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Research Article

CrowdBox: Crowdsourced Network-in-Box Recruitment for Edge Computing-Enabled Industrial Internet of Things

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The rapidly increasing number of smart devices deployed in the Industrial Internet of Things (IIoT) environment has been witnessed. To improve communication efficiency, edge computing-enabled Industrial Internet of Things (E-IIoT) has gained attention recently. Nevertheless, E-IIoT still cannot conquer the rapidly increasing communication demands when hundreds of millions of IIoT devices are connected at the same time. Considering the future 6G environment where smart network-in-box (NIB) nodes are everywhere (e.g., deployed in vehicles, buses, backpacks, etc.), we propose a crowdsourcing-based recruitment framework, leveraging the power of the crowd to provide extra communication resources and enhance the communication capabilities. We creatively treat NIB nodes as edge layer devices, and CrowdBox is devised using a Stackelberg game where the E-IIoT system is the leader, and the NIB nodes are the followers. CrowdBox can calculate the optimal reward to reach the unique Stackelberg equilibrium where the utility of E-IIoT can be maximized while none of the NIB nodes can improve its utility by deviating from its strategy. Finally, we evaluate the performance of CrowdBox with extensive simulations with various settings, and it shows that CrowdBox outperforms the compared algorithms in improving system utility and attracting more NIB nodes.

1. Introduction

The Industrial Internet of Things (IIoT), an important part of IoT [1], brings Internet access to all industrial assets including industrial devices and control systems [2]. As one of the basic pillars of digital manufacturing, IIoT changes the traditional manufacturing lines and systems significantly [3]. With the flexibility and scalability brought by wireless links [4], it paves the way for efficient and sustainable production in the era of Industry 4.0.

However, the emergence of IIoT applications results in a tenfold increase in the amount of data generated by industrial devices [5]. It would be a disaster for the network if that size of data which is produced at the edge of the network is transferred to the cloud directly. Not only the data volume but also traditional cloud computing is unable to deal with the various requirements such as data privacy and response time limitation. So, it will be more efficient to process the data at the edge of the network.

Edge computing (EC) is a new architecture [6–8] extending the cloud paradigm to the network edges, and it has attracted attention from both academia and industry recently since a large number of critical problems in IIoT (e.g., resource limitation [9], latency [10], and privacy [11]) could be solved with it easily. The combination of EC and IIoT, the so-called edge computing-enabled Industrial Internet of Things (E-IIoT), enables the design of high-performance and adaptive systems for IIoT [12]. Therefore, many edge computing-enabled new IIoT architectures and platforms have been proposed and devised to improve the service efficiency [13–15] from different aspects in the last few years.

With the rapid development of wireless communication technologies (e.g., the sixth-generation communication technology) and new urban infrastructures (e.g., personal communication devices, edge servers, and smart vehicles), many new smart devices will emerge. Chen et al. [16] believe that 6G will merge computation and sensing with communications, so the functions of new smart devices will be more complex. In addition, the strong mobility of edge nodes has become the trend of development [17].

Network-in-box [18, 19] is a burgeoning technology to enhance network reliability, and its application significance is becoming more and more obvious with the development of edge computing and sixth-generation communication techniques. The design of NIB is focused on portability, so the NIB can move according to the requirement of the whole network. An NIB node can work alone as well as cooperate with other network elements. Some typical use cases of NIB including after-disaster scenario, connectivity provisioning in challenging contexts, and tactical networks are investigated in [20]. With the NIB node as the edge server, a more reliable and more flexible networking environment can be provided for the E-IIoT system.

1.1. Motivation. Crowdsourcing has been proven to be effective in task delivering applications including Amazon Mechanical Turks (AMT) [21–23]. The requirements for communication resources of devices can be regarded as a task, and NIB is responsible for fulfilling the task. In this paper, we propose to utilize the power of crowdsourced NIB nodes to improve communication capabilities at the edge layer. Although NIB brings great flexibility to the E-IIoT system, it is still an urgent problem to motivate NIB nodes to provide additional communication resources for devices. In order to better understand the problem, we build a Stackelberg game between the E-IIoT system and NIB nodes. By studying the Nash equilibrium, we can find the best response strategy of an NIB node, and the incentive problem could be solved at the same time.

1.2. Contributions. In this paper, we establish a crowdsourcing-based network-in-box recruitment platform. As far as we know, our work is the first to conceive a crowdsourcing-based recruitment platform in the E-IIoT environment. The main contributions of this paper are summarized as follows:

(i) We present an analytical model for the recruitment of NIB nodes where they can improve the system communication capabilities by crowdsourcing

(ii) For the recruitment problem, the utility function for the system and NIB nodes are formulated; then, the whole process is described as a Stackelberg game with two stages

(iii) The Nash equilibrium is defined, and CrowdBox is proposed to calculate the Nash equilibrium point. Finally, the best strategy of NIB nodes and E-IIot are both found

(iv) To prove the effectiveness and feasibility of CrowdBox, we both put forward the theoretical explanation and conduct extensive simulations. It turns out that CrowdBox achieves better performance than other benchmarks

1.3. Organization of the Paper. The rest of this paper is organized as follows. Section 2 discusses the related work. We introduce the system model of our network and the formulated problem in Section 3. Section 4 presents the definition of CrowdBox and details of the whole game process. Evaluation settings and numerical results are presented in Section 5. Finally, Section 6 concludes the paper.

2. Related Work

By leveraging the concept of crowdsourcing, many IIoT problems have been solved. The author in [24] emphasizes the impressive amounts of data by introducing crowdsourcing to IIoT which provides the opportunity to perform more advanced processes and applications. Also, a mobile crowdsensing and mobile crowdsourcing-based IIoT architecture is proposed in their work. In the field of the smart city which is an important application scenario of IIoT, Kong et al. [25] utilize crowdsourcing to collect and compute decentralized ubiquitous sensing data. The objective is to solve major urbanization problems in smart cities. As crowdsourcing is widely used for data collection and computing, privacy protection in this process has also become a direction of crowdsourcing research. A personalized privacy protection framework is proposed for mobile crowdsensing in [26]. Theoretical analysis and simulations show that the framework can make a balance between the quality of crowdsensing services and privacy. When the crowdsourcing IIoT data is stored in the cloud, Karati et al. [27] propose a new identity-based signcryption schema to meet the requirement of authenticity and confidentiality.

From the perspective of IIoT devices, resources from the edge servers are shared to enhance the ability of the whole network. So, our work is also somewhat similar to resource allocation in the E-IIoT system, and we also summarize it briefly. In [28], mobile edge computation offloading is considered on different multiple access technologies. Resource allocation is formulated as an optimization problem with mobile energy consumption as the constraint. Sun etal. [29] discuss the joint optimization problem of network economics and resource allocation in mobile edge computing. They propose two double auction schemes which both use dynamic pricing to establish connections of IIoT devices and edge servers. To improve the cognitive ability of edge intelligent IIoT, an ML-enabled framework is proposed in [30]. Via this framework, IIoT is able to make reasonable decisions at the network edge. Furthermore, deep reinforcement learning is invoked and shows good performance in an observable IIoT environment.

To realize the objective of optimization, game-based approaches have been applied in communication networks [31]. The Stackelberg game is a typical one to design interactive schemes in wireless networks. When the problem comes to resource allocation, Zhang etal. [32] formulate a Stackelberg game to analyze the problem and apply a matching game to achieve satisfying performance. Yao et al. [33] invoke the Stackelberg game to model the interaction between the resource provider and miners. In [34], Jie et al. transfer the resource allocation problem to a double-stage Stackelberg game to maximize resource utilization. The Stackelberg game is also used in [35] to offload computation in IIoT, and the existence and uniqueness of equilibrium are analyzed. To sum up, the insight of crowdsourcing can help us formulate the problem as a recruitment problem. After that, the Stackelberg game can be utilized to motivate the NIB nodes to share their resources and make sure the IIot devices get the resources they need.

3. System Model and Problem Formulation

This section first introduces the system model of the edge computing-enabled Industrial Internet of Things (E-IIoT) system, then formulates the crowdsourcing-based network-inbox recruitment problem as a Stackelberg game.

3.1. System Model. Figure 1 is utilized to aid our description of the E-IIoT system. Similar to the other edge computing systems, E-IIoT mainly includes three layers—the cloud layer, the edge layer, and the device layer. To fulfill industrial missions from factories, E-IIoT devices have to upload their sensing data to edge/cloud nodes, and the following instructions will be directed to E-IIoT devices after the uploaded sensing data are processed by edge and cloud servers.

However, the existing communication resource at the edge layer may not be enough to satisfy the E-IIoT system when some edge nodes are broken down or sudden communication demands (e.g., factory adds many IIoT at the same time suddenly) are required. To overcome these difficulties, we propose to recruit crowdsourcing network-in-box nodes (e.g., box in buses, vehicles, packages, etc.) as temporary edge nodes to expand the network and offload sensing data from IIoT devices to servers and meet the communication needs finally.

Here, we treat the communication resource collection of the NIB nodes for E-IIoT as a task. To be specific, different from the general NIB deployment system where NIB nodes contribute their communication resource passively, the enterprise (i.e., resource consumer) could buy communication resources from participating NIB nodes with the total reward within a specific time period (e.g., one hour). Further, the NIB nodes could also select their participating levels (i.e., how long to contribute their communication resource) when using CrowdBox during daily life. The NIB nodes will select to participate only when the received reward could cover its cost in both data communication and data processing. Eventually, the NIB nodes could obtain the corresponding reward based on the participating levels of the total reward of the system and all NIB nodes.

In a word, crowdsourcing NIB nodes will have some costs when they provide communication resources to the system, and E-IIoT will offer some corresponding rewards to stimulate crowdsourcing E-IIoT nodes who perform the communication task and provide the communication resource. Actually, this is a gaming process, and we will formulate it with the Stackelberg gaming theory in the next subsection.

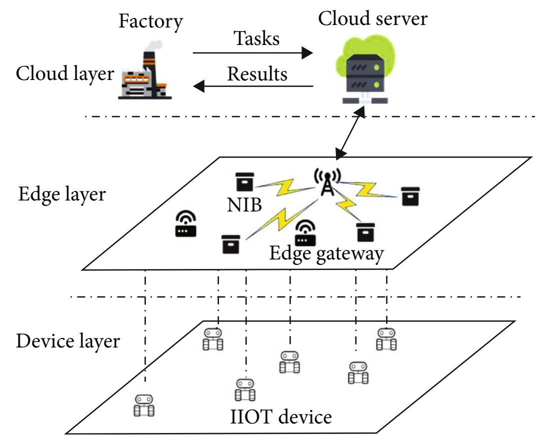


Figure 1: The E-IIoT architecture.

3.2. Problem Formulation. The E-IIoT system has one communication task (i.e., provide communication resources as more as possible) for all NIB nodes at the edge layer. To recruit NIB nodes fulfilling the communication task, the E-IIoT system announces a total reward R, where $R > 0$. According to the reward, each participant will choose their own participation level. To be specific, the participation level (strategy) of NIB node i is $t_i(\geq 0)$ which denotes the time duration it can provide the communication service. It is assumed that all NIB nodes are available when they choose to participate in the task, and they contribute equally at any time during the task period. The unit cost of NIB node i is denoted as c_i, and we can compute the utility of NIB node i as

$$u_i = \frac{t_i}{\sum_{j\in U} t_j} R - c_i t_i, \tag{1}$$

where $t_i / \sum_{j\in U} t_j R$ is the reward that NIB node i will get after participating in the task and $c_i t_i$ is its total cost for completing the task. It should be noticed that a rational NIB node will not cooperate with a negative utility, so NIB node i will do nothing (i.e., $t_i = 0$) when $t_i / \sum_{j\in U} t_j R < c_i t_i$. Thus, the equation should be rewritten as

$$u_i = \begin{cases} \dfrac{t_i}{\sum_{j\in U} t_j} R - c_i t_i, & \dfrac{R}{\sum_{j\in U} t_j} > c_i, \\ 0, & \dfrac{R}{\sum_{j\in U} t_j} \leq c_i. \end{cases} \tag{2}$$

According to equation (2), it is not hard to find that NIB nodes would like to choose the same plan (strategy) to maximize their utility when they have the same unit cost. Here, we define the unit cost set $S = \{s_1, s_2, \cdots, s_X\}$, and we have $c_i \in S$. All NIB nodes with the same unit cost will choose the same strategy if they want to maximize their utilities.

Therefore, the expected participation time duration for a specific unit cost s_x is denoted by $\widehat{t}_x (x \in X)$, and we also have the expected participation time duration set $\widehat{T} = \{\widehat{t}_1, \widehat{t}_2, \cdots, \widehat{t}_X\}$ correspondingly. Besides, the number of NIB nodes whose unit costs are the same is defined as $n_x (x \in X)$, and the set of the number of NIB nodes is $N = \{n_1, n_2, \cdots, n_X\}$. Based on the above definitions, the utility function of E-IIoT can be computed as follows:

$$u_0 = f\left(\widehat{T}, N\right) - R, \tag{3}$$

where $f(\widehat{T}, N)$ presents the valuation function of all NIB nodes' participation time of the E-IIoT system.

The goal of E-IIoT is to choose the optimal value of reward R to maximize equation (3). It is assumed that the utility function of E-IIoT is a strictly concave function in variables T for any fixed N and increasing monotonically for every t_i of NIB node i, and this is a general assumption in many other related papers [36]. Each NIB node $i \in U$ decides its strategy (i.e., t_i) to maximize equation (2) with a given reward value R.

In the next section, we will model the whole NIB node recruitment process as a *Stackelberg game* with two stages and depict how to determine the optimal reward value R^* to maximize the utility of the E-IIoT system. Besides, detailed explanations of employed notations in this paper are concluded in Table 1.

Table 1: Major notations employed in this paper.

Notation	Explanation
R	Reward of the E-IIoT system
R^*	Optimal reward value
R_{others}	Feasible reward values
U	Crowdsourcing NIB node set
U_i	NIB nodes except i
u_i	Utility function of NIB node i
u_0	Utility function of the E-IIoT system
n	Number of crowdsourcing NIB nodes
t	Strategy profile of all users
t_{-i}	Strategy profile of all users except NIB node i
t_i	Participation level (strategy) of NIB node i
c_i	Unit cost of NIB node i
S	Unit cost level set
X	Number of unit cost levels
s_x	xth unit cost level
$\widehat{T}$	Expected participation time duration set
$\widehat{t}_s$	Expected participation time duration for s_x
N	Set of the NIB node number at different unit cost levels
n_x	Number of NIB nodes at the same unit cost level

4. CrowdBox

The crowdsourcing-based network-in-box recruitment for edge computing-enabled Industrial Internet of Things process is modeled as a Stackelberg game (CrowdBox), and it has two stages. In the first stage, the E-IIoT system posts its reward R for the communication task and recruit NIB nodes to participate. Accordingly, the NIB node chooses a response strategy (i.e., service time duration it could provide) to maximize its own utility based on the given reward R in the second stage. Essentially, the E-IIoT system is the leader and the NIB nodes are the followers.

The Nash equilibrium is a stable status and very important for a game since no players can obtain extra profits by changing their strategy. For the NIB node, we first define the Nash equilibrium and its best response strategy. We prove that NIB nodes have a unique Nash equilibrium for any given reward R. Based on the utility function of the NIB node, we analyze the best response strategy of NIB nodes and show how to compute it. For the E-IIoT system, we also define its Nash equilibrium and the corresponding best response strategy and propose how to calculate the optimal reward R^* (i.e., the best response strategy for the E-IIoT system) to maximize the E-IIoT system's utility.

In sum, we show that the Stackelberg game we proposed has a unique Stackelberg equilibrium and how to calculate the optimal reward value to maximize E-IIoT's utility in this section.

4.1. NIB Node Nash Equilibrium. To study the NIB node strategy, we first define the Nash equilibrium of NIB node i as below.

Definition 2 (Nash equilibrium of NIB nodes). A strategy set $(t_1^{ne}, t_2^{ne}, \cdots, t_n^{ne})$ is a Nash equilibrium, when any NIB node i meets equation (18):

$$u(t_i^{ne}, t_{-i}^{ne}) \geq u(t_i, t_{-i}^{ne}). \tag{4}$$

We also give the definition of the best response strategy for NIB node i as the following.

Definition 3 (best response strategy of NIB nodes). Strategy t_i for NIB node i, denoted by B_i, is the best response strategy if it maximizes $u(t_i, t_{-i})$ over all $t_i \geq 0$.

Given a reward R from the E-IIoT system, NIB node i would like to choose the best response strategy to maximize its utility (i.e., equation (2)). An NIB node would like to play its best response strategy in Nash equilibrium.

To study the best response strategy of NIB node i, we compute the derivatives and second order of utility function u_i with respect to t_i as

$$\frac{\partial u_i}{\partial t_i} = \frac{R}{\sum_{j \in U} t_j} - \frac{t_i R}{\left(\sum_{j \in U} t_j\right)^2} - c_i, \tag{5}$$

$$\frac{\partial^2 u_i}{\partial t_i^2} = -\frac{2Rt_i}{\left(\sum_{j\in U} t_j\right)^3}. \quad (6)$$

It is very obvious that the second-order derivative $\partial^2 u_i/\partial t_i^2 \le 0$, so the utility function of NIB node i is a strictly concave function. By setting the first-order derivative $\partial u_i/\partial t_i = 0$, we have

$$\frac{R}{\sum_{j\in U} t_j} - \frac{t_i R}{\left(\sum_{j\in U} t_j\right)^2} - c_i = 0. \quad (7)$$

Sorting out equation (7), we can obtain

$$t_i = \sqrt{\frac{\left(\sum_{j\in U_{-i}} t_j\right)R}{c_i}} - \sum_{j\in U_{-i}} t_j. \quad (8)$$

Obviously, the best response strategy of node i can be summarized as

$$B_i = \begin{cases} \sqrt{\frac{\left(\sum_{j\in U_{-i}} t_j\right)R}{c_i}} - \sum_{j\in U_{-i}} t_j, & R \ge c_i \times \sum_{j\in U_{-i}} t_j, \\ 0, & R < c_i \times \sum_{j\in U_{-i}} t_j. \end{cases} \quad (9)$$

The above analysis shows that any NIB node $i(0 < i < n)$ has its best response strategy B_i for any given reward $R > 0$ and strategy profile t_{-i} of other NIB nodes. Next, we define the NIB node set $\tilde{U} = \{i \in U \mid t_i > 0\}$, and it is easy to get that $\sum_{j\in\tilde{U}} t_j = \sum_{j\in U} t_j$. Therefore, we can get

$$\frac{R}{\sum_{j\in\tilde{U}} t_j} - \frac{t_i R}{\left(\sum_{j\in\tilde{U}} t_j\right)^2} - c_i = 0. \quad (10)$$

Adding up equation (10) over all NIB nodes in $\tilde{U}$, we have

$$-R + \left|\tilde{U}\right| \times R - \left(\sum_{j\in\tilde{U}} k_j\right) \times \left(\sum_{j\in\tilde{U}} t_j\right) = 0. \quad (11)$$

Therefore, we obtain

$$\sum_{j\in\tilde{U}} t_j = \frac{\left(\left|\tilde{U}\right| - 1\right)R}{\sum_{j\in\tilde{U}} k_j}. \quad (12)$$

To calculate t_i for NIB node i, equation (10) can also be rewritten as

$$t_i = \sum_{j\in\tilde{U}} t_j - \frac{k_i}{R} \times \left(\sum_{j\in\tilde{U}} t_j\right)^2. \quad (13)$$

Substituting equation (12) into equation (13), we can calculate the best response strategy for NIB node i as

$$t_i = \frac{\left(\left|\tilde{U}\right| - 1\right)R}{\sum_{j\in\tilde{U}} k_j} - k_i \times R \times \left(\frac{\left(\left|\tilde{U}\right| - 1\right)}{\sum_{j\in\tilde{U}} k_j}\right)^2. \quad (14)$$

In addition, the unit cost set is denoted as $\tilde{C} = \{\tilde{c}_1, \tilde{c}_2, \cdots, \tilde{c}_l\}$, where $c_i \in \tilde{C}$ for any NIB node i. The distribution of $\tilde{C}$ usually could be learned from the historical data by the E-IIoT system, and it is also a realistic assumption adopted in the literature [37]. According to equation (14), we can compute the Nash equilibrium of NIB nodes.

So far, we have known how to calculate the Nash equilibrium for any NIB node i with any given reward value R in the E-IIoT system. In the next subsection, we will show how to choose the optimal reward value R^* to maximize the E-IIoT system's utility.

4.2. Maximizing Utility of E-IIoT. Obviously, the E-IIoT system, which is the leader of the Stackelberg game, can know the existing NIB node Nash equilibrium based on the above analysis. To be specific, E-IIoT can select the optimal reward value R to maximize its utility based on the following equations:

$$u_0 = \left(\frac{f\left(\widehat{T}, N\right)}{R-1}\right)R, \quad (15)$$

where

$$\begin{aligned} \widehat{T} &= \{t_1^{ne}, t_2^{ne}, \cdots, t_X^{ne}\}, \\ N &= \{n_1, n_2, \cdots, n_X\}. \end{aligned} \quad (16)$$

For each $t_i^{ne} \in \widehat{T}$, we have

$$\frac{t_i^{ne}}{R} = \frac{\left(\left|\tilde{U}\right| - 1\right)}{\sum_{j\in\tilde{U}} k_j} - k_i \times \left(\frac{\left(\left|\tilde{U}\right| - 1\right)}{\sum_{j\in\tilde{U}} k_j}\right)^2, \quad (17)$$

where u_0 is a strictly concave function, $\widehat{T}$ could be obtained by Algorithm 1, and N could be calculated according to the previous statistics by analyzing the historical data.

Next, we define the Nash equilibrium of the E-IIoT system as below.

Definition 4 (Nash equilibrium of the E-IIoT system). The chosen reward value R is a Nash equilibrium of the E-IIoT system if it can make the E-IIoT system reach the maximum utility.

Besides, the best response strategy of the E-IIoT system is defined as below.

Definition 5 (best response strategy of the E-IIoT system). The optimal reward value R^* is the best response strategy

Input: E-IIoT Reward R, NIB node set U and $\tilde{U}$.
Output: Nash equilibrium strategy set for all NIB nodes $t^n e = \{t_1^{ne}, t_2^{ne}, \cdots, t_n^{ne}\}$
1: $t^{ne} \longleftarrow \Phi$;
2: **for** $i \longleftarrow 1$ to n **do**
3: $t_{tmp} \longleftarrow (|\tilde{U}| - 1)R/\sum_{j\in\tilde{U}} k_j - k_i \times R \times ((|\tilde{U}| - 1)/\sum_{j\in\tilde{U}} k_i)^2$;
4: **if** $t_{tmp} > 0$ **then**
5: $t_i^{ne} \longleftarrow t_{tmp}$;
6: **else**
7: $t_i^{ne} \longleftarrow 0$;
8: **end if**
9: $t^{ne} \longleftarrow t^{ne}.add(t_i^{ne})$;
10: **end for**
11: **return** t^{ne};

Algorithm 1: Computing the Nash equilibrium of all NIB nodes.

with the given NIB node Nash equilibrium strategy set $(t_1^{ne}, t_2^{ne}, \cdots, t_n^{ne})$, and R^* meets

$$u_0(R^*) \geq u_0(R_{\text{others}}). \tag{18}$$

In summary, it can be concluded that the Nash equilibrium exists in this Stackelberg game, and the optimal reward R^* can maximize the utility function u_0 in equation (15) over $R \in [0,+\infty)$. To calculate R^*, many efficient methods could be leveraged, such as Newton's method [38].

5. Performance Evaluation

We have studied CrowdBox theoretically, and this section evaluates the performances of CrowdBox in realistic problem settings. In the following, we mainly elaborate on the simulation settings, compared algorithms, performance metrics, and results separately.

5.1. Simulation Settings. We assume that the E-IIoT system has been widely deployed in the industry, and a large amount of IIoT devices require the communication resources to communicate with the edge and cloud servers. To satisfy the demands, a set of NIB nodes could be employed at the edge layer to improve the communication capacity of the system with a given reward value R.

The default values of simulation settings are defined as the following. In the E-IIoT system, the costs of NIB nodes are distributed uniformly over $S = \{1, 2, 3, \cdots, 10\}$, and the number of NIB nodes is equal to $n = 1000$. We set the $f(\widehat{T}, N) = \lambda \log(1 + \sum_{c_j\in S}(n_j \log(1 + t_j)))$, where $n_j \in N$ and $t_j \in \widehat{T}$, since $j \log(1 + t_j)$ represents E-IIoT's diminishing return on the work of an NIB node with unit cost c_j, and $\log(1 + \sum_{c_j\in S}(n_j \log(1 + t_j)))$ denotes E-IIoT's diminishing return on the number of participating NIB nodes. Unless otherwise specified, we use the default values to conduct the following simulations.

5.2. Compared Algorithms (Strategies). In order to evaluate the performances of CrowdBox, we adopted two compared strategies (benchmarks)—random and best effort strategy. Both two strategies are general game theory-based methods adopted in many related fields, and the basic ideas are as follows.

5.2.1. Best Effort Strategy. NIB node i is always trying its best to provide the communication resource (i.e., $t_i = t_{i(\max)}$, where $t_{i(\max)}$ could be computed by setting $u_i = 0$ for NIB node i) only if it can obtain the profit (i.e., the NIB node utility is larger than zero) from the E-IIoT system.

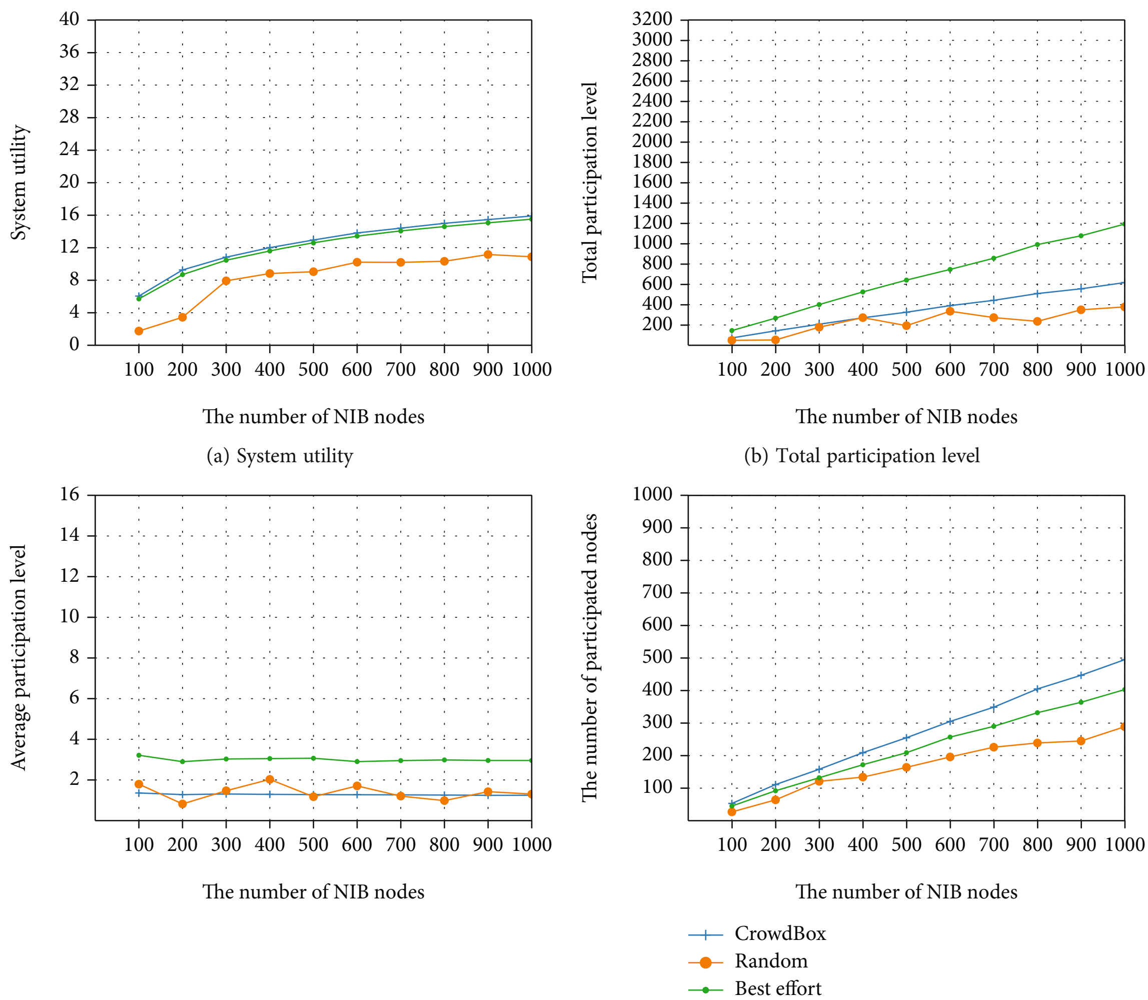
5.2.2. Random Strategy. The strategy of NIB node i is selected by itself based on its own preferences at random. For each NIB node i, we define a maximum cooperation time duration $t_{i(\max)}$, and NIB node i can choose the random value in $[0, t_{i(\max)}]$.

5.3. Performance Metrics and Results. Four major metrics are leveraged to measure the effectiveness of our proposed algorithm and benchmarks, including the system utility, total participation level, average participation level, and the number of participating NIB nodes during the whole Stackelberg game process.

The system utility u_o has been introduced in Section 3, and it is the main metric to measure the algorithm performance; the total participation level is defined as the sum of NIB node strategy t_i; the average participation level can be computed by the total participation level divided by the number of participating NIB nodes; the number of participating NIB nodes is the number of nodes whose $t_i > 0$ during the game process.

By changing the value of NIB nodes and the number of NIB nodes' maximum cost for the system, we show the performances of CrowdBox and the other two benchmarks in the following.

5.3.1. The Number of NIB Nodes. Here, we verify the effectiveness of CrowdBox with different numbers of NIB nodes. In particular, the number of NIB nodes is changed from 100 to 1000 with the increment of 100 nodes, and the results are depicted in Figure 2.



(a) System utility

(b) Total participation level

(c) Average participation level

(d) The number of participating nodes

Figure 2: Performances with different numbers of NIB nodes.

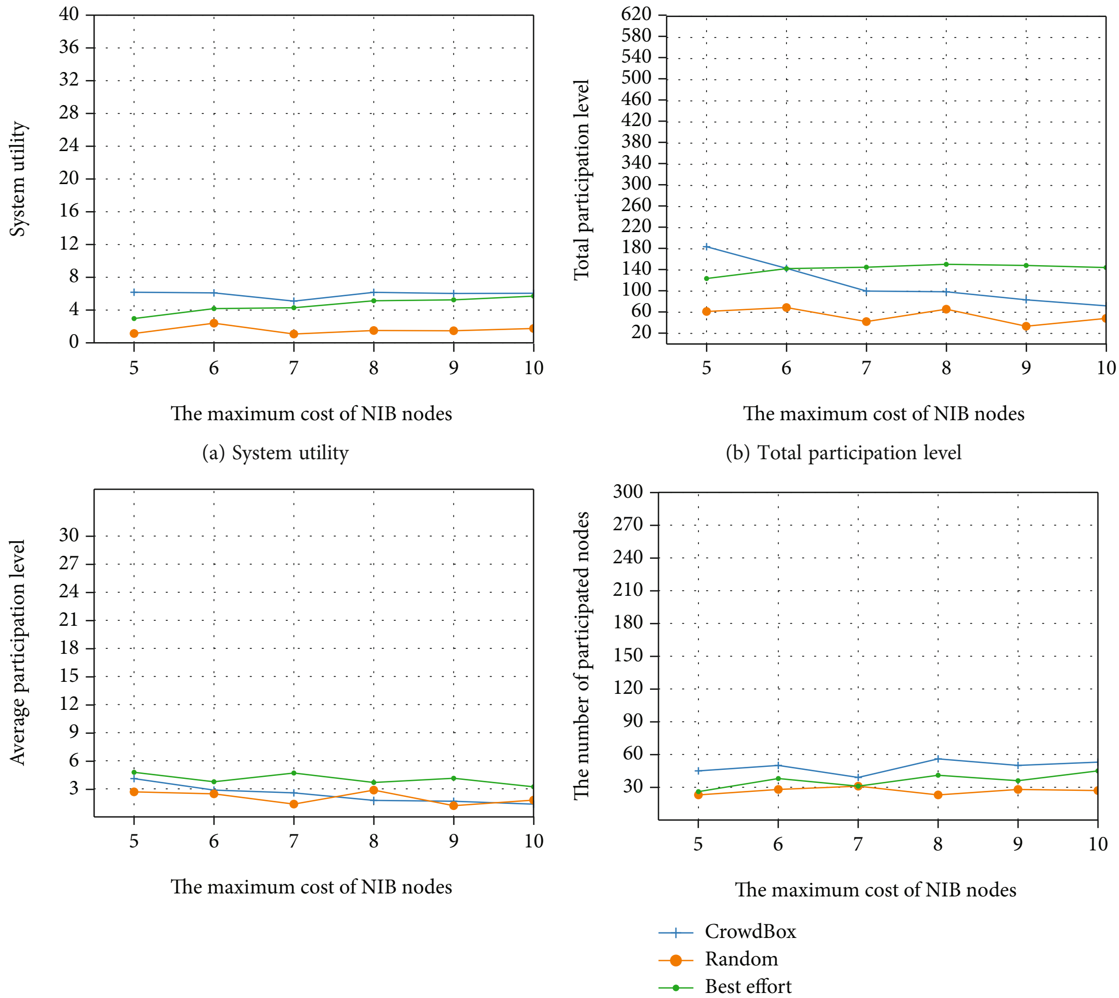
To be specific, Figure 2(a) shows that CrowdBox has the highest system utility contrasting with the other two algorithms, and this is our key goal to design CrowdBox which chooses the best response strategy to maximize the system utility. As it is expected, the total participation level of the best effort strategy is the highest as shown in Figure 2(b). The main reason here is that all NIB nodes try their best to do the task, but this is not a Nash equilibrium status in practice. Besides, CrowdBox is better than random strategy in the total participation level, and it is more obvious with the increase of the number of NIB nodes.

In terms of the average participation level depicted in Figure 2(c), both CrowdBox and best effort strategy reach a stable state. In contrast, the average participation level of random strategy varies as the number of NIB nodes increases, and this is mainly because the NIB nodes randomly choose how to cooperate (e.g., whether participate or not and how to participate). Similar to the result of system utility, the number of participating nodes for CrowdBox also achieves the highest with the number of NIB nodes increasing according to Figure 2(d). This is mainly because CrowdBox is a Nash equilibrium status and an NIB node will cooperate only if it can obtain profits from it. In addition, the random strategy is still the worst case among the three algorithms, and we notice it results from that it is not a Nash equilibrium status.

We can see that CrowdBox has the highest system utility and the number of participating nodes compared with the other two benchmarks. Although the participation level of the best effort strategy is higher than CrowdBox and the random strategy, it is difficult to reach since nodes are rational in practice. Thus, CrowdBox outperforms the other two strategies with the increase in the number of NIB nodes.

5.3.2. The Number of NIB Nodes' Maximum Cost. Then, we evaluate all three strategies with different numbers of NIB nodes' maximum cost. In particular, the maximum cost value varies from 5 to 10 with the increment of 1, and Figure 3 depicts the final results.

From the perspective of system utility (i.e., Figure 3(a)), CrowdBox still outperforms the other two strategies (i.e., random and best response strategy) since it is the Stackelberg Nash equilibrium status. Furthermore, the best effort strategy is better than the random strategy in system utility



(a) System utility

(b) Total participation level

(c) Average participation level

(d) Performances with different numbers of NIB nodes

FIGURE 3: Performances with different numbers of NIB nodes' maximum cost.

with different maximum costs, and this is mainly because those NIB nodes with best strategy effort are always doing their best to provide communication resources.

The participation levels (i.e., Figures 3(b) and 3(c)) of the three strategies show similar trends where the best strategy is the highest and the random strategy is the lowest in most cases. The number of participating NIB nodes depicted in Figure 3(d) concludes that CrowdBox also can stimulate more nodes to participate in providing extra communication resources under different maximum costs of NIB nodes, and this is also the main goal of this paper. Specifically, CrowdBox can reach a Stackelberg Nash equilibrium where all participating NIB nodes cannot obtain more extra profits if it derives from the current strategy.

Similar to the last simulation, we can get that although CrowdBox does not perform as well as the best effort strategy in the participation level (i.e., total and average), CrowdBox also has the highest system utility and number of participating nodes compared with the other two benchmarks with varying maximum costs of NIB nodes.

To summarize, CrowdBox can achieve the highest system utility and number of participating NIB nodes, the two key metrics of this paper, contrasting with the other two benchmarks under various settings based on the realistic simulation scenario. CrowdBox also performs better than random strategy in the other two metrics (i.e., total and average participation level), and the best effort strategy is not practiced since NIB nodes are usually rational (selfish).

6. Conclusion

The edge computing-enabled Industrial Internet of Things (E-IIoT) has aroused strong attentions recently since it creates a favorable communication environment to realize the concept of smart industry under the 6G scenario. In this paper, we propose CrowdBox, a crowdsourcing-based NIB node recruitment algorithm, leveraging the Stackelberg game theory, to improve the communication capacities with the power of crowds. CrowdBox shows the Nash equilibrium of the Stackelberg game and can choose the best response strategy for both E-IIoT and NIB nodes. Finally, extensive evaluations are conducted to verify the performance of CrowdBox under different realistic simulation scenarios, and the result shows that CrowdBox outperforms the other two strategies.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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