers in social circles to complete tasks. As shown in Fig. 3, W_1 performs task t_1 by himself/herself and assigns t_2 to expatriate worker EW_1^1 and t_3 to EW_1^6. Suppose the platform assigns k tasks to W_i, who completes k_0 by himself/herself (at different times) and assigns k_1 tasks to expatriate workers, and its profit is $k_0\beta_W + k_1(\beta_W - \beta_{EW})$.

3) Trust evaluation and worker recruitment. As mentioned before, task results can be verified. Therefore, by continuously accumulating completion results of expatriate workers, workers clearly know the trust of their social circles. In addition, since workers not

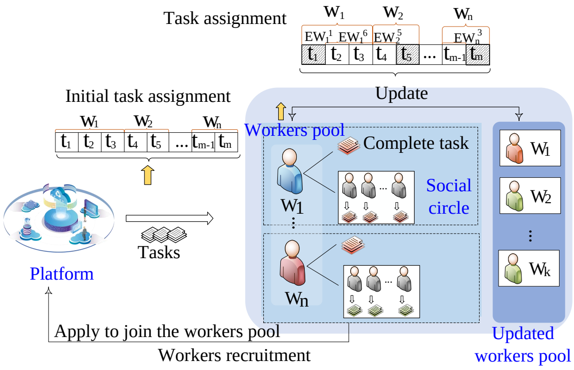

Fig. 3. ITTS framework.

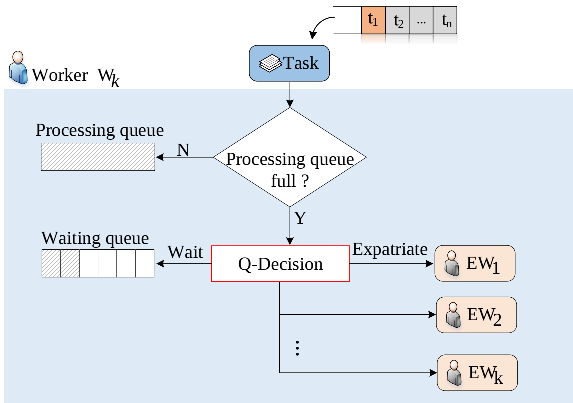

Fig. 4. Task assignment decision process.

only get rewards by completing tasks, they can also make profits by assigning tasks to expatriate workers. Therefore, expatriate workers want to become workers to obtain more tasks and profits. To gain trust from the platform, they actively submit task completion feedback to the platform. With the increase in the number of feedback, the platform can grasp the willingness and credibility of expatriate workers. Finally, the platform evaluates the willingness, trust, and task completion efficiency of expatriate workers, and recruits high-quality expatriate workers to be regular workers. The specific implementation of ITTS can be summarized by Algorithm 1.

Algorithm 1 Implementation of ITTS

Input: workers $\mathbb{W}$, expatriate workers $\mathbb{EW}$, tasks $\mathbb{T}$
Output: $TR_{P\to W}$, $TR_{W\to EW}$, $TR_{P\to EW}$

```
for each worker W_k in 𝕎 do
    Compute N^k_TASK with Formula (2)
end for
Platform performs initial task allocation
for each worker W_k in 𝕎 do
    for each t_i of W_k do
        Performs task allocation with Algorithm 2
    end for
end for
for each time interval t_Θ do
    Update TR_{P→W} of workers with Formula (6)
    Update TR_{W→EW} of expatriate workers with Formula (6)
    Update TR_{P→EW} of expatriate worker with Formula (7)
    for each expatriate worker EW_k ∈ 𝔼𝕎 do
        Compute P_{EW_k} with Formula (8)
    end for
    Update workers pool based on P_{EW_k}
end for
```

4.1. Q-Decision based distributed task assignment

Each worker has two important queues. One is the processing queue used to store tasks that are being processed or to be processed. This queue can store at most one task at a time. The other is the waiting queue used to store tasks waiting to be processed. We do not set a limit length on the waiting queue to deal with the situation that expatriate workers can no longer take on tasks. Fig. 4 shows the processing flow. When allocating t_1, W_k first obtains the current state of his/her processing queue. If the processing queue is empty, W_k puts t_1 into the processing queue and completes it by himself/herself; otherwise, t_1 is allocated based on the Q-Decision mechanism, that is, decides whether to put t_1 in the waiting queue or assign it to an expatriate worker.

