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An Improved Artificial Bee Colony Algorithm for Community Detection in Bipartite Networks

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ABSTRACT In the past few decades, although people have conducted in-depth research on community detection in one-mode networks, community detection in bipartite networks has not been extensively researched. In this paper, we propose an improved artificial bee colony algorithm named IABC-BN, which is used to detect the communities in two-mode graphs (i.e. bipartite graphs) with two kinds of vertices in the cluster (i.e. community). Firstly, this paper proposed a novel population initialization process of artificial bee colony (ABC) method for two-mode graph cluster identification. This initialization method can improve the diversity of initial population of ABC and speed up its convergence rate. Secondly, in the employed bee search step of the algorithm, a new combinatorial search equation is proposed. This equation is guided by the global optimal solution and the better neighbour solution of the current solution. By using this combination equation and the increased parameter perturbation frequency, the exploitation ability of the algorithm is further enhanced. Thirdly, in the onlooker bees step, another new combination search equation is also proposed. This equation improves the exploitation level of the algorithm, and an opposition based studying method is employed to promote the exploitation ability of the algorithm. Lastly, in scout bee stage, a probability threshold β is introduced to enhance the exploration ability of the algorithm and improve the population diversity of the algorithm. To our knowledge, the IABC-BN method presented in this paper is the first ABC method used to cluster identification in two-mode graphs with two kinds of vertices in the cluster. For verifying the accuracy of the results of the proposed method, a large number of experiments are carried out making use of synthetic bipartite graphs and real bipartite graphs. The test outcomes show that this algorithm is an excellent algorithm for cluster discovery in two-mode graph.

INDEX TERMS Swarm intelligence, social network, two-mode network, cluster partition.

I. INTRODUCTION

Network science is a basic subject across computer science, social science, biology and other disciplines. Complex graphs stand for different complex systems of various subjects. In general, complex networks consist of nodes (or vertices) and links (or edges). A vertex stands for an individual of a complex graph, and a link represents the interaction and communication between two individuals of a complex graph. Biological researchers try to comprehend the relevance between disease genes and all known phenotypes from a network of disease genes and disorders. Sociologists study the behavior characteristics of various user groups in online social networks. A lot of other examples can be from transportation, computer science, marketing, economics, politics, etc.

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Many studies concentrate on one-mode network or unipartite network, which includes only one kind of nodes. However, networks in the real world usually include many types of nodes. The most simple case is two-mode network or bipartite network including two different types of nodes. In bipartite networks, edges exist only between different types of nodes. Community structure not only reveals coarse-grained connections in networks, but also plays important roles in the functioning of networks. A classical concept is that a cluster is a set of nodes, nodes in the cluster are densely connected, while nodes in different clusters are sparse interlinked. A key feature of the majority of bipartite networks is cluster structure, in which the networks are split into groups of nodes and links. Also, the community offers a preferable way to comprehend modular structure of bipartite networks. With regard to bipartite community, there are two views in the previous literature. Nodes in the same community are

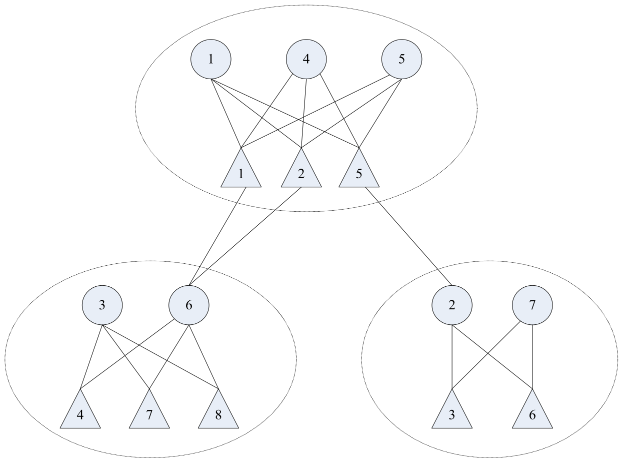

FIGURE 1. A bipartite network containing three clusters.

considered the same or different types. Figure 1 demonstrates an instance of a two-mode network containing three clusters.

The study of community partition (i.e. community detection) algorithm has been widely concerned. The typical algorithms such as using core-vertices, intimate degree, maximal sub-graph, neighborhood etc. are presented. But all these algorithms are merely appropriate for unipartite (i.e. one-mode) networks. Two-mode networks (i.e. bipartite networks) include more complicated hidden information, relationships and structures than unipartite networks. Therefore, the detection of clusters set in two-mode networks has evolved into a research hotspot.

In two-mode graphs, a lot of community identification (i.e. community detection) methods [14]–[16] have been presented. These algorithms can be divided into two categories. The first category is to project two-mode networks into one-mode networks. However, one of the main disadvantages of these algorithms is that some important information is lost in the projection process, and some unvaluable information is added. This situation leads to the decline of community identification precision. The second type of method directly deals with two-mode networks. These algorithms try their best to retain the merits of the original network structure information, making them a better option.

Recently, swarm intelligence and evolutionary computation have developed into research hotspots in optimization technology. Evolutionary computing is a problem solving model based on evolutionary process. It mainly contains Differential Evolution (DE), Evolutionary Programming (EP), Genetic Programming (GP), Genetic Algorithms (GA) and Evolution Strategies (ES), and so forth. Swarm intelligence refers to the characteristic that many simple individuals cooperate with each other to produce complex intelligent behaviors. The swarm intelligence model mainly includes Artificial Bee Colony algorithm (ABC), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), etc. These methods provided new ways for research workers to solve complex majorization problems. More and more research workers began to participate in the study of swarm intelligence and evolutionary computing optimization method. These research workers have made significant advance in enhancing the search ability of these algorithms and applying them in different areas.

Since the ABC algorithm was first proposed by Karaboga [11] in 2005, it has attracted a large number of researchers for its good majorization effect, easy implementation, few control parameters and simple concept. It has been extensively used for various fields. Basturk and Karaboga have carried out detailed experimental studies on the ability of the basic ABC in the references [12], [13]. In Ref. [12], the authors compare ABC with evolutionary algorithm (EA), DE and PSO on multidimensional functions. Ref. [13] also compared ABC algorithm with PSO, DE, GA and various versions of ES. Comparison outcomes demonstrated that all evaluation indexes of ABC method were better than or analogous to the rest of majorization methods. Therefore, the artificial bee colony method is widespread employed to solve a variety of majorization problems.

However, like other methods, ABC is slow in convergence speed. Due to its solution update formula only modifies one component of the solution vector every time, the artificial bee colony algorithm has good exploration performance and poor exploitation performance. To address the above disadvantages, this paper proposes an improved artificial bee colony method named IABC-BN for two-mode community detection in two-mode graphs. For expediting the rate of convergence, a novel ABC population initialization method is presented. In the employed bees search step of the proposed IABC-BN, a new combination search strategy is proposed to find novel candidate solutions. This search strategy accelerates the convergence rate of the method and improves the exploitation ability of the method. In this strategy, we use the Manhattan similarity formula to choose a better neighbour solution of the current solution. Then, this better neighbour solution is used to guide the search process. Inspired by the classical variation strategy DE/rand/1, we present another new combination search strategy in the onlooker bees phase of IABC-BN. This strategy improves the exploitation ability of the algorithm and enhances the precision of the solution. In the scout bees step, we introduce a control parameter β. It is used to control whether a novel food source is generated stochastically for the exhausted food source. This not only improves the exploration ability of the IABC-BN, but also enhances its population diversity. To our knowledge, the presented IABC-BN is the first ABC algorithm used for cluster partition in two-mode graphs with two kinds of vertices in the cluster. In order to verify the solution ability of the IABC-BN, this paper conducted a good deal of tests on 5 synthetic social graphs and 6 real social graphs. In the experiment, IABC-BN was compared with the existing three well-known two-mode graph cluster partition algorithms. The test outcomes indicate that the proposed algorithm is better than the existing algorithms.

The organization of the rest sections of this article is described below. The relevant work of this study is introduced in Section II. Some basic notions and preliminary knowledge relevant to this study are formulated in Section III. In the meantime, this section states the basic artificial bee colony (ABC) algorithm. In Section IV, the presented IABC-BN algorithm for cluster detection in the two-mode network is proposed. This section introduces the initialization step, the employed bees step, the onlooker bees step and the scout bees step of IABC-BN algorithm in detail. Section V shows the test outcomes on synthetic bipartite graphs and real-world bipartite graphs. Finally, the conclusions of this study are given in Section VI.

