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Adaptive information sharing approach for crowd networks based on two stage optimization

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Abstract

Purpose – This paper aims to optimize and evaluating the performance of the crowd networks through analyzing their information sharing patterns. That is, in a crowd network, the qualities of accomplishing tasks are highly dependent on the effective information sharing among intelligent subjects within the networks. Hence, proposing an adaptive information-sharing approach can help improve the performance of crowd networks on accomplishing tasks that are assigned to them.

Design/methodology/approach – This paper first introduces the factors that affect effectiveness of information-sharing pattern: the network topology, the resources owned by intelligent subjects and the degree of information demand. By analyzing the correlation between these factors and the performance of crowd networks, an Adaptive Information Sharing Approach for Crowd Networks (AISCN approach) is proposed. By referring to information needed for accomplishing the historical tasks that are assigned to a crowd network, the AISCN approach can explore the optimized information-sharing pattern based on the predefined composite objective function. The authors implement their approach on two crowd networks including bee colony and supply chain, to prove the effectiveness of the approach.

Findings – The shared information among intelligent subjects affects the efficiency of task completion in the crowd network. The factors that can be used to describe the effectiveness of information-sharing patterns include the network topology, the resources owned by intelligent subjects and the degree of information

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demand. The AISCN approach used heuristic algorithm to solve a composite objective function which takes all these factors into consideration, so that the optimized information-sharing pattern can be obtained.

Originality/value – This paper introduces a set of factors that can be used to describe the correlation between information-sharing pattern and performance of crowd network. By quantifying such correlation based on these factors, this paper proposes an adaptive information-sharing approach which can explore the optimized information-sharing pattern for a variety of crowd networks. As the approach is a data-driven approach that explores the information-sharing pattern based on the network's performance on historical tasks and network's characteristics, it is adaptive to the dynamic change (change of incoming tasks, change of network characteristics) of the target crowd network. To ensure the commonality of the information-sharing approach, the proposed approach is not designed for a specific optimization algorithm. In this way, during the implementation of the proposed approach, heuristic algorithms can be chosen according to the complexity of the target crowd network.

Keywords Supply chain, Information sharing, Crowd network

Paper type Research paper

1. Introduction

The phenomenon of crowd intelligence can be widely found in nature and human society. In the nature, the crowd intelligence leads to the ant colony effect, the formation of birds flying, etc. In the human society, the phenomenon of crowd intelligence can be leveraged to enterprises' operation and management process, industrial chain, etc. (Jiang and Jiang, 2004; Li and Qiao, 2015). Unlike the networks (such as computer networks, IoT networks) that are designed for accomplishing specific tasks, as a network that consists of human subjects, asset subjects and digital agent subjects, crowd network is required to accomplish different tasks (Prpic and Shukla, 2017). To accomplish these tasks, intelligent subjects within the crowd networks need to cooperate with each other through making interactions carried by information and behaviors. The completion of different tasks requires the possession of different information (Fehrenbacher and Djamasbi, 2017). In a crowd network with high network complexity, redundant information and limited resources, information should be exchanged selectively to achieve "low cost and high efficiency" under limited resources. When cooperating to complete tasks, intelligent subjects in the crowd network can choose to share specific information among their neighbors or spread to network to help each other better accomplish their tasks (He *et al.*, 2006; Rose *et al.*, 2003). Therefore, it is particularly important to determine the object and scope of information sharing. Because of the complexity of the topological structure of the crowd network, it is more difficult to consider the information-sharing scope of an intelligent subject in the whole network (under global conditions) than that in the neighborhood (under local conditions). Therefore, this paper proposes an Adaptive Information Sharing Approach for Crowd Networks (AISCN approach) to explore the optimized information-sharing pattern for crowd networks The approach adopts the idea of first local optimization and then overall optimization, and quantifies the effectiveness value of shared information IV(t) for a task t in the crowd network. As different intelligent subjects have different needs for information when doing different tasks, the demands of different information are also different. Moreover, a crowd network has limited resources instead of redundant resources. Therefore, we defined a set of factors that can be used to describe the effectiveness of information-sharing patterns, which include the network topology, the resources owned by intelligent subjects and the degree of information demand. The AISCN approach used heuristic algorithm to solve a composite objective function which takes all these factors into consideration, so that the optimized information-sharing pattern can be obtained. We implement our approach on two crowd networks including bee colony and supply chain, to prove the effectiveness of our approach.

This paper is organized as follows. The background and related works are introduced in Section 2. The shared information content is introduced in Section 3. Section 4 analyses factors of shared information. Section 5 introduces AISCN approach based on task. Section 6 describes using AISCN approach to analyze the applications of shared information in bee colony and supply chain. In Section 7, the paper is summarized.

2. Background and related work

2.1 Background

Intelligence refers to the responsiveness of an intelligent subject to environmental or external stimuli, including the corresponding speed, quality and learning ability. It is a measure of an intelligent subject's ability to achieve goals in various environments (Legg and Hutter, 2007; Legg and Veness, 2011). Intelligent subjects are entities with certain intelligence, including any human agent (individual, enterprise, institution) and machine agent (intelligent equipment, intelligent robot or goods). Crowd network is a simple regular network, random network or any complex network where complexity is between regular network and random network. A crowd network is usually formed by many intelligent subjects (network nodes) and the relationship among these subjects includes administrators, subordinators, cooperators, competitors, interest-related parties, irrelevant parties, etc.

Figure 1 illustrates the general workflow of a crowd network in which intelligent subjects interconnect, influence and interact with each other. The crowd network needs to complete different tasks assigned by the external environment. Tasks can be divided into a series of subtasks, which require intelligent subjects with specific professional abilities to complete. Action1 refers to the interaction between intelligent subjects (the interaction of information, behavior, etc.). Action2 refers to the interaction between different types of professional intelligent subjects, to interact with the completion results of subtasks and finally output the completion results of tasks. Accomplishment is the completion results of tasks by the crowd network. Rewards is the evaluation of the external environment for the completion results of tasks. The performance of a crowd network refers to its expected finishing quality (also called expected rewards) of a series of tasks that are assigned to the crowd network by the external environment. It can be seen that the interaction between intelligent subjects (such as information interaction) has an impact on the accomplishment rewards of tasks, and hence it affects the performance of the crowd network. Therefore, the objective of this paper is to improve the performance of a crowd network through optimizing the information-sharing pattern of the network.

2.2 Related work

In the crowd network, a large number of intelligent subjects cooperate with each other to complete specific complex task (Liang *et al.*, 2018). In the crowd network, an intelligent

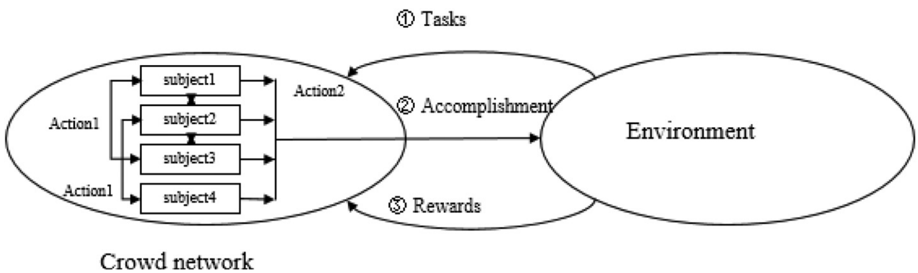

Figure 1.
A sample of the crowd network

subject may be an individual, organization, enterprise or a robot or other intelligent tool. The types of intelligent subjects in the crowd network are heterogeneous, and they operate in a complex environment which includes the information space, physical space and intelligence space (Liang *et al.*, 2018). One form of complexity in intelligent environments arises from their heterogeneous nature. The growing variety of environments and countless stereotypes of users operating intelligent environments will, theoretically, increase the complexity and resources needed to use them (Ananta *et al.*, 2013). At the same time, the structure of the hybrid space will be affected by the changes of the intelligent subject's class and task. The problem of big data in the network also has a certain impact on target analysis (Wang *et al.*, 2018). Therefore, it is not feasible to comprehensively evaluate the performance of intelligent subjects. Nowadays, people and computers can interact with each other in different ways, which is a process of information exchange between people and computers to complete certain tasks. Information interaction between people is also carried out in a certain way (Russell *et al.*, 2017). Forbrig *et al.* (2017) introduced the classification of human–computer interaction. Meanwhile, task response theory estimation and algorithm information theory can be used to test machine intelligence (Araiza-Illan *et al.*, 2016; He *et al.*, 2006). Sharing information should also be applied in various fields to promote the development of corresponding fields.

In medicine, information sharing integrates genome-based informatics, modernizes global disease surveillance and ensures more effective detection, prevention and control of endemic diseases (Aarestrup *et al.*, 2012). In modern commerce, supply chain also has competition, which is intrinsically complex. Information sharing and collaboration have shown an important role in the performance of supply chain (Wu *et al.*, 2014). Schloetzer (2012) also analyzed information sharing in supply chains. Li *et al.* (2015) proposed an information-sharing mechanism (ISM) to improve the performance of particle swarm optimization (PSO). The ISM allows each particle to share its best search information, so that all the other particles can take advantage of the shared information by communicating with it. In this way, the particles could enhance the mutual interaction with the others sufficiently and heighten their search ability greatly by using the search information of the whole swarm. Sharing of knowledge, information and practices across cultural and national boundaries has become a means to address critical global problems. Sharon *et al.* (2012) proposed a conceptual dynamic model to explain the further application of information sharing.

The existing works regarding optimizing the information sharing patterns have the following limitations: all the existing approaches are proposed for specific applications such as supply chain and information networks, and no comprehensive approach has been proposed; because most of the existing approaches did not take both the information demand of different kinds of tasks and dynamic characteristic of a network into consideration, these approaches cannot operate in an adaptive manner; the correlation between information sharing and network performance is not described in detail by most of the existing works. To explicitly describe the correlation between information sharing and network performance, this paper introduces a set of factors that can be used to describe such correlation. These factors are comprehensive enough to be mapped into most of the crowd networks. By quantifying such correlation based on these factors, this paper proposes an adaptive information-sharing approach which can explore the optimized information-sharing pattern for a variety of crowd networks. As the approach is a data-driven approach that explores the information-sharing pattern based on the network's performance on historical tasks and network's characteristics, the approach is adaptive to the dynamic change (change of incoming tasks, change of network characteristics) of the target crowd network.

3. Shared information content

Every individual in the crowd network has its own ontology information. The more information it has, the more predictability the behavior of the intelligent subject is (He *et al.*, 2006; Hu and Yang, 2009). This is because the intelligent subject who obtains more information and has higher intelligence level are more likely to trigger the optimized behavior scenario for a certain task. Therefore, to improve the performance of the crowd network, the information obtained by intelligent subjects within the crowd network should be maximized.

There are three basic elements in the crowd network: environment, individual and individual behavior rules (Liu and Wang, 2000; Wu *et al.*, 2003). All intelligent subjects perform tasks according to a cluster of rules in a specific environment, and complex collective behavior is carried out by the interactions among subjects. Through interacting with their neighbors or subjects that can be reached, the intelligent subjects can acquire information/knowledge, such as detail of the sub-tasks and collaborative rules, so that the sub-tasks that are assigned to the subject can be accomplished.

To describe the ISM, we need to describe the information-sharing behavior pattern between intelligent subjects. Specifically, the information-sharing behavior between intelligent subjects can be described by the amount of information shared between intelligent subjects by a behavior. The amount of information can be calculated through giving weight to all kinds of information shared and determining the scope (class) of information. The calculation equation (1) is as follows:

$$\mathrm{I}_s = \sum_{i=0}^{N} \sum_{j=0}^{M_i} R_j W_j F_j \tag{1}$$

where R_j is the scope of information exchanged and shared by class j of the first i intelligent subjects, $R_j = N$ (number of global sharing behavior) or K (number of local sharing behavior), W_j is the weight of exchangeable and sharable information in class j of the first i intelligent subjects, $F_j = 1$ (class j information exchanged and shared by the first i intelligent subjects) or 0 (class j information not exchanged and shared by the first i intelligent subjects).

According to equation (1), it is necessary to determine R_j and W_j of the information j of intelligent subject i in the network when calculating I_s, which is relatively difficult to determine effectively. Through exploring the factors that may affect the effectiveness of information-sharing patterns, we can explicitly describe the detail of R_j and W_j. In the following sections, we introduce these factors and propose an approach to obtain the optimal information-sharing pattern.

4. The analysis of factors of information sharing

In the crowd network, each individual can obtain local information from neighbors and obtain global information from intelligent subjects other than neighbors. Through learning from neighbors (also known as local information sharing), intelligent subjects can collect all the information owned by their neighbors (Bala and Goyal, 2010). On the other hand, the learning from intelligent subject other than neighbors (also known as global information sharing) can make intelligent subject escape from the local optimum to explore more information for completing the tasks. Hence, both local information sharing and global information sharing can promote the improvement of intelligence level of an intelligent subject. In this way, the whole crowd network will be evolved to gain higher finishing qualities of tasks and the high efficiency of task accomplishments. Figure 2 illustrates a typical ISM in the crowd network. We use Ind to represent the individual, and individuals that can directly interact with the ith individual are represented by 1-nei. Individuals that need to interact through 1-nei are represented by 2-nei, and so on. Individuals can directly obtain 1-nei information, but it needs to be obtained indirectly by a-nei ($1 \leq a < b$) to obtain b-nei information ($1 < b$).

4.1 The topological structure of the crowd network

In the crowd network, it is difficult to directly determine the optimal sharing scope for information owned by an intelligent subject. According to the content and scope of information and the topology of the network, the intelligent subject chooses whether to share information in the whole network (through the n-nei interaction mode in Figure 2) or only in the neighborhood. When determining this condition, it is necessary to consider whether the network structure can achieve global sharing and whether the resources owned by intelligent subjects can achieve global sharing. As shown in Figure 3(b), a network is divided into several sub-networks, in which case it is difficult to achieve global sharing. For a more regular network, as shown in Figure 3(a), global or local sharing is selected while considering resources. According to the x-nei ($1 \leq x < n$) interaction mode in Figure 2, the cost, benefit and resources to obtain the optimal implementation performance should be considered. Here we simplify the scope of information sharing. When a certain information is shared with the neighbor, the information owned by the neighbor changes. When sharing information with its neighbors, it is necessary to consider both information the received shared and the original, so as to realize the dynamic change of the information owned by the intelligent subject.

4.2 The degree of information demand

Intelligent subjects have their own information, and different intelligent subjects may contain different kinds of information. Suppose there are intelligent subjects a and b, where a contains two kinds of information, x_1 and x_2. Intelligent subject a can share these two kinds of information to subject b, where x_1 is useful for subject b to complete task t_1 and x_2 is

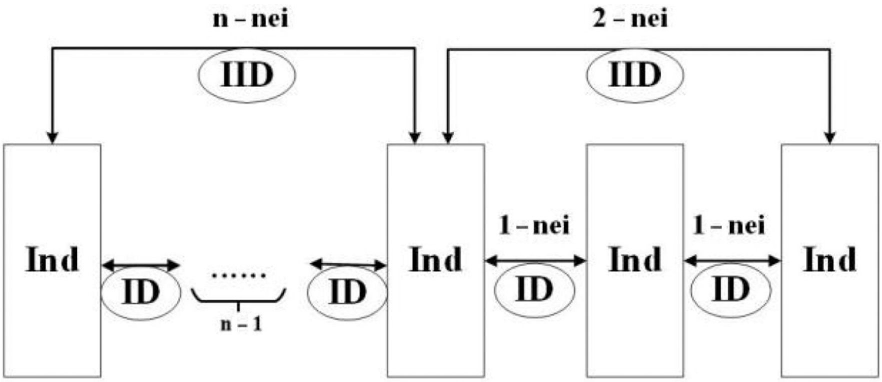

Figure 2.
Neighbor interaction pattern graph

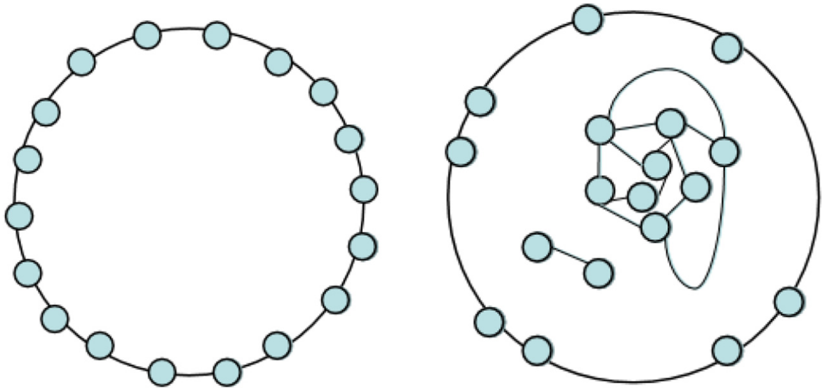

Figure 3.
Example diagram of sparse network a, and local dense network b

useless. And x_2 is useful when subject *b* completes task t_2, but x_1 is useless. Both x_1 and x_2 are useful when subject *b* completes task t_3, and x_2 is more useful. Therefore, in the process of information sharing, subject *b* receives the information from subject *a* equally without considering any conditions. It will be useless to share the information x_2 when task t_1 is completed, which results in unnecessary operations and waste of resources. Similarly, when subject *b* completes task t_2, the sharing of x_1 is also unnecessary. When task t_3 is completed, subject *b* is more likely to give priority to the information that plays a greater role in receiving shared information. For different tasks, different intelligent subjects have different needs for information. For a task, when an intelligent subject shares information, it should consider the degree of information demand of other intelligent subjects. The higher the degree of information demand ID, the greater the reward *R* for sharing the information. It is assumed that the two factors satisfy the polynomial relationship $R = \alpha * \mathrm{ID}^3 + \beta$ (α and β are polynomial coefficients), which can be expressed by $R = f(\mathrm{ID})$.

4.3 The resources owned by intelligent subjects

The resources owned by intelligent subjects are limited, and when sharing information, certain resources are needed. Therefore, when intelligent subjects share information, they need to do it under certain conditions. Once they exceed this limit, they canno*t* share information. During the information sharing, it is necessary to analyze the resources needed by information and the total resources owned by intelligent subjects. The resources needed for information are related to many factors, such as the form of information sharing, the type, storage and dissemination of information.

5. Adaptive information sharing approach for crowd networks based on task

5.1 Adaptive information sharing approach for crowd networks

By analyzing the factors of information sharing in Section 4, we can know that the topology structure of the crowd network, the degree of information demand and the resources owned by intelligent subjects will have an impact on information sharing. Given a complicated network topology, it is much more complicate to determine the sharing scope of each intelligent subject's information by taking both the limited resources and information demand into consideration. To make such sophisticated decision, the information-sharing process should be operated in a recurrent manner. For instance, given the information demand of information i for the current task and the resources owned by the target network, intelligent subject a makes decision whether to share information i with neighbor b and then updates the state of crowd network if information i is shared. In such a new state, subject b makes decision whether to share i with neighbors of b. After a set of iteration, the sharing pattern of information i to the whole network is finally determined.

The AISCN approach is proposed by combining the local optimization and global optimization together as a two-stage process. Here, we use Cost-effectiveness ratio (EC) and Reward as optimization criteria. EC evaluates the relative magnitude of improved effectiveness and increased costs, calculated by equation (3). Reward is the total reward for sharing information among the neighbors, $\text{Reward}_i = \text{Sum}(R_i*X_i)$ is the total reward of shared information by intelligent subject i and its neighbors. In the first stage, which is for performing local optimization, we select an appropriate optimization algorithm, to find the optimal information-sharing pattern among neighbors (information owned by each intelligent subject is changing dynamically, and information sharing is also changing dynamically). When obtaining optimal information-sharing pattern, Reward_i is mainly considered. If $\text{Reward}_i > 0$, then EC_i is calculated. The maximum value of Reward_i is obtained when $EC_i > 1$, and then the optimal information-sharing pattern of intelligent subject i is obtained. In the second stage, which is for performing global optimization, we use optimization algorithm to adjust the information-sharing pattern of each intelligent subject, by considering both Reward and EC. For each intelligent subject i, to get Reward_i and EC_i in equilibrium, where Reward_i and EC_i are relatively large. After the second stage, the optimized information-sharing pattern corresponding to the current task will be obtained.

The input of the optimization algorithm is TS_i, M_i, ID_i, S_i, $Nei(i)$, X_i. TS_i refers to the total amount of resources of intelligent subject i; M_i refers to the total information of intelligent subject i; ID_i refers to the degree of demand neighbors of i for information owned by intelligent subject i, specifically, the demand of subject i's neighbor k for information j is ID_{ijk}; S_i refers to the resources needed by intelligent subject i to share information with its neighbors, specifically, resources needed when sharing information j with neighbor k is S_{ijk}; Nei(i) is an array which refers to the neighbors of subject i; X_i represents the information-sharing pattern of intelligent subject i, X_{ijk} is 0 or 1 (1 indicates the information j of intelligent subject i shared with neighbor k, 0 indicates the information is not shared). Here, TS_i is a number, and M_i, ID_i, S_i, $Nei(i)$, X_i are all matrices with sizes of $1 \times M$, $M \times P$, $M \times P$, $1 \times P$, $M \times P$, respectively, where M represents the number of information owned by intelligent subject i, and P represents the number of neighbors of intelligent subject i. Therefore, the objective function is:

$$\text{Reward}_i = \text{Max}\Big(\text{Sum}\Big(R_i * \text{X}_i\Big)\Big) \quad s.t.\, Sum(S_i * X_i) <= TS_i \tag{2}$$

where R_i is a matrix with size $M \times P$, which refers to the reward for intelligent subject i after sharing information with neighbors; the reward of sharing information j with neighbor k is R_{ijk} ($R_{ijk} = \alpha * ID^3_{ijk} + \beta$). M_i, R_i, S_i and X_i all change in real time according to the change of information they own after sharing. $Reward_i$ is the total reward for sharing information among the neighbors, and it is meaningful to share information when $Reward_i$ is greater than 0 [$Reward_i > 0$, $\theta(Reward_i) = 1$, and $Reward_i \leq 0$, $\theta(Reward_i) = 0$.]. If $EC_i > 1$ (calculated by equation (3)), X_i is the required information-sharing pattern when $Reward_i$ is maximum:

$$EC_i = \frac{(E_s - E)/E}{(C_s - C)/C} = \frac{(E_s - E)*C}{(C_s - C)*E} \tag{3}$$

where C_s and E_s, respectively, represent the cost and effectiveness under the condition of sharing information, while C and E, respectively, represent the cost and effectiveness under the condition of non-sharing information (the cost and effectiveness need to be obtained according to the actual situation). EC_i evaluates the relative magnitude of improved effectiveness and increased costs. Only when $EC_i > 1$ (effectiveness is relatively higher than cost) can we choose to share information. On the contrary, we do not share information, and the sharing of intelligent subjects in this pattern is updated. The value of EC_i can be determined based on the following rules: $EC_i > 1$, $\theta(EC_i - 1) = 1$, and $EC_i \leq 1$, $\theta(EC_i - 1) = 0$.

Solving the EC_i and $Reward_i$ of intelligent subject i in the optimal information-sharing pattern ($EC_i > 1$ and $Reward_i > 0$, to avoid these two values being too large and causing calculation trouble, *ln* function can be used to standardize), and then using the optimization algorithm to optimize the information-sharing pattern of the whole network. Considering that the effectiveness improvement of each intelligent subject is large relative to the cost increase and the reward of information sharing is relatively large. Finally, under a certain task, the objective function is

$$IV(t) = \sum_{i=1}^{N} \left(\ln(Reward_i) + \ln(EC_i)\right)*\theta(Reward_i)*\theta(EC_i - 1) \; s.t. EC_i > 1, \; Reward_i > 0 \tag{4}$$

where N is the number of intelligent subjects in the network; IV(t) is an evaluation of the efficiency of information-sharing pattern for the whole network under task t, and the goal is to find the maximum value of IV(t); N represents the number of intelligent subjects in the crowd network; $\theta(x)$ is the heavyside function, where $x > 0$, $\theta(x)=1$ and $x \leq 0$, $\theta(x) = 0$.

AISCN based on task t is mainly divided into two stages: local optimization and global optimization.

- *Stage 1*: local optimization. For the input of TS_i, M_i, ID_i, S_i, *Nei(i)* and X_i, according to the characteristics of case to select an appropriate optimization algorithm, to obtain the optimal information-sharing pattern X_i for intelligent subject i. The goal is as follows: Max($Reward_i$) = Max(Sum(R_i*X_i). If $Reward_i > 0$, Sum(S_i * X_i) $\leq TS_i$ and $EC_i > 1$, X_i are desired.
- *Stage 2*: global optimization. $Reward_i$ and EC_i are obtained by Stage 1, and equation (4) is used to calculate IV(t). Using optimization algorithm to adjust the information-sharing pattern of some intelligent subjects, the goal is as follows: Max (IV(t)). Finally, the optimal information-sharing pattern of the whole crowd network is obtained.

5.2 AISCN implementation process

The implementation process of AISCN approach is proposed as follows:

Algorithm: AISCN implementation process

```
Input: Task t, Network topology TL, Degree of information demand ID,
       Total resources of each intelligent subject TS, Resources
       needed for each type of information S, Information of each
       intelligent subject M.
Output: Sharing pattern X, Sharing information value IV(t).
Initialization X, X_ijk = 0;
while( IV(t) is not max ) do
     for i = 1,2,3,..., N do
       get Nei(i) from TL;
       for j = 1,2,3,..., M do
         for k = 1,2,3,..., P do
           R_ijk = α*ID^3_ijk + β;
         end
       end
     Take TS_i, M_i, R_i, S_i, Nei(i), X_i as input of algorithm, to get
     best X_i
       Reward_i = Max(Sum(R_i*X_i)) s.t. Sum(S_i*X_i) <= TS_i;
       if Reward_i > 0 then
          EC_i = ((E_s − E)*C) / ((C_s − C)*E)
       end
       if EC_i <= 1 then
          Adjust X_i
       end
       Adjust M, need, S according to X_i
      end
     Take Reward_1,..., Reward_N, EC_1,..., EC_N as input of algorithm,
     to get max IV(t)
        IV(t) = Σ_{i=1}^{N} (ln(Reward_i) + ln(EC_i))*θ(Reward_i)*θ(EC_i − 1)
       if(IV(t) is max) then:
         return X, IV(t)
       else
       Adjusting the information sharing pattern of
       intelligent subjects
end
```

6. Case analysis

6.1 Information sharing in bee colony

In nature, the crowd network is equivalent to an ecological network, which contains all kinds of information, including physical information, chemical information and behavioral information. When an individual receives this information, they will make corresponding choices according to their needs or their environment, and first respond to the most useful or needed information. Bee colony is typical ISM in nature; when a worker bee finds a source of honey within 100 meters from the nest, it tells its peers through a waltz. When it finds a source of honey 100 meters away from the nest, it tells its peers through a wagging dance. They dance to convey information and share it throughout the colony, avoiding the repetition of useless behavior by other bees and reaping more food by more bees.

Bee colony can be divided into queen bee, male peak bee and worker bee according to the division of labor. Worker bee is divided according to different works. According to Figure 4(a), for task t_1 = "collecting honey," we use 1, 2, 3, 4, 5, 6 to represent queen bee, male peak bee, honey bee 1 responsible for search and collecting honey, honey bee 2 responsible for search and collecting honey, scout bee 1 responsible for looking for a new nest, scout bee 2 not responsible for looking for a new nest, six intelligent subjects, $N = 6$. The intelligent subjects can communicate with each other. In fact, the information owned by queen bee, male peak bee, scout bee 1 and scout bee 2 is useless to task t_1. The information owned by each intelligent subject is simply expressed as one kind. The input of AISCN is as follows: TS = (40, 30, 20, 20, 30, 30), M = ("information owned by the queen," "information owned by the male peak," "specific information about the honey source within 100 meters from the nest," "specific information about the honey source beyond 100 meters from the nest," "scout bee 1 scouted out the detailed location of the new nest," "scout bee 2 scouted out the detailed location of the new nest"), Nei = {(2,3,4,5,6), (1,3,4,5,6), (1,2,4,5,6), (1,2,3,5,6), (1,2,3,4,6), (1,2,3,4,5)}, ID = {(0,0,0,0,0),(0,0,0,0,0),(0,0,4,0,0),(0,0,4,0,0),(0,0,0,0,0),(0,0,0,0,0)}, S = {(3,3,3,3,3), (2,2,2,2,2),(3,3,2,2,3),(3,3,2,2,3),(3,3,1.5,1.5,3),(2,2,2,2,2)}. (Because the number of information and neighbors of each intelligent subject is different, the format of *Nei(i)*, ID_i, S_i and R_i is not unified, to make the meaning of *Nei(i)*, ID_i, S_i and R_i clear.) Suppose $\alpha = 0.25$ and $\beta = 0$. Therefore, according to $R_{ijk}=0.25*ID^3_{ijk}+0$, the initial rewards for sharing information is R={(0,0,0,0,0),(0,0,0,0,0), (0,0,16,0,0),(0,0,16,0,0),(0,0,0,0, 0), (0,0,0,0,0)}. Assuming that using the resource-reward ratio to represent the cost-effectiveness ratio in the case analysis, $EC_i = \mathrm{Sum}(R_i*X_i)/\mathrm{Sum}(S_i*X_i)$, it needs detailed calculation in practical application. The case is simple, and different situations can be analyzed; therefore, the violence enumeration method is chosen to obtain the optimal information-sharing pattern of intelligent subjects.

Stage 1: For intelligent subject 1, using optimization algorithm, we can get X_1 = (0, 0, 0, 0, 0), according to equation (2), $\mathrm{Reward}_1 = \mathrm{Sum}\ (R_1 * X_1) = 0$. Similarly, $\mathrm{Reward}_2 = 0$, X_2 = (0, 0,

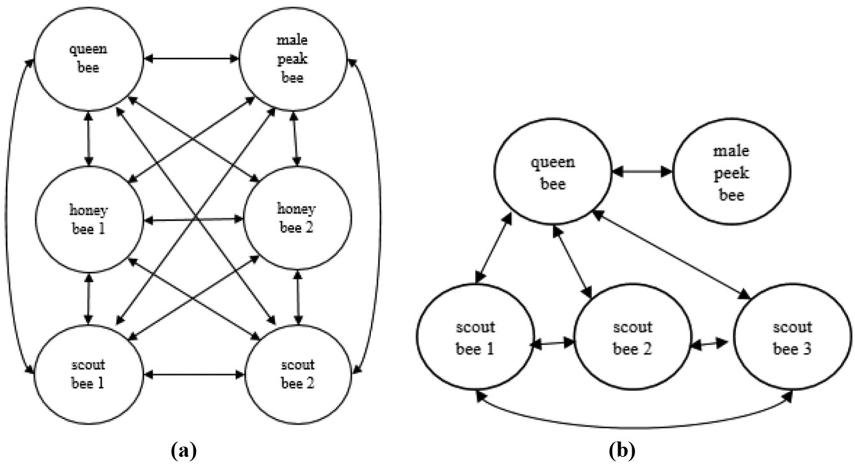

Figure 4. Two simple bee colony-sharing models

0, 0, 0); $\text{Reward}_3 = 16$, $\text{EC}_3 = 8$, $X_3 = (0, 0, 1, 0, 0)$. At the same time, adjust M, ID, S. M_4 = ("specific information about the honey source beyond 100 meters from the nest," "specific information about the honey source within 100 meters from the nest"). $ID = \{(0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,4,0,0;0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0)\}$, $S_4 = \{(3,3,3,3,3), (2,2,2,2,2), (3,3,2,2,3), (3,3,2,2,3;3,3,2,2,3), (3,3,1.5,1.5,3), (2,2,2,2,2)\}$. Similarly, $\text{Reward}_4 = 32$, $\text{EC}_4 = 8$, $X_4 = (0,0,1,1,0;0,0,0,0,0)$; $\text{Reward}_5 = 0$, $X_5 = (0,0,0,0,0)$; $\text{Reward}_6 = 0$, $X_6 = (0,0,0,0,0)$.

Stage 2: $\text{Reward}_1,\ldots, \text{Reward}_6$ and $\text{EC}_1,\ldots, \text{EC}_6$ are substituted into equation (4), $\text{IV}(t1) = 11.0904$. Here the optimization algorithm is used to optimize and adjust the intelligent subject's information-sharing pattern, until the optimal information-sharing pattern of the whole network is obtained.

The output of AISCN approach is as follows: under the optimal information-sharing pattern, $\text{IV}(t1) = 11.0904$, X_{313}, $X_{412} = 1$ and the rest of X is 0. The optimal information-sharing pattern is as follows: honey bee 1 shares the information, that is, "specific information of honey source within 100 meters from the nest" to honey bee 2, and honey bee 2 shares the information, that is, "specific information of honey source beyond 100 meters from the nest" to honey bee 1. And queen bee, male peak bee, scout bee1 and scout bee 2 do not share information. Finally, honey bee 1 and honey bee 2 all have these information: "specific information of honey source within 100 meters from the nest" and "specific information of honey source beyond 100 meters from the nest." According to the information of honey source been detected, the honey bee resources should be allocated reasonably. Specifically, honey bees should be allocated to collect honey source with higher quality honey.

To prove the adaptivity of our approach on different tasks and on different network topologies, we conducted another four implementations for the AISCN approach. To test the adaptivity of our approach on different network topologies, we implement our approach on a bee colony network with another network topology [see Figure 4(b)]. We represent queen bee, male peak bee, scout bee 1, scout bee 2 and scout bee 3 within the figure with discrete labels (1, 2, 3, 4, 5). To test the adaptivity of our approach on different tasks, we implement our approach on the case when bee colony network receives other kinds of tasks including t_2 = "Queen bee fertilization" and t_3 = "Get a new nest." Through implementing the AISCN approach, the optimal information-sharing patterns corresponding to two network topologies and two tasks are shown in Table I.

6.2 Information sharing in the supply chain

For supply chain management, through the effective information sharing among members of the supply chain, the efficiency of the supply chain can be improved. In practical operation, coordination and collaboration among supply chain members are mainly reflected in information sharing (Lu *et al.*, 2004). Obviously, because of the existence of organizational barriers and the needs of self-interests, effective information sharing is not easy to achieve. The quantification of the value of shared information will greatly promote the coordination of supply chain members in such case. The profit that can be made by information sharing includes promoting the investment of supply chain members in information infrastructure, improving the informatization level of supply chain members and promoting the integration among supply chain members. We used two simple supply chains to implement our approach, which are shown in Figures 5 and 6.

According to the supply chain structure in Figure 5, for task t_1 = "retailers retail a product to obtain net revenue," 1, 2, 3, 4, 5, 6, 7 are used to represent customers, retailers, distributors, manufacturers, transporter 1, transporter 2 and transporter 3, respectively; N = 7. According to the actual-to-preliminarily analysis, we can know that the information

Table I.
The optimal information-sharing pattern for different network topologies and tasks in bee colony

Different network topologies and tasks	Results obtained after stage 1	Optimal information-sharing pattern obtained after stage 2
Figure 4(a), t_2, ID = {(4,0,0,0,0), (3,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0)} TS, M, S, Nei, α and β remain unchanged	X_1 = (1,0,0,0,0), adjust ID. ID = {(0,0,0,0,0), (3,0,0,0,0; 0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0),(0,0,0,0,0)} X_2 = (1,0,0,0,0;0,0,0,0,0)	X_{111}, X_{211} = 1, and the rest of X is 0. Queen bee shares the information "information owned by the queen" to male peak bee Male peak bee shares the information "information owned by the male peak" to queen bee Honey bee 1, honey bee 2, scout bee 1 and scout bee 2 do not share information
Figure 4(a), t_3, ID = {(0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,4), (0,0,0,0,4)} TS, M, S, Nei, α and β remain unchanged	X_5 = (0,0,0,0,1), adjust ID. ID = {(0,0,0,0,0), (0,0,0,0,0; 0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,0), (0,0,0,0,4;0,0,0,0,0)}	X_{515}, X_{615} =1, and the rest of X is 0. Scout bee 1 shares the information "Scout bee 1 scouted out the detailed location of the new nest" to scout bee 2 Scout bee 2 shares the information "Scout bee 2 scouted out the detailed location of the new nest" to scout bee 1 Queen bee, male peek bee, honey bee 1 and honey bee 2 do not share information
Figure 4(b), t_2, TS = (20, 10, 15, 15, 15), M = ("The mating information owned by the queen," "The mating information owned by the male peak," "Scout bee 1 scouted out the detailed location of the new nest," "Scout bee 2 scouted out the detailed location of the new nest," "Scout bee 3 scouted out the detailed location of the new nest"), Nei = {(2,3,4,5), (1), (1,4,5), (1,3,5), (1,3,4)}, ID = {(4,0,0,0), (4), (0,0,0), (0,0,0), (0,0,0)}, S = {(4,2,2,2), (4), (2,2,2), (2,2,2), (2,2,2)}, α and β remain unchanged	X_1 = (1,0,0,0), adjust ID. ID = {(0,0,0,0), (3; 0), (0,0,0), (0,0,0),(0,0,0)} X_2 = (1;0)	X_{111}, X_{211} = 1, and the rest of X is 0. Queen bee shares the information "The mating information owned by the queen" to male peak bee Male peak bee shares the information "The mating information owned by the male peak" to queen bee Scout bee 1, scout bee 2 and scout bee 3 do not share information
Figure 4(b), t_3, ID = {(0,0,0,0), (0), (0.1,3,3), (0.1,3,3), (0,3,3)}, TS = (20, 10, 4, 4, 4), M, Nei, S, α and β same as the upstream in the table	X_3 = (0,1,1), adjust ID ID = {(0,0,0,0),(0),(0,0,0), (0.1,3,3;0,0,0),(0,3,3;0,0,0)} X_4 = (0,1,1;0,0,0), adjust ID ID = {(0,0,0,0),(0), (0,0,0;0,0,0),(0,0,0;0,0,0), (0,3,3;0,0,0;0,0,0)}	X_{312}, X_{313}, X_{412}, X_{413}, X_{412}, X_{513} = 1, and the rest of X is 0. Scout bee 1 shares the information "Scout bee 1 scouted out the detailed location of the new nest" to scout bee 2 and scout bee 3 Scout bee 2 shares the information "Scout bee 2 scouted out the detailed location of the new nest" to scout bee 1 and scout bee 3 Scout bee 3 shares the information "Scout bee 3 scouted out the detailed location of the new nest" to scout bee 1 and scout bee 2 Queen bee and male peek bee do not share information

owned by the transporter is not very useful for task t_1. For the consumer's consumption and distributor's storage and pricing of the product, they are useful for task t_1. The manufacturer's manufacturing capacity has no direct impact on task t_1. The input of AISCN approach is TS = (10, 10, 16, 10, 10, 10, 10), M={("the consumption of the product," "the highest acceptable price of the product"), ("the purchase of the product," "pricing of the product"), ("the storage of the product," "price of the product"), "the production of the product," "the transportation in transporter 1 of the product," "the transportation in transporter 2 of the product," "the transportation in transporter 3 of the product")}. Business 3 Transportation Situation. As seen from Figure 5, Nei = {(2,7), (1,3,6,7), (2,4,5,6), (3,5), (3,4), (2,3), (1,2)}, ID = {(2,0;1.5,0),(0.5,0.5,0,0;0.1,0.2,0,0), (3,0.5,0,0;2,0.5,0,0), (0.5,0), (0,0), (0,0), (0,0)}, S = {(2,2;2,2), (2,2,2,2;2,2,2,2), (2,2,2,2;2,2,2,2), (2,2), (2,2), (2,2), (2,2)}. (Because the number of information and neighbors of each intelligent subject is different, the format of $Nei(i)$, ID_i, S_i and R_i is not unified, to make the meaning of $Nei(i)$, ID_i, S_i and R_i clear.) Suppose $\alpha = 1$ and $\beta = 0$. Therefore, according to $R_{ijk} = 1{*}ID^3_{ijk} + 0$, the initial rewards for sharing information is R = {(8,0;6.25,0), (0.125,0.125,0,0;0.001,0.008,0,0), (27,0.125,0,0;8,0.125,0,0), (0.125,0), (0,0), (0,0),(0,0)}. Assuming that using the resource-reward ratio to represent the cost-effectiveness ratio in the case analysis, EC_i = Sum $(R_i{*}X_i)$/Sum $(S_i{*}X_i)$, it needs detailed calculation in practical applications. The case is simple, and different situations can be analyzed; therefore, the violence enumeration method is chosen to obtain the optimal information-sharing pattern of intelligent subjects.

Stage 1: For intelligent subject 1, using optimization algorithm, we can get X_1= (1,0;1,0), according to equation (2), Reward$_1$= Sum$(R_1{*}X_1)$ = 14.25, EC$_1$ = 3.5625, X_1 = (1,0;1,0). At the same time, adjusting M, ID, S, M_2=("the purchase of the product," "pricing of the product," "the consumption of the product," "the highest acceptable price of the product for customers"), ID_1 = (0,0;0,0), ID_2 = (0.5,0.5,0,0;0.1,0.2,0,0; 0,0.2,0,0;0,0.2,0,0), S_2 = (2,2,2,2;2,2,2,2;2,2,2,2;2,2,2,2); Similarly, EC$_2$ < 1, Reward$_2$ = 0; Reward$_3$ = 35.25, EC$_3$ =

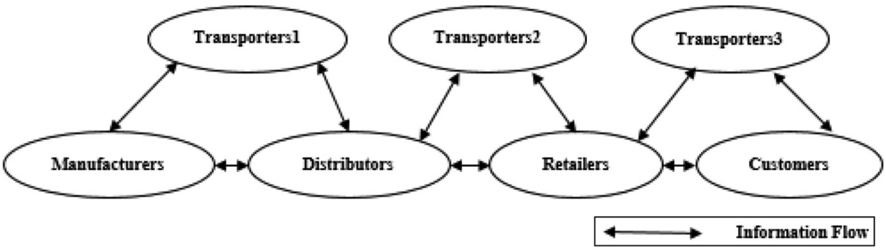

Figure 5.
A generalized supply chain-sharing model

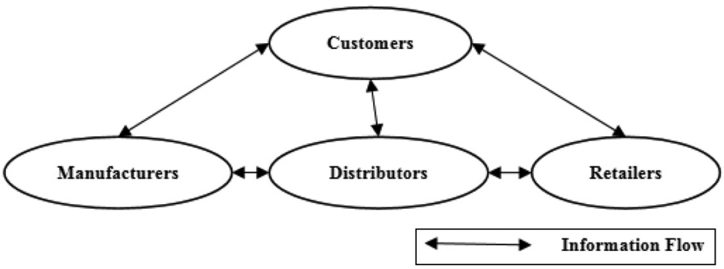

Figure 6.
A simple supply chain-sharing model

4.40625, X_3 = (1,1,0,0;1,1,0,0); $\text{Reward}_4 = \text{Reward}_5 = \text{Reward}_6 = \text{Reward}_7 = 0$ (for $EC_i < 1$, i = 4,5,6,7).

Stage 2: $\text{Reward}_1, \ldots, \text{Reward}_7$ and $\text{EC}_1, \ldots, \text{EC}_7$ are substituted into equation (4), IV(t1) = 8.9550. Using the optimization algorithm to optimize, adjust the intelligent subject's information-sharing pattern, until the optimal information sharing pattern of the whole network is obtained.

The output of AISCN approach is as follows: under the optimal information-sharing pattern, IV(t2) = 9.6339, X_{111}, X_{121}, X_{311}, X_{321} = 1, and the rest of X is 0. The optimal information-sharing pattern is as follows: customers share the information "the consumption of the product" and "the highest acceptable price of the product" to retailers, and distributors share the information "the storage of the product" and "price of the product" to retailers. And retailers, manufacturers, transporter 1, transporter 2 and transporter 3 do not share information. Finally, retailers have these information: "the purchase of the product," "pricing of the product," "the consumption of the product," "the highest acceptable price of the product for customers," "the storage of the product" and "price of the product." According to t, the consumer's consumption and the highest acceptable price, as well as the reserve and pricing of the product by the distributor, the retailer determines the quantity of the product purchased and the selling price of the product. Thus, the net income of retail sales of this product is the highest, that is, the effectiveness of task t is the largest.

In order to prove the adaptivity of our approach on different tasks and on different network topologies, we conducted another four implementations for the AISCN approach. To test the adaptivity of our approach on different network topologies, we implement our approach on a supply chain network with another network topology [see Figure 5(b)]. We represent customers, retailers, distributors, manufacturers and transporters within the figure as discrete labels (1, 2, 3, 4). To test the adaptivity of our approach on different tasks, we implement our approach on the case when supply chain networks receive other kinds of tasks, including t_2 = "Storage and price of a product for distributors" and t_3 = "Production of a product for manufacturers." Through implementing the AISCN approach, the optimal information-sharing patterns corresponding to two network topologies and three tasks are shown in Table II.

7. Conclusion

To optimize and evaluate the performance of the crowd networks through analyzing their information-sharing patterns, this paper introduced the factors that affect effectiveness of information-sharing pattern: the network topology, the resources owned by intelligent subjects and the degree of information demand. To analyze the correlation between these factors and the performance of crowd networks, an Adaptive Information Sharing Approach for Crowd Networks (AISCN approach) is proposed. By referring to information needed for accomplishing the historical tasks that are assigned to a crowd network, the AISCN approach can explore the optimized information-sharing pattern based on the predefined composite objective function. As the approach is a data-driven approach that explores the information-sharing pattern based on the network's performance on historical tasks and network's characteristics, the approach is adaptive to the dynamic change (change of incoming tasks, change of network characteristics) of the target crowd network. To ensure the commonality of the information-sharing approach, the proposed approach is not designed for a specific optimization algorithm. In this way, during the implementation of our approach, heuristic algorithms can be chosen according to the complexity of the target crowd network. We implement our approach on two crowd networks, including bee colony

Table II. The optimal information-sharing pattern for different network topologies and tasks in supply chain

Different network topologies and tasks	Results obtained after stage 1	Optimal information-sharing pattern obtained after stage 2
Figure 5, t_2, ID = {(1.5,0;1.5,0), (0.4,2.5,0,0;0.2,2.5,0,0), (0.4,0.5,0,0;0.5,0.5,0,0), (2.5,0), (0,0), (0,0), (0,0)} TS, M, S, Nei, α and β remain unchanged	X_1 = (1, 0;1, 0), adjust ID. ID = {(0.4,0;0.2,0), (0.4,2.5,0,0;0.2,2.5,0,0;0,2.5,0,0;0,2.5,0,0), (0.4,0.5,0,0;0.5,0.5,0,0),(2.5,0), (0,0), (0,0), (0,0)} X_2 = (1,1,0,0;0,1,0,0;0,1,0,0;0,1,0,0). X_4=(1,0)	X_{111}, X_{121}, X_{212}, X_{222}, X_{232}, X_{242}, X_{411} = 1, and the rest of X is 0. Customers share the information "the consumption of the product" and "the highest acceptable price of the product" to retailers Retailers share the information "the purchase of the product," "pricing of the product," "the consumption of the product," "the highest acceptable price of the product for customers" to distributors Manufacturers share the information "the production of the product" to distributors Distributors, transporter 1, transporter 2, transporter 3 do not share information
Figure 5, t_3, ID = {(1.5,0;0.5,0), (0.5,0.5,0,0;0.1,0.2,0,0), (0.5,3,0,0;0.5,0.5,0,0), (0.5,0), (0,0), (0,0), (0,0)} TS, M, S, Nei, α and β remain unchanged	X_1 = (1, 0; 0, 0), adjust ID. ID = {(0.4,0;0.2,0), (0.5,0.5,0,0;0.1,0.2,0,0;0,1.5,0,0), (0.5,3,0,0;0.5,0.5,0,0),(0.5,0), (0,0), (0,0), (0,0)} X_2 = (0,0,0,0;0,0,0,0;0,1,0,0),adjust ID. ID = {(0.4,0;0.2,0), (0.5,0.5,0,0;0.1,0.2,0,0;0,0.5,0,0), (0.5,3,0,0;0.5,0.5,0,0;0,3,0,0),(0.5,0), (0,0), (0,0), (0,0)} X_3 = (1,1,0,0;1,1,0,0;0,1,0,0)	X_{111}, X_{232}, X_{312}, X_{332} = 1, and the rest of X is 0. Customers share the information "the consumption of the product" to retailers Retailers share the information "the consumption of the product" to distributors Distributors share the information "the storage of the product" and "the consumption of the product" to manufacturers Manufacturers, transporter 1, transporter 2, transporter 3 do not share information

(*continued*)

Different network topologies and tasks	Results obtained after stage 1	Optimal information-sharing pattern obtained after stage 2
Figure 6, t_2, TS = (8, 10, 15, 10), M = {("the consumption of the product," "the highest acceptable price of the product"), ("the purchase of the product," "pricing of the product"), ("the storage of the product," "price of the product"), "the production of the product"}, Nei = {(2,3,4), (1,3), (1,2,4), (1,3)} ID = {(1.2,3,1;1.2,3,1), (0,1.5;0,1.5), (0,0.5,0.5;0,0.5,0.5), (0,1.5)} S = {(2,2,2;2,2,2),(1.5,2;1.5,2), (2,2,3;2,2,3),(1,2)} α and β remain unchanged	X_1 = (1,1,0;1,1,0), adjust ID. ID = {(0,0,0;0,0,0),(0,1.5;0,1.5;0,0;0,0), (0,0.5,0.5;0,0.5,0.5;0,0,0;0,0,0), (0,1.5;0,0;0,0)} X_2 = (0,1;0,1;0,0;0,0) X_4 = (0,1;0,0;0,0)	X_{112}, X_{122}, X_{212}, X_{222}, X_{412} = 1, and the rest of X is 0. Customers share the information "the consumption of the product" and "the highest acceptable price of the product" to distributors Retailers share the information "the purchase of the product" and "pricing of the product" to distributors Manufacturers share the information "the production of the product" to distributors Distributors do not share information
Figure 6, t_3, TS = (6,12,6,8), ID = {(0.8,1,3;0.5,0.8,1), (0,0.5;0,0.5), (0,0.5,3;0,0.5,0.5), (0,0.5)}, M, Nei, S, α and β same as the upstream in the table	X_1 = (0,1,1;0,0,1), adjust ID. ID = {(0,0,0;0,0,0),(0,0.5;0,0.5), (0,0.5,3;0,0.5,0.5;0,0.5,0), (0,0.5;0,0;0,0.5)}, adjust ID. X_3 = (0,1,1;0,0,0;0,0)	X_{113}, X_{313} = 1, and the rest of X is 0. Customers share the information "the consumption of the product" to manufacturers Distributors share the information "the storage of the product" to manufacturers Manufacturers and retailers do not share information

Table II.

and supply chain, to prove the effectiveness of our approach. Based on network topologies and incoming tasks of different bee colony and supply chain networks, the AISCN approach is implemented to adjust adaptively to obtain the optimal information-sharing pattern for each task. In the future, we will further study different complex network structures and propose appropriate optimization algorithms to make the AISCN approach less complex and more efficient, and make a deeper analysis of the impact of shared information on the crowd network.

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