In this paper, a Q-Decision task assignment mechanism is proposed by modifying Q-learning [43, 44]. The reason why Q-learning is not directly adopted is that the trust and social circles of workers and expatriate workers are constantly changing, and there is only one state space, so we propose a new Q-Decision, which is similar to single-step Q-learning. In the Q-Decision mechanism, we treat each worker as the object making assignment decisions. When the processing queue is full, the possible actions include waiting, assigning to EW_k^1, assigning to EW_k^2,.... Because the size of social circles are limited, the actions that workers take can be measured. Assume worker W_k assigns task t_i, W_k, EW_k^1,..., EW_k^n are objects can be assigned, where W_k indicates that t_i is placed in the waiting queue and EW_k^1,..., EW_k^n indicates that the task is assigned to an expatriate worker. Then, the feedback function is established by considering the following factors:

1) Waiting time. For idle expatriate workers, the waiting time is 0; for W_k and expatriate workers who are processing tasks, the waiting time is calculated based on the number of queued tasks and task processing rate. Only when the waiting time is less than the time constraint of the task, the task can be assigned.

2) Trust. The trustworthiness of workers is quantified as a trust value between 0 and 1. Because W_k is the decision maker, it is completely credible and $TR_{W_k} = 1$. While the trust of other expatriate workers is evaluated by accumulating task feedback. If an expatriate worker performs a positive behavior (i.e., the task feedback is positive), his/her trust value is increased. Otherwise, his/her trust value is punished due to negative behaviors.

3) Profit. In this paper, we adopt a static pricing model. If a worker completes a task, he/she gets a

profit β_W; if the worker assigns the task to an expatriate worker, then he/she gets a profit $\beta_W - \beta_{EW}$, and the expatriate worker earns β_{EW} by completing task.

Assume processing queue is full, and the feedback function of W_k for taking action A is:

$$\gamma_{W_k,A} = \frac{\sigma TR_{W_k} + (1-\sigma)\, PR_{W_k,A}}{\frac{\sum_{i=0}^{z} \mathfrak{D}_{t_i}}{f_{W_k}} + \vartheta} \tag{3}$$

Here, σ is the weight parameter, TR_{W_k} is the trust, $PR_{W_k,A}$ is the profit, the denominator is the waiting time, f_{W_k} is the task processing efficiency per unit time. ϑ=0.001 prevents the denominator from being 0 when the waiting queue is empty. The higher the trust, the more profitable, and the shorter the waiting time, the greater the value of the feedback function.

Based on Formula (3), we get a matrix $\mathbb{R}$ in Table 2. Each value in the matrix represents the feedback of performing a certain action A when the processing queue is full. In the initial stage, the platform neither knows trust of workers and expatriate workers, nor the reliability of social circles, so it explores using ε-greedy strategy. During the exploration, the feedback matrix $\mathbb{R}$ is constantly updated to select the optimal action. Note the initial assignment here is different from Formula (2), and Formula (2) is the initial task assignment of the platform, while the task assignment here is done by workers. After the platform performs the initial assignment, the workers reassign these tasks.

Table 2 Feedback matrix for taking different actions.

A_1 (Wait)	A_2 (to EW_1)	A_3 (to EW_2)	
$\frac{\sigma+(1-\sigma)\beta_W}{\frac{\sum_{i=0}^{z} \mathfrak{D}_i^{W_k}}{f_D^{W_k}}+\vartheta}$	$\frac{\sigma TR_{EW_1}+(1-\sigma)\beta_{EW}}{\frac{\sum_{i=0}^{z} \mathfrak{D}_{t_i}^{EW_1}}{f_D^{EW_1}}+\vartheta}$	$\frac{\sigma TR_{EW_2}+(1-\sigma)\beta_{EW}}{\frac{\sum_{i=0}^{z} \mathfrak{D}_{t_i}^{EW_2}}{f_D^{EW_2}}+\vartheta}$	...