II. RELATED WORKS

A. COMMUNITY DETECTION ALGORITHMS IN BIPARTITE NETWORKS

There are two cluster detection methods in two-mode graphs: one is a unipartite projection method, and the other is a method that directly handles two-mode networks.

1) UNIPARTITE PROJECTION

Unipartite projection method transforms a two-mode graph into unipartite graph through projecting to obtain cluster structure. Unipartite projection algorithms are divided into two kinds of algorithms: weighted projection algorithm and unweighted projection algorithm. For the analysis of bipartite network, the unweighted projection algorithm is the most commonly used and the easiest to implement. For example, Comar *et al.* [14] put forward a method to detect the set of clusters simultaneously in diverse two-mode graphs. The experimental outcomes indicated that compared with the weighted projection algorithms, this method has fast convergence speed and is easy to expand. Lehmann *et al.* [21] proposed an algorithm on the basis of extension of the k-clique cluster partition method to identify overlapping two-mode cluster structure. However, a major disadvantage of these algorithms is that some important information is lost and some unvaluable information is added in the projection process. Due to the disadvantages of unweighted projection methods, weighted projection algorithms are presented. Such as Zhang and Ahn [22] presented a weighted symmetric binary matrix factorization to identify reduplicated community structure. Zhao *et al.* [23] generalized the Louvain method to the Bi-Louvain method, and presented a two-phase algorithm for identifying the set of clusters in two-mode graphs. In [24], the authors extended unipartite cluster identifying method Louvain to biological two-mode network, and presented a high-efficiency biLouvain method. This method is a group of high-efficiency heuristic algorithms to identify the community structure of bipartite networks. Inspired by the dynamics of information exchange based on network, Wu *et al.* [15] presented a unified projection frame. It can be used to identify the cluster structure of two-mode networks. To some extent, the disadvantages of information loss and poor accuracy resulted from unweighted projection method can be solved by weighted projection method, because the performance of cluster detection largely relies on the weight. But the weighted projection algorithm still has the problem of information loss and poor accuracy.

2) HANDLING BIPARTITE NETWORKS DIRECTLY

Different from the unipartite projection algorithms, these algorithms directly deal with two-mode networks and retain the initial information structure to the hilt. For example, Du *et al.* [25] presented an algorithm to identify clusters in large-scale sparse two-mode networks. The main idea of this algorithm is to gradually expand each cluster core until each node belongs to a cluster. Yang *et al.* [26] designed a new cluster partition algorithm on the basis of the utilization of link directedness and the connectivity structure of clusters. Authors of [16] employed the free node and key bi-cluster notion, and presented a method to identify cluster structure in two-mode networks. According to this algorithm, the authors of [27] defined two parameters for the relations between vertices of the same kind and vertices of different kinds. Afterward, by searching and expanding the core cluster, they can get the sub-cluster. Finally, global clusters were obtained through a certain merge rule. Chen *et al.* [28] proposed a new cluster partition method. This method uses a nonnegative matrix factorization model to identify clusters from unipartite and two-mode networks.

Unipartite projection method has the problem of information loss in the process of projection. The unipartite projection method first transforms a bipartite graph into unipartite graph through projection, and then detects the community structure on the obtained unipartite graph. Therefore, the unipartite projection method is complicated and difficult to implement. In addition, the accuracy of the results of the unipartite projection method is very poor, and its running time is generally very long. A class of algorithms that directly deal with the bipartite network does not have the problem of information loss. In contrast, this kind of algorithm has made great progress in the aspects of easy implementation, accuracy of results, convergence speed and so on. But in these aspects, these algorithms still need further improvement. The algorithm proposed in this paper belongs to the category of algorithms dealing with bipartite networks directly. It meets the above requirement. Compared with previous such algorithms, our proposed algorithm has made great progress. Our algorithm is much simpler and easier to implement, the result accuracy is much higher, and the convergence speed is much faster.

B. DEVELOPMENT OF ARTIFICIAL BEE COLONY METHOD

Since the ABC method was first presented in 2005, it has attracted a large number of researchers' interest, and has been widely used for a variety of fields [11]. The ABC method has strong exploration ability, but weak exploitation ability. In order to enhance its exploitation ability, research workers have done much study work.

Enlightened by PSO algorithm, Zhu and Kwong [29] integrates the information of the optimal solution so far into the search formula to enhance the exploitation capability of ABC method. The authors of Ref. [30] used the universal gravitational formula in onlooker's search formula to improve the exploitation capability. Motivated by differential evolution method, Banharnsakun *et al.* [31] shared the optimal solution up to now in the whole population so as to let the novel solution close to the best solution to the maximum extent. Taking advantage of the randomness, irregularity and ergodicity of chaotic map, the Chaotic ABC method is presented by Alatas [32]. Based on the variation (i.e. mutation) operator in DE method, Gao *et al.* [33] proposed two novel search formulas ABC/best/1 and ABC/best/2 to enhance the exploitation ability of ABC. The new formulas produce new solutions in the vicinity of the optimal solution up to now. To improve the exploitation ability of the onlooker bees, Lin *et al.* [34] presented a new search formula and a novel probability choice formula for the onlooker bees. In order to enhance exploitation ability, the CABC presented by Luo *et al.* [35] uses a novel search formula in the onlooker bee phase. This formula produces novel candidate individuals in the vicinity of the optimal solution up to now. In Ref. [36], Gao *et al.* presented a novel search formula, whose operation is analogous to the crossover operator of the genetic algorithm. The EABC proposed by Gao *et al.* [37] employed two novel search formulas and introduced normal distribution into the scale factor to better retain the diversity of population. The authors of Ref. [38] used a novel search formula in the onlooker bees step. This formula improved the local optimization capability of the method by means of the optimal solution in the neighbours. In Ref. [39], direction information is added to each component of a solution, and the search equation is modified based on the direction information to produce a new solution. In distABC [40], in order to prevent the population from falling into the local best solution, instead of the traditional difference update rule, the distributed update rule is used and a novel equation is presented.

The hybrid method is also a valuable way to enhance the optimization ability of ABC. In order to promote the optimization capability of ABC, research workers have done a lot of research on hybrid methods. Some research workers combine ABC with local search. In Ref. [41], the rotation method was combined with ABC for local search to improve exploitation. Gao *et al.* [36] used the orthogonal learning method in the searching process of CABC. Gao *et al.* [42] use Powell's method for local search. Zhang *et al.* [43] presented GABC1 and GABC2 to enhance exploitation ability through offering a best dimension. Kang *et al.* [44] proposed HABC algorithm, whose exploration stage was completed by artificial bee colony algorithm and the exploitation stage was realized through pattern search method. For overcoming the shortcomings of an onefold search equation, other research workers integrate multiple search equations to enhance the optimization ability of artificial bee colony algorithm. To promote the optimization capability of ABC, Gao and Liu [45] integrated standard ABC with ABC/best/1 on the strength of probability 'p' to equilibrate exploration and exploitation. Enlightened by the division of labor and cooperation, the authors of Ref. [46] developed the ILABC algorithm. This algorithm dynamically split the population into several subpopulations, and introduced two novel search formulas to realize the information exchange between one swarm and other swarms. In Ref. [47], gene combination was introduced into the original ABC to enhance the solution ability of the method.

In order to promote the performance of artificial bee colony algorithm, some research workers combined parameter adaptation with it. Liang *et al.* [48] added a scale factor to the new designed search strategy to enhance the search performance by obtaining a proper scale factor for the present step in the search process of the algorithm. The authors of Ref. [49] add inertia weight, acceleration coefficient and the optimal solution up to now into the search strategy to equilibrate the exploration and exploitation of the method. For reducing the running time of the algorithm, Akay and Karaboga [50] introduced the scaling factor and disturbance frequency into ABC to promote the algorithm's performance.

The traditional ABC algorithm is good at exploration but not good at exploitation. This results in poor accuracy and slow convergence speed of the traditional ABC algorithm. The above variants of ABC algorithm improve the exploitation ability of ABC algorithm to a certain extent, so as to improve the accuracy of the results of ABC algorithm and the convergence speed of the algorithm. However, further improvement is still needed in these aspects. The IABC-BN algorithm proposed in this paper achieves this. Since the IABC-BN algorithm is the first ABC algorithm to be applied to bipartite network community detection, there is no comparison of the performance of IABC-BN and other ABC algorithms on the community detection of the bipartite network in the experiment of this paper.