Here, we take the task assignment of W_k as an example to illustrate the specific assignment process. (1) First, we analyze the processing queue status of W_k. If the queue is empty, we directly assign the task to W_k and update the allocation and processing queue status. (2) If the processing queue is full, the first-exploration-then-utilization strategy is adopted to allocate tasks. At this point, we introduce an exploration parameter ε, which is a decimal between 0 and 1, and ε gradually decreases as the number of assigned tasks increases. $\varepsilon = {}^1/_{\sqrt{p}}$, where p is the number of tasks assigned. Specifically, we generate a random number between 0-1 based on a random function rand(). If rand()<ε, we randomly pick an action for the task assignment (e.g., assigns the task to W_k and wait, assigns the task to EW_1,.... Because ε gradually decreases with the increase of assigned tasks, the probability of random selection also gradually decreases. (3) If rand()≥ ε, we perform task assignments based on feedback matrix $\mathbb{R}$. In this case, we select the action with the largest feedback value in $\mathbb{R}$. If there are several actions with the largest feedback value, one is randomly selected. (4) Finally, update the task allocation status, queue status, profit, and parameter p, and go to the next task assignment until all tasks are assigned.

In the above process, we first explore with probability ε and then utilize based on matrix $\mathbb{R}$ with a probability of 1-ε. This ensures that Q-decision can accumulate experience in the early stage, utilize experiences and select the optimal action in the later stage. Finally, the task assignment based on Q-Decision is summarized in Algorithm 2. Assume there are m tasks and n workers, the complexity of Algorithm 2 is $O(mn)$.

Algorithm 2 Q-decision based task assignment

Input: feedback matrix $\mathbb{R}$, workers $\mathbb{W}$, expatriate workers $\mathbb{EW}$
Initialize: p=1
for each worker W_k in $\mathbb{W}$ **do**
  for each t_i of W_k **do**
    Obtain current queue and social status
    if processing queue is empty **then**
      Assign t_i to W_k
      Let $\mathcal{A}_{i,W_k} = 1$
      Update the status of processing queue
    else
      Let $\varepsilon = {}^1/_{\sqrt{p}}$
      if rand()<ε **then**
        Pick an action A_i at random
      else
        Pick action A_i with max value in $\mathbb{R}$
      end if
      Update status $\mathcal{A}_{i,W_k}$ or $\mathcal{A}_{i,W_k \to EW_k^j}$
      Update queue status and profit of W_k
      p=p+1
    end if
  end for
end for

After the task assignment is completed, the profit of worker W_k can be calculated as follows:

$$PR_{W_k} = \sum_{i=1}^{m} \left(\mathcal{A}_{i,W_k}\beta_W + \sum_{j=1}^{z} \mathcal{A}_{i,W_k \to EW_k^j} (\beta_W - \beta_{EW}) \right) \tag{4}$$

Here, m is the number of tasks, z is the number of expatriate workers of W_k, $\mathcal{A}_{i,W_k}\beta_W$ is the profit of W_k completing tasks by himself/herself, $\mathcal{A}_{i,W_k \to EW_k^j} (\beta_W - \beta_{EW})$ is profit of W_k by assigning tasks to expatriate workers.

4.2. *Worker recruitment based on trust and social relations*

To address the worker shortage problem as well as the cold start issue, ITTS leverages workers' social relations to recruit workers on demand, while taking into account participants' trust in the task assignment to further enhance service quality. As shown in Fig. 5, there exist trust relations between the platform and the worker, the worker and the expatriate worker, the platform and the expatriate worker. Therefore, the trust relation is considered in three situations: (1) The platform initially assigns tasks to workers; (2) Workers

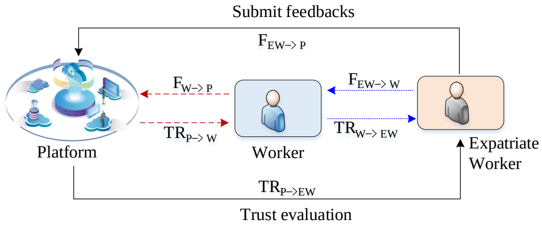

Fig. 5. Task feedback and trust evaluation.

assign tasks to expatriate workers; (3) The platform recruits workers.

Trust evaluations between the platform and worker, the worker and expatriate worker are the same, which infers trust based on verifying task results. For a task t_i, its completion quality is represented by a U-dimensional attributes, $Q_{t_i}=\left[Q_{t_i}^1, Q_{t_i}^2, \ldots, Q_{t_i}^i, \ldots, Q_{t_i}^U\right], Q_{t_i}^i$ is the i-th attribute. Attributes can be set differently according to the requirements. For example, for multimedia data, we can set its multi-dimensional attributes as type, sound, image, text, etc.; while for traffic data, attributes may be type, data size, the data content. Then, we update the trust relation by continuously accumulating the results of multiple attributes. As mentioned in Section 3, the task results can be verified. So, a data difference threshold Π is introduced. In this article, $\Pi = 80\%$, and its value can be adjusted according to the trust requirements of the system. If the difference between the task result and the real value is less than Π, we consider it is a successful record, donated as $c_s = 1$. Assume that ω_k represents the weight of the k-th attribute, and we have:

$$c_s = \begin{cases} 1 & if\ \left(\sum_{k=1}^{U} \omega_k \left|Q_{REAL}^{t_i,k} - Q_{t_i}^k\right|\right) < \Pi \\ 0 & else \end{cases} \tag{5}$$

where

$$\sum_{k=1}^{U} \omega_k = 1,\ 0 \le \omega_k \le 1$$

Then, accumulate all success and failure records of the worker or expatriate worker. With the increase in the number of feedback records, the evaluation value is close to the true trust. Assume the number of successful records is $\sum c_s$, the total number of feedback records is c_{TOT}, the trust of workers evaluated by the platform is $TR_{P\to W}$, and the trust of the expatriate worker evaluated by the worker $TR_{W\to EW}$ is calculated as:

$$TR_{P\to W,W\to EW} = \frac{\sum c_s}{c_{TOT}+1} + \frac{1}{2\left(c_{TOT}+1\right)} \tag{6}$$

Here, $\frac{\sum c_s}{c_{TOT}+1}$ is the proportion of successful records in all feedback and we add c_{TOT} by 1 to avoid the denominator being 0. $\frac{1}{2(c_{TOT}+1)}$ is an adjustment parameter to guide the value of Formula (6) toward the true trust. Initially, $c_{TOT} = 0$, $\sum c_s = 0$, and the value of Formula (6) is 0.5, indicating the likelihood that the evaluated object falling into the confidence (i.e., 0.5-1) and the untrusted interval (i.e., 0-0.5) is equal.

Furthermore, the trust relations between the platform and expatriate workers are more complicated because they involve the interference of subjective factors. In ITTS, workers can earn profits not only by completing tasks but also by introducing and assigning tasks to expatriate workers. Therefore, expatriate workers are willing to submit their result feedback to prove their efficiency and reliability. Of course, to be recruited as official workers, they only submit positive feedback. Taking this into account, the platform comprehensively evaluates the trust of expatriate workers based on two factors. On the one hand, it considers the feedback submitted by expatriate workers themselves, at the same time, it obtains the trust of expatriate workers from workers. Thus, the trust of an expatriate worker evaluated by the platform is calculated as:

$$TR_{P\to EW} = \sigma\left(\frac{\sum c_s}{c_{TOT}+1} + \frac{1}{2\left(c_{TOT}+1\right)}\right) + (1-\sigma)\,TR_{W\to EW} \tag{7}$$

In Formula (7), $\frac{\sum c_s}{c_{TOT}+1} + \frac{1}{2(c_{TOT}+1)}$ is the trust based on the feedback provided by expatriate workers, which also reflects the willingness and frequency of expatriate workers to submit feedback. $TR_{W\to EW}$ is the trust evaluated by workers on expatriate workers in their social circles, which is based on the objective result verification in Formula (6). Based on the subjective willingness and objective evaluation of expatriate workers, the platform finally obtains the trust relations.

After obtaining the trust relations among the platform, workers, and expatriate workers, we initiate worker recruitment at regular intervals according to the quality of tasks and workers, thus expanding the workers pool. There are two factors in worker recruitment. One is the intensity of an expatriate worker's willingness; the other is the trust of the expatriate worker. Finally, the platform recruits the most willing and trustworthy workers from all expatriate workers. The probability of being recruited is:

$$P_{EW_i} = \frac{\sum F_{EW_i\to P}}{\sum_{j=1}^{k}\sum F_{EW_j\to P}} + \frac{TR_{P\to EW_i}}{\sum_{j=1}^{k} TR_{P\to EW_j}} \tag{8}$$

Here, $\sum F_{EW_i\to P}$ is the cumulative number of feedback submitted by EW_i to the platform, $TR_{P\to EW_i}$ is the trust of EW_i evaluated by the platform.