III. BASIC NOTIONS AND BACKGROUND KNOWLEDGE

A. DEFINITION OF TWO-MODE NETWORK AND ITS CLUSTER

A given graph $G = (V, E)$ is two-mode (or bipartite) if V is divided into two sub sets V_1 and V_2, such that $V_1 \bigcap V_2 = \emptyset$ and $E \subseteq V_1 \times V_2$, where V is the set of nodes or vertices, E is the set of edges or links. Let $|V_1| = p, |V_2| = q$, and $p + q = n$. Link e_{ij} only exists between different kinds of vertices, that is to say, $e_{ij} \in E\ (v_{1i} \in V_1, v_{2j} \in V_2)$. $|E| = m$ represents the number of links in graph G. The following matrix AM is the adjacency matrix of G.

$$AM = \begin{vmatrix} 0_{p*p} & AM'_{p*q} \\ AM'^{T}_{p*q} & 0_{q*q} \end{vmatrix}$$

where AM'_{p*q} is a non-zero matrix, 0_{p*p} and 0_{q*q} are all-zero matrices. AM'_{p*q} is a simplified matrix of AM, which can be used as the matrix representation of G. In AM'_{p*q}, the vertices of V_1 are represented by the rows of the matrix, and the vertices of V_2 are represented by the columns of the matrix.

Cluster detection in a two-mode network G=(V, E)=($V_1 \cup V_2$, E) is carried out to divide G as s subnetworks $G_r = (V_{1r} \cup V_{2r}, E_r)$, r=1, 2, ..., s, here s is the number of clusters in G, $V_{1r} \subset V_1, V_{2r} \subset V_2, \cup_{r=1}^{s} V_{1r} = V_1$ and $\cup_{r=1}^{s} V_{2r} = V_2$. This paper researches the cluster partition of connected two-mode networks.

B. A TWO-MODE MODULARITY FORMULA OF TWO-MODE NETWORKS

In this subsection, we will describe a two-mode modularity formula for the two-mode graph employed in test subsequently in this article. It is described below:

$$Q_b = \frac{1}{m} \sum_{i=1}^{p} \sum_{j=1}^{q} \left(AM'_{ij} - \frac{d_i g_j}{m} \right) \delta \left(c_i, c_j \right) \tag{1}$$

where d_i is the degree of the ith vertex in the vertex set V_1, g_j is the degree of the jth vertex in the vertex set V_2, and c_i, c_j stand for the clusters to which vertex i and j belong. When $c_i = c_j$, $\delta \left(c_i, c_j\right) = 1$, otherwise, $\delta \left(c_i, c_j\right) = 0$. With regard to the implication of AM'_{ij}, m, p, and q, see III-A.

C. BASIC ARTIFICIAL BEE COLONY ALGORITHM

Through simulating the intelligent finding food behavior of real bees, a new artificial bee colony (ABC) method was presented by Karaboga in 2005. In this method, artificial bee colony is composed of three kinds of bees: employed bees, onlooker bees and scout bees. Half of the swarm is made up of employed bees and the other half consists of onlooker bees. The scout bee takes charge of helping the colony escape the local minimums. To be specific, when the food source is not improved after several successive iterations, the employed bees will become scouts. This process is determined by an algorithm parameter named "limit". The execution of the basic ABC is described below.

1) INITIALIZATION

First, according to formula (2), a population of food sources with the size of SN is stochastically produced.

$$x_{i,j} = x_{min,j} + rand\,(0, 1)\,(x_{max,j} - x_{min,j}) \tag{2}$$

where $i = 1, 2, \ldots, SN$, $j = 1, 2, \ldots, D$, $x_{i,j}$ is the jth dimension of ith food source which will be assigned to ith employed bee, $x_{min,j}$ and $x_{max,j}$ are the lower and upper bounds of the jth dimension, respectively. Rand(0,1) is a random number between [0,1], SN is the number of food sources and D is the dimensionality (the number of decision variables) of the problem or function optimized. Here, each solution x_i represents a food source, which contains D components. Then, for the minimization problem, the fitness $fitness_i$ of every food source x_i is calculated according to formula (3).

$$fitness_i = \begin{cases} \dfrac{1}{1 + obj_i} & \text{if } obj_i \geq 0, \\ 1 + \left|obj_i\right| & \text{else`} obj_i < 0. \end{cases} \tag{3}$$

For the maximization problem, the fitness $fitness_i$ of every food source x_i is calculated by formula (4).

$$fitness_i = obj_i \tag{4}$$

In formulas (3) and (4), obj_i is the objective function value of food source x_i.

2) EMPLOYED BEES STEP

In this step, according to formula (5), every employed bee creates a candidate individual $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$.

$$v_{i,j} = x_{i,j} + \varphi_{i,j} \left(x_{i,j} - x_{k,j}\right) \tag{5}$$

In formula (5), $i = 1, 2, \ldots, SN$; j and k are stochastically determined indexes from $\{1, 2, \ldots, D\}$ and $\{1, 2, \ldots, SN\}$ sets, and k must be also different from i, $\varphi_{i,j}$ is a stochastically generated number among $[-1, 1]$. After that, a greedy selection process is used between v_i and x_i.

3) CALCULATION OF THE PROBABILITY OF ONLOOKER BEES' CHOICE OF FOOD SOURCE

After the completion of the employed bees step, according to a probability value calculated by formula (6), the onlooker bees select a goal individual.

$$p_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \tag{6}$$

where $fitness_i$ is the fitness value of individual x_i. It is not difficult to see that the bigger the $fitness_i$ is, the higher the probability of the ith food source being chosen.

4) ONLOOKER BEES STEP

In this step, each onlooker bee chooses an individual using the above probability value. Then, according to formula (5), the onlooker bee conducts further search near the selected individual. In like manner, a greedy choice process is as well used to the novel generated individual and the selected individual x_i. Of the two solutions, the preferable solution is preserved.

5) SCOUT BEES STEP

In this step, when a bee depletes a food source by several successive cycles, the relevant bee turns into a scout bee. Then, this scout bee seeks for a novel food source randomly on the basis of formula (7).

$$v_{i,j} = x_{min,j} + rand\,(0, 1)\,(x_{max,j} - x_{min,j}) \tag{7}$$

In formula (7), j=1, 2, ..., D. In addition, the meaning of other parameters in formula (7) can be seen in the explanation of corresponding parameters in formula (2).

It is not difficult to see that some parameters perhaps take illegal values during the search process, and they can be reassigned legal values. Here, the following reassign rule employed in [52] is also used.

$$x_{i,j} = \begin{cases} x_{min,j} + rand(0, 1)\left(x_{max,j} - x_{min,j}\right), & \text{if } x_{ij} < x_{min,j} \\ x_{max,j} - rand(0, 1)\left(x_{max,j} - x_{min,j}\right), & \text{if } x_{ij} > x_{max,j} \end{cases} \tag{8}$$

In basic ABC, the above steps will be repeated in turn (except for the initialization process) until a stop condition is satisfied.

IV. AN IMPROVED ARTIFICIAL BEE COLONY METHOD

Here, a new ABC method named IABC-BN for bipartite cluster discovery in two-mode graphs is proposed. At first, the representing method of solutions in a population are described. In the meantime, an objective function is presented to assess the solutions in the population. Then, this paper proposes a novel swarm initialization method, which can accelerate the convergence rate of the swarm and improve the diversity of the swarm. Next, we put forward a combinatorial food source search formula in the employed bees step. This search formula is guided by the global optimal solution and the better neighbour solution of the current solution. By using this combination equation and increasing parameter perturbation frequency, the exploitation capability of the algorithm is further enhanced. Afterward, we propose another new combination food source search formula in the onlooker bees step to improve the exploitation capability of the algorithm. In addition, in this step, an opposition-based learning (OBL) method is employed to equilibrate the exploitation level of the algorithm. Finally, we introduce a probability threshold β in the scout bees stage. It is used to enhance the exploration capability of the method and improve the population multiformity of the method. The above contents will be discussed in detail in the following subsections. Figure 2 shows the flowchart of the IABC-BN method.