Finally, we recruit workers based on P_{EW_i} and each time we select an expatriate worker with the largest P_{EW_i} as an official worker, and continuously update the worker pool until the number reaches the requirement. When an expatriate worker is recruited as a worker, he/she is required to: (1) Exit the original social circle, and no longer receive tasks as an expatriate worker; (2) Explore and build his/her own social

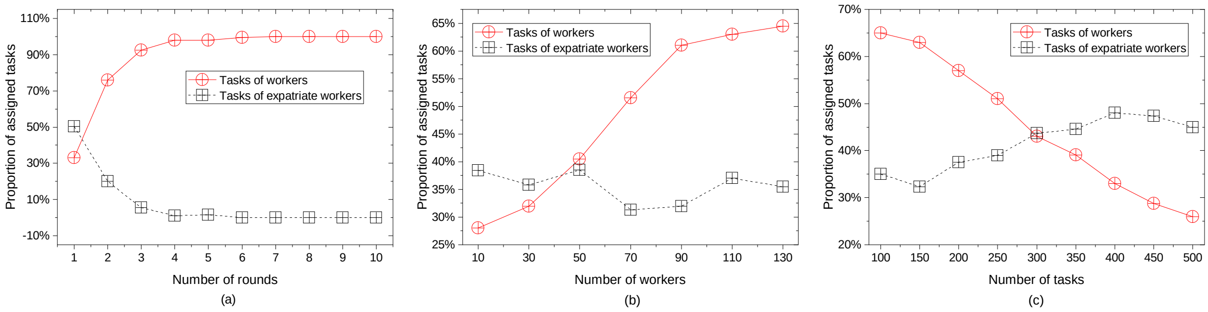

Fig. 6. Proportion of assigned tasks under ITTS with the increase of (a) running rounds, (b) number of workers, and (c) number of tasks.

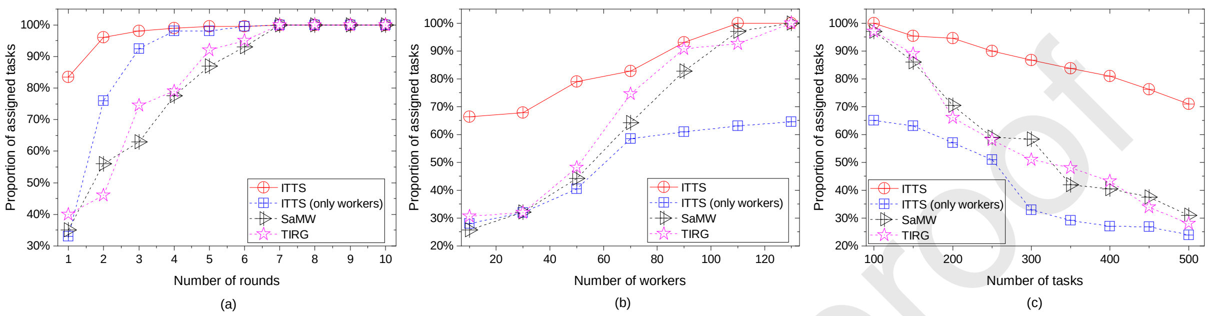

Fig. 7. Proportion of assigned tasks under ITTS, SaMW and TIRG with increase of (a) running rounds, (b) number of workers, (c) number of tasks.

circle. In the beginning, the new official worker randomly selects surrounding idle neighbors as initial expatriate workers, then continuously updates the trust relations according to the task feedback, and gradually builds a stable social circle.

5. Performance analysis

5.1. Experiment setup

In this paper, we conduct simulation experiments using IntelliJ software with Java. Specifically, we consider an MTFW scenario, which initially includes 30 workers and 200 tasks. Experiment setup are as follows: (a) We randomly generate workers and tasks, workers have different data processing capabilities and their data processing rates are limited to 10KB/s. Tasks have different time constraints, and each task must be assigned within 2-10 minutes. Initially, the assignment status of all tasks is 0; (b) We adopt a fixed price, and the payment of each task is 5 currencies. If task is assigned to an expatriate worker, the reward of the expatriate worker is 2 currencies; (c) Initially, the trust of all participants is set as a median value of 0.5, and the trust is updated as the task feedback increase. To avoid some tasks being monopolized by individual workers, the platform allows each worker to have at most five expatriate workers; (d) To better evaluate the security performance, we randomly generate 10% malicious expatriate workers, and they launch data tampering and data discarding attacks [45]. (e) We validate task completion results based on the data type, data size, and content integrity, and set the similarity threshold Π=80%. When the difference between task results submitted by workers and the actual results is less than 20%, it is a successful record.

For comparison, we choose two benchmark methods. The first is the Social-assisted Minimum Waiting assignment, referred to as SaMW [17, 46]. The second is the Task Incentive-based Random Greedy assignment, referred to as TIRG [47, 48].

- SaMW is based on the SocialRecruiter [17] with minimum waiting time [46]. First, SaMW leverages social networks and the SIR epidemic model to propagate tasks outward. When enough workers are recruited, SaMW selects the workers with the least waiting time to undertake tasks each time until all tasks are assigned.

- TIRG is based on incentive pricing [47] and random greedy allocation (baseline method in [48]). In TIRG, participants determine their willingness to join task based on incentives. The platform recruits the willing participant with the lowest price. For task assignments, workers and tasks are randomly matched with constraints.

5.2. Results analysis

First, we analyze the effectiveness of ITTS. Fig. 6 shows the proportion of tasks assigned to workers and expatriate workers under our ITTS method. As shown in Fig. 6(a), at the beginning (round 1), there are not enough workers, most of the tasks are assigned to expatriate workers, and workers only complete about

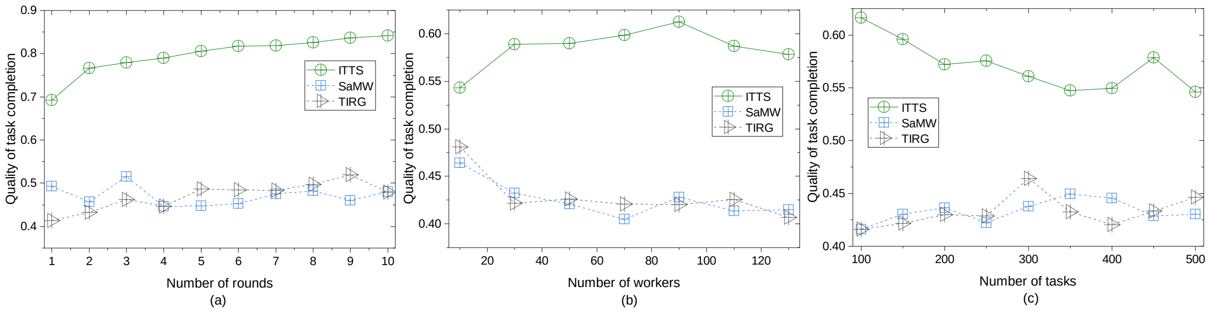

Fig. 8. Task completion quality under ITTS, SaMW, and TIRG with the increase of (a) running rounds, (b) number of workers, and (c) number of tasks.

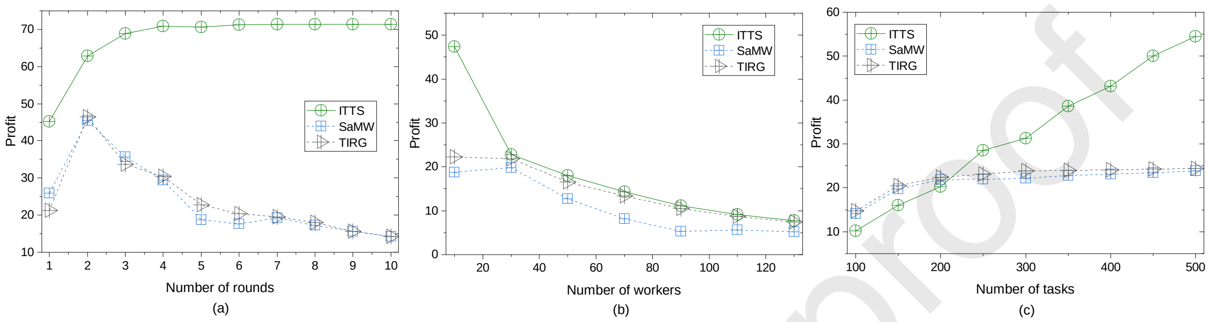

Fig. 9. Profits of workers under ITTS, SaMW, and TIRG with the increase of (a) running rounds, (b) number of workers, and (c) number of tasks.