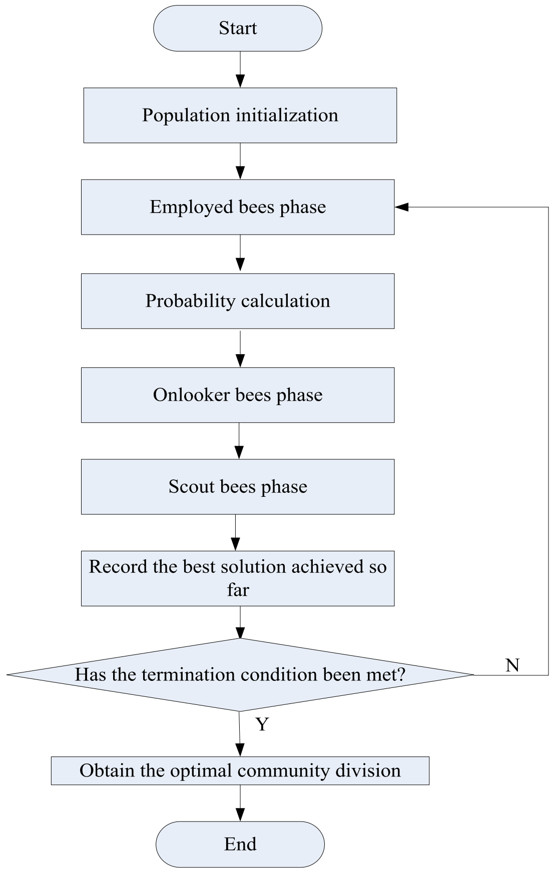

FIGURE 2. The flowchart of the IABC-BN method.

A. FOOD SOURCE REPRESENTATION

In ABC, each possible cluster partition is denoted by a food source, also called a solution or an individual. A set of food sources is known as a population of ABC, i.e., population $P=\{F_1, F_2, \ldots, F_{SN}\}$, where SN is the size of the population and F_i is the ith food source in the population. In the context of cluster partition in bipartite networks in this article, the ith solution in population P can be denoted as: $F_i = [s_1, s_2, \ldots, s_n]$. Among them, n is the count of vertices in the bipartite graph, and s_j is the jth parameter of individual F_i. Each parameter can be assigned an integer value on the interval $[1, p]$, the meaning of p is shown in III-A of this paper. This situation is caused by the initialization method proposed in this paper. Parameters stand for the vertices in network G=(V, E), and the value of the ith parameter represents the cluster including vertex i. In an individual, if $s_a = s_b$, then vertices a and b are in the identical cluster.

An individual representation of the network shown in Figure 3 (a) is demonstrated in Figure 3 (b). This two-mode graph contains nine vertices. The numbers of the vertices are from 1 to 9. As can be seen from Figure 3 (b), the parameter values assigned to vertices 1, 2, 5 and 6 are 1. At the same time, the parameter value assigned to other vertices is 2. This shows that the bipartite network contains two clusters, vertices 1, 2, 5 and 6 are in one cluster, while the remaining vertices are in another cluster. The cluster partition obtained from the individual in Figure 3 (b) is shown in Figure 3 (c).

B. OBJECTIVE FUNCTION

Here, we use a novel assessment function proposed in Ref. [53] to evaluate the quality of cluster detection in two-mode network. This function is called density based two-mode modularity. This function is defined as:

$$Q_D = \sum_{i=1}^{t} \frac{D\left(V_{1C_i}, V_{2C_i}\right) - D\left(V_{1C_i}, \overline{V_2}\right) - D(\overline{V_1}, V_{2C_i})}{\left|V_{1C_i}\right| \times \left|V_{2C_i}\right|} \tag{9}$$

where C_i is the ith cluster in cluster structure, t is the totality of clusters in the two-mode graph. $D\left(V_{1C_i}, V_{2C_i}\right) = \sum_{j\in V_{1C_i}} \sum_{k\in V_{2C_i}} AM'_{jk}$ is the number of links in cluster $C_i \cdot D\left(V_{1C_i}, \overline{V_2}\right) = \sum_{j\in V_{1C_i}} \sum_{k\in \overline{V_2}} AM'_{jk}$ is the number of links between the vertices in the vertex set V_1 in the community C_i and the vertices in the vertex set V_2 outside $C_i \cdot \overline{V_2} = V_2 - V_{2C_i}, \overline{V_1} = V_1 - V_{1C_i}$. $\left|V_{1C_i}\right|$ is the number of vertices in the vertex set V_1 included in $C_i \cdot \left|V_{2C_i}\right|$ is the number of vertices in the vertex set V_2 included in C_i. The higher the Q_D value, the better the quality of the cluster structure detected. Authors of Ref. [53] allege that formula (9) is relevant to the links density in the cluster, hence conquering the shortcomings of the resolution limit.

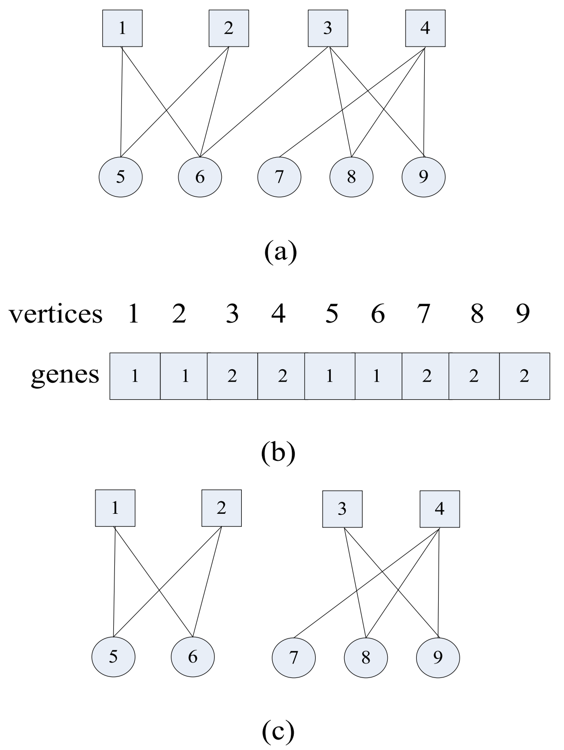

FIGURE 3. **(a) A two-mode network with 9 vertices; (b) an individual generated by the network in (a); (c) the corresponding community graph of individual illustrated in (b).**

C. POPULATION INITIALIZATION

Like other population-based algorithms, the establishment of initial swarm is very important to enhance the precision of the final results of IABC-BN and reduce the algorithm's running time. Thus, this paper presents a new initialization method to enhance the quality of the initial swarm and reduce the running time of the presented IABC-BN.

In 2005, Tizhoosh [54] first proposed the idea of opposition-based learning (OBL). The core concept of opposition-based learning is that in order to obtain a better approximation of the current candidate individual, one estimate and its relevant reverse estimate need to be considered simultaneously. So far, the opposition-based learning has been triumphantly used to differential evolution, genetic algorithm, and so on. Therefore, in this paper, it is employed to enhance the diversity of the initial swarm. In the context of community detection of bipartite networks in this paper, the formula (2) for generating the initial food source x_i of ABC is changed to the following formula (10).

$$x_{i,j} = \mathrm{round}(1 + \mathrm{rand}\,(0, 1)\,(p - 1)) \tag{10}$$

where $j = 1, 2, \ldots, p$, the function round (r) rounds the real number r to an integer, the meaning of p is shown in III-A. The other parameters are the same as those of formula (2). Accordingly, according to the OBL strategy, the opposite individual x_i' of x_i is generated by formula (11).

$$x_{i,j}' = 1 + p - x_{i,j} \tag{11}$$

where $x_{i,j}'$ is the jth component of x_i'. The other parameters are the same as those of formula (10).

Algorithm 1 describes the initialization method of the presented IABC-BN algorithm.

D. EMPLOYED BEES STEP

1) A NEW METHOD OF SELECTING A NEIGHBOUR SOLUTION

Because a neighbour is randomly selected during the search, the artificial bee colony algorithm is adept in exploration, but not adept in exploitation. That is to say, compared with the effect of information exchange between a better neighbour and a present solution x_i, the effect of information exchange between a poorer neighbour and a present solution x_i is worse. Therefore, selecting a better neighbour is of great significance to promote the exploitation of ABC. To conquer the deficiency of completely random selection of neighbour solution in basic ABC method, a similarity computational formula named Manhattan similarity is used. It is used to select a preferable neighbour. With regard to each food source x_i, the Manhattan similarity between x_i and its neighbour solutions is calculated as:

$$\mathrm{sim}_{iq} = \sum\nolimits_{j=1}^{n} \left|x_{i,j} - x_{q,j}\right| \tag{12}$$

where $q \in \{1, 2, \ldots, SN\}$, $q \neq i$, and x_q is a neighbour of x_i.

On the basis of Manhattan similarity, a novel neighbour individual probability selection formula is designed. This formula can be formulated as:

$$\mathrm{pr}_{iq} = 1 - \frac{\mathrm{sim}_{iq}}{\sum\nolimits_{m=1}^{SN} \mathrm{sim}_{im}} \tag{13}$$

where $q \in \{1, 2, \ldots, SN\}$ and $q \neq i$.

2) THE COMBINATION SEARCH FORMULA IN THE EMPLOYED BEES STEP

For each solution x_i, according to formula (13), a neighbour is selected with a probability in the employed bees step. Afterwards, the selected neighbour and the global optimal solution so far are used to direct the search course. In other words, based on formula (14) and formula (15), the IABC-BN algorithm carries out the search mechanism of employed bees step. In formula (14), the selected neighbour x_q and the current global optimal solution x_{best} will jointly guide the search process.

$$v_{i,j} = \mathrm{round}(x_{q,j} + \frac{1}{2}\emptyset_{i,j}(x_{best,j} - x_{i,j}) + \frac{1}{2}\Psi_{i,j}(x_{best,j} - x_{q,j})) \tag{14}$$

where $q \in \{1, 2, \ldots, SN\}$ is determined by the probability pr_{iq}, j is a stochastically selected dimension and an integer value on the interval [1, n], x_{best} is the optimal solution in the present population, the function round (r) rounds the real number r to an integer, and $\emptyset_{i,j}$ and $\Psi_{i,j}$ are random numbers between [−1, 1]. From formula (14), when the optimal neighbour x_q is poorer than the present solution x_i, the search ability may turn into poorer than before. Therefore, to further

Algorithm 1 Pseudo-Code of Initialization Phase of IABC-BN Method

Parameters: swarm size SN;
Input: a matrix representation AM of a two-mode graph;
Output: original food source swarm;
for count1=1; count1<=SN; count1++ do
  for count2=1; count2<=n; count2++ do
    if count2<=p then
      F_1[count2]= Use formula (10) to generate a parameter value;
      F_2[count2]= Use formula (11) to generate a parameter value, where $x_{i,j}$ is F_1[count2];
    else
      $F_1[count2]=\arg\max_{i\in L_{count2}} \sum_{j\in N_{count2}} \delta(c_j, i)$, L_{count2} is a set of community labels owned by neighbour vertices of vertex count2, N_{count2} is the set of neighbour vertices of vertex count2, c_j is the community label of vertex j. If a = b, then δ (a, b) =1, otherwise, δ(a, b) = 0. If there are multiple labels that meet the above equation, one of them is randomly selected.
      $F_2[count2]= \arg\max_{i\in L_{count2}} \sum_{j\in N_{count2}} \delta(c_j, i)$, L_{count2} is a set of community labels owned by neighbour vertices of vertex count2, N_{count2} is the set of neighbour vertices of vertex count2, c_j is the community label of vertex j. If a = b, then δ (a, b) =1, otherwise, δ(a, b) = 0. If there are multiple labels that meet the above equation, one of them is randomly selected.
    end if
  end for
  for count2=1; count2<=p; count2++ do
    $F_1[count2]= \arg\max_{i\in L_{count2}} \sum_{j\in N_{count2}} \delta(c_j, i)$, L_{count2} is a set of community labels owned by neighbour vertices of vertex count2, N_{count2} is the set of neighbour vertices of vertex count2, c_j is the community label of vertex j. If a = b, then δ (a, b) =1, otherwise, δ(a, b) = 0. If there are multiple labels that meet the above equation, one of them is randomly selected.
    $F_2[count2]= \arg\max_{i\in L_{count2}} \sum_{j\in N_{count2}} \delta(c_j, i)$, L_{count2} is a set of community labels owned by neighbour vertices of vertex count2, N_{count2} is the set of neighbour vertices of vertex count2, c_j is the community label of vertex j. If a = b, then δ (a, b) =1, otherwise, δ(a, b) = 0. If there are multiple labels that meet the above equation, one of them is randomly selected.
  end for
  q_1 =The Q_D function value of F_1 computed by formula (9);
  q_2 =The Q_D function value of F_2 computed by formula (9);

Algorithm 1 *(Continued.)* Pseudo-Code of Initialization Phase of IABC-BN Method

  if $q_1 \geq q_2$ then
    pop[count1]= F_1; //Pop is a two-dimensional //array.
  else
    pop[count1]= F_2;
end for
return pop;

improve the exploitation level of employed bees step of ABC, a search formula with global optimal solution information is employed. It is employed to enhance the optimization ability. This search formula can be described as:

$$v_{i,j} = \mathrm{round}(x_{best,j} + \varnothing_{i,j}(x_{q,j} - x_{k,j})) \tag{15}$$

where j∈{1, 2, . . ., n} is a stochastically chosen dimension, x_{best} is the optimal individual in the current population, and x_k is a solution stochastically chosen from the current population and k≠i. The meaning of the parameter $\varnothing_{i,j}$ and the function round (r) are the same as those in formula (14). From the above, we get the following combination search strategy in the employed bees phase:

$$v_{i,j} = \begin{cases} \mathrm{round}(x_{q,j} + \frac{1}{2}\varnothing_{i,j}(x_{best,j} - x_{i,j}) + \frac{1}{2}\Psi_{i,j}(x_{best,j} - x_{q,j})), & obj_q \geq obj_i \\ \mathrm{round}(x_{best,j} + \varnothing_{i,j}(x_{q,j} - x_{k,j})), & obj_q < obj_i \end{cases} \tag{16}$$

where obj_i and obj_q denote the objective function values of the individuals x_i and x_q, respectively. In this article, the objective function obj is the function Q_D in section IV-B. The meaning of the function round (r) is the same as that in formula (14). The meaning of other parameters in this formula is the same as that of formula (14) or formula (15).

Another reason for the poor exploitation ability of ABC is that only one component of each individual x_i is modified in the search process. This leads to the long running time of ABC algorithm. For improving the level of information exchanging and accelerating the artificial bee colony algorithm, the parameter perturbation frequency presented by the authors of Ref. [50] is also used in this employed bees phase. In our study, the modification rate MR is fixed and the number of parameters disturbed each time is fixed. Concretely speaking, with regard to each individual x_i, the number of disturbed parameters is equivalent to $\lfloor MR\cdot n \rfloor$. That is to say, the number of dimensions modified of each individual is equal. More detailed steps of the employed bees phase are presented in Algorithm 2.

E. PROBABILITY CALCULATION

After the completion of the employed bees step, according to a probability value calculated by formula (6), the onlooker bees select a goal food source.

F. ONLOOKER BEES STEP

In order to improve the exploitation performance of onlooker bees step, enlightened by DE/rand/1 mutation strategy, we present a new search formula used in onlooker bees step. First, as in the employed bees step, a neighbour is selected with a probability according to formula (13). On this basis, the new search equation is described as:

$$v_{i,j} = \begin{cases} \mathrm{round}(x_{q,j} + \emptyset_{i,j}(x_{a,j} - x_{b,j})), & obj_q \geq obj_i \\ \mathrm{round}(x_{i,j} + \emptyset_{i,j}(x_{a,j} - x_{b,j})), & obj_q < obj_i \end{cases} \tag{17}$$

where $j \in \{1, 2, \ldots, n\}$ is a stochastically chosen dimension, x_a and x_b are stochastically chosen solutions from the present population and $a \neq b \neq i$, and $\emptyset_{i,j}$ is a random number between $[-1, 1]$. The objective function obj is the function Q_D in section IV-B. In addition, the OBL strategy is also employed to balance the exploitation ability of formula (17). In other words, a new combinatorial search formula for the onlooker bees phase is constructed as:

$$v_{i,j} = \begin{cases} \mathrm{round}(x_{q,j} + \emptyset_{i,j}(x_{a,j} - x_{b,j})), \\ \qquad \mathrm{rand}\ (0, 1) < \alpha \wedge obj_q \geq obj_i \\ \mathrm{round}(x_{i,j} + \emptyset_{i,j}(x_{a,j} - x_{b,j})), \\ \qquad \mathrm{rand}\ (0, 1) < \alpha \wedge obj_q < obj_i \\ \mathrm{round}(1 + \Omega_{i,j}(p - x_{i,j})), \\ \qquad \mathrm{rand}\ (0, 1) \geq \alpha \end{cases} \tag{18}$$

where rand(0, 1) is a random number between [0, 1), α is a control parameter between [0, 1], and $\Omega_{i,j}$ is a random number between [0, 1]. The meaning of the function round (r) is the same as that in formula (14). For the meaning of other parameters, please refer to the explanation of corresponding parameters in formula (17). Same as the employed bees search step, for each solution, the number of disturbed parameters is equivalent to $\lfloor MR \cdot n \rfloor$. More detailed steps of the onlooker bees phase are presented in Algorithm 2.

G. SCOUT BEES STEP

Different from the basic ABC which only regenerates one food source in the scout bees step, IABC-BN regenerates a food source for each of several food sources that can not be further improved by a predetermined number of iterations. The number of regenerated food sources is controlled by a threshold value β. The threshold value β not only improves the exploration ability of algorithm, but also enhances the population diversity of the algorithm. More detailed steps of the scout bees phase are presented in Algorithm 2.

H. THE PRESENTED IABC-BN ALGORITHM

On the basis of the aforementioned discussions, Algorithm 2 describes the main steps of the presented IABC-BN algorithm.

V. EXPERIMENTAL SETTINGS AND RESULTS

A. ALGORITHM USED FOR COMPARISON AND METRICS USED

In this part, we will evaluate IABC-BN in detail by a lot of tests. In five synthetic two-mode graphs and six real

Algorithm 2 IABC-BN algorithm

Parameters: number of food sources SN, maximum cycle number MCN, modification rate MR, a threshold value used in the onlooker bees phase α, number of cycles without ameliorating limit, a value β of threshold used in the scout bees phase;
Input: a matrix representation AM of a two-mode graph;
Output:a cluster partition C of the graph;

pop= The original food source swarm achieved by employing algorithm 1;
Initialize $trial_i = 0$ (i=1, 2, ..., SN);
cycle=1;
while cycle $\leq$ MCN do
  for i=1 to SN do //the employed bees step
    Calculate the Manhattan similarity sim_{iq} according to formula (12);
    Calculate the probability value pr_{iq} base on formula (13);
    Stochastically select a neighbour with an odds pr_{iq};
    $v_i = x_i$;
    Calculate W= $\lfloor MR \times n \rfloor$;
    W different integers are randomly generated from the set [1..n], and the result is represented by permutation;
    for w=1 to W do
      j= permutation (w);
      if $obj(x_i) \leq obj(x_q)$ then
        Produce a novel parameter $v_{i,j}$ of individual v_i according to formula (14);
      else
        x_k=A solution is selected randomly from pop;
        Produce a novel parameter $v_{i,j}$ of individual v_i according to formula (15);
      end if
      The boundary constraint is treated according to formula (8);
    end for
    if $obj(v_i) > obj(x_i)$ then
      $x_i = v_i$;
      $trial_i = 0$;
    else
      $trial_i = trial_i + 1$;
    end if
  end for
  The probability value p_i of each onlooker bee was computed by formula (6);
  // the onlooker bees phase
  o=0;
  i=1;
  while o<SN do
    if rand(0,1)< p_i then //rand (0,1) is a stochastic //number between 0 and 1
      o++;
      $v_i = x_i$;
      Calculate the Manhattan similarity sim_{iq} according to formula (12);

Algorithm 2 *(Continued).* IABC-BN algorithm

```
            Calculate the probability value pr_iq base on
             formula (13);
            Stochastically select a neighbour with an odds
             pr_iq;
            Two integers a, b are produced randomly and
             a ≠ b ≠ i;
            Calculate W= ⌊MR × n⌋;
            W different integers are randomly generated
              from the set [1..n], and the result is represented
              by permutation;
            for w=1 to W do
              j= permutation (w);
              r=rand(0,1); //rand (0,1) is a stochastic
                     number //between 0 and 1
            if r < α then
             if obj(x_q) ≥ obj(x_i) then
               A novel parameter v_i,j of solution v_i is
                generated from the expression in the first
                line of formula (18);
             else
               A novel parameter v_i,j of solution v_i is
                generated from the expression in the second
                line of formula (18);
             end if
          else
               A novel parameter v_i,j of solution v_i is
                generated from the expression in the third
                line of formula (18);
          end if
        The boundary constraint is treated according to
         formula (8);
     end for
     if obj(v_i) >obj(x_i) then
       x_i = v_i;
       trial_i =0;
     else
       trial_i = trial_i + 1;
     end if
   end if
   if (SN+1) == ++i then
     i=1;
   end if
 end while
//the scout bees step
for i=1 to SN do
  if trial_i >limit ⋀ rand(0,1)< β then
   x_i=A solution generated randomly by formula (10);
     trial_i = 0;
  end if
end for
Store the optimal solution found so far;
cycle++;
end while
C=The community partition obtained by the best
  solution found so far;
return C;
```

two-mode graphs, the performance of IABC-BN is compared with three famous methods. The following is a brief introduction to the three algorithms used for comparison.

LP BRIM. Through combining BRIM with label propagation (LP), a two-mode network cluster partition algorithm LP BRIM is presented by Liu *et al.* [55], which further improved the performance of BRIM. In the worst case, the time complexity of LP BRIM method is $O(n^2)$, in which n is the count of vertices in the network. In actual two-mode graphs, such time complexity can meet the requirements.

AsymIntimacy. In Ref. [27], the authors define two parameters to represent the relationships between vertices of the same type and those of different types respectively. In the proposed method, two different kinds of nodes are treated respectively based on different closeness. Firstly, based on the asymmetric intimacy, the nodes of the same type are clustered into subsets. Then, to create a core cluster, the second kind of nodes are partitioned into the relevant set. Like this, the AsymIntimacy algorithm obtains a group of kernel clusters. When the overlay ratio of the two kernel clusters surpasses a threshold of the algorithm, the two clusters are merged. If there are kernel clusters in the kernel clusters group that can be merged, this process will be repeated. The time complexity of the AsymIntimacy method is $O(2n^2 + mn)$. In this expression, n is the count of nodes in the network and m is the count of edges in the network.

Adaptive BRIM. Barber [56] present bipartite, recursively induced modules (BRIM) method based on the iterative majorization notion of modularity formula Q_b in two-mode graphs. In the apiece cycle of the method, Q_b is nondecreasing. Nevertheless, it is disappointing that this method usually can not seek out the global best solution, but can only seek out the local best solution. Meanwhile, it is not necessary to specify the number of modules beforehand.

In the experiments in this paper, the test data of methods LP BRIM, AsymIntimacy and Adaptive BRIM are from [57]. In the Microsoft Visual Studio 2010 environment, IABC-BN is implemented by C# 4.0.

Measurements. For comparing the detection results of different methods, two kinds of metrics formula are usually used. If the cluster partition is known beforehand, the normalized mutual information (NMI) metric is used in obtaining an evaluation result. This result is a score between 0 and 1. If the cluster partition is not known in advance, the modularity [58] is used for comparing different methods. The modularity metric was originally presented for unipartite networks. Barber [56] extends the modularity formula to evaluate the community partition of bipartite networks. The extended formula is Q_b in III-B. The bigger the value of Q_b, the better the detected community structure.

B. SYNTHETIC BIPARTITE NETWORKS

A lot of existing cluster partition algorithms depend on optimization of modularity. But, these algorithms may have the flaw of resolution limitation [1]. They generally cannot discover clusters smaller than a certain size. This scale is $\sqrt{2L}$.

CHART 1. The main topological properties of the five synthetic bipartite networks employed in the test in this article.

Network	p	q	n	m	$<k>$	C	r
4 *bicliques*	12	8	20	28	2.800	0.482	-0.5
8 *bicliques*	24	16	40	56	2.800	0.482	-0.5
16 *bicliques*	48	32	80	112	2.800	0.482	-0.5
64 *bicliques*	192	128	320	448	2.800	0.482	-0.5
128 *bicliques*	384	256	640	896	2.800	0.482	-0.5

CHART 2. Comparison of running results of IABC-BN, Adaptive BRIM, AsymIntimacy and LP BRIM on the five synthetic bipartite networks. The normalized mutual information is the identification precision of disparate two-mode cluster partition methods. N_C is the number of clusters identified by disparate methods.

Network	IABC-BN		LP BRIM		Adaptive BRIM		AsymIntimacy	
	(NMI)	(N_C)	(NMI)	(N_C)	(NMI)	(N_C)	(NMI)	(N_C)
4 *bicliques*	**1.000**	**4**	**1.000**	4	**1.000**	4	0.714	4
8 *bicliques*	**1.000**	**8**	**1.000**	8	**1.000**	8	0.759	8
16 *bicliques*	**1.000**	**16**	0.802	13	0.934	15	0.785	16
64 *bicliques*	**1.000**	**64**	0.887	56	0.986	63	0.816	64
128 *bicliques*	**1.000**	**128**	0.900	113	0.993	127	0.826	128

L in the expression is the count of edges in the graph. For verifying the performance of IABC-BN, we have produced many synthetic bipartite graphs composed of different counts of bicliques. It can be seen from Figure 4 that a bipartite graph is composed of four in turn concatenated bicliques, and the other is a bipartite graph composed of eight sequentially concatenated bicliques. Each biclique consists of two kinds of vertices, and the vertices of different kinds are completely connected. In Chart 1, we list the main topological properties of the five synthetic bipartite graphs used in our experiments. On bipartite graphs with disparate counts of bicliques, the subjacent tests are carried out. The test outcomes are described in Figure 5 and Chart 2.

From Chart 2, we can see that for graphs with only four and eight bicliques, IABC-BN, Adaptive BRIM and LP BRIM can exactly identify clusters. Further tests show that when there are 16 bicliques in the graph, 15 clusters are identified by Adaptive BRIM, and NMI = 0.934 is achieved. 13 clusters are identified by LP BRIM, and NMI = 0.802 is gained. Nevertheless, IABC-BN can still get a precise solution. Compared with the other three algorithms, it has a great improvement. On the graph with 64 bicliques, we get analogous outcomes. With regard to LP BRIM, IABC-BN obtained approximately 13% enhancement, while for Adaptive BRIM, it increased by approximately 2%. Tests on 128 bicliques networks also showed similar results. With regard to LP BRIM, IABC-BN obtained approximately 12% enhancement, while for Adaptive BRIM, it increased by approximately 1%. On the basis of the normalized mutual information result values of the five synthetic graphs used in the tests, the performance of AsymIntimacy is the worst compared with the other three algorithms. However, unlike the two algorithms except IABC-BN, AsymIntimacy can invariably obtain the correct count of clusters. Because of the influence of the defect of the resolution limit, LP BRIM, Adaptive BRIM and AsymIntimacy are difficult to identify small clusters precisely, while the IABC-BN method can accurately identify little clusters.

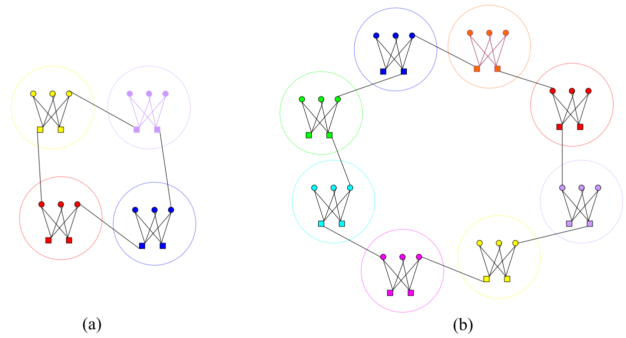

FIGURE 4. A bipartite network is composed of bicliques. (a) A bipartite network composed of 4 bicliques. Each biclique consists of 2 rectangle vertices and 3 circular vertices, and the circular vertices are completely concatenated to the rectangle vertices. (b) A bipartite network consists of 8 bicliques. The connection rules are the same as those of the network in (a).

We found that in the synthetic bipartite network, compared with the initialization method of the basic ABC algorithm using formula (2), the initialization method of the IABC-BN algorithm improves the diversity of the population, the accuracy of the results, and speeds up the convergence speed of the algorithm. Compared with the basic ABC algorithm using formula (5) in employed bees phase, formula (16) improves the exploitation ability of the IABC-BN and the accuracy of algorithm results, and reduces the running time of the

CHART 3. The main topological properties of the actual two-mode graph used for the test in this article.

Network	*p*	*q*	*n*	*m*	*<k>*	*C*	*r*
AR	136	5	141	160	2.270	0.781	-0.743
SW	18	14	32	89	5.563	0.328	-0.337
PCD	680	739	1419	3690	1.746	0.407	-0.140
MG	297	806	1103	2965	5.376	0.227	-0.300
CN	829	551	1380	1476	2.139	0.427	-0.166
SCI	108	136	244	358	3.140	0.303	-0.171

CHART 4. Comparison of running results of IABC-BN, Adaptive BRIM, AsymIntimacy and LP BRIM on real two-mode graphs. Q_b denotes the modularity score in each bipartite graph. N_c is the count of bipartite communities found by disparate methods.

Network	*IABC-BN*		*Adaptive BRIM*		*AsymIntimacy*		*LP BRIM*	
	(Q_b)	(N_c)	(Q_b)	(N_c)	(Q_b)	(N_c)	(Q_b)	(N_c)
AR	**0.778**	5	0.602	5	0.480	3	0.591	5
SW	**0.502**	4	0.345	4	0.333	4	0.313	2
PCD	**0.857**	171	0.770	113	0.784	79	0.806	107
MG	**0.831**	152	0.687	28	0.604	48	0.592	60
CN	**0.869**	174	0.798	104	0.821	142	0.823	203
SCI	**0.752**	56	0.660	24	0.668	40	0.648	36

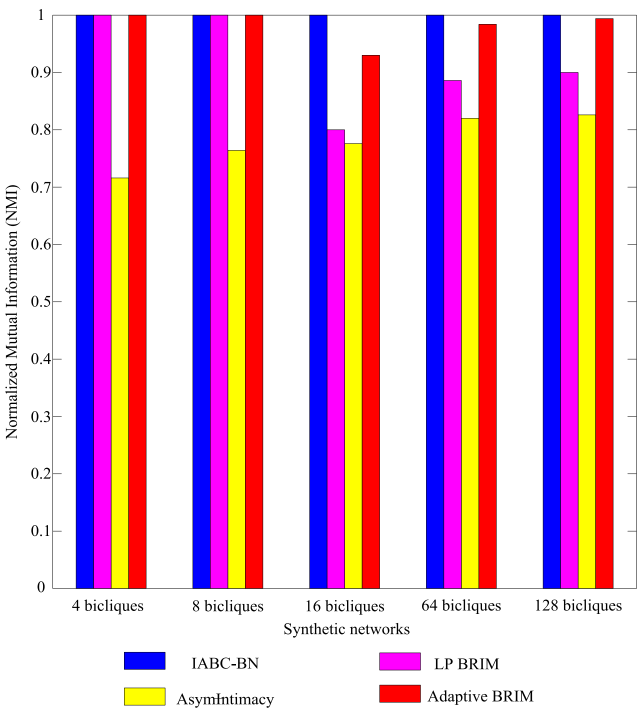

FIGURE 5. Comparison of the running results of IABC-BN, AsymIntimacy, Adaptive BRIM and LP BRIM on synthetic two-mode graphs. NMI is the identification precision of different two-mode cluster identification methods.

algorithm. Compared with the basic ABC algorithm using formula (5) in onlooker bees phase, formula (18) improves IABC-BN's exploitation ability, population diversity, accuracy of results, and speeds up the convergence speed of the algorithm. We also find that compared with the scout bees phase of the basic ABC algorithm, the scout bees phase of IABC-BN algorithm improves the exploration ability and population diversity of the algorithm.

C. ACTUAL BIPARTITE NETWORKS

In this part, several tests are carried out on the actual bipartite networks, that is, the true community partition is unknown, the accuracy of the algorithm is verified by Q_b. The actual two-mode networks used in our tests cover America Revolution (AR), Southern Women Events Participation (SW), Protein Complex and Drug network (PCD), Malaria and var Genes (MG), Crime Network (CN) and Scotland Corporate Interlock (SCI). In Chart 3, the important topological properties of all actual bipartite graphs are listed. Each of the following tests is conducted on actual bipartite graphs. Chart 4 and Figure 6 show the test results respectively.

1) AMERICAN REVOLUTION (AR)

Membership records of 136 members of 5 organizations are included in this data set. Before the American Revolution, these organizations had been established [2]. The data set contains a good deal of famous American people. Through a two-mode network, the relationship between members and organizations in this data set can be denoted. If a person is a member of an organization, there is an edge between the person and the organization. The important topological properties of this graph are formulated in detail in Chart 3. Chart 3 shows that the graph consists of 141 vertices and 160 links. Then, we will compare the IABC-BN algorithm with the other three algorithms to discover the cluster structure in this graph. Chart 4 shows the performance comparison outcomes of the four methods.

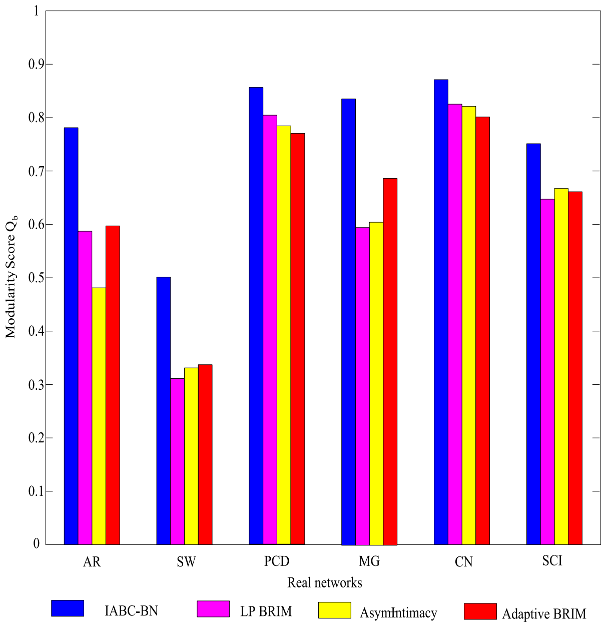

FIGURE 6. Comparison of the running results of IABC-BN, Adaptive BRIM, AsymIntimacy and LP BRIM on actual two-mode graphs. Q_b denotes the modularity score in each bipartite graph.

From Chart 4, it can be seen that the best modularity score ($Q_b = 0.778$) achieved by the IABC-BN method is better than the other three comparative methods.

IABC-BN identified 5 disparate clusters in the AR graph. In the 5 clusters identified, there is an identical organizational structure. Each cluster is composed of a particular institution and its memberships. According to the identification outcomes, it can be seen that the 5 institutions lie in the center of their severally clusters. These institutions are surrounded by their respective memberships.

2) SOUTHERN WOMEN EVENTS PARTICIPATION (SW)

Davis *et al.* [3] generated a Southern Women data set in the southern United States in the 1930s. This data set shows the interaction between eighteen women who participated in fourteen informal social events. The initial objective of this study is to explore the relationship between unofficial contact and social stratum. Since SW data set naturally takes shape a two-mode graph with a handful of data, research workers have done many studies on it. This graph is a connected unweighted graph. This graph includes 32 nodes and 89 edges. The topological properties of the SW graph are shown in Chart 3. In this experiment, four different cluster partition methods are compared to identify the community partition of the graph. Chart 4 shows the comparison outcomes. In this test, IABC-BN divides Southern Women events participation Network into 4 different sizes of two-mode clusters. The largest cluster contains eight women and six activities. The second largest cluster is composed of four women and four activities. Four women and three events were included in the third largest cluster. Two women and one activity were contained in the last cluster.

3) THE PROTEIN COMPLEX AND DRUG NETWORK (PCD)

For the past few years, some protein complexes have been found to be associated with corresponding diseases by the researches in the area of biology. The two-mode graphs analyzed by Schwartz and Nacher consist of two kinds of nodes: protein complexes and drugs. This graph contains 739 protein complexes and 680 drugs [18]. It discloses the relationship between human illnesses and molecules. Chart 3 shows the main topological properties of the Protein Complex and Drug network (PCD). As indicated in Chart 3, PCD contains 1419 vertices and 3690 links. From Chart 4, it can be seen that compared with the other three methods, IABC-BN has better performance, and the modularity value obtained is $Q_b = 0.857$. LP BRIM is the second, and the modularity value obtained is $Q_b = 0.806$.

4) MALARIA AND VAR GENES (MG)

Parasites evade the human immune mechanism through a protein disguise coded in var gene [19]. Parasites usually recombine var genes to produce novel disguise to escape the human immune mechanism, which naturally generates the cluster partition [20]. Thus, the bipartite network composed of two kinds of vertices is made up of the var genes and their genetic subsequences. The cluster structure of this bipartite network is natural. As indicated in Chart 3, this bipartite network is composed of 297 genes and 806 subsequences. In this bipartite network, 2965 links are used to connect different types of vertices.

In this graph, four different identification methods identify the cluster structure of the genes and their genetic subsequences severally. From Chart 4, it can be seen that compared with LP BRIM, Adaptive BRIM and AsymIntimacy, IABC-BN obtains the optimal cluster structure with a modularity value of $Q_b = 0.831$.

5) CRIME NETWORK (CN)

The data set contains people who have been recorded in at least one commit a crime event. The person is a suspect, victim or witness of a criminal event [2].

A two-mode graph is naturally formed by the relations between criminals and criminal events. This graph has 1476 links. These links concatenate 829 criminals and 551 criminal events. It can be seen from Chart 4 that the precision ($Q_b = 0.869$) of IABC-BN is better than that of the other three algorithms.

6) SCOTLAND CORPORATE INTERLOCK (SCI)

The Scotland corporate interlock data set is the sixth data set employed in our test. The Scottish commercial chain network from 1904 to 1905 was disclosed by the SCI data set [4]. This chain network contains 136 directors in 108 joint-stock companies. If there is an unweighted link between a person and a company, that person is a member of the board of the corporation. But this two-mode graph itself is not connected, it is made up of several connected parts.

From Chart 4, it can be seen that among the four comparison methods, IABC-BN acquires the optimal cluster structure with ($Q_b = 0.752$).

We found that, as in the synthetic bipartite network, in the actual bipartite network, the initialization method of the IABC-BN algorithm improves the accuracy of the algorithm results and the diversity of the population, and reduces the running time of the algorithm. Formula (16) improves the exploitation ability of the IABC-BN and the accuracy of algorithm results, and speeds up the convergence speed of the algorithm. Formula (18) improves the exploitation ability of IABC-BN, the accuracy of algorithm results, the diversity of population, and reduces the running time of the algorithm. The scout bees phase of IABC-BN algorithm improves the exploration ability and population diversity of the algorithm.

VI. CONCLUSION

In the study of bipartite networks, cluster structure is an important network characteristic. The purpose of detecting the set of clusters of the bipartite network is to better research and use this network. This article proposes a new ABC method named IABC-BN for cluster partition of bipartite graphs. For enhancing the convergence speed and population diversity of the method, we presented a new population initialization algorithm for cluster partition in two-mode graphs. The objective function of IABC-BN method makes use of the Q_D function presented in [53], which settles the resolution limit problem of the traditional modularity formula. In the employed bees step, a combinatorial individual search formula is proposed. It is guided by the global optimal individual and the better neighbour individual of the current individual. This combination equation and the increased parameter perturbation frequency are used to a greater degree enhance the exploitation capability of the algorithm. In the onlooker bees step, an opposition-based learning method is employed to equilibrate the exploitation performance of the algorithm, and a new combination individual search formula is also proposed to improve the exploitation capability. In scout bees step, a probability threshold β is introduced to improve the exploration ability of the method and enhance the population diversity of the method. We have performed many experiments on 5 synthetic bipartite graphs and 6 real bipartite graphs to verify the performance of the proposed algorithm. We also compare the test outcomes with three well-known two-mode graph cluster partition algorithms. The comparison outcomes indicate that the IABC-BN algorithm is better than the other three algorithms, which indicates that our method is a good method for cluster detection in two-mode networks. One disadvantage of IABC-BN algorithm proposed in this paper is that it can't detect overlapping communities. In our future work, we will solve this problem.

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