30%. This proves that in the MTFW scenario, there is indeed a cold start problem in task allocation. As the rounds increase, new workers are continuously recruited, the size of the worker pool expands, and more tasks are assigned to workers, resulting in a gradual increase in the tasks assigned to workers and a decrease trend in tasks assigned to expatriate workers. Finally, when the number of workers is saturated, the task distribution ratio also tends to stabilize. In Fig. 6(b), as the number of workers continues to increase, the proportion of tasks assigned to workers also gradually expands, while expatriate workers have little effects. In Fig. 6(c), as the number of tasks increases, it is difficult for workers to complete the tasks by themselves, so they mobilize friends in social circles to complete tasks. It can be seen that more tasks are assigned to expatriate workers as the number of tasks increases.

Then, we analyze the performance of ITTS and the two benchmark methods, comparing metrics including task completion rates, quality, and profits.

Task completion. Fig. 7 shows the proportion of assigned tasks under ITTS, SaMW, and TIRG. In Fig. 7, ITTS (only workers) represents the situation where tasks are completed by workers without relying on social relations. When the number of workers is small, the proportion of assigned tasks in ITTS is significantly higher than that of SaMW and TIRG. With the continuous recruitment of workers, the proportion of the three schemes presents no differences. When workers increase to a certain number, the task assignment is saturated and the results tends to stabilize. Finally, we show the proportion of assigned tasks with an increase in tasks. Because SaMW and TIRG need time to recruit enough workers, therefore, when the number of workers is fixed, the proportion of assigned tasks under SaMW and TIRG decreases significantly as the number of tasks increases. The task assignment of ITTS is less affected by the increase in tasks because when there are too many tasks, it can complete tasks with social circles. Therefore, it can be seen from the figure, the tasks completed by workers under ITTS gradually decreases as the task number increases, because most tasks are completed by social circles.

According to Fig. 7, the following conclusions can be obtained: (a) In MTFW scenarios, social relations can be used to solve the worker shortage as well as cold start problem in the task assignment and worker recruitment; (b) The proportion of assigned tasks is not increased simply as the number of workers grows or the number of tasks decreases. When the number of workers and tasks reach a harmonious ratio, the task assignment and resource utilization are optimized.

Quality. Fig. 8 is the comparison of task completion quality. Our proposed ITTS evaluates the trust of workers and expatriate workers based on task completion rates. Therefore, as the number of rounds increases, high-quality workers are more likely to be selected, thereby improving the task completion quality. According to Fig. 8, the following conclusion can be drawn: (a) SaMW and TIRG lack the trust and quality evaluation mechanism, and therefore so the quality

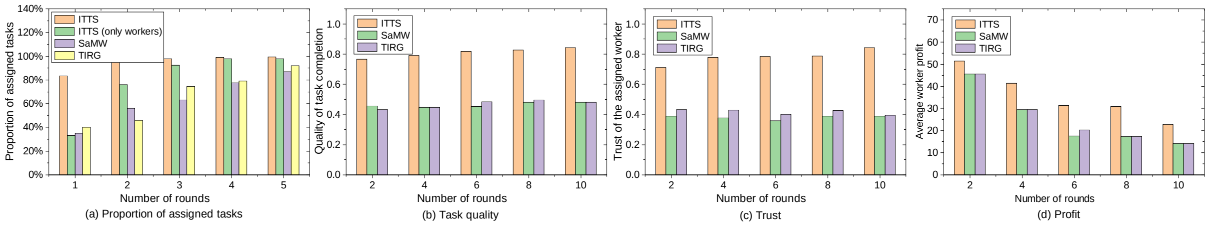

Fig. 10. Performance analysis of ITTS, SaMW, and TIRG with the increase of running rounds.

in each round of task completion is not much different, basically 0.4-0.5. That is, malicious workers have an impact on task quality of SaMW and TIRG. While in ITTS, the trust relations between workers and expatriate workers are continuously updated based on task feedback, and trust is regarded as an important reference for task allocation. Then, task completion quality improves with increasing running rounds, basically 0.7-0.85. (b) As the number of workers and tasks increases, the task quality of SaMW and TIRG does not change much, while that of ITTS slightly improves with the increase of the number of workers and decreases slightly with the increase in tasks. Overall, ITTS is of higher quality than SaMW and TIRG.

Profit. Fig. 9 presents the average profit of workers. As mentioned in the analysis of Fig. 7, with the increase in running rounds, the proportion of tasks completed by workers in ITTS gradually increases. Therefore, as shown in Fig. 9(a), the profit of workers under ITTS gradually increases, while the number of workers under SaMW and TIRG continues to expand in each round. Therefore, the task budget is divided among more workers and profits show a gradual downward trend. According to Fig. 9(b) and Fig. 9(c), the average profit of workers gradually decreases with the increase in workers, and gradually increases with the increase in tasks. Under ITTS, workers get rewards not only for completing tasks but also assigning tasks to expatriate workers, so therefore its profit growth is more obvious.

Fig. 10 illustrates the performance comparison of ITTS, SaMW, and TIRG with the increase in running rounds. Compared with SaMW, ITTS improves the proportion of assigned tasks by 61.53%, and compared with TIRG, ITTS improves the proportion of assigned tasks by 56.49%. According to Fig. 10(b), compared with SaMW, ITTS improves task quality by 42.6%, and compared with TIRG, ITTS improves task quality by 42.08%. Fig. 10(c) shows the trust of the workers undertaking tasks. The higher the workers' trust, the better task completion quality. Since ITTS introduces a trust evaluation mechanism, compared with SaMW and TIRG, it has a higher trust level. Finally, Fig. 10(d) shows the profit of workers in task assignments. Compared with SaMW, ITTS increases the profit by 47.19%, and compared with TIRG, it increases the profit by 42.34%.

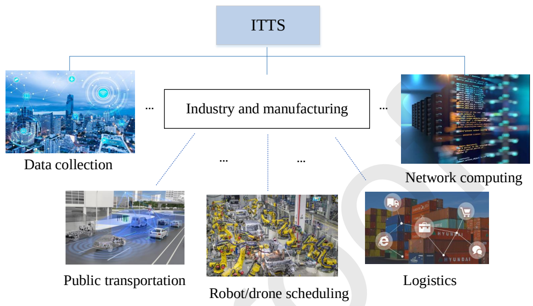

Fig. 11. Practical engineering applications of ITTS.

5.3. *Engineering applications*

As illustrated in Fig. 11, our proposed ITTS can be applied to numerous social applications, such as public transportation, robot/drone scheduling, logistics, and network computing. In public transportation, we regard urban buses as workers, which take the transportation of passengers as a task. With ITTS, the daily transportation of cities can be improved. What's more, relying on ubiquitous smartphones and camera probes, when urban traffic is congested, every user with a mobile terminal can act as a worker who collects real-time traffic information. Therefore, ITTS can be applied to collect traffic big data. In addition, in the current era of e-commerce and online shopping, the intelligent and trusted task allocation of ITTS can help realize efficient logistics. Especially in Industry 4.0 and smart manufacturing, with the proposed ITTS, various production tasks can be efficiently allocated to robots/machines and complete collaboratively by workers, thus improving automation, intelligence, and production efficiency.

6. Conclusion and future work

The rapid increase in various application tasks in industrial communication systems has made the task assignment in the MTFW scenario a research hotspot. In this article, an intelligent and trustworthy task assignment method called ITTS is proposed by utilizing workers' trust and social relations. Compared with previous methods, ITTS has the following novel contributions. First, it transforms the centralized task allocation of the platform into small-scale task allocation of each worker. It makes an initial assignment based on the trust and social influence, and then initiates on-demand recruitment in the social circle. Second, ITTS establishes workers' social circles and trust relations for task assignments and worker recruitment, thereby creating a high-quality worker pool to improve effectiveness and security. In addition, extensive simulation results fully demonstrate the advantages of ITTS in improving task completion rates and profits. For the future work, we will fully exploit social and trust relations in task assignments to further improve efficiency and security. For example, workers with sufficient resources and computing power can also act as expatriate friends, thereby realizing the collaborative task assignment and execution among workers. What's more, an expatriate worker can belong to multiple social circles, so that the spare time of expatriate workers can be further utilized.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: