Swarm and Evolutionary Computation 63 (2021) 100885

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

Survey Paper

A review of heuristics and metaheuristics for community detection in complex networks: Current usage, emerging development and future directions

Bara'a A. Attea[a,*], Amenah D. Abbood[a], Ammar A. Hasan[b], Clara Pizzuti[c], Mayyadah Al-Ani[d], Suat Özdemir[e], Rawaa Dawoud Al-Dabbagh[a]

[a] College of Science, University of Baghdad, Iraq
[b] College of Engineering, University of Baghdad, Iraq
[c] National Research Council of Italy (CNR), Institute for High Performance Computing and Networking (ICAR), Via Pietro Bucci, 4-11C, Rende (CS) 87036, Italy
[d] School of Business, Kwantlen Polytechnic University, British Columbia, Canada
[e] Department of Computer Engineering, Hacettepe University, Turkey

ARTICLE INFO

Keywords:
Community detection
Complex networks
Hybrid metaheuristic
Hyper heuristics
Metaheuristic

ABSTRACT

Sensibly highlighting the hidden structures of many real-world networks has attracted growing interest and triggered a vast array of techniques on what is called nowadays community detection (CD) problem. Non-deterministic metaheuristics are proved to competitively transcending the limits of the counterpart deterministic heuristics in solving community detection problem. Despite the increasing interest, most of the existing metaheuristic based community detection (MCD) algorithms reflect one traditional language. Generally, they tend to explicitly project some features of real communities into different definitions of single or multi-objective optimization functions. The design of other operators, however, remains canonical lacking any intense interest to reflect the domain knowledge. Moreover, all the published reviews did not make any direct effort to link heuristic and metaheuristic based community detection approaches, rather, they simply state them separately. The review introduced in this paper attempts to address this issue. Mainly, we review the main heuristic and metaheuristic based community detection algorithms. Then, we introduce two new taxonomies for community detection algorithms: *hybrid metaheuristic* and *hyper heuristic* that can serve as common grounds for designing a collection of new and more effective MCD algorithms. To this end, we introduce four new systematic frameworks integrating both heuristic and metaheuristic algorithms, illustrating the possible issues that would fuel the desire for researchers to direct their future interest towards developing more effective community detection instances from the context of these frameworks.

1. Introduction

The emergence of many complex networks for modeling many phenomena everywhere in our daily life suggests the uttermost need for reliable approaches to understand and analyze them. Social networks, scientific collaboration networks, protein–protein interaction (PPI) networks, metabolic networks, communication and transport networks, technological networks, ecological networks, food webs and information networks are typical types, to name but a few.

Communities in such networks may be groups of individuals, Web pages, biochemical pathways etc. Applicable value of community structures in such complex networks is often interpreted as organizational units in different forms. For example, nowadays an urgent example with a particular significance occurs almost all the world is our social network and the diverse connections of people being proved to be infected or not (or even unchecked) with Coronavirus disease (COVID-19) to detect healthy communities from infected ones and further to advise individuals and communities for mandatory medical quarantine, house quarantine, or keep free. Other examples of modular organizations are biological networks (protein–protein interaction networks, gene regulatory networks, and metabolic networks). For example, the cellular modules of proteins, reflect both complexes and functional modules. As proteins and whole modules may have different biological functions, their communities turn to be overlapped. Further, communities of genes in

* Corresponding author.
E-mail addresses: bara.a@sc.uobaghdad.edu.iq (B.A. Attea), Amenah.Abbood@sc.uobaghdad.edu.iq (A.D. Abbood), mr.ammaradel@coeng.uobaghdad.edu.iq (A.A. Hasan), clara.pizzuti@cnr.it (C. Pizzuti), malani@columbiacollege.ca (M. Al-Ani), ozdemir@cs.hacettepe.edu.tr (S. Özdemir), rawaa.hassan@sc.uobaghdad.edu.iq (R.D. Al-Dabbagh).

https://doi.org/10.1016/j.swevo.2021.100885
Received 1 August 2020; Received in revised form 14 February 2021; Accepted 8 April 2021
Available online 20 April 2021
2210-6502/

a network of gene co-occurrence can be used to find out which genes are relevant for a specific disease. Communities of authors citations in citation networks can be used to reveal relationships between different disciplines. Such natural and artificial systems can rigorously be represented as nodes (objects of the system) and edges connecting these objects in nontrivial, i.e., complex, topological properties [210].

Although complex, a key feature of a networked system is the general tendency toward grouping its entities into hidden structures, usually known as communities (originated after Girvan and Newman [94]), with tightly connections within the same community (intra-connections) and loosely connections between communities (inter-connections). Unfortunately, the lack of any well-defined model for the precise characteristics of a "community" is creating, in itself, a challenging field of study known as *community detection* (CD) problem. Informally speaking, the CD problem is an optimization problem asking for a data analysis technique to uncover the hidden structure of large-scale networked dataset into disjoint and compact clusters, where the number and size of the subgroups are unknown [94].

The CD problem is proved to be a non-deterministic polynomial time hard (NP-hard) problem [39,40,84,149,212]. Generally speaking, the work on this problem has many implications on classifying the existing approaches into two mainstreams: heuristic based community detection (HCD) algorithms and metaheuristic based community detection (MCD) algorithms. Generally, heuristic algorithms can be defined as control flow of well-defined rules that systematically explore the search space for the problem [92] to hopefully reach an acceptable solution at a minimum time consumption. On the other hand, metaheuristics are global search algorithms sharing common grounds. While emphasizing the role of solution representation, these algorithms implicitly sample the search space of the problem into different regions. They qualify, in terms of single objective or multi-objective functions, different regions and samples of the search space. Further, they try to zoom in interested regions based on the quality of the sampled solutions. New samples from the search space can also be visited by perturbation (both samples interaction/recombination and sample mutation) operators. Generally speaking, the foundation of these metaheuristics is laid on two complementary cornerstones: *convergence velocity* (i.e. path- or line-oriented search ability) and *convergence reliability* (i.e. volume-oriented search ability) [25,30].

1.1. Existing reviews

Due to the exponential growth in the search space with respect to the network size, exact/deterministic algorithms are infeasible for detecting communities in sufficiently large networks. This has triggered a race for developing new non-deterministic optimization algorithms with different formulations. Amongst the proposed approaches, metaheuristic algorithms, particularly evolutionary algorithms (EAs), are getting increased attention while supporting powerful performance.

An earliest rich effort to review CD approaches is presented by Fortunato [84] to relate different heuristic algorithms to graph partitioning. This relatively complete review has been followed by a sequence of reviews with extensive discussions for the problem from different points of view, but mainly separated into heuristic and metaheuristic CD approaches.

Three essential elements are now widely recognized as critical strategies for designing an effective metaheuristic algorithm [96], namely, intensification, diversification, and learning (IDL as a mere abbreviation). With a few exceptions, all the developed MCD algorithms reflect the traditional and the more canonical picture of IDL in the design of the algorithm's components. Almost all existing MCD algorithms rely on an explicit projection of community definition and on modeling several single and multi-objective optimization functions. This helps to model the search space of the problem and, accordingly, to qualify the individual solutions. In general, the existing optimization models focus on debating the relative importance of intra-connections and inter-connections of nodes to extract the hidden community structures.

In the literature, the MCD approaches showed that when the definition of the objective function properly reflects "community structure", the search of the algorithm will be more constructive in terms of IDL. Otherwise, it will be executed anyway, yet destined to unreasonable performance. Two well-known scientific reviews on MCD algorithms have been published in the past few years [46,231]. In [46], a survey effort is directed to put the literature on evolutionary computation (EC) under both single objective optimization (SOO) and multi-objective optimization (MOO) problems. The network models reviewed in this paper are static/dynamic, unsigned/signed, unweighted/weighted, and non-overlapping/overlapping. Also, in [231] a comprehensive description of the state-of-the-art evolutionary based CD algorithms have been reviewed. The main focus of the review is on presenting the published work of MCD algorithms, mainly EA, for different types of networks, including undirected, directed, weighted, signed, multi-dimensional, overlapping, and time evolving ones. The review simply discusses how the main components (including individual representation, fitness function, recombination and mutation operators) of the EA and other bio-inspired algorithms have been implemented in the related literature of CD.

Recently, Osaba et al. [220] provides an overview of the MCD algorithms while emphasizing on the new-generation bio-inspired algorithms. In [220], extensive set of experiments is investigated to assess the performance of seven new-generation metaheuristics over weighted directed network instances. Additionally, in [220] two design principles (blind movement and ah-hoc heuristic) are suggested as the individual's perturbation operators to assess the performance of the reviewed algorithms. Due to the simple heuristic mechanisms injected into their MCD algorithms, they end with no clear high-performance winner.

Very recently, Huang et al. [131] offered an overall comparison of the existing works on shared community detection in multiplex networks. They presented a general classification for the adopted strategies in such coupled networks. Based on [274], three main categories are identified: flattening methods, aggregation methods, and direct methods. They presented several models, quality evaluation, and algorithms (including label propagation-based algorithm, nonnegative matrix factorization, random walk methods, and multi-objective optimization) for community detection in multiplex networks. They referred to the lack of existence of universal and efficient algorithms for obtaining reasonable partitions among large-scale multiplex networks. There are as yet no clues to design such universal algorithms.

Due to the reliance of the HCD and MCD algorithms on two different, but, complementary classes, it is a surprising fact that general review combining both classes was not performed earlier. One step towards customizing the never-ending design of new MCD algorithms is to recapitulate again their main components and stimulate further collaboration between the hitherto nearly isolated HCD and MCD research groups. This eventually would improve the performance of such algorithms.

1.2. Contributions

In this paper, we try to encourage researchers to carefully reconsider the design of the MCD algorithms while relaxing them to cover the essential concepts of the IDL. For this purpose:

- We present a review of the main and up-to-date research progress of the heuristic and metaheuristic works developed in the literature for solving the CD problem. Throughout the discussion, we point out that there is an important aspect of design characteristics in the MCD algorithms that is almost unexplored in the literature.
- Rather than promoting a certain heuristic or metaheuristic from the many different algorithms found in the literature arsenal, the purpose of this paper is to explore the potential ways in solving the CD problem using different perspectives of collaborations be-

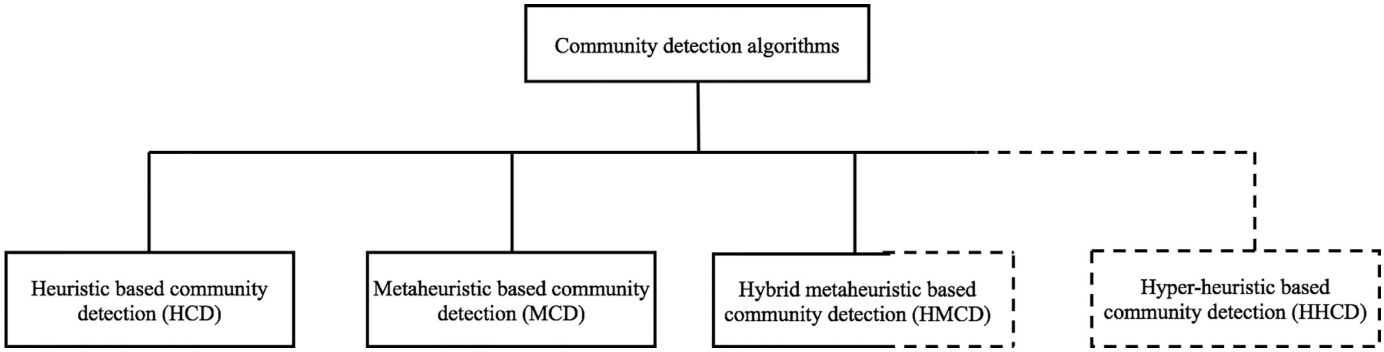

Fig. 1. The proposed taxonomy illustrating community detection algorithms as four classes. From left to right: the existing heuristic and metaheuristic based community detection (HCD and MCD) algorithms, the emerging hybrid metaheuristic based community detection (HMCD) algorithms, and the new hyper heuristic based community detection (HHCD) algorithms. Solid and dashed lines indicate, respectively, the existing and the new trends in the design. Both HMCD and HHCD frameworks can be devised while treating the MCD algorithms in a fresh and more systematic way to control the IDL elements.

tween these two types of algorithms. We first reconsider the IDL elements in the MCD algorithms and identify their contributions as hybrid metaheuristic based community detection (HMCD) algorithms. While some proposals have been emerged in the literature for HMCD algorithms [1,2,20,21,23,24], there remains a significant unexplored area and different possibilities for hybridization that could be speculated.

- Then, we go to identify a new, flexible and more comprehensive community detection framework, called hyper heuristic community detection (HHCD) framework. This paper offers an interesting possibility for developing new CD algorithms. While hybridization models focus on debating the relative importance of intensification and diversification while searching the problem space, the new perspective points out that there is another important space that is yet unexplored in all related literature of community detection. The proposed HHCD framework introduces a more general optimization framework. The foundation of this framework is laid on a decomposition of the search space into two spaces: algorithms space and solutions space. By simply designing new instances from the components found in the laundry list of the algorithms space in the HHCD framework, we can open the door for the interested researchers to the design of new CD algorithms in a more constructive manner.

Fig. 1 depicts the proposed classification of CD algorithms: HCD, MCD, HMCD, and HHCD algorithms. The classification names the existing algorithms (HCDs and MCDs) together with the emerging and the new class for algorithms design (HMCDs and HHCDs). To this end, the design of a new CD algorithm can be reduced to the design of a new instance from the main frameworks suggested in this review paper.

1.3. Terminology

Throughout our presentation, a set of terms and mathematical notations is used. To allow quick access, the following four tables comprising complementary search/optimization terms, names of several well-known metaheuristics, problem related notations and algorithm related notations are presented in Tables 1, 2, 3, and 4, respectively.

1.4. Paper organization

In the remainder of this review, a brief expression relating to the graph modeling of complex networks with a related taxonomy, datasets and evaluation measures are presented. This is followed by reviewing a number of well-known heuristic and metaheuristic based community detection algorithms. New frameworks are then suggested to let the design of community detection algorithms to be more constructive to transcend the limits of the existing algorithm designs. Understanding the need for more meaningful frameworks is also coupled with the challenges that should be addressed accurately. Finally, we summarize the major points recommended in this paper.

Table 1
Complementary terms.

Term	Complementary term
Convergence velocity	Convergence reliability
Deterministic algorithm	Non-deterministic algorithm
Exploitation	Exploration
Heuristic	Metaheuristic
Intensification	Diversification
Local search heuristic	Global search heuristic
Low-level heuristic (LLH)	High-level heuristic (HLL)
Path(line)-oriented search	Volume-oriented search
Problem specific operator	Problem independent operator
Single point search algorithm	Population based search algorithm

Table 2
Nomenclature of several well-known metaheuristics.

Nomenclature	Metaheuristic name
ACO	Ant colony optimization
CA	Cultural algorithm
DE	Differential evolution
EA	Evolutionary algorithms
GA	Genetic algorithm
GRASP	Greedy Randomized Adaptive Search Procedure
IA	Immune algorithm
MA	Memetic algorithm
MOEA/D	Multi-objective evolutionary algorithm with decomposition
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PSO	Particle swarm optimization
SA	Simulated annealing
TS	Tabu search

2. A taxonomy for community detection problem and datasets

In Fig. 2, we present a general taxonomy for the different types of complex networks realized in the community detection literature. The purpose of the taxonomy introduced in Fig. 2 is to capture all the aspects that are essential in characterizing complex networks while expressing different levels of difficulties. Four participants characterize complex networks: network data type, communities, nodes, and relations. These components individually and/or jointly serve for adjusting different levels of difficulties to count for complex networks and thus, in turn, steer us towards designing appropriate detection models. In what follow, we present how these components can add different levels of difficulties to the community detection problem.

Table 3
Problem related notations.

Notation	Description
A	Adjacency matrix
C	Community, or partial solution
$\mathcal{C} = \{C_1, C_2, \dots, C_K\}$	Predicted community structure, or complete solution
$\mathcal{C}^* = \{C_1^*, C_2^*, \dots, C_{K^*}\}$	Ground-truth community structure
$\mathcal{G} = (V, E)$	A graph of a set of vertices and a set of edges
$\mathcal{G} = (V, \mathbb{E})$	A multiplex graph
$\mathcal{G} = (\mathbb{V}, E)$	A multipartite
$\mathbb{G} = (\mathbb{V}, \mathbb{E})$	A graph set
$E = \{e_1, e_2, \dots, e_m\}$	A set of m edges/connections
$K \in \mathbb{N}$	Number of communities in a predicted community structure
$K^* \in \mathbb{N}$	Optimal number of communities
$m(C_k)$	Number of connections for community C_k
$\overline{m}(C_k)$	Number of inter-connections for community C_k
$\underline{m}(C_k)$	Number of intra-connections for community C_k
$m(v_i)$	Number of connections for node v_i
$\overline{m}(v_i)$	Number of inter-connections for node v_i
$\underline{m}(v_i)$	Number of intra-connections for node v_i
$\mathcal{N}(n, m)$	Complex network of n nodes and m connections
$\mathbb{N} = \{\mathcal{N}^1, \mathcal{N}^2, \dots, \mathcal{N}^T\}$	Dynamic network with T time steps
$\text{NMI} : (\mathcal{C}, \mathcal{C}^*) \to \mathbb{R}$	Normalized mutual information between a predicted community structure and the ground-truth community structure
$Q : \mathcal{C} \to \mathbb{R}$	Modularity of a community structure
$QD : \mathcal{C} \to \mathbb{R}$	Modularity density of a community structure
$V = \{v_1, v_2, \dots, v_n\}$	A set of n vertices/nodes
$\text{wNMI} : (\mathcal{C}, \mathcal{C}^*) \to \mathbb{R}$	Weighted normalized mutual information between a predicted community structure and the ground-truth community structure

Table 4
Algorithms (HCD, MCD, HMCD, and HHCD) related notations.

Notation	Description
$\Gamma : \mathcal{I} \to \mathcal{C}$	A decoding function from an individual to a community structure
$\iota : \mathbb{I} \to \{true, false\}$	A termination criterion for a community detection algorithm
$\iota_{hyper} : \mathbb{I} \to \{true, false\}$	A termination criterion for a hyper heuristic based community detection algorithm
Υ	Search space of a hyper heuristic based community detection algorithm
$\Phi : \mathcal{C} \to \mathbb{R}^+$	A single objective (fitness) function maps a community structure to a real value
$\overline{\Phi} : \mathcal{C} \to \overline{\mathbb{R}^+}$	Multi-objective functions mapping a community structure to a vector of real values
$\Phi_{CO} : \mathcal{C} \to \mathbb{R}^+$	Conductance function
$\Phi_{CS} : \mathcal{C} \to \mathbb{R}^+$	Community score function
$\Phi_{EX} : \mathcal{C} \to \mathbb{R}^+$	Expansion function
$\Phi_{ID} : \mathcal{C} \to \mathbb{R}^+$	Internal density function
$\Phi_{\text{Inter}} : \mathcal{C} \to \mathbb{R}^+$	Inter-score function
$\Phi_{\text{Intra}} : \mathcal{C} \to \mathbb{R}^+$	Intra-score function
$\Phi_{KKM} : \mathcal{C} \to \mathbb{R}^+$	kernel K-mean function
$\Phi_{NC} : \mathcal{C} \to \mathbb{R}^+$	Normalized cut function
$\Phi_{NRA} : \mathcal{C} \to \mathbb{R}^+$	Negative ratio association function
$\Phi_{RC} : \mathcal{C} \to \mathbb{R}^+$	Ratio cut function
$\varphi : \mathcal{C} \to \mathcal{C}$	Network perturbation function
Ω	The space of candidate community structures
Ω_{HCD}	A space of candidate heuristic based community detection functions
Ω_{MCD}	A space of candidate metaheuristic based community detection functions
$h_{CD} : \mathcal{C} \to \mathcal{C}$	A heuristic based community variation operator
$\text{HCD} : \mathcal{C} \to \mathcal{C}$	A heuristic based community detection (transformation) function
$\text{HHCD} : \mathbb{I} \to \mathbb{I}$	Hyper heuristic based community detection (population transformation) function
$\text{HMCD} : \mathbb{I} \to \mathbb{I}$	Hybrid metaheuristic based community detection (population transformation) function
$\mathcal{I}$	Individual, or encoded solution for a community structure
$\mathbb{I} = \{\mathcal{I}_1, \mathcal{I}_2, \dots, \mathcal{I}_N\}$	A population of $N \in \mathbb{N}$ individual solutions
$mu : \mathcal{I} \to \mathcal{I}$	Traditional mutation operator
$mu_h : \mathcal{I} \to \mathcal{I}$	A heuristic based mutation operator
$\text{MCD} : \mathbb{I} \to \mathbb{I}$	A metaheuristic based community detection (population transformation) function
N	Population size
$r : \mathcal{I} \times \mathcal{I} \to \mathcal{I}$	Traditional recombination operator
$r_h : \mathcal{I} \times \mathcal{I} \to \mathcal{I}$	A heuristic based recombination operator
$s : \mathbb{I} \to \mathbb{I}$	Mating pool selection operator
t	Generation (iteration) number

Regarding the origin of the tested data, there are two different classes of complex networks used in the literature. These are synthetic networks and real-world complex networks. The objects and their connections in real-world networks display the hidden structures of real systems. Such structures may refer, e.g., to social ambient or functional groups. Synthetic or model networks, on the other hand, are computer generated networks with pre-defined modular structure and used to test the robustness of a CD algorithm against the inappropriateness of setting the intra-connections and inter-connections between objects with multi-levels of deception. Different deception models are proposed in the literature to identify the built-in community structure in which the distributions of node degree and community size are controlled [94,156,160].

Most complex networks, however, are inherently dynamic in nature where the objects and their mutual interactions are generally subject to

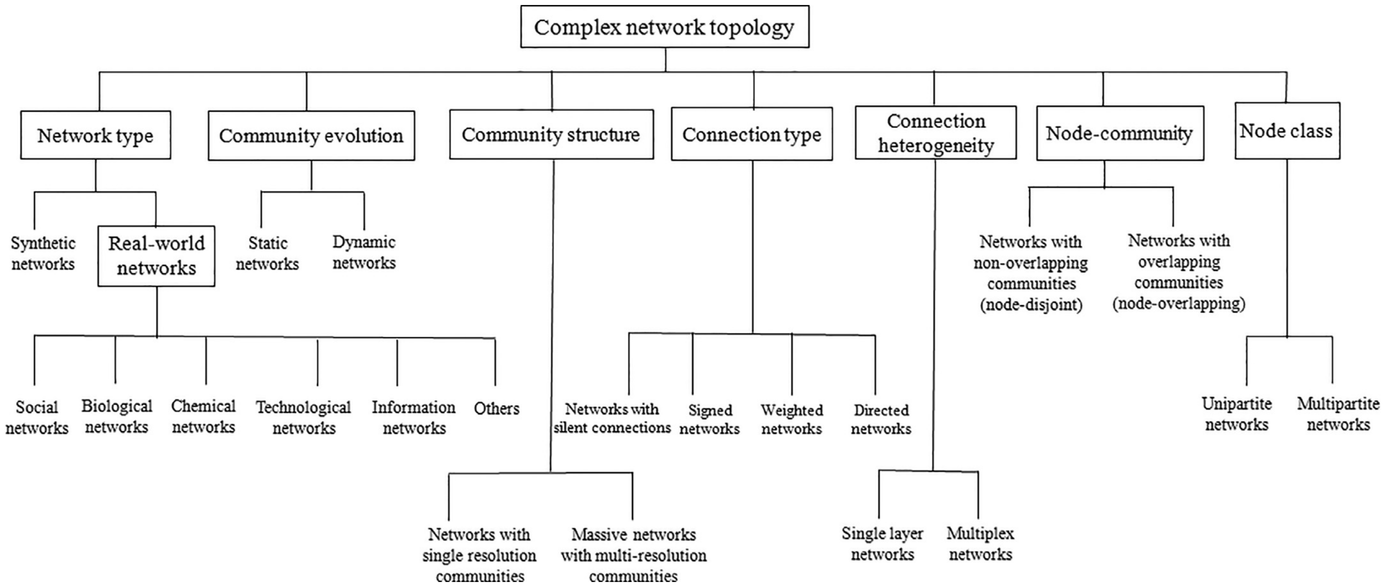

Fig. 2. A taxonomy of complex network topology in community detection problem. The taxonomy illustrates different aspects of complex networks based on their intrinsic characteristics. Generally, four participants characterize the networks: network data type, communities, nodes, and relations. These components reflect different levels of difficulties from: synthetic to real data, static to evolved community, single to multi-resolution community structure, silent to non-silent connections, homogeneous to heterogeneous connections, node disjoint to node overlapping, and single-class nodes to multi-class nodes.

steady change. Also, community structure in massive networks such as mobile communication networks and Web networks can be displayed at different scales. Here, communities inside other communities are identified in a hierarchical or multi-resolution structure.

Further, complex networks can be classified according to the type of connections. The simple case is silent connections in unsigned, undirected and unweighted graphs, as CD problem is already NP-hard. However, connections between the objects of many real-world networks are directed and may carry signs or weights to indicate, respectively, the positive/negative relations or the importance of the connections.

Further, a multiplex network is used to represent multiple modes of interactions or relationships among the same type of entities. This network system is used to study and analyze different systems of living organisms, human societies, transportation systems and critical infrastructures. In some living organisms, e.g., the interacome in protein–protein interaction networks may involve several distinct modes of interactions among thousands of protein molecules [70]. Air transportation systems illustrate another example where different commercial airlines can be seen as different modes of connections among airports [49].

Moreover, node to community membership can be extended to more than single community to account for the existence of overlapping communities (node-overlapping community structure [197]). In many real-world networks, however, the connected nodes commonly belong to different classes. For a multipartite network, e.g., scientists and papers network and Large shopping networks, community detection have interesting applications such as recommendation and marketing.

Researchers interested with CD problem should first experiment with computer generated networks of different complexity levels in order to make a controlled check of how well their algorithms perform. The well-known synthetic networks with varying degree of complexities are proposed by Girvan and Newman [94] and then extended by Lancichinetti et al. [160] and Lancichinetti et al. [159] to reflect heterogeneity of node degree and community size. The distributions of node degree and community size for the synthetic networks proposed in [159] follow power laws with exponents $\tau_1 = 2$ and $\tau_2 = 1$, respectively. Each node shares with a fraction $p_{in} = 1 - \gamma$ of edges with other nodes belonging to the same community, and with a fraction $p_{out} = \gamma$ of edges with nodes of other communities. Thus, community structures are made fuzzier by increasing the mixing parameter γ to vary from 0 to 1.

Extended benchmark models are also proposed in the literature to account for the different features of real networks. For example, dynamic benchmarks for evolving networks [106,107,151], benchmark graphs with signed connections [10,24,182], benchmark graphs with overlapping communities having weighted and/or directed connections [155].

A number of well-known social networks with known ground-truth partitions have also furnished the literature. Examples are Zachary's karate club network [307], Bottlenose Dolphins network [191], American football game of Division I-A colleges [94], American college football 2001 [78], and Krebs [212]. Another group of real-life networks, but, with unknown correct partitions is also provided in the literature. Examples are scientists collaborations network [94], jazz musicians network [95], Netscience coauthors [212], and email communication network [111].

Detecting complexes in PPI networks plays a key role in understanding the organization and dynamics of most cellular processes [285]. It has been recognized that functionally related genes tend to lie close to one another in a network of protein–protein or functional interactions and, hence, the interacting proteins may lead to the same process or disease phenotype when perturbed [28,221].

Additionally, the aspect of a community can account several types of membership drifting over time resulting in continuous changes in interaction signatures. Thus, by identifying network's communities (and their evolution), several functional phenomena can be depicted and predicted from the network structure through different snapshots over a time window. A well-known real-world dynamic network is the evolving network of Twitter connections between UK Members of Parliament (MPs) in the 85 consecutive weeks from December 2014 to August 2016 [296]. Another example is the Cell phone call network with 400 Paraiso cell-phones introduced by IEEE Visual Analytics Science and Technology (VAST) 2008 Challenge [108].

Moreover, there is an ongoing challenge to develop a better understanding of the community structures role when connections hold signs that represent particular types of social correlation rather than simple nodes-wiring [234]. Examples of such signed networks are votes of users in global computer networks [43], or the number of votes made by nine justices to give a decision in the Supreme Court (2006–2007 U.S.) [74]. Additional examples are Slovene National Parliamentary Political Party (SPP) [80] and Gahuku-Gama Subtribes (GGS) networks [240].

Some networks have other social conflicts, but, based on estimating the strength of the current relation between networks entities. Such networks are known as weighted networks. A weighted network indicates the weak/strong relations according to their reinforcement relations [179]. Additionally, many real-world social networks hold overlapping communities where communities are not necessarily to be separate [84]. Some of the well-known datasets are summarized in Table 5.

3. Preliminary concept

The informal description of complex network topology presented in the previous section and Fig. 2 is put into concrete terms and notations in this section. Canonically, a complex network, $\mathcal{N}(n,m)$, can be expressed as a graph $\mathcal{G}=(V,E)$, where V represents the set of n nodes or vertices, $V(\mathcal{G})=\{v_1,v_2,\dots,v_n\}$ with $n=|V|$ and $E(\mathcal{G})$ represents a set of m links or edges between nodes; $m=|E(\mathcal{G})|$. In its abstract form, a graph is considered to be undirected, unsigned, and unweighted. Each node v_i has a number of connections to other nodes, usually denoted by the degree $m(v_i)$. Also, $\mathcal{G}$ can be represented by an adjacency matrix $A=[a_{ij}]^{n\times n}$, where $a_{ij}=1$ if there is a connection between v_i and v_j, otherwise $a_{ij}=0$. Thus, from A, the degree of v_i can be calculated as:

$$m(v_i)=\sum_{j=1}^{n}a_{ij} \tag{1}$$

The objective of a community detection algorithm is to partition $\mathcal{G}$, or equivalently, A into a set of K (usually unknown) communities $\mathcal{C}=\{C_1,C_2,\dots,C_K\}$. We denote the number of nodes in community C_k as $n_k=|C_k|$. The number of links within a particular community and between the community and other communities are both essential for *prototyping the definition of communities* and thus formulating the problem. The degree, the number of intra-connections, and the number of inter-connections for community C_k is defined, respectively, as $m(C_k)$, $\underline{m}(C_k)$, and $\overline{m}(C_k)$:

$$m(C_k)=\sum_{i\in C_k}\sum_{j=1}^{n}a_{ij} \tag{2}$$

$$\underline{m}(C_k)=\frac{\sum_{i\in C_k}\sum_{j\in C_k}a_{ij}}{2} \tag{3}$$

$$\overline{m}(C_k)=\sum_{i\in C_k}\sum_{j\notin C}a_{ij} \tag{4}$$

which, respectively, count the number of all connections of C_k, the number of connections from nodes in C_k to other nodes also in C_k, and the number of connections between nodes in C_k to nodes outside C_k. Note that $\underline{m}(C_k)$ is divided by 2 as each edge is counted twice in the undirected graph. Similarly, inter-connections for a node v_i in community C_k can be defined as:

$$\overline{m}(v_i\in C_k)=\sum_{j\notin C_k}a_{ij} \tag{5}$$

Likewise, the intra-connections of node $v_i\in C_k$ is

$$\underline{m}(v_i\in C_k)=\sum_{j\in C_k}a_{ij} \tag{6}$$

Then, the degree of node v_i is:

$$m(v_i)=\underline{m}(v_i\in C_k)+\overline{m}(v_i\in C_k) \tag{7}$$

Further, a node v_i in a community C_k is strong if

$$\underline{m}(v_i\in C_k)>\overline{m}(v_i\in C_k) \tag{8}$$

and it is weak if

$$\underline{m}(v_i\in C_k)<\overline{m}(v_i\in C_k) \tag{9}$$

This comes up with what is called strong and weak communities [235]. A community C_k is termed strong if all its nodes make more connections to other nodes in the community than they do to nodes in other communities (Eq. (10)). A community is weak (Eq. (11)) if only the summation of the nodes' internal connections is more than the sum of connections to external nodes:

$$\underline{m}(v_i\in C_k)>\overline{m}(v_i\in C_k),\quad \forall i\in C_k. \tag{10}$$

$$\sum_{v_i\in C_k}\underline{m}(v_i)>\sum_{v_i\in C_k}\overline{m}(v_i). \tag{11}$$

The formal definition of a complex network $\mathcal{G}=(V,E)$ can be extended to reflect other classes of networks depicted in Fig. 2. The extension can touch any or all of the graph components: $\mathcal{G}$, V, and E. For example, a dynamic network $\mathbb{N}=\{\mathcal{N}^1,\mathcal{N}^2,\dots,\mathcal{N}^T\}$ with time steps $1,2,\dots,T$, can be expressed as a graph set $\mathbb{G}=(\mathbb{V},\mathbb{E})$, where $\mathbb{G}=\{\mathcal{G}^1,\mathcal{G}^2,\dots,\mathcal{G}^T\}$. At each time step, t, we have a complex network $\mathcal{G}^t=(V^t,E^t)$ with n^t nodes and m^t connections. On the other hand, networks with non-silent connections such as signed networks, weighted networks, and directed networks, $\mathcal{G}$ can be represented, respectively, by the triple (V,E,s), (V,E,w), and (V,E,d). Here, $s:(v_i,v_j)\in E\to\{-1,+1\}$, $w:(v_i,v_j)\in E\to[0,1]$, and $d:(v_i,v_j)\in E\to\{(v_i\to v_j),(v_i\leftarrow v_j)\}$. A multiplex network is defined as a graph $\mathcal{G}=(V,\mathbb{E})$, where V represents the set of n nodes, and $\mathbb{E}=\{E_1,E_2,\dots,E_L\}$ such that at each layer $1\leqslant i\leqslant L$, $E_i\subseteq V\times V$ is the set of connections of type i. A multipartite network is defined as a graph $\mathcal{G}=(\mathbb{V},E)$, where $\mathbb{V}$ represents multi-class nodes, and each edge in E connects two nodes from two different classes.

4. Evaluation measures

There are several evaluation measures that could be used to evaluate how well the network partition reached by a community detection algorithm matches the ground-truth partition. Purity [319], F-measure (harmonic mean) [283], Jaccard Index [133] are some of such measures. However, one of the most widely used similarity measures is normalized mutual information (NMI) [66]. Let $\mathcal{N}(n,m)$ be a complex network. Let $\mathcal{C}^*$ and $\mathcal{C}$ be, respectively, the ground-truth partition with K^* communities and a candidate partition obtained by a community detection algorithm with K communities. Also, let $c=\left[c_{ij}\right]^{K^*\times K}$ be the confusion matrix whose elements c_{ij} are defined as the number of nodes in community i of the ground-truth $\mathcal{C}^*$ that are also in community j of partition $\mathcal{C}$. If c_i and c_j be the number of nodes in community i and community j in $\mathcal{C}^*$ and $\mathcal{C}$, respectively. Then NMI is defined as follows:

$$\mathrm{NMI}(\mathcal{C},\mathcal{C}^*)=\frac{-2\sum_{i=1}^{K^*}\sum_{j=1}^{K}c_{ij}\log(c_{ij}n/c_ic_j)}{\sum_{i=1}^{K^*}c_i\log(c_i/n)+\sum_{j=1}^{K}c_j\log(c_j/n)} \tag{12}$$

Further, Romano et al. [244] suggested weighted normalized mutual information (wNMI). They showed that NMI may inhibit selection bias when the partitioning solution has many small divisions, or with too few nodes as compared with the ground-truth solution $\mathcal{C}^*$. wNMI guarantees bias free selection. Further, Lancichinetti et al. [159] introduced a generalized normalized mutual information as a measure of similarity between overlapping communities. A generalized normalized mutual information is also proposed in [159] to measure the similarity between covers, i.e. divisions of a network into overlapping communities.

$$\mathrm{wNMI}(\mathcal{C},\mathcal{C}^*)=e^{\frac{-|K^*-K|}{K^*}}\times\mathrm{NMI}(\mathcal{C},\mathcal{C}^*) \tag{13}$$

However, if the ground-truth partition for the network is unknown then the modularity (Q) is often used as the internal measure to assess the network partitions [213]. For a community structure $\mathcal{C}$ with K modules or communities, the modularity is defined as:

$$Q(\mathcal{C})=\sum_{k=1}^{K}\left[\frac{\underline{m}(C_k)}{m}-\left(\frac{\sum_{v_i\in C_k}m(v_i)}{2m}\right)^2\right] \tag{14}$$

Table 5
Main characteristics of several well-known complex networks.

Network name	Network type	Community evolution	Community hierarchy	Connection type	Connection heterogeneity	Node-overlapping	Node class	Reference
GN	Synthetic	—	—	—	—	—	—	[94]
LFR	Synthetic	—	—	—	—	—	—	[160]
Zacharys karate club	Social	—	—	—	—	—	—	[307]
Dolphins	Social	—	—	—	—	—	—	[191]
American college football	Social	—	—	—	—	—	—	[94]
American college football 2001	Social	—	—	—	—	—	—	[78]
Krebs	Social	—	—	—	—	—	—	[212]
Scientists collaboration	Social	—	—	—	—	—	—	[94]
Jazz musicians	Social	—	—	—	—	—	—	[95]
Netscience coauthors	Social	—	—	—	—	—	—	[212]
DIP	Biological	—	—	—	—	—	—	[300]
Yeast-D1	Biological	—	—	—	—	—	—	[200–202]
Yeast-D2	Biological	—	—	—	—	—	—	[200–202]
Kim and Han	Synthetic	Dynamic	—	—	—	—	—	[151]
Intermittent communities	Synthetic	Dynamic	—	—	—	—	—	[107]
Expansion and contraction	Synthetic	Dynamic	—	—	—	—	—	[107]
Birth and death	Synthetic	Dynamic	—	—	—	—	—	[107]
Merging and splitting	Synthetic	Dynamic	—	—	—	—	—	[107]
Cell phone calls	Social	Dynamic	—	—	—	—	—	http://www.cs.umd.edu/hcil/VASTchallenge08/
Enron mail	Social	Dynamic	—	—	—	—	—	[252]
Email communication	Social	Dynamic	—	—	—	—	—	[111]
LiveJournal	Social	Dynamic	—	—	—	—	—	[203]
LFR	Synthetic	—	Multi-resolution	—	—	—	—	[156,157,160]
Amazon co-purchase network	Social	—	Multi-resolution	—	—	—	—	[58]
LFR	Synthetic	—	—	Signed	—	—	—	[155]
LFR	Synthetic	—	—	Weighted	—	—	—	[155]
Slovene Parliamentary Party (SPP)	Social	—	—	Signed	—	—	—	[80]
Gahuku-Gama Subtribes (GGS)	Social	—	—	Signed	—	—	—	[240]
Metabolic pathways	Chemical	—	—	Directed	—	—	—	https://en.wikipedia.org/wiki/Metabolic_pathway
European airports	Others	—	—	—		—	—	[49]
Synthetic 4D network	Synthetic	—	—	—	Multiplex	—	—	[276]
DBLP	Social	—	—	—	Multiplex	—	—	http://www.dblp.org
Bibsonomy	Social	—	—	—	Multiplex	—	—	[135]
Rattus	Biological	—	—	—	Multiplex	—	—	[268]
Parliament (MPs)	Social	Dynamic	—	—	Multiplex	—	—	[296]
LFR	Synthetic	—	—	Signed	—	Overlapping	—	[155]
LFR	Synthetic	—	—	Weighted	—	Overlapping	—	[155]
Coauthorship network	Social	—	—	—	—	Overlapping	—	[211]
Southern women	Social	—	—	—	—	—	Multipartite	[68]
20 newsgroups	Social	—	—	—	—	—	Multipartite	[161]
e Internet Movie Database	Social	—	—	—	—	—	Multipartite	[195]

It measures the fraction of intra edges falling within communities minus the expected number in an equivalent network with the same number of communities but with random distribution of edges in the communities. If the number of intra connections is no better than the random distribution, Q approaches its minimum, i.e. 0. On the other hand, Q approaches 1 while meeting strong community structures. To avoid the resolution limit of Q, another variant called modularity density (QD in Eq. (15)) is proposed [55,177]. It measures the ratio of the difference between internal and external degree corresponding to the size of the community.

$$QD(C) = \sum_{k=1}^{K} \frac{\underline{m}(C_k) - \overline{m}(C_k)}{|\, C_k \,|} \tag{15}$$

Other variants of Q are also proposed in the literature, e.g., modularity ratio in [164] and neighbor modularity in [173]. More formulations of Q are also provided in the literature to meet different types and features of complex networks. For example: multi-resolution modularity [138] for multi-resolution community detection, Q_s and Q_{sw} for, respectively, signed networks and signed-weighted networks [100], Q_d for directed networks [15,163], Q_{dw} for directed and weighted networks [15,163], Q_{ov} for overlapping communities [251,314], Q_{dov} for directed networks with overlapping communities [216], principal modularity maximization (PMM) [276] and multi-slice modularity [207] for multiplex networks, and bipartite modularity functions [29,113] for bipartite networks.

5. Community detection (CD) algorithms

In this section, we literally divide the CD based algorithms into two classes: heuristic and metaheuristic based algorithms. We briefly present an informal description for these algorithms together with some formal expressions. The notations used throughout the description are summarized in Tables 3 and 4.

5.1. Heuristic based community detection (HCD) algorithms

Generally, a heuristic algorithm is defined as a set of deterministic rule-based algorithm for locating a locally optimal sub-solutions while incorporating some problem domain knowledge. It repeatedly computes some local variation for a given solution and with a specific decision determines whether the neighborhood solution is promising or not.

A heuristic based community detection algorithm HCD : $C \to C$ is an iterated transformation function that can be defined by the tuple in Eq. (16). It is based on iterative learning process, starting from an initial partitioning solution C in the search space Ω of all potential solutions. Then, it repeatedly changes the solution towards better and better solutions by means of a local variation operator (h_{CD}), an evaluation function (Φ), and a termination criterion (ι).

$$\text{HCD} = (\Omega, C, h_{CD}, \Phi, \iota) \tag{16}$$

Generally, the existing approaches for HCD are classified into: hierarchical methods, stochastic block model, spectral clustering, and random walk. Traditionally, hierarchical methods have been used to reveal the structure of communities in real-world networks. The basic idea behind such traditional methods is that any complex network can be represented by dendrograms where each dendrogram displays a multilevel (i.e. hierarchical) structure. Each level reflects the grouping of nodes with small groups inside large groups, which are in turn within larger groups, etc. There are two types of strategies for constructing hierarchical structures: agglomerative algorithms and divisive algorithms. Agglomerative algorithms (bottom-up) start with every single node forming one cluster as the initial partition. After that, in each iteration, the most similar pair of clusters are merged and so on until all clusters are merged into one cluster [134]. Top-down Divisive algorithms, on the other hand, reverse the process: initially they consider all vertices as one big cluster. Recursively a division is implemented as each iteration moves down a level by removing edges. A similarity measure between clusters is required in each iteration for both algorithms. There are two advantages of the hierarchical methods: (1) There is no need to specify in advance the number or size of the clusters in the network. (2) It can find a large number of network partitions. On the other hand, these methods are unable to correct any mistake that made in early iterations.

Stochastic Block Model (SBM) [125] have also been used in complex network analysis. By maximization of the a likelihood function, SBM is classified as a random model for generating communities in networks to fit the observed adjacency matrix. In SBM, each node is assigned to one block or community. Links between paired nodes are generated according to probabilities depending on cluster memberships of the connecting nodes.

Spectral clustering [284] uses the eigenvectors of matrices to partition a network into clusters. The initial set of objects are transformed into a set of points, elements of eigenvectors are coordinated for these points.

Random walk has been used by several algorithms for community detection. The idea is to find the similarity between nodes based on a random walk. Random walk overcomes the limitation of finding similarity (distance) between nodes based on the shortest path.

–Static networks with silent connections

Girvan and Newman used a divisive clustering method to detect community structure in biological networks [94]. The process is performed by calculating the edge betweenness. The edge with the highest edge betweenness is removed, and betweenness is recomputed. Then, they improved their method by maximizing Q (Eq. (14)) [213]. Iteratively, edges with high edge betweenness are removed to divide the network into communities, and the partition with maximum Q is selected. In the same year, Clauset et al. [59] also proposed an agglomerative clustering algorithm to greedily maximize Q without computing the edge betweenness. While this algorithm has the advantage that the number of communities does not have to be pre-specified, the greedy nature of the search means that just sub-optimal partitions may be located.

Hofman and Wiggins proposed a general Bayesian approach to infer community assignments. Each observed link is modeled with a mixture of Bernoulli distributions. A community label for each node is assigned with a prior probability [123]. Newman and Leicht proposed a mixture model with the expectation–maximization algorithm to model the community structure of networks [214]. The authors classified nodes into groups based on the observed connections between them. In general, these studies model the distribution of nodes and determine the structures of communities. However, most SBM methods do not consider the distribution of the degree of nodes as these methods generate edges randomly between nodes. Karrer and Newman proposed degree-corrected SBM [147]. They incorporated degree heterogeneity into block models. In this case, the expected degrees are close to the observed degrees.

Recent example on adopting spectral clustering for CD can be found in [128]. Also, many algorithms based on the modularity measure of Newman and Girvan [213] are proposed in the literature. The greedy algorithm is the first algorithm that has been used to maximize Q [16,188,248,287,322,324]. It is an agglomerative algorithm with max-heaps data structures [59]. Although this algorithm is fast, it biases large communities. Danon et al. [65] suggested a better modularity optima (in terms of community size) compared with the previous one by normalizing the variation in modularity. This normalization was accomplished by merging of pairs of communities by the fraction of edges incident to one of the pair communities.

Zhou [321] used random walks to find a distance between two nodes. The distance is the average number of links that a random walker visits from node v_i to node v_j. The nodes that have small distance are more likely to be in the same community. Another distance measure was introduced by Pons and Latapy [232] and used in their walktrap CD algorithm. A random walk is used to find similarity between nodes in the graph based on the diffusion distance. The distance is defined as the probability of random walker moves from one node to another (one of its neighbour in one step) with a constant number of steps. In this algorithm, communities are merged based on the short random walk as existing in one community is better than leaving it. Although this approach works well to capture the information on the community structure, it needs more memory space.

–Dynamic networks

SBM is used for detecting communities in static complex networks [12,34,147,192]. SBM is also used for detecting communities and their evolution in dynamic networks [180]. Embedding-based community detection models have also been proposed in the literature of community detection in static and dynamic networks [292,293,306]. The main aim of embedding-based community detection methods is to model microscopic node structure and mesoscopic community structure in different forms of nonnegative matrix factorization (NMF).

–Massive networks with multi-resolution communities

Ronhovde and Nussinov [245] proposed a Potts model community detection algorithm to identify multi-resolution structures of a graph. Our multi-resolution algorithm calculates correlations among multiple replicas of the same graph over a range of resolutions. Significant multi-resolution structures are then identified by strongly correlated copies. The average normalized mutual information, the variation of information, and other measures in principle give a quantitative estimate of the best resolutions and indicate the relative strength of the structures in the graph. Huang et al. [129] proposed a local quality function, called similarity-based tightness, and design a greedy Local Tightness Expansion (LTE) algorithm to infer the local communities in large-scale undirected networks. LTE is tested to identify overlapping and non-overlapping communities and to acquire communities at any resolution. However, a resolution parameter should be adjusted to identify overlapping communities in multi-resolution. Jeub et al. [138] proposed a consensus clustering method for identifying community structure at different scales based on multi-resolution modularity. Their method is based on sampling the entire range of possible resolutions for the multi-resolution modularity quality function. Then, a hierarchical consensus clustering procedure is used to construct a hierarchical consensus structure given a set of input partitions. Although, multi-resolution modularity based heuristics may encounter a kind of intrinsic limitation (or contradiction) regardless of the size of the whole network. When increasing the values of the resolution parameters, large communities may break up before small communities become visible [301].

–Networks with non silent connections

In 2008, Blondel et al. [35] proposed a different greedy algorithm (known as Louvain algorithm) to find communities in weighted networks. This method starts by considering each node as a community and merging these communities based on the maximizing Q. This process is repeated on the set of nodes until a maximum Q is reached. This method is low in time complexity. However, it depends on the order in which nodes are visited. As a result, the greedy optimization tends to be inaccurate. Yan et al. [303] proposed a graph sparsification method, called linear thresholding, to remove all links with weight below a given threshold. They also proposed the minimum absolute spectral similarity (MASS), to estimate the effect that sparsification procedures have on spectral features of the network. They showed that MASS behaves similarly to traditional group structure measures when there is correlation between weight and degree. For signed networks, Zhao et al. [318] presented a statistical inference method for community detection in signed networks. A probabilistic model is proposed to model signed networks and the expectation–maximization-based parameter estimation method is deduced to find communities in signed networks. Their model can automatically determine the number of communities and to, efficiently, partition signed networks.

*–Networks with overlapping communities*Zhang et al. [317] developed a symmetric binary matrix factorization model (SBMF) to identify overlapping communities and proposed a modified version for partition density of [6] to evaluate the quality of the overlapped structures. Their model assigns community memberships to nodes and also distinguishes outliers from overlapping nodes. Also, Eustace et al. [77] proposed overlapping community detection method using the overlapping neighborhood ratio to represent relations between nodes. Matrix factorization is also utilized to assign nodes into their corresponding community structures.

–Multiplex networks and multipartite networks

Two types of algorithms are provided in the literature for heuristic based community detection in multiplex networks [197]. These are global and local algorithms. Generally, global methods are classified into flatting, layer-by-layer, and multilayer. Flatting methods are the simplest approaches. For global based community detection methods, the flattening algorithms simplify the multiplex network into one graph by merging its layers and then apply any of the traditional community detection algorithms [32]. Weighted flattening algorithms [150], on the other hand, reflect some structural properties of the original multiplex network in the form of weights assigned to the output edges. The weights are computed from some structural properties of the input multiplex network and assigned to the output edges. Although such methods are less vulnerable to noise, they could encounter two main deficiencies. They may only detect pillar communities in which the resulting communities are biased towards edges appearing on several layers. Further, some communities may emerge because of edges spread on different layers that would not constitute a community on any individual layer [150].

Layer-by-layer methods, on the other hand, apply traditional community detection algorithms to each layer, then merge their results. Examples of layer-by-layer methods are: association rule mining methods (such as ABACUS [33]), consensus or ensemble-based multilayer community detection (EMCD) methods [158,274], and spectral-clustering methods such as principal modularity maximization (PMM) [276].

Multilayer methods, on the other hand, operates directly on the multiplex network model. Four classes of multilayer methods are: Density-based methods [4], random walks (LART [152] and Infomap [69]), optimization methods (e.g., Generalized Louvain [142]), and label propagation [38].

Two methods are suggested for multiplex local community detection: ML-LCD [132] and ACLcut [137]. Based on an optimization of the internal and external connectivity of the local community, ML-LCD searches for the local community associated with a seed actor through an incremental exploration of its neighborhood. ACLcut, on the other hand, exploits the solution of a personalized PageRank approximated for an input seed-set in order to find the local communities, using a sweep cut method based on the lowest conductance values. Almost all multiplex community detection methods have a considerable reduction in the achieved accuracy scores in detecting non-pillar community structures [197].

Almost all community detection methods in multipartite complex network are extensions to modularity based unipartite heuristics. For example, Guimerà et al. [113] devised a bipartite modularity from Newman–Girvan modularity [213] and employed simulated annealing to identify module in complex bipartite networks. Also, Barber [29] defined a null model appropriate for bipartite networks and use it to define a bipartite modularity. They proposed a bipartite recursively induced modules (BRIM) algorithm to iteratively maximize the bipartite modularity. In general, BRIM identifies partition which corresponds to a local, rather than global maximum of bipartite modularity. Lehmann et al. [162] extended the k-clique community detection [222] to bipartite networks. Liu and Zeng [186] proposed a joint strategy of two phases from label propagation (LP) and BRIM. LP is used to probe an initial, coarse, partition, then BRIM is used to iteratively refining the initial partition while maximizing the bipartite modularity of Barber [29].

Recently, Tackx et al. [273] and Gmati et al. [97] suggested other score functions. Tackx et al. [273] proposed a community detection algorithm for bipartite networks. Their algorithm relies on a measure of similarity between nodes exploiting the bipartite ties. Then the algorithm looks for cycles of connections maximizing the similarity between the nodes, thus defining the core of the communities. Gmati et al.

[97] proposed a heuristic multi-criteria method to optimize a quality score function. The score function is determined through aggregation of four different criteria: intensional stability, extensional stability, modularity, and overlapping.

5.2. Metaheuristic based community detection (MCD) algorithms

The natural motivations behind many traditional and new-generation metaheuristics have inspired many researchers to deal with difficult global optimization problems. The family of evolutionary algorithm (EA), particle swarm optimization (PSO), memetic algorithm (MA), ant colony optimization (ACO), bee colony optimization (BCO), differential evolution (DE), cultural algorithm (CA), and simulated annealing (SA) are examples of metaheurisics derived from the different living phenomena, organic evolution and biological reality (refer to Table 2). Without loss of generality, all these metaheuristic algorithms are adaptive sampling search techniques which try, through a number of search operators, to exploit the information gathered from candidate samples taken from the search space. A brief overview of these metaheuristics is presented in the coming two paragraphs.

Evolutionary algorithms (EAs) and genetic algorithms (GAs) [61,99,124] are the first family in proposing the utilization of evolutionary concepts for optimization tasks. They adopt the main concepts of Darwinian evolution with the behaviors of some biological systems to use: fitness assignment, selection, crossover, and mutation. Particle swarm optimization (PSO) [76] motivated from the simulation of swarm of birds behavior. The PSO as a swarm flies in the search space with a velocity which is dynamically adjusted with respect to its own and counterpart flying experiences. Memetic algorithm (MA) follows a sequence of operations aimed at having a population of tentative solution evolve (through parent selection, parent combinations, offspring local improvement, and population update) from an initial high-diversity and scattered state to a low-diversity and more homogeneous state [204,209]. Ant colony optimization (ACO) [37] and bee colony optimization (BCO) [281] mimic the foraging behavior of real ant and bee colonies to find short paths between their colonies and food sources. Differential evolution (DE) is a stochastic search algorithm working as a vector-based metaheuristic [67,269,270]. In terms of vectors, a mutation is carried out by GAs at one or more genes of a chromosome, while in DE, the mutation is carried out at difference vectors obtained randomly from population vectors to perturb a particular vector. Akin to the development of many adaptive EAs [62,189], the development of adaptive and self-adaptive DE algorithms has resulted in better performance in both terms of convergence velocity and convergence reliability in many benchmarks than the traditional DE algorithms with manual parameter settings [41,271,311,325]. Several issues for designing and implementing adaptive DE algorithms are introduced in [7]. The proposed design framework provides readers with the main steps required to integrate any proposed DE into parameter and/or strategy adaptation schemes.

Cultural algorithm (CA) is an evolutionary model proposed by Reynolds [243]. It consists of belief and population spaces and a communication channel. CA also contains the cultural knowledge sources that reside in the belief space to influence the search of the individuals in the population. Five general categories of those knowledge sources include normative knowledge, topographical knowledge, domain knowledge, situational knowledge, and history or temporal knowledge [153]. Several other nature- and human- inspired algorithms are also developed as global population based search techniques. For example, immune algorithm (IA) is a global optimization algorithm based on the principle of biological immune system in the organism that can be used to recognize some multiple antigens [315].

By nature, however, many real life optimization problems have contradictory objectives to be fulfilled simultaneously. Due to its success, the field of multi-objective optimization (MOO) has attracted several researchers in developing many multi-objective metaheuristics, mainly multi-objective genetic algorithms (MOGAs) and multi-objective evolutionary algorithms (MOEAs) [60,320] to solve many real-world problems [19,143,238]. Instead of single optimal or near-optimal solution, a set of non-dominated solutions can simultaneously be obtained, by MOO model, providing the decision maker with an optimal tradeoff between the conflicting objectives.

For the CD problem, many metaheuristic algorithms (MCDs) have been proposed in the literature. In general, a metaheuristic based community detection algorithm MCD : $\mathbb{I} \rightarrow \mathbb{I}$ is an iterated transformation function that can be defined by the tuple in Eq. (17):

$$\mathrm{MCD} = (\Omega, \mathbb{I}, \Gamma, \Phi, s, r, mu, \iota) \tag{17}$$

It is based on iterative learning process, starting from an initial population $\mathbb{I} = \{\mathcal{I}_1, \mathcal{I}_2, \ldots, \mathcal{I}_N\}$ of N *encoded* solutions in the search space, Ω, of all potential solutions. For individual representation, several proposals exist in the literature. These are label-based representation [98,127,215,277], locus-based adjacency representation [118,226], Medoid-based representation [81], and permutation-based representation [187]. Many MCD approaches, however, adopted the locus-based representation. Afterwards, the algorithm repeatedly change the population towards better and better solutions by means of: 1) a decoding function, $\Gamma : \mathcal{I} \rightarrow \mathcal{C}$, 2) a community structure evaluation function, $\Phi : \mathcal{C} \rightarrow \mathbb{R}^+$ (or a multi-objective evaluation function, $\overline{\Phi} : \mathcal{C} \rightarrow \overline{\mathbb{R}^+}$), 3) selection of mating pool $s : \mathbb{I} \rightarrow \mathbb{I}$, 4) recombination of parents, usually in pairs, to generate child individuals, $r : \mathcal{I} \times \mathcal{I} \rightarrow \mathcal{I}$, 5) mutation of child individuals, $mu : \mathcal{I} \rightarrow \mathcal{I}$, and 6) a termination criterion $\iota : \mathbb{I} \rightarrow \{true, false\}$. For recombination operator, many algorithms adopted the standard uniform crossover which fits well for the locus-based representation. Other algorithms used one-way and two-way crossover operators which are analogous to the group-based crossover of Falkenauer [79]. For DE based community detection approaches, binomial crossover is used [67]. For mutation operator, on the other hand, many MCD algorithms with label-based representation or medoid-based representation used the simplest alternation strategy which randomly change the membership of a node by assigning it to one of the other existing communities. Also, the rand/1 mutation strategy of differential evolution [67] has been employed by DE based detection algorithms. With locus-based representation, many algorithms adopted a simple strategy where the neighbor of a mutated node is substituted with another of neighboring nodes. Others adopted a Markov random walk strategy [122]. Further details on the representation schemes and evolutionary operators employed in MCD algorithms are presented in [231].

Despite their different families, many of such MCD algorithms follow one common strategy: modeling the problem design as a single objective, Φ, or a multi-objective, $\overline{\Phi}$, *community structure evaluation score*. Besides Q and its variants (e.g., QD, Qs, Q_{sw} Q_{ov}, Q_d, Q_{dov}, and Q_{dw}), different community structure evaluation scores are also proposed. Some of the *well-known* scores are: community fitness (Φ_{CF} in Eq. (18)) [159], conductance (Φ_{CO} in Eq. (19)) [260,264,305], community score (Φ_{CS} in Eq. (20)) [225,226], expansion (Φ_{EX} in Eq. (21)) [235], internal density (Φ_{ID} in Eq. (22)) [235,305], inter-score (Φ_{Inter} in Eq. (24)), intra-score (Φ_{Inter} in Eq. (24)) [257], Kernel K-Mean (Φ_{KKM} in Eq. (25)) [14], normalized cut (Φ_{NC} in Eq. (26)) [72,260], negative ratio association (Φ_{NRA} in Eq. (28)) [105], and ratio cut (Φ_{RC} in Eq. (27)) [72,86,101].

$$\text{Maximize} \quad \Phi_{CF}(C) = \sum_{k=1}^{K} \frac{\underline{m}(C_k)}{(\underline{m}(C_k) + \overline{m}(C_k))^{\alpha}} \tag{18}$$

$$\text{Maximize} \quad \Phi_{CO}(C) = \sum_{k=1}^{K} \frac{\overline{m}(C_k)}{2m(C_k) + \overline{m}(C_k)} \tag{19}$$

$$\text{Maximize} \quad \Phi_{CS}(C) = \sum_{k=1}^{K} \left(\frac{2\underline{m}(C_k)}{\mid C_k \mid} \right)^{r} \tag{20}$$

$$\text{Minimize} \quad \Phi_{EX}(C) = \sum_{k=1}^{K} \frac{\overline{m}(C_k)}{\mid C_k \mid} \tag{21}$$

$$\text{Maximize} \quad \Phi_{ID}(C) = \sum_{k=1}^{K} 1 - \frac{\underline{m}(C_k)}{\mid C_k \mid (\mid C_k \mid -1)/2} \tag{22}$$

$$\text{Minimize} \quad \Phi_{\text{Inter}}(C) = \sum_{k=1}^{K} \left[\frac{m(C_k)}{2L}\right]^2 \tag{23}$$

$$\text{Minimize} \quad \Phi_{\text{Intra}}(C) = 1 - \sum_{k=1}^{K} \frac{\underline{m}(C_k)}{2L}, \tag{24}$$

$$\text{Maximize} \quad \Phi_{KKM}(C) = 2(n-K) - \sum_{k=1}^{K} \frac{\underline{m}(C_k)}{\mid m_k \mid} \tag{25}$$

$$\text{Minimize} \quad \Phi_{NC}(C) = \sum_{k=1}^{K} \left(\frac{\overline{m}(C_k)}{2\underline{m}(C_k) + \overline{m}(C_k)} + \frac{\overline{m}(C_k)}{2(m - \underline{m}(C_k)) + \overline{m}(C_k)}\right) \tag{26}$$

$$\text{Minimize} \quad \Phi_{RC}(C) = \sum_{k=1}^{K} \frac{\overline{m}(C_k)}{\mid C_k \mid (n - \mid C_k \mid)} \tag{27}$$

$$\text{Minimize} \quad \Phi_{NRA}(C) = -1 \times \sum_{k=1}^{K} \frac{\underline{m}(C_k)}{\mid C_k \mid} \tag{28}$$

Shi et al. in [257,258] were the first to analyze the intrinsic correlations among several community structure objectives. They study the correlations (positively correlated, independent, or negatively correlated) of objective functions that have been used or can potentially be used for community detection. They showed that optimizing a pair of negatively correlated objectives remarkably improve the performance over optimizing either of the original objectives, and even better than other well-established community detection approaches.

In the remaining of this section, some of the MCD algorithms, mainly EA based CD algorithms are briefly presented, with a special focus on how these algorithms drew on the different challenges of community detection. In the presentation, we attempted to, more or less, follow in the sequence of the taxonomy introduced in Fig. 2. However, the characteristic components of these algorithms and more other algorithms are summarized in a Supplementary table.

–Static networks with silent connections

An earliest published work considering metaheuristic algorithms for social networks clustering is [81]. They investigated the use of GA with a random walk to partition static complex networks into, however, a pre-specified number of K clusters. In the same year, other genetic based community detection algorithms are proposed while surmounting the major deficiency of fixing K in [81]. They automatically specify the number of communities [98,278]. In 2008, Pizzuti used a single objective genetic algorithm for community detection problem (GA-Net), potentially avoiding some of the problems associated with the greedy search which could get stuck in local minima [225,226]. Further, Pizzuti proposed community score function (Φ_{CS} in Eq. (20)) as a global quality measure and used a single objective genetic algorithm to optimize it. Φ_{CS} considers r to control the size of communities, as an attempt to increase the weight of the degree of the internal nodes within the community. Also, in 2009, a GA with locus-based adjacency encoding scheme and Q-based evaluation is proposed in [253]. In the same year, an agglomerative clustering genetic algorithm (ACGA) is proposed by Lipczak and Milios [181]. Each individual, however, represents only one cluster and the number of individuals is equal to the current number of clusters and the complete solution is represented by the whole population. The crossover operator allows two individuals to exchange genetic material of two clusters to locally improve the quality of the generated two communities. The quality is measured by Q, NC, and *silhouette width*. In the late of 2009, a genetic algorithm with ensemble learning (GAEL) for detecting community structure in complex networks is also proposed [122]. GAEL adopts a multi-individual crossover operator based on ensemble learning to recombine clustering contexts of different individuals into new and better ones. Local search based genetic algorithms were proposed in 2010 [141,169]. Both algorithms employ modularity (Q) as objective function and locus-based adjacency representation (LAR) as genetic presentation. However, the local search operator presented in [141] was based on the concept of marginal gene, while in [169] was based on two concepts: the connected nodes in a network should be located in the same community, and efficient message delivery underlying the smallworld phenomenon. Akin to the GA based community detection algorithm proposed in many works, the single objective GA algorithm of Liu and Zeng [186] is proposed while maximizing modularity density (QD).

Pizzuti [230] in 2012 developed a single objective genetic algorithm to optimize the modularity function (named as GAMod). The main contribution in [230], however, is that improving the quality of the best modular network structure obtained from GAMod while performing a local search operator similar to that employed in [36].

Recognizing that many complementary definitions could reflect how to structure a given complex network into communities, Pizzuti [227], was the first to formulate CD problem as a multi-objective optimization problem (MOGA-Net). Apart from the modularity and its variants, the work of [227] evaluated the quality of the community structure as multi-objective optimization function. The first objective is Φ_{CS} (proposed in [226]) while the second objective is Φ_{CF} (proposed in [159]). The Φ_{CS} objective biases partitions with many intra-connections, while the value of the second objective (Φ_{CF}) is increased with partitions having few inter-connections. Solutions to the multi-objective problem are partitions which are globally non-dominated. The algorithm adopted the non-dominated sorting genetic algorithm II (NSGA-II) to approximate the optimal trade-off between two, but contradictory measures of community quality. The results showed that MOGA-Net reflects a good performance to produce accurate community structures compared with the state-of-the-art methods at that time. The work of Pizzuti [227] is, then, followed by the multi-objective community detection (MOCD) algorithm of Shi et al. [254], 259]. They divided the modularity (Q) into two optimization terms (describing, respectively, intra strength and inter strength) to be optimized simultaneously by MOCD. They showed that the simultaneous optimization of these two objectives can yield a wide range of possible community structures, placing more or less weight on intra and inter-community connections. Since Q is the sum of these two objectives, it is clear that the partition that maximizes Q must be a member of the Pareto set. Their algorithm is only compared against three other modularity based CD algorithms: two heuristic algorithms [213,246] and one single objective genetic algorithm [253]. Although, their algorithm achieved more accurate results, albeit, there are still room for further improvement in terms of quality evaluation and/or algorithm design.

At this point, it is worth to mention that the interfusion of Pizzuti's work in 2009 [227] and her following work [230] and [229] in 2012, opened up the door for more research activities in two directions: 1) to formulate the CD problem as a multi-objective optimization problem, and 2) to improve the performance of a given metaheuristic based community detection algorithm by means of coupling it with another heuristic model. With few exceptions (e.g., Attea et al. [21]), however, many researchers were only encouraged to the first research area. Some of the state-of-the-art algorithms are presented in what follows. In general, they develop different multi-objective metaheuristics (mainly MOGAs and MOEAs) for community detection problem. In their algorithms, a set of near-optimal solutions (different community structures) will be generated rather than a single solution generated by a single objective metaheuristic.

Not until the work of [21], did they realize well the importance of the two main participants endorsed by Pizzuti [229], 230] for solving the problem. Attea et al. [21] proposed two contradictory objectives to formulate the problem. The adopted algorithm is the multi-objective evolutionary algorithm with decomposition (MOEA/D) of Zhang and Li

[313]. Further, they proposed a new heuristic mutation operator (migration operator) to emphasize the search for tolerable intra- and interconnections within and between communities. They demonstrated the effectiveness of their multi-objective CD model to compete other state-of-the-art models proposed in [229,254]. Further, they validated the ability of the heuristic mutation operator to improve the detection quality of the tested models. In [57], Cheng et al. developed a multi-objective evolutionary algorithm, termed local information based evolutionary algorithm (LMOEA) to solve the community detection problem. Two conflicting objectives are optimized: Φ_{NRA} (Eq. (28)) and Φ_{RC} (Eq. (27)), respectively. Minimizing Φ_{NRA} promotes partitions with communities meeting a high proportion of internal connections. This objective is conflict to Φ_{RC} which minimizes the connections between communities.

Gao et al. [90] and Liang et al. [178] employed the current reinforcement (CR) model of a physarum-inspired computational framework to generate a diffusivity matrix. Rather than the adjacency matrix, information on diffusivities from the CR model is then used to improve upon the initialization of single-objective genetic algorithm, ant colony optimization algorithm, and Markov clustering algorithm. They showed that the convergence speed and the performance measure (in terms of modularity) of these can be improved.

–Dynamic networks

In dynamic networks, many authors proposed evolutionary algorithms to capture the evolution of communities over time. For example, Folino and Pizzuti [82,83] proposed a dynamic multi-objective genetic algorithm (DYN-MOGA) for detecting dynamic communities. They used the non-dominated sorting algorithm (NSGA-II) of Srinivas and Deb [267]. The authors used Φ_{CS} in Eq. (20) as the first objective to maximize the quality of community structure at the current time step. The second objective is NMI to minimize the difference between the structures of communities over consecutive time steps as the dramatic shift between successive time steps is undesirable. They also investigated the impact of different scores as the first objective such as Q, Φ_{CO} (Eq. (19)), Φ_{EX} (Eq. (21)), Φ_{ID} (Eq. (22)), Phi_{NC} (Eq. (26)), $\Phi_R C$ (Eq. (27)).The results showed that their algorithm has a good performance for detecting dynamic communities and particularly when Q or CS is used as the first objective.

Also, Ma et al. [193] proposed a multi-objective evolutionary algorithm for dynamic community detection algorithm (DYN-DMEA). They employed the multi-objective evolutionary algorithm based on decomposition (MOEA/D) [313] to detect dynamic communities over time. Akin to the multi-objective community detection model of Folino and Pizzuti [83], the authors also used Q as the first objective to measure the quality of the structure of communities and NMI as the second objective to measure the temporal cost. However, the partition maximizing Φ_{QD} (Eq. (15)) is chosen as the best partition at each timestep. Further, they consider the label propagation method of Raghavan et al. [236] as a local search operator to modify the label of each node until no label change is going to happen. The whole algorithm is termed as multi-objective evolutionary algorithm with local search for community detection in dynamic networks (DYN-DMLS). This algorithm has a good contribution to capture community evolution with high modular community structures. However, depending on just Q for snapshot quality is not enough as Q has the resolution limitation problem [55,85,157].

Attea and Khoder also proposed a multi-objective evolutionary evolutionary clustering (MOEC) algorithm for community detection in dynamic networks. They proposed an extension to the community detection model of [21] to cope with dynamic networks. While the first object considers an intra-community score, the second objective handles a cross-fertilization of the inter snapshot quality and the temporal costs [23]. The model provides more accurate results than other state-of-the-art models presented in [82,83]. They also adopted the migration operator of Attea et al. [21] to replace the traditional mutation operator and again they validated the effectiveness of the heuristic mutation operator to improve the detectability of all dynamic CD models proposed in [82,83].

*–Massive networks with multi-resolution communities*Gong et al. [103] proposed a multi-objective immune algorithm to simultaneously optimize modified ratio association and ratio cut. The optimization of modified ratio association favors to partition a network into small communities, while ratio cut tends to divide the network into large communities. In [299], a multi-objective memetic community detection (MMCD) algorithm is proposed. It combines a multi-objective evolutionary algorithm with a local search procedure to find multi-resolution structures of networks. Although modularity experiences resolution limit, they decomposed it into two terms: Intra$Q$ and Inter$Q$ to be optimized simultaneously. Then, a local search strategy based on label propagation rule is suggested to search the local optimal solutions efficiently. In [316], a network reduction-based multi-objective evolutionary algorithm for community detection in large-scale networks is proposed. Network size is recursively reduced as the evolution proceeds. In each reduction of the network, the local communities found by the best individuals in the population are identified as nodes of the reduced network for further evolution. A local community repairing strategy is also suggested to correct the misidentified nodes after each network reduction during the evolution.

–Networks with non silent connections

Although metaheuristic based community detection has been addressed in the literature for the last several years, the majority of the work has primarily focused on complex networks with silent connections. Relatively few researchers were directed their focus towards analyzing community structures with the existence of signed, weighted, and/or directed connections. For example, in signed networks an early effort has been suggested by Li et al. [172]. They developed a single objective evolutionary algorithm and memetic algorithm for maximizing the signed modularity and relaxed modularity density. However, Amelio and Pizzuti [8] were the first to formulate this problem as a multi-objective optimization model. In 2013, they put forward an initial work on a multi-objective optimization model for community detection in signed networks. They suggested to maximize signed modularity (Q_s) of [100] and the minimization of a frustration (FS) function defined by Doreian and Mrvar [73]. Their model emphasizes the need for searching for partitioning solutions with high modularity and low frustration structures, since these qualitative measures are essential to surpass the limits of random topological structures and erroneous community-assignment of positive and negative relations.

Also, in the early of 2014, Gong et al. [101] developed a multi-objective particle swarm optimization (MOPSO) algorithm while considering both negative of signed ratio association (nSRA) and signed ratio cut (SRC) in their multi-objective minimization model. Then, by the late of 2014, Liu et al. [182] proposed a multi-objective optimization model for community detection in signed networks. The basic principle for their model is laid out after the definition of Huang et al. [129] for structural similarity between two nodes. Their multi-objective optimization model reflect the role of positive intra and inter structural similarities in one maximization function and the role of negative intra and inter structural similarities in a second maximization function. With regular analysis, they verified the effectiveness and efficacy of their model over the graph-based heuristic FEC model of Yang et al. [304], an extension to the optimization method for modularity proposed by Blondel et al. [35], and the model of Li et al. [172]. Then, Amelio and Pizzuti [10] extended their initial work to further improve the signed modularity of the final solutions reached by their model in [8]. Akin to the local improvement suggested by Pizzuti [230], a local refinement is adopted. The suggested improvement implies the movement of nodes having positive inter connections from their communities to neighboring communities while maintaining an increase in the value of Q_s. Through extensive experimental evaluations on synthetic and real life networks, they reported the efficacy of their model against other state-of-the-art methods including [101,182]. However, they didn't report the robustness of their multi-objective optimization model against models in [101,182] when adopted alone with no solution improvement. In other words, it is guessing whether the local refinement operator could also refine the solutions obtained by Gong et al. [101] model and Liu et al. [182] model to converge to more competitive community structures.

More recently, Girdhar and Bharadwaj [93] extended the multi-objectives of modularity and frustration model with additional objective (social balance factor) to be optimized using NSGA-II algorithm. However, in order to better claim the robustness of a particular community detection model is to be honored, Attea et al. [24] were the first to pose a challenge that must be overwhelmed by the formulation of the community detection model and by the design of the local refinement operator. They investigated the robustness of their multi-objective evolutionary based optimization model against the state-of-the-art models [10,129,182]. Further, they proposed a heuristic anti-frustration operator and then studied its positive impact on improving the convergence accuracy of all tested models. They clarified the robustness of their model to generate more accurate community structures. Also, they validated the positive collaboration of the anti-frustration heuristic operator with their model and the models proposed in [182] and [10]. Finally, they demonstrated that their model is worthy as reaching more accurate results when operated alone and as receiving clear collaboration from the heuristic operator.

–Networks with overlapping communities

An earliest MCD work in this direction is the algorithm proposed by Pizzuti [228]. Pizzuti in [228] extended her work in [225,226] and proposed a single objective GA based community detection, named GA-NET+, to discover overlapped communities in complex networks. The algorithm adopts community score function (Φ_{CS} in Eq. (20)) as a partition quality measure. To handle overlapping communities, GA-NET+ uses the line graph to model the network instead of the original graph. Also, GA-NET+ employs locus-based adjacency representation. GA-NET+ outperforms other state-of-the-art HCD algorithms, e.g., [154,222]. Due to the large dimensionality of line graph, high computational complexity is the main deficiency of GA-NET+. However, the main recommendation of this work is to define the problem as a multi-objective optimization function. A multi-objective evolutionary algorithm with three objective functions concerning community quality, community separation, and community overlapping is proposed by Liu et al. [187]. Line graph representation is also adopted in [173] while developing an improved multi-objective quantum-behaved particle swarm optimization (IMOQPSO). Li et al. [173] proposed a variant of modularity (called neighbor modularity) and akin to the idea of Shi et al. [259], they divided it into two terms as multi-objective optimization function. The main limitation of line graph individual representation is then left off while adopting MOEAs with maximal clique in [297] and mixed representation in [312].

–Multiplex networks and multipartite networks

Amelio and Pizzuti [9] proposed a multidimensional multi-objective genetic algorithm for shared community detection in multiplex networks (MultiMOGA). It iteratively optimizes both facet quality and sharing cost. For facet quality, they employed maximization of the modularity function [213]. However, for sharing cost, they suggested maximization of the normalized mutual information between two consecutive facets. Further, to select the ordering under which networks should be examined, they employed a heuristic based on the concept of clustering coefficient of the network (defined in [295]). Here, a high clustering coefficient means that nodes tend to be more connected, thus they are biased to form groups. Then, Amelio and Pizzuti [11] extended their work in [9] to discover the evolution of community structure in temporal multiplex networks. They adopted Hungarian approach to detect the best cluster correspondence between two consecutive timestamps. Recently, Karimi et al. [144] employed the multi-objective evolutionary algorithm with decomposition (MOEA/D) Tabu Search (TS) and Clustering Coefficient (CC) to detect shared communities in multiplex networks. they used the social networks analysis measure of CC for the generation of the initial population. Also, they exploited the neighborhood search authority of TS for discovering Pareto optimal solutions.

Souam et al. [266] proposed a two-phase based approach for identifying overlapping communities in bipartite networks. Although modularity suffers from the resolution limit problem, they adopted it in a dual optimization functions. In the first phase, the used a single objective genetic algorithm for global optimization of the Newmans modularity on the line graph. In the second phase, they adopted a heuristic algorithm to locally optimize the overlapping modularity (Mancoridis modularity), and adapted it to bipartite networks.

Additionally, there are many other evolutionary algorithms that have been used to detect community structures in complex networks, e.g., [5,17,26,53,54,63,64,109,117,148,165,168,171,198,239,255, 256,279,286,326]. Adopting several PSO variants for solving CD problem can be found in [44,45,47,48,56,89,166,170,175,217,218, 233,237,241,261,262,302,310]. MA based community detection algorithms can be found in [87,104,119,167,194,205,288,289,309]. Both ACO and BCO are also used for solving CD problem, as reported in [13,31,50,51,115,116,120,121,126,136,139,247,265,294,323].

Recently, a number of researchers proposed different community detection algorithm based on new versions of metaheuristics. Here, we list some of these works. Examples of CA algorithms for solving CD problem in complex networks can be found in [27,308]. A number of DE based algorithms have also been proposed, e.g., [130,140,174,183]. Single point metaheuristics are also considered in the literature for solving CD problem besides population based algorithms. These are simulated annealing (SA), tabu search (TS), and greedy randomized adaptive search procedure [88,110,112,190,208,223]. Some researchers were interested in investigating the applicability of IA for the CD problem, as reported in [52,105,145]. However, before closing this section, it is worth to mention our envisioned status (and as will be clarified in the next section) that the key issues while considering the design of a new competitive metaheuristic algorithm for solving the CD problem are: 1) *to identify community structure with more robust (mostly multi-objective) optimization models, and* 2) *to develop a cross-fertilization mechanism for combining heuristic operators (that are tailored specifically to fit the CD problem) with the designed metaheuristic. Otherwise, the algorithm would mostly be useless, noncompetitive, but has a new name*. We encourage the interested readers to [71] for further details concerning the current status of bio-inspired optimization and what are the main keys to focus our understanding of this family of optimization techniques to reach on more valuable methods while tackling a diverse spectrum of problem domains.

6. Open research area and challenges

Actually, many of the recently published works and review papers made significant efforts to focus on the computational capabilities of many metaheuristics for effectively solving the CD problem. Despite the increasing interest in this research direction, the design of such MCD algorithms is general. As presented in the previous section, when looking at these algorithms, many if not most of them solely adhere to the canonical characteristics of specific metaheuristics and to reflect several definitions (i.e. models) of community structure on the formulation of appropriate objective functions (refer to Eqs. (14)–(27)). However, after the No Free Lunch Theorem (NFLT) [30,298], the interested researchers in proposing metaheuristics for the CD problem had really to change their algorithmic designs from the general metaphors to more specific components. In other words, the features of the CD problem have to be capitalized on building up the different components for the adopted metaheuristic.

In fact, exploiting problem specific knowledge in the best possible way, picking the right algorithmic components, and cross-fertilizing them in the most appropriate way are essential ingredients for designing a prominent metaheuristic based optimization algorithms. Unfortunately, most of the proposed MCD algorithms generally lack the adequate potential for picking the right algorithmic components and for projecting problem specific knowledge to tune the design of such components.

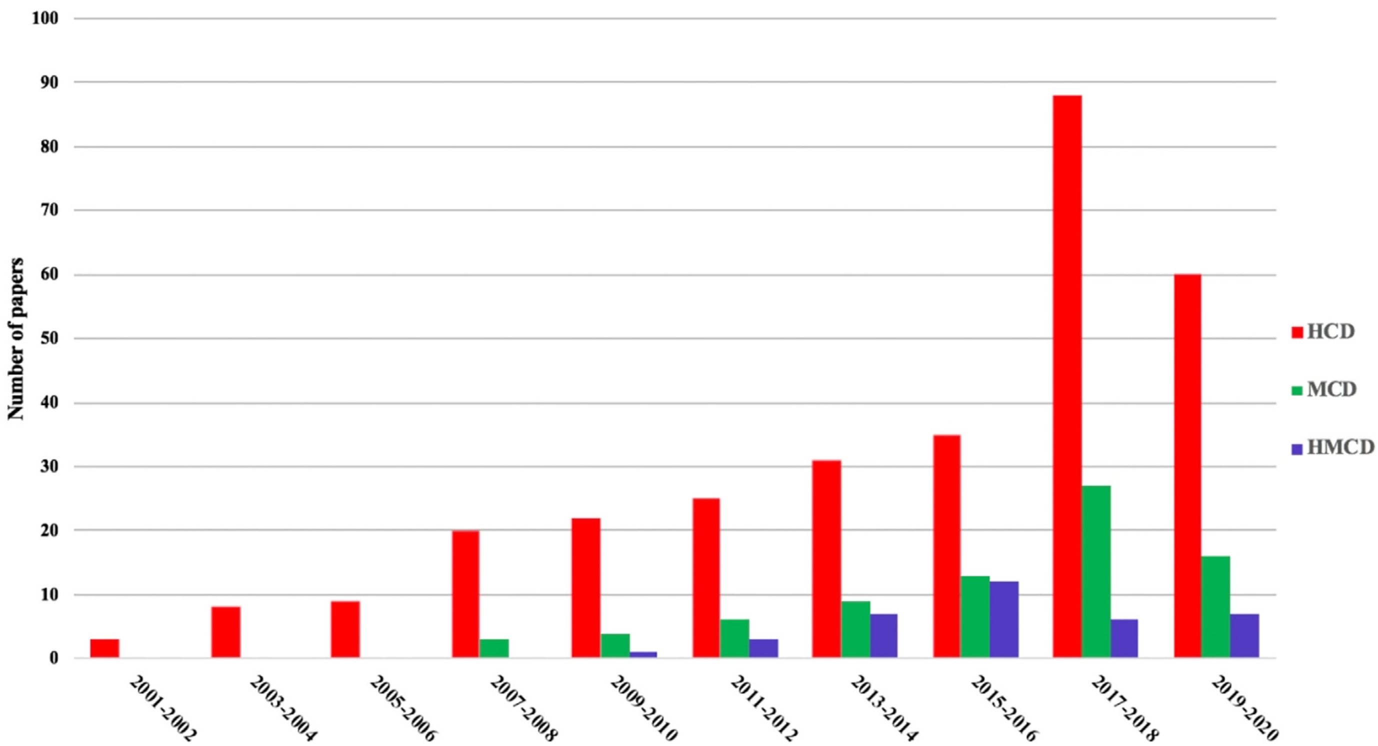

Fig. 3. Year wise distribution of the published papers in different journals indexed by ISI Web of Science and Scopus during the period 2001–2020. The distribution includes: HCD algorithms (red) occurring in the early of the period followed by MCD algorithms (green) and then by HMCD algorithms (blue).

Being able to identify future directions of research work, let us first statistically depict the interest of the main streams of CD algorithms in the literature: HCD, MCD, and HMCD algorithms. Recall that heuristics and metaheuristics refer to the rule-based local search algorithms and global population based search algorithms, respectively. It is worth to mention here that we evaluate our statistics while examining more than 400 related works published in journals indexed by ISI Web of Science and Scopus. The characteristics of all algorithms mentioned in these works are provided in the Supplementary table. The year wise distribution of the related works that appeared in different journals during the period 2001–2020 is capitulated in Fig. 3. Recall that a CD algorithm is classified as HCD or MCD when its general framework matches, respectively, the formulations expressed in Eq. (16) or Eq. (17). However, an existing CD algorithm is classified as HMCD when its general framework can be expressed by either Eq. (29) (Algorithm 1), Eq. (30) (Algorithm 2

Algorithm 1: General framework of LT-HMCD

begin
- $t = 0$;
- initialize $\mathbb{I}^t \leftarrow \{\mathcal{I}_1^t, \mathcal{I}_2^t, \dots, \mathcal{I}_N^t\}$;
- decode: $\Gamma(\mathbb{I}^t): \{C_1^t, C_2^t, \dots, C_N^t\}$;
- evaluate: $\mathbb{I}^t: \{\Phi(C_1^t), \Phi(C_2^t), \dots, \Phi(C_N^t)\}$;
- **while** $(\iota(\mathbb{I}^t) \neq true)$ **do**
  - select: $\mathbb{I}^{t+1} \leftarrow s(\mathbb{I}^t)$;
  - recombine: $\mathbb{I}^{t+1} \leftarrow r_h(\mathbb{I}^{t+1},)$;
  - mutate: $\mathbb{I}^{t+1} \leftarrow mu_h(\mathbb{I}^{t+1},)$;
  - decode: $\Gamma(\mathbb{I}^{t+1}): \{C_1^{t+1}, C_2^{t+1}, \dots, C_N^{t+1}\}$;
  - evaluate: $\mathbb{I}^{t+1}: \{\Phi(C_1^{t+1}), \Phi(C_2^{t+1}), \dots, \Phi(C_N^{t+1})\}$;
  - $t \leftarrow t + 1$;
- output: $C_{1\leqslant i\leqslant N}^t$ with best Φ;

), or Eq. (31) (Algorithm 3) to be formulated in the coming discus-

Algorithm 2: General framework of HR-HMCD

begin
- $t = 0$;
- initialize $\mathbb{I}^t \leftarrow \mathrm{HCD}_s(\{\mathcal{I}_1^t, \mathcal{I}_2^t, \dots, \mathcal{I}_N^t\})$;
- decode: $\Gamma(\mathbb{I}^t): \{C_1^t, C_2^t, \dots, C_N^t\}$;
- evaluate: $\mathbb{I}^t: \{\Phi(C_1^t), \Phi(C_2^t), \dots, \Phi(C_N^t)\}$;
- **while** $(\iota(\mathbb{I}^t) \neq true)$ **do**
  - select: $\mathbb{I}^{t+1} \leftarrow s(\mathbb{I}^t)$;
  - recombine: $\mathbb{I}^{t+1} \leftarrow r(\mathbb{I}^{t+1},)$;
  - mutate: $\mathbb{I}^{t+1} \leftarrow mu(\mathbb{I}^{t+1},)$;
  - decode: $\Gamma(\mathbb{I}^{t+1}): \{C_1^{t+1}, C_2^{t+1}, \dots, C_N^{t+1}\}$;
  - evaluate: $\mathbb{I}^{t+1}: \{\Phi(C_1^{t+1}), \Phi(C_2^{t+1}), \dots, \Phi(C_N^{t+1})\}$;
  - $t \leftarrow t + 1$;
- $\mathbb{I}^t \leftarrow \mathrm{HCD}_e(\{\mathcal{I}_1^t, \mathcal{I}_2^t, \dots, \mathcal{I}_N^t\})$;
- decode: $\Gamma(\mathbb{I}^t): \{C_1^t, C_2^t, \dots, C_N^t\}$;
- output: $C_{1\leqslant i\leqslant N}^t$ with best Φ;

sion. The figure shows the distributions of HCD algorithms against MCD and HMCD algorithms. Also, we can see that the actual efforts concerning population based MCD and HMCD algorithms have been investigated but only since 2007 [81] and 2010 [185], respectively. The figure clearly demonstrates that the heuristic algorithms *quantitatively* dominate the main interest of the community detection works in complex networks, although MCD and *more significantly* HMCD algorithms have been proved to successfully outperform them.

For all these works included in our statistics, a proportion of the chart in Fig. 4(a) is assigned to each of the three available community detection algorithms: more than 300, about 75, and about 35 published works for, respectively, HCD, MCD, and HMCD algorithms. The magnitude of the distributions of the literature work in terms of HCD, MCD, and HMCD algorithms with respect to static complex networks are also

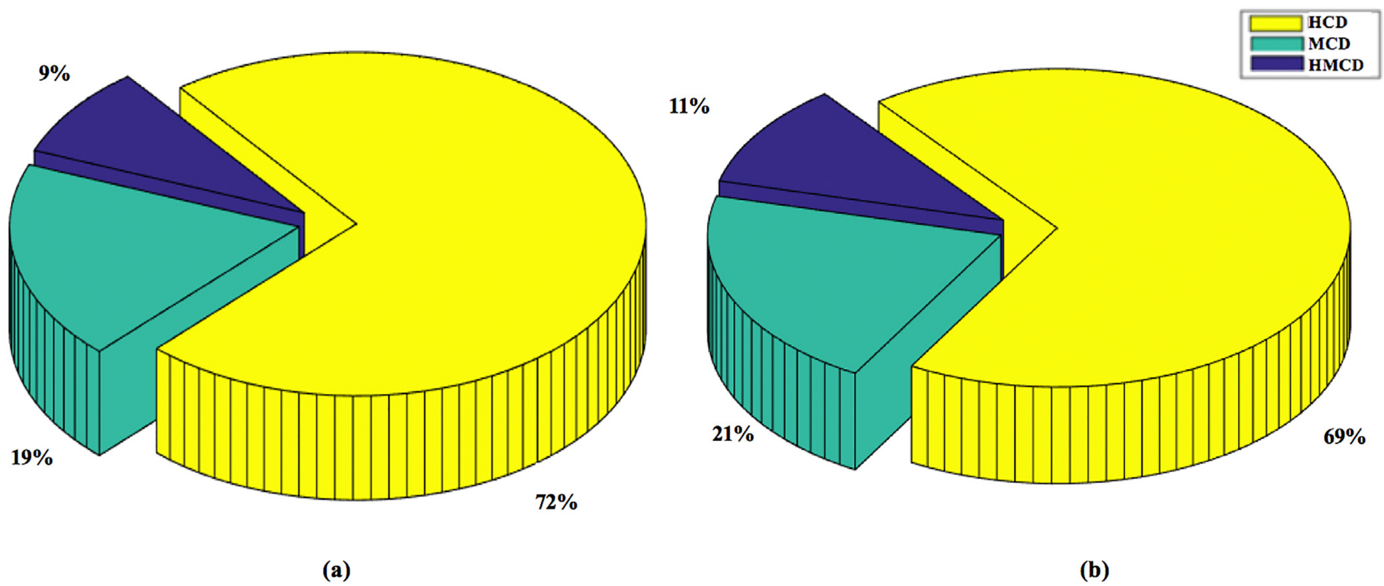

Fig. 4. (a) Distribution of community detection algorithms during the period 2001-2020 by means of HCD (yellow), MCD (turquoise), and HMCD (blue) algorithms. (b) The magnitude of the distributions of HCD (yellow), MCD (turquoise), and HMCD (blue) algorithms found in the literature with reference to static complex networks. In both charts, a greater proportion of about 70% of the works was directed to the HCD algorithms. About 66% of the remaining interest were acknowledged to MCD algorithms, leaving HMCD algorithms to play with the smallest percentage.

Algorithm 3: General framework of HT-HMCD

begin
 $t = 0$;
 initialize $\mathbb{I}^t(\text{MCD}_{1\leqslant i\leqslant dim}) \leftarrow \{\mathcal{I}_1^t, \mathcal{I}_2^t, \dots, \mathcal{I}_N^t\}$;
 decode: $\Gamma(\mathbb{I}^t(\text{MCD}_{1\leqslant i\leqslant dim})) : \{C_1^t, C_2^t, \dots, C_N^t\}$;
 evaluate: $\mathbb{I}^t(\text{MCD}_{1\leqslant i\leqslant dim}) : \{\Phi(C_1^t), \Phi(C_2^t), \dots, \Phi(C_N^t)\}$;
 while $(\iota(\mathbb{I}^t) \neq true)$ **do**
  select: $\mathbb{I}^{t+1}(\text{MCD}_{1\leqslant i\leqslant dim}) \leftarrow s(\mathbb{I}^t)$;
  recombine: $\mathbb{I}^{t+1}(\text{MCD}_{1\leqslant i\leqslant dim}) \leftarrow r(\mathbb{I}^{t+1},)$;
  mutate: $\mathbb{I}^{t+1}(\text{MCD}_{1\leqslant i\leqslant dim}) \leftarrow mu(\mathbb{I}^{t+1},)$;
  decode: $\Gamma(\mathbb{I}^{t+1}(\text{MCD}_{1\leqslant i\leqslant dim})) : \{C_1^{t+1}, C_2^{t+1}, \dots, C_N^{t+1}\}$;
  evaluate: $\mathbb{I}^{t+1}(\text{MCD}_{1\leqslant i\leqslant dim}) : \{\Phi(C_1^{t+1}), \Phi(C_2^{t+1}), \dots, \Phi(C_N^{t+1})\}$;
  communicate: $com(\text{MCD}_i, \text{MCD}_j | \exists e(i,j)$;
  $t \leftarrow t + 1$;
 output: $C^t_{1\leqslant i\leqslant dim, 1\leqslant j\leqslant N}$ with best Φ;

given in Fig. 4(b). For weighted networks, overlapping communities, signed networks, and dynamic networks, the magnitude of the distributions for HCD, MCD, and HMCD algorithms are also depicted in Figs. 5 and 6.

Further, the distribution of the types of the metaheuristic algorithms used in MCD and HMCD is shown in Fig. 7. The distribution reveals that the bulk of the works for both metaheuristic and hybrid metaheuristic based community detection algorithms came from the contribution of the EA family while the minority of other metaheuristic families constituting the remaining works. Finally, Fig. 8 presents the distribution of most popular against non-traditional objectives that have been used in different journals over around 20 years ago. The figure demonstrates that modularity (and its variants mentioned in Section 4) is the dominated function that has been optimized by many community detection algorithms (HCD, MCD and HMCD). This statistic takes into account the objectives that have been used just in optimization algorithms

While this review revisits many MCD works, we found that almost all such developed algorithms heavily relied on defining the CD problem in different formulations of single objective optimization (SOO) or multi-objective optimization (MOO) functions. By objective (fitness) functions, they try to qualify diverse regions of the search space in terms of objective values of the individual solutions and use that information as a *learning* method to decide which region(s) of the search space to explore and exploit next. Obtaining indications of which objective (or more importantly a combination of contradictory objectives) to work well was the main contribution of such works to achieve superior performance over other HCD algorithms. Despite the improving performance of these MCD algorithms over HCD algorithms, we still observe a lack of works regarding the design of such MCD algorithms in a more optimistic picture concerning the main participants of the search process. The manifold variations of MCD algorithms found in the literature can mainly reflect IDL, but in a more or less, traditional design.

Thus, despite the prevalence of heuristics and metaheuristics in this field of study, the need for hybrid metaheuristics and other potential for cross-fertilization between HCD and MCD algorithms will emerge and continue to increase. The purpose of the following subsections is to provide the researchers with new design issues for CD algorithms that, to date, have either paid little attention or as yet unexplored.

6.1. Hybrid metaheuristic based community detection (HMCD) frameworks

Hybrid metaheuristics (HMs) are general frameworks for *implicit* or *explicit* combination of metaheuristics with other (meta)heuristic techniques [275]. The primary motivation comes from the observation that hybridization is essential for exploiting the benefits and transcending the limits of its pure counterpart algorithms. Because of its fruitful application in many complex real-world optimization problems, HMs nowadays become increasingly dominated over their participant algorithms. Despite the increasing interest for solving CD problem in complex networks, there exist, however, few cross-fertilization in the current development and usage of HM strategies (Table 6). The charts presented in Figs. 3–6 clearly bring out that the majority of the work in the literature belongs to HCD algorithms and then to MCD algorithms, leaving HMCD algorithms with little attention. In the quest for improved performance, we suggest pushing aside both HCD and MCD, when working as alone algorithms, and draw more attention to HMCD algorithms as a powerful tool to describe the interplay between HCD and MCD algorithms.

Table 6
Main characteristics of HMCD algorithms proposed in the literature.

Reference	Name	CD optimization problem	Network's type	Dynamic community	Non silent connections	Overlapping	Multiplex/multi partite	Heuristic	HMCD type
[185]	SA	SOO	Social	—	—	—	—	k-means	LT-HMCD
[230]	GA	SOO	Social	—	—	—	—	local search operator	HR-HMCD
[102]	MA	SOO	Social	—	—	—	—	Mutation	LT-HMCD
[105]	EA & IA	MOO	Social	✓	—	—	—	Mutation	LT-HMCD
[139]	ACO& fitness threshold	SOO	Social	—	—	✓	—	Local optimization	LT-HMCD
[126]	ACO & vertices correlation	SOO	Social	—	—	—	—	Initialization	HR-HMCD
[103]	EA & IA	MOO	Social	—	—	—	—	Mutation	LT-HMCD
[45]	PSO	SOO	Social	—	Signed/weighted	—	—	initialization	HR-HMCD
[101]	PSO	MOO	Social	—	Signed/weighted	—	—	Initialization	HR-HMCD
[194]	MA	SOO	Social	—	Signed/weighted	—	—	Child perturbation	LT-HMCD
[266]	GA	SOO	Social	—	—	Overlapping	multipartite	Final solution	HR-HMCD
[299]	MA	MOO	Social	—	—	—	—	Local search operator	LT-HMCD
[44]	PSO	MOO	Social	—	Signed/weighted	—	—	initialization	HR-HMCD
[91]	ACO& BCO	SOO	Social	—	—	—	—	Child perturbation	LT-HMCD
[323]	ACO	SOO	Social	—	—	✓	—	Initialization	HR-HMCD
[145]	IA & greedy algorithm	SOO	PPI	—	—	—	—	Child perturbation	LT-HMCD
[206]	SA & MA	SOO	Social	—	—	—	—	Child perturbation	LT-HMCD
[23]	EA	MOO	Social	✓	—	—	—	Mutation	LT-HMCD
[21]	EA	MOO	Social	—	—	✓	—	Mutation	LT-HMCD
[115]	BCO	SOO	Social	—	—	—	—	Heuristic searching progress	LT-HMCD
[176]	EA	SOO	Social	—	—	—	—	Mutation	LT-HMCD
[174]	DE & Spider	SOO	Social	—	—	—	—	Crossover	LT-HMCD
[2]	EA	MOO	PPI	—	—	—	—	Mutation	LT-HMCD
[18]	EA& frog leaping	MOO	Social	—	—	✓	—	mutation	LT-HMCD
[20]	EA	MOO	PPI	—	—	✓	—	Mutation	LT-HMCD
[1]	EA	SOO	PPI	—	—	—	—	Mutation	LT-HMCD
[250]	GA	MOO	Social	—	—	✓	—	Mutation	LT-HMCD
[24]	EA	MOO	Social	—	Signed	—	—	Mutation	LT-HMCD
[184]	EA	SOO	PPI	—	Signed	—	—	Mutation	LT-HMCD
[280]	EA	SOO	Social	—	Signed	✓	—	Mutation	LT-HMCD
[114]	EA	SOO	Social	—	signed	—	—	Mutation	LT-HMCD
[279]	EA	MOO	social	—	—	—	—	child perturbation	LT-HMCD
[144]	EA	MOO	social	—	—	—	multiplex	Initialization and Pareto final solutions	HR-HMCD
[249]	ACO	MOO	social	—	—	—	—	Initialization	HR-HMCD
[288]	MA & IA	SOO	social	—	—	—	—	Child perturbation	LT-HMCD

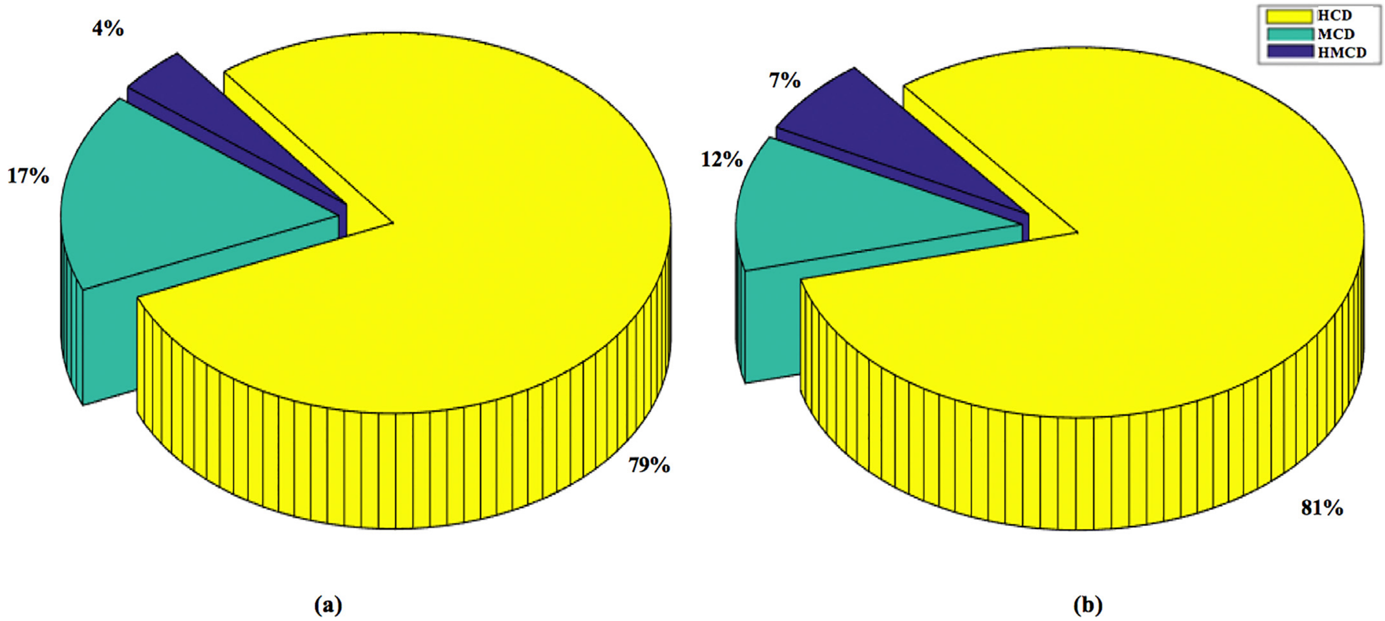

Fig. 5. The magnitude of the distributions of HCD (yellow), MCD (turquoise), and HMCD (blue) algorithms found in the literature with reference to: (a) weighted complex networks, and (b) unveiling overlapping communities in complex networks. Again, in both charts, a large proportion with 80% of the works was directed to the HCD algorithms. About 75% of the of the remaining interest was acknowledged to MCD algorithms, leaving HMCD algorithms to play very rarely in the remaining percentage.

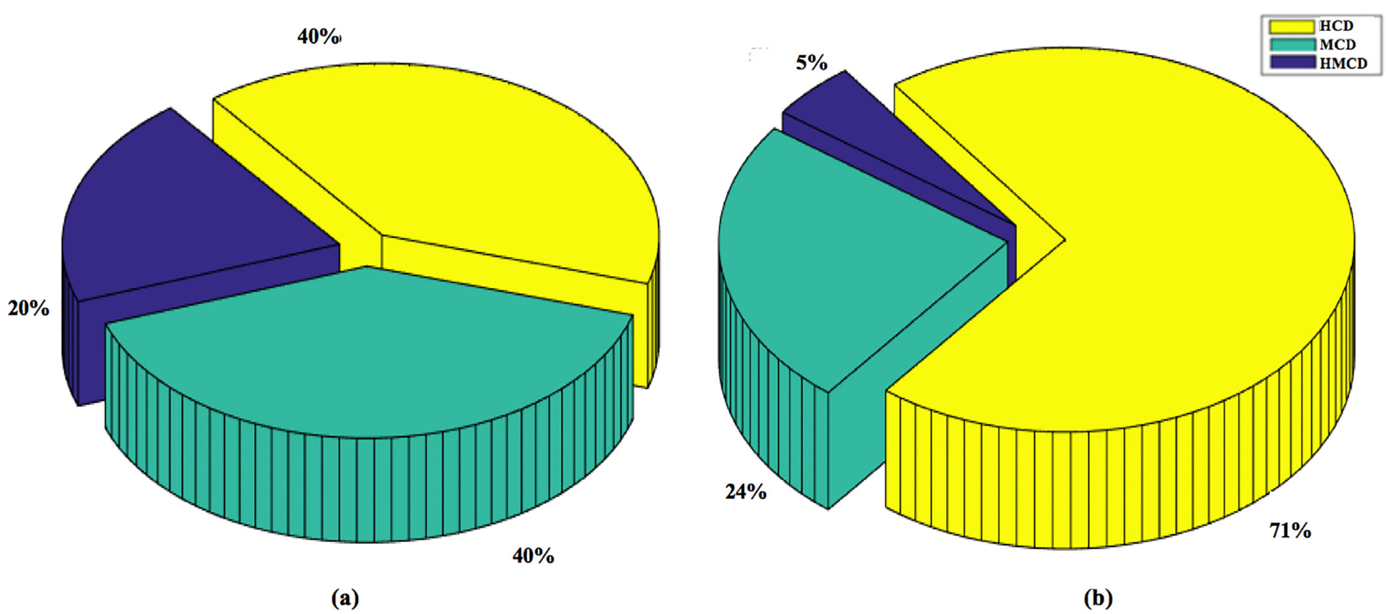

Fig. 6. The magnitude of the distributions of HCD (yellow), MCD (turquoise), and HMCD (blue) algorithms found in the literature with reference to: (a) signed complex networks, and (b) dynamic complex networks. In signed complex networks, the literature provides an equal contribution for both HCD and MCD algorithms reaches to 40%, while HMCD algorithms give only 20% contributions. For dynamic networks, on the other hand, HCD algorithms return to their domination to about 70%, while MCD and HMCD algorithms share, respectively, about 25% and 5% works.

One of the well-known taxonomies for hybrid metaheuristics (HMs) that have been proposed in the literature is suggested by Talbi [275]. In [275], four main classifications for hybridization between individual heuristics, individual metaheuristics, and between heuristics and metaheuristics are identified. These are Low-level relay hybrid (LRH), Low-level teamwork hybrid (LTH), High-level relay hybrid (HRH), and High-level teamwork hybrid (HTH). For further details, one can refer to [275]. Akin to the taxonomy of Talbi [275], we introduce here a new taxonomy for three HMCD frameworks. These frameworks can provide researchers with primary design issues for developing CD algorithms. While the classification in [275], stated all possible cooperation between a pair of heuristics, a pair of metaheuristics, and a heuristic with a metaheuristic, we are only interested with the possible algorithmic pairs that give raise to cooperative behaviors between individual metaheuristics and/or between heuristics and metaheuristic ones. In other words, the class which represents a collaboration between only heuristic algorithms in which a given heuristic is embedded into another heuristic (i.e. LRH) is ignored in our discussion. Thus, we can derive three different design issues for HMCD.

*Framework*1: *Low-level teamwork hybrid metaheuristic for community detection* (LT-HMCD) In this class of hybridization, the characteristic components of a given heuristic based community detection (HCD) algo-

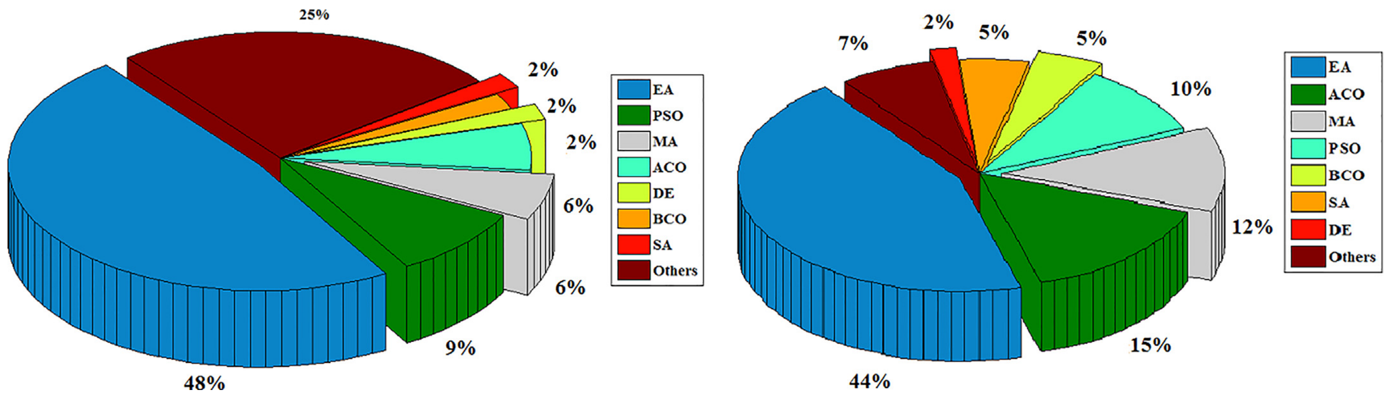

Fig. 7. Family distribution of metaheuristics adopted in (a) MCD algorithms. (b) HMCD algorithms. In both charts, the family of evolutionary algorithm (EA) dominates more than 40% of the interest, while the remaining metaheuristic families have been presented with minor interest of 2% up to 25% works during the period 2001-2020.

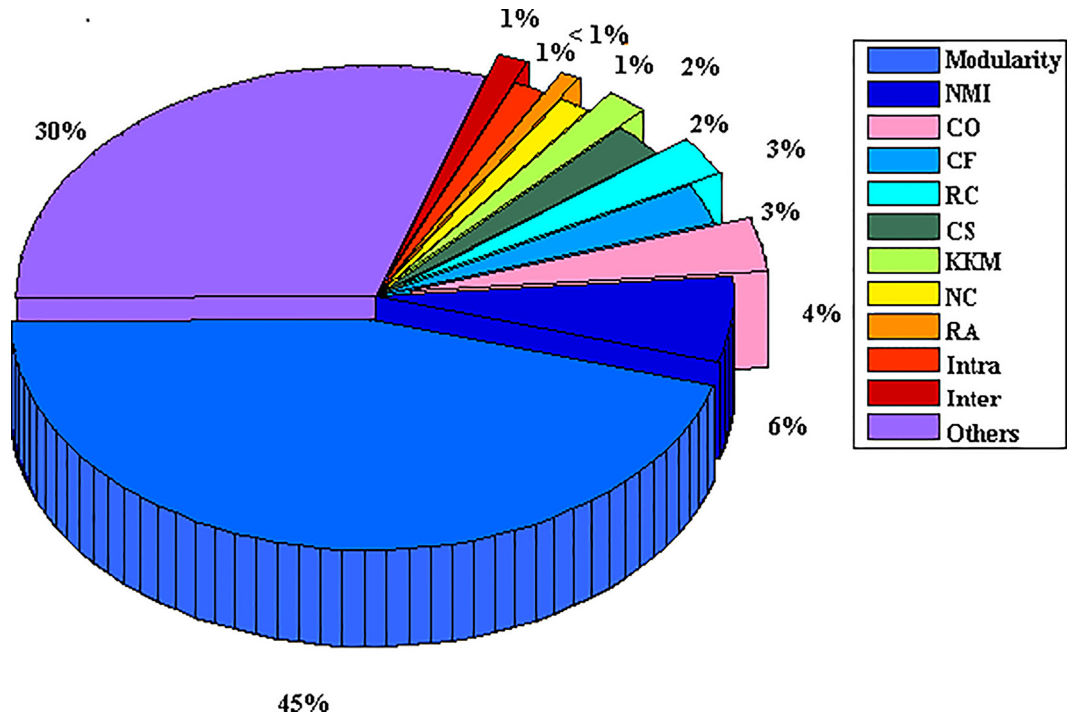

Fig. 8. The distribution of the most popular objectives (Modularity with all its variants, NMI, CO, CF, RC, CS, KKM, NC, NRA, Intra, Inter and Others) against non-traditional objectives that have been used in different journals over around the 20 years ago. Typically, non-traditional formulations outperform the detection ability of the counterpart objectives.

rithm, either proposed in the literature or a newly suggested one, will be embedded into the functional parts of a single MCD algorithm. In successive iterations of an MCD algorithm, the building blocks of regular communities often emerge and grow by the collaboration of IDL components of the MCD algorithm. There are, however, intra- and inter-connections of some nodes that may prevent such building blocks to complete to form fine-tuning structures. The traditional perturbation operators most probably have difficulty in improving the explored communities to either optimally or near optimally structures. To this end, a unified view to approach LT-HMCD is to consider the perturbation operator(s) of an MCD algorithm as a fit template for either: 1) assembling the materials of an effective HCD algorithm, or 2) building a new HCD algorithm.

We can define LT-HMCD : $\mathbb{I} \rightarrow \mathbb{I}$ as an iterated transformation function wit the tuple in Eq. (29). From the whole space of community structures (i.e. Ω), an initial population $\mathbb{I} = \{\mathcal{I}_1, \mathcal{I}_2, \ldots, \mathcal{I}_N\}$ of N encoded individuals is randomly generated. The population evolves in consecutive cycles of individual decoding Γ and evaluation Φ functions, mating pool selection operator s, a heuristic based perturbation operator (any or both of recombination operator $r_h : \mathcal{I} \times \mathcal{I} \rightarrow \mathcal{I}$ and mutation operator $mu_h : \mathcal{I} \rightarrow \mathcal{I}$), and the termination criterion ι. The general algorithmic description of LT-HMCD framework can be specified in Algorithm 1.

$$\text{LT-HMCD} = (\Omega, \mathbb{I}, \Gamma, \Phi, s, r_h, mu_h, \iota) \tag{29}$$

Almost all of the existing state-of-the-art HMCD algorithms, e.g., [1,2,20,21,23,24,102] augment their volume-oriented mutation operators with the line-oriented search ability of the HCD algorithm. They have been applied to unsigned, signed, and dynamic complex networks and to social and PPI networks. They showed plausible behaviour supporting their performance against the state-of-the-art HCD and MCD algorithms. For example, the foundation of the heuristic mutation operators, the so-called migration operators, proposed in [2,20,21,23,24] is to harness the existence of strong intra-connections among the nodes at the expense of weak ones. The proposed migration operators can discover the connections necessary to form strong intra-connections and moving nodes towards such structures. Thus making the communities more vulnerable to destruction by weak intra-relations. This approach of hybridization brings the diversification-aware mutation operator closer to the intensification role.

Further investigations on the applicability of the migration-based mutation operator can be performed to other types of complex networks such as those forming overlapped communities. Moreover, different types of migration operators can be suggested that can change the community belongingness of any node depending on the influence of its intra- and inter-connections with respect to, e.g., modularity (Eq. (14)), modularity density (Eq. (15)), community score (Eq. (20)), ratio cut (Eq. (27)), etc. of the host community. Simply stated such migration operators should allow detached yet salient nodes, in terms of tight community structure, to be brought closer. Node-wise migration operator can further be extended towards a condensed graph of nodes. A set of nodes which altogether form a condensed graph among them but weak intra-connections with the remaining nodes of a single community can be migrated to another community. Also, another immediate extension to this heuristic mutation operator is to project it into the recombination operator. For example, the mixed communities resulted from the two parent community structures can be repaired to remedy the problem of weak intra-connections. Further, the incorporation of nonnegative matrix factorization (i.e. network embedding) for the adjacency matrix in modeling new migration operators is another interesting extension. Both the mesoscopic and the microscopic descriptions of network structures can be utilized for migrating nodes between different communities. Modularized Nonnegative Matrix Factorization (M-NMF) [292], Deep Autoencoder-like NMF [306], are some examples of effective network embedding models for static networks, while evolutionary nonnegative matrix factorization [293] is an example to detect dynamic communities.

*Framework*2: *High-level relay hybrid metaheuristic for community detection* (HR-HMCD) This type of hybridization identifies an explicit handshaking between HCD and MCD algorithms. The general sequence of an HR-HMCD algorithm could be started by one of the potentials of HCD algorithms followed by an MCD alternative and then ended with another HCD algorithm. Thus, HR-HMCD : $\mathbb{I} \rightarrow \mathbb{I}$ can be defined as an iterated transformation function with the tuple in Eq. (30). The general algorithmic description of the HR-HMCD framework can be specified in Algorithm 2.

$$\text{HR-HMCD} = \text{HCD}_s \times \text{MCD} \times \text{HCD}_e \tag{30}$$

The first HCD algorithm can be viewed as a generator for a good initial population for the midway MCD. The quality of this initial population most probably has a positive impact on the performance of the adopted MCD algorithm. A bottom-up or top-down greedy local search heuristic generators can be used to generate the initial population of diverse, yet promising individuals. The main idea of these local search heuristics is to repeatedly move nodes between neighboring communities and merging communities (in case of bottom-up) or splitting communities (in case of top-down). Merging and splitting can be repeated as long as the objective value (again modularity in Eq. (14), normalized cut in Eq. (26), and community score in Eq. (20)) are just few examples) improves.

The near optimal set of solutions achieved by the adopted MCD algorithm in the final generation can also be fine-tuned by a greedy local search heuristic. In other words, the final population can be departed, as next to the MCD, to an HCD algorithm. The strength of the metaheuristic is on approaching high performance community structures from the vast space of community structures. Such basins of attraction can further be improved and fine-tuned to find the optimal structures as efficiently as possible.

*Framework*3: *High-level teamwork hybrid metaheuristic for community detection* (HT-HMCD)

The general framework of this class can be expressed as a parallel collaboration of several MCD algorithms. The collaboration can be applied among MCD algorithms of a single family (*homogeneous MCDs*) or different families (*heterogeneous MCDs*). The MCDs and their connections can be represented by a graph, where each vertex corresponds to an MCD algorithm and an edge $e(i, j)$ exists if both MCD_i and MCD_j are connected. As an example of a potential collaboration can be implemented by connecting 8 MCD algorithms in a 4-D hypercube topology. Further, We suggest to allow different MCD algorithms from different families, LT-MCDs, and HR-MCDs as the basic entities for this model. The connected vertices can be *communicated* together to search the vast and complex search space of the problem and to find the optimal solution or a set of solutions with high quality community structures. The communication model com between the connected MCD nodes includes a migration strategy to control the replacement of the solutions between the nodes, a migration rate to control the number of migrant solutions, and a migration interval to control how often migration occurs. In general, HT-HMCD : $\mathbb{I} \rightarrow \mathbb{I}$ can be defined as an iterated transformation function with the tuple in Eq. (31). The general algorithmic description of HT-HMCD framework can be specified in Algorithm 3.

$$\text{HT-HMCD} = (\{\text{MCD}_1, \text{MCD}_2, \dots, \text{MCD}_{dim}\}, com) \tag{31}$$

where dim is the number of connected MCD algorithms.

The proposed HT-HMCD framework which realizes the importance of collaboration of different MCDs, offers more interesting works. Despite the success of MCD algorithms which are based on MOO models against those based on SOO models, determining the most fruitful combination of contradictory objectives is often as difficult as finding a high-quality solution for the problem itself. Hence, another interested research work that could deserve a real effort is to examine the singleton MCD algorithms in HT-HMCD with different MOO models. The HT-HMCD framework can also explore the possibility of defining collaborations among MCD members with different parameter settings and/or different evolution operators.

6.2. hyper heuristic based community detection (HHCD) framework

The continued arrival of more new heuristics to design new HMCDs (as presented in the previous subsection) is thus in need and we will witness a race of such efforts in the next few years. Meanwhile, we will continue to lack any claim concerning which heuristic and metaheuristic collaboration is to be honored. Generally, the success in HMCD will be tied with the successes along the direction of both the connected HCD and MCD algorithms and their connections. To this end, it will be wise to encourage how such heuristics can be used with MCDs to the fullest. Thus, we further suggest the need for selecting or searching for the appropriate heuristic from the large space of heuristic models. The hyper heuristic (HH) does that and is worth to explore its potential on the performance of community detection approaches. hyper heuristic (HH) methodology means search heuristic or learning mechanism for intelligently selecting heuristics from the space of singleton well-defined heuristics/metaheuristics or generating new heuristics from the space of ill-defined heuristics (heuristic components) to solve hard combinatorial search problems [42,75,272].

We can say that hyper heuristics are black-box optimization (BBO) tools or high-level heuristics (HLHs) while both heuristics and metaheuristics constitute its search space Υ of low-level heuristics (LLHs). It is also mildly to say that an HH represents a *high-level* metaheuristic (HLM) while its search space constitutes a finite set of *low-level* metaheuristics (LLMs) and their individual components. Two main classes for hyper heuristics are given in the literature: selection hyper heuristics and generation hyper heuristics. Selection hyper heuristics are methodologies for choosing or selecting a LLH from a space of well-defined heuristics and metaheuristics. Generation hyper heuristics, on the other hand, have to generate a new LLH from a space of already existing heuristic components. Recently, several studies have been made to examine the computational benefit of HH in solving different real-world optimization problems, e.g., routing problem, packing problem, and timetabling problem [224], scheduling problem [282], multi-objective optimization [196], and expensive numerical optimization [219]. Unfortunately, till the data of writing this paper, no effort has been addressed to explore its potential in the specialized literature of CD problem.

Here, we provide the researchers with a new alternate for community detection framework. The new perspective realizes the importance of the decision makings in both community structure space and heuristics space. The major computational aspect of a hyper heuristic based community detection (HHCD) framework could decouple the CD problem into two sub-problems with two distinct search spaces, namely the *partitions space* Ω and the *heuristics space* Υ. Searching for the appropriate communities in the partitions space is already accomplished in all existing heuristic and metaheuristic based community detection frameworks through different algorithmic components including selection, objective functions, and perturbation operators. However, instead of directly searching the whole search space for the optimal/near optimal partitioning solution from the beginning of the search, an HHCD algorithm repeatedly tries to find and/or generate the best low-level heuristics and use these heuristics community detection workers to locate the subspace containing the optimal/near optimal solution. It is worth to mention that the framework suggested here is called a *general* HHCD in the sense that it cuts across the two main classes of hyper heuristic methodologies presented in the literature. We can define HHCD : $\mathbb{I} \to \mathbb{I}$ as an iterated transformation function wit the tuple in Eq. (32). The general algorithmic description of the HHCD framework can be specified in Algorithm 4 . The main characteristic components of the suggested HHCD framework are:

Algorithm 4: General framework of HHCD

begin
$t = 0$;
initialize $\mathbb{I}^t \leftarrow \{\mathcal{I}_1^t, \mathcal{I}_2^t, \ldots, \mathcal{I}_N^t\}$;
decode: $\Gamma(\mathbb{I}^t) : \{C_1^t, C_2^t, \ldots, C_N^t\}$;
evaluate: $\mathbb{I}^t : \{\Phi(C_1^t), \Phi(C_2^t), \ldots, \Phi(C_N^t)\}$;
while ($\iota_{hyper}(\mathbb{I}^t) \neq true$) **do**
  select CDW: $CDW \leftarrow S_{LLH}(\Upsilon)$;
  /* select a CD worker */
  apply CDW: $\mathbb{I}^{t+1} \leftarrow CDW(\mathbb{I}^t)$;
  if $CDW \in \Omega_{HCD}$ **then**
    /* if the selected CD worker is an HCD */
    Accept: $\mathbb{I}^{t+1} \leftarrow Accept(\mathbb{I}^{t+1})$;
  else
    /* if the selected CD worker is an MCD */
    Replace: $\mathbb{I}^{t+1} \leftarrow Repl(\mathbb{I}^{t+1})$;
  evaluate CDW: $\Theta(CDW) \leftarrow evaluate(CDW)$;
  /* convergence detection for the selected CD worker */
  intensification detection: $ID(CDW)$;
  diversification detection: $DD(CDW)$;
  $t \leftarrow t + 1$;
output: $C^t_{1 \leqslant i \leqslant N}$ with best Φ;

$$\text{HHCD} = (\Upsilon, \mathbb{I}, \Phi, \Theta, S_{LLH}, \text{Accept/Repls}, \text{ID}, \text{DD}, \iota_{hyper}) \tag{32}$$

1. Search space Υ of Low-level heuristic based community detection (LLHCD) algorithms : The construction of this *union* space is basically controlled by the different heuristics and metaheuristics based community detection algorithms (along with their basic entities) that are pre-existing in the literature arsenal. Let $\Omega_{\text{HCD}} = \{\text{HCD}_1, \text{HCD}_2, \ldots, \text{HCD}_{n_1}\}$ and $\Omega_{\text{MCD}} = \{\text{MCD}_1, \text{MCD}_2, \ldots, \text{MCD}_{n_2}\}$ be, respectively, the space of n_1 candidate HCD algorithms and the space of n_2 MCD algorithms. Then, $\Upsilon = \Omega_{\text{HCD}} \cup \Omega_{\text{MCD}}$ can be constructed as a pool from the union of n_1 HCDs and n_2 MCDs. Note that the formulations of each HCD $\in$ $Omega_{\text{HCD}}$ and each MCD $\in \Omega_{\text{MCD}}$ follow, respectively, the expressions in (16) and (17). It is worth to mention that when the mechanism of the generation hyper heuristic is also to be used, then the size of the search space Υ can be increased to more than $n_1 + n_2$. A new HMCD algorithm could be generated and added to Υ while selecting a particular HCD algorithm and incorporating it to fill in a given component of a selected MCD algorithm.

2. Low-level heuristic selection operator (S_{LLH}): Akin to the basic concept of selection operator of the different metaheuristics is the role of the low-level heuristic selection operator (S_{LLH}). Once the LLHCD algorithms are ranked in terms of their importance in properly delineating the LLHCD search space (i.e. Υ) with different degree of confidence, they can be selected as *community detection workers* (CDWs) for future considerations. Different selection operators and their impact on the performance of the HHCD algorithm can be suggested which can go to the extremes of completely random to completely deterministic in considering only high-ranked LLHCD algorithms while discarding low-ranked LLHCD algorithms. Note that if the selected CDW is an HCD algorithm (i.e. CDW $\in \Omega_{\text{HCD}}$), then its mechanism should be applied for each individual solution in the population.

3. Acceptance/replacement operators (Accept/Repl): After applying the selected LLHCD to the current population of solutions, an acceptance operator (Accept) should decide whether to accept or reject the newly generated solutions. It should take an individual decision for each solution in the generated population. The Accept operator works when the selected CDW is an HCD (i.e. $CDW \in \Omega_{\text{HCD}}$). However, when the selection operator selects an MCD from Ω_{MCD} as a community detection worker (i.e. when $CDW \in \Omega_{\text{MCD}}$) to evolve the population, a replacement (Repl) operator can be used.

4. Performance evaluation (Θ : LLHCD $\to \mathbb{R}^+$): An HHCD algorithm has to evaluate the performance of all LLHCD algorithms found in the search space Υ. The performance evaluation for each LLHCD algorithm has to depend on one or more of the following parameters: the quality of the generated solutions (i.e. improvement in the objective value of the community structures), the time required for the computation of the LLHCD algorithm, and the time the LLHCD algorithm was last used. Different measures for comparing and evaluating the performance of LLHCD algorithms can be defined. An open research area that is worth to explore is to investigate the effect of different ranking methodologies on the overall success probability of the adopted HHCD algorithm.

5. Convergence-wise detection operators: During the convergence process, both intensification-wise detection (ID) and diversification-wise detection (DD) operators should be used to balance between convergence velocity (path-oriented search ability) and convergence reliability (volume-oriented search ability) in the search of high-performance community structure solutions. The main role of the intensification-wise detection (ID) operator is to decide when to select a new LLHCD algorithm from the pool Υ of LLHCD algorithms. It can check the quality of the solution(s) achieved by the current worker (i.e. CDW). If the selected CDW can not significantly improve the quality of the solution(s) for a predefined number of iterations, the ID will trigger the HHCD algorithm in leaving the current cold CDW and to select another CDW, or even, to generate a new CDW. Diversification-wise detection (DD) operator, on the other hand, enables the HHCD algorithm to adequately explore the whole search space Υ and to prevent premature convergence. Diversity is crucial for finding several global optima and for dynamic optimization, when the problem landscape changes over time. Also, it facilitates search for the whole Pareto front in evolutionary multi-objective optimization. The mechanism of DD can be implemented through checking the presence or absence of population diversity (i.e. population homogeneity) using different diversity metrics. The DD will direct the HHCD algorithm to choose another worker when the current worker produces only poor population. Further, the strength of the DD can be controlled to give more adaptive decisions while population evolves.

6.3. Challenges

The previous discussion points out that there is another important aspect of algorithm design that is almost unexplored in the literature of community detection problem. The discussion realizes the importance of combination of both worlds of HCD and MCD algorithms into HMCD and HHCD, and offers some interesting possibilities that should become more common for community detection in the next few years. Here, we illustrate a couple of challenges that lies ahead these new research directions. The challenges mainly account the effectiveness and the efficiency of the algorithms.

–Algorithm effectiveness and model robustness

In spite of the fact that many models, i.e. quality functions, have been introduced in the literature of HCD and MCD to identify the goodness of community structures, the need for reaching a more robust model becomes more evident and is still a challenge. Robust quality functions (whether single objective or multi-objective optimization functions) should evaluate the goodness of the partitioning solutions such that high quality corresponds only to meaningful or significant solutions. The concept of significant solutions has been related to their stability against random perturbations [84]. Given a random and fairly small fluctuation function $\varphi : C \rightarrow \bar{C}$, then C is said to be truly significant or stable if it will be recovered from the modified partition $\bar{C}$, otherwise it is insignificant. An important question that remains to be answered systematically is: How to design a community detection model that can recover *a priori* and with high accuracy a significant community structure? Although this is a key issue, little effort has been devoted for determining whether the structure found by a given CD algorithm is statistically significant or, conversely, it is just a byproduct of chance and basic features of the graph structure [20,24,146,242,263,290,291]. A measure of the significance for network community structure being detected by a CD algorithm is addressed in [146]. The network perturbation function φ of Karrer et al. [146] keeps the modified community structure $\bar{C}$ up with the same numbers of nodes, n, and connections, m, of the original unperturbed partition C. However, it evenly corrupts C from its original graph (no perturbation) towards the maximal perturbation (i.e. null model). It takes off each connection with probability $0 \leqslant \alpha \leqslant 1$ and displaces it with another connection between a pair of nodes v_i and v_i selected at random with probability $\frac{m(v_i)m(v_j)}{2m}$. With modularity optimization (Eq. (14)), the best partition, $\bar{C}$, for each perturbed graph is then identified and compared with C in terms of information-theoretic distance metric known as the variation of information [199]. Strong community structure of a network as a whole, rather than on single part of the network, is successfully stated in [146]. Based on a function of the separation between the communities, an analytical method is provided by Reichardt and Leone [242] for the planted partitioning problem. They showed that the sparsity of a network may limit the performance of unsupervised graph partitioning methods. Even though community structure could be reached by these methods, it remains undetectable and obscure behind alternative solutions that have zero correlation with the true solution. Community assortativity (r_{com}) is proposed in [263] to accompany the modularity for assessing the robustness of community assignment against sampling errors in animal social networks. In [291], the robustness of communities against structural attacks and errors is evaluated using another significance metric based on the normalized mutual information (R_{NMI}) and a simulated annealing algorithm is devised to mitigate the damage on communities under attacks or errors. The robustness of communities is evaluated to reflect the variation of integral network communities. Attea and Abdullah [20] tested the robustness of their complex detection model against several state-of-the-art models when noise interactions are added either to random protein pairs, or to proteins with the highest number of interactions, or to those proteins with the lowest number of interactions. Recently, Wang and Liu [290] extended the definition of community robustness into interdependent networks. They proposed a memetic optimization algorithm, to enhance the community robustness of various synthetic and real-world networks through rewiring topologies. Attea et al. [24] validated the robustness of their community detection model over other stater-of-the-art models [10,11,182] over a set of synthetic signed networks with varying number of positive and negative intra and inter links.

Another relevant challenge regarding algorithm effectiveness is the design of the community quality objective. As presented previously, it is more common that multi-objective optimization functions tend to become more effective to trade-off between compactness and separation of the identified communities. However, designing the quality function to fulfill the contradictory nature of community structure does not appear straightforward. Some important questions that remain to be answered in this regard are: how to design a negatively correlated objective functions that can identify compactness and separation of the community structure as well as possible? Can nonnegative matrix factorization be exploited to define multi-objective community detection models? A more relevant question concerning the robustness of a multi-objective community detection model is: how to generalize the contradictory features of both compactness and separation to be adaptable to handle different network topologies (e.g., dynamic networks, massive networks, multiplex networks, networks with overlapping communities, multipartite networks) with different community size?

Some research activity has been involved in this regard. For example, Attea et al. [21] developed a multi-objective community detection model that disassociates the search for intra-community structures from the inter-community structures. They concluded that the convergence reliability of a multi-objective community detection algorithm can be improved while maintaining more contradictory objectives for community compactness and separation. Their model is extended to handle dynamic networks [23], PPI networks [2,20], and signed networks [24]. Further interesting study that is worth to explore is to reflect the compactness and separation of the multi-objective optimization model in Attea et al. [21] to define, respectively, the *intralayer* and *interlayer* community structures in multiplex network systems. On the other hand, developing contradictory objectives for both community compactness and separation from nonnegative matrix factorization models (e.g., [292,293,306]) or from the CR model (e.g., [90]) still remains an open problem and is worth of future investigations.

Another relevant question while designing an effective HMCD or HHCD is: how must heuristic operator(s) be designed and combined with a given multi-objective community detection model to continually play up the opposite features of community structures? In other words: how can the interaction between the heuristic operator(s) and the multi-objective detection model of a given MCD be well co-ordinated? Such key issue has been recently done in some published work [1,3,21,22].

In the light of interfusing the research activities depicted in Figs. 4 and 8, a more respectful design for new HMCDs and HHCDs can be summarized here. The design statement is to: *play with more collaboration alternatives between HCDs and MCDs to increase the percentage of HMCD and null HHCD in Fig.* 4 and at the same time to engage in more open-minded multi-objective optimization functions to decrease the percentage of the traditional objectives in Fig. 8. Otherwise, the design of an MCD algorithm would mostly be useless but has a new name!

–Algorithm efficiency

New algorithmic proposals are considerably debated in the previous discussions regarding the paradigms of hybrid metaheuistic and hyper heuristic for CD problem. However, it seems quite obvious at this point to mention that the main problem of metaheuristic algorithms is that they are often involve fairly cumbersome computations. The computational complexity of the metaheuristic algorithm grows with respect to: 1) the network size, 2) the requirement for high number of objective function evaluations, and 3) how often aids come from the heuristic operator to the metaheuristic algorithm. The main approach to defeat this limitation is the development of HMCD and HHCD to work in a parallel manner. Examples of parallel approaches have been developed in [20,144].

7. Conclusions

Community detection problem is proved to be NP-hard problem and still an open research area to question what communities are and consequently how valid are the algorithms that detect them. Despite the success of the metaheuristic based community detection algorithms over the counterpart heuristics, the development of more effective metaheuristic based community detection algorithms is rarely addressed in the literature. They primarily emphasize the role of objective functions where the main difference among them seems to be in the formulation of more contradictory optimization models. The main issue addressed in this review is to encourage the researchers to redirect their traditional interest from developing only heuristic and metaheuristic based community detection algorithms towards a new generation of more effective hybrid metaheuristic based community detection (HMCD) and hyper heuristic based community detection (HHCD) algorithms.

The central argument that evolves out of our review is that the different collaboration forms between metaheuristic and heuristic based algorithms which can play an important role in solving hard combinatorial problems with vast search spaces should really be investigated from the perspective of CD problem. Interesting leap in terms of performance can be achieved from the collective switching of both exploitation and exploration strengths of, respectively, heuristic and metaheuristic based community detection algorithms. In this paper, we realize several forms of hybridization between the two counterparts of community based community detection algorithms. A more advanced step towards improving the performance of the community detection algorithms and to fill in the remaining lacuna of heuristics, metaheuristics, and hybrid metaheuristics is also suggested using the recent and unexplored effort of hyper heuristics.

Credit author statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the Swarm and Evolutionary Computation.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Declaration of Competing Interest

Authors declare that they have no conflict of interest.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.swevo.2021.100885.

References

[1] A.H. Abdulateef, B.A. Attea, A.N. Rashid, Heuristic modularity for complex identification in protein-protein interaction networks, Iraqi J. Sci. 60 (8) (2019) 1846–1859.
[2] A.H. Abdulateef, B.A. Attea, A.N. Rashid, M. Al-Ani, A new evolutionary algorithm with locally assisted heuristic for complex detection in protein interaction networks, Appl. Soft Comput. 73 (2018) 1004–1025.
[3] Q.Z. Abdullah, et al., Aheuristic strategy for improving the performance of evolutionary based complex detection in protein-protein interaction networks, Iraqi J. Sci. 57 (4A) (2016) 2513–2528.
[4] N. Afsarmanesh, M. Magnani, Finding overlapping communities in multiplex networks, arXiv preprint arXiv:1602.03746(2016).
[5] R. Agrawal, Bi-objective community detection (BOCD) in networks using genetic algorithm, in: Proceedings of the 2011 IC3, 2011.
[6] Y.-Y. Ahn, J.P. Bagrow, S. Lehmann, Link communities reveal multiscale complexity in networks, Nature 466 (7307) (2010) 761–764.
[7] R.D. Al-Dabbagh, F. Neri, N. Idris, M.S. Baba, Algorithmic design issues in adaptive differential evolution schemes: review and taxonomy, Swarm Evol. Comput. 43 (2018) 284–311.
[8] A. Amelio, C. Pizzuti, Community mining in signed networks: a multiobjective approach, in: Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ACM, 2013, pp. 95–99.
[9] A. Amelio, C. Pizzuti, Community detection in multidimensional networks, in: Proceedings of the IEEE 26th International Conference on Tools with Artificial Intelligence, IEEE, 2014, pp. 352–359.
[10] A. Amelio, C. Pizzuti, An evolutionary and local refinement approach for community detection in signed networks, Int. J. Artif. Intell. Tools 25 (04) (2016) 1650021.
[11] A. Amelio, C. Pizzuti, Evolutionary clustering for mining and tracking dynamic multilayer networks, Comput. Intell. 33 (2) (2017) 181–209.
[12] A.A. Amini, A. Chen, P.J. Bickel, E. Levina, et al., Pseudo-likelihood methods for community detection in large sparse networks, Ann. Stat. 41 (4) (2013) 2097–2122.
[13] L.P. de Andrade, R.P. Espíndola, N.F.F. Ebecken, Community detection by an efficient ant colony approach, in: Proceedings of the International Symposium on Methodologies for Intelligent Systems, Springer, 2014, pp. 1–9.
[14] L. Angelini, S. Boccaletti, D. Marinazzo, M. Pellicoro, S. Stramaglia, Identification of network modules by optimization of ratio association, Chaos: Interdiscip. J. Nonlinear Sci. 17 (2) (2007) 023114.
[15] A. Arenas, J. Duch, A. Fernández, S. Gómez, Size reduction of complex networks preserving modularity, New J. Phys. 9 (6) (2007) 176.
[16] N. Arinik, R. Figueiredo, V. Labatut, Multiple partitioning of multiplex signed networks: application to european parliament votes, Social Netw. 60 (2020) 83–102.
[17] N. Arora, H. Banati, Multiobjective group search optimization approach for community detection in networks, Int. J. Appl. Evol. Comput. (IJAEC) 7 (3) (2016) 50–70.
[18] Y. Atay, M. Aslan, H. Kodaz, A swarm intelligence-based hybrid approach for identifying network modules, J. Comput. Sci. 28 (2018) 265–280.
[19] B. Attea, Multi-objective set cover problem for reliable and efficient wireless sensor networks, Iraqi J. Sci. 56 (2015) 1147–1160.
[20] B.A. Attea, Q.Z. Abdullah, Improving the performance of evolutionary-based complex detection models in protein–protein interaction networks, Soft Comput. (2018) 1–24.
[21] B.A. Attea, W.A. Hariz, M.F. Abdulhalim, Improving the performance of evolutionary multi-objective co-clustering models for community detection in complex social networks, Swarm Evol. Comput. 26 (2016) 137–156.
[22] B.A. Attea, H.S. Khoder, Community tracking in time evolving networks: an evolutionary multi-objective approach, Iraqi J. Sci. 57 (4A) (2016) 2539–2548.
[23] B.A. Attea, H.S. Khoder, A new multi-objective evolutionary framework for community mining in dynamic social networks, Swarm Evol. Comput. 31 (2016) 90–109.
[24] B.A. Attea, H.M. Rada, M.N. Abbas, S. Özdemir, A new evolutionary multi-objective community mining algorithm for signed networks, Appl. Soft Comput. 85 (2019) 105817.
[25] T. Bäck, H.-P. Schwefel, An overview of evolutionary algorithms for parameter optimization, Evol. Comput. 1 (1) (1993) 1–23.
[26] S. Bandyopadhyay, S. Ray, A. Mukhopadhyay, U. Maulik, A multiobjective approach for identifying protein complexes and studying their association in multiple disorders, Algorithms Mol. Biol. 10 (1) (2015) 24.
[27] H. Baofang, A cultural algorithm based on artificial bee colony optimization for community detection in signed social networks, in: Proceedings of the 10th International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA), IEEE, 2015, pp. 404–409.
[28] A.-L. Barabasi, Z.N. Oltvai, Network biology: understanding the cell's functional organization, Nat. Rev. Genet. 5 (2) (2004) 101–113.
[29] M.J. Barber, Modularity and community detection in bipartite networks, Phys. Rev. E 76 (6) (2007) 066102.
[30] T. Bartz-Beielstein, M. Preuss, K. Schmitt, H.-P. Schwefel, Challenges for Contemporary Evolutionary Algorithms, Citeseer, 2010.
[31] Y. Belkhiri, N. Kamel, H. Drias, S. Yahiaoui, Bee swarm optimization for community detection in complex network, in: Proceedings of the World Conference on Information Systems and Technologies, Springer, 2017, pp. 73–85.
[32] M. Berlingerio, M. Coscia, F. Giannotti, Finding and characterizing communities in multidimensional networks, in: Proceedings of the 2011 International Conference on Advances in Social Networks Analysis and Mining, IEEE, 2011, pp. 490–494.
[33] M. Berlingerio, F. Pinelli, F. Calabrese, Abacus: frequent pattern mining-based community discovery in multidimensional networks, Data Min. Knowl. Discov. 27 (3) (2013) 294–320.
[34] P.J. Bickel, A. Chen, A nonparametric view of network models and Newman–Girvan and other modularities, Proc. Natl. Acad. Sci. 106 (50) (2009) 21068–21073. pnas–0907096106
[35] V. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Stat. Mech. 2008 (10) (2008) P10008. P10008
[36] V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Stat. Mech.: Theory Exp. 2008 (10) (2008) P10008.
[37] C. Blum, Ant colony optimization: introduction and recent trends, Phys. Life Rev. 2 (4) (2005) 353–373.
[38] O. Boutemine, M. Bouguessa, Mining community structures in multidimensional networks, ACM Trans. Knowl. Discov. Data (TKDD) 11 (4) (2017) 1–36.

[39] U. Brandes, D. Delling, M. Gaertler, R. Görke, M. Hoefer, Z. Nikoloski, D. Wagner, Maximizing Modularity is Hard, arXiv preprint physics/0608255(2006).
[40] U. Brandes, D. Delling, M. Gaertler, R. Gorke, M. Hoefer, Z. Nikoloski, D. Wagner, On modularity clustering, IEEE Trans. Knowl. Data Eng. 20 (2) (2008) 172–188.
[41] J. Brest, B. Bošković, S. Greiner, V. Žumer, M.S. Maučec, Performance comparison of self-adaptive and adaptive differential evolution algorithms, Soft Comput. 11 (7) (2007) 617–629.
[42] E.K. Burke, M. Gendreau, M. Hyde, G. Kendall, G. Ochoa, E. Özcan, R. Qu, Hyper-heuristics: a survey of the state of the art, J. Oper. Res. Soc. 64 (12) (2013) 1695–1724.
[43] M. Burke, R. Kraut, Mopping up: modeling Wikipedia promotion decisions, in: Proceedings of the 2008 ACM Conference on Computer Supported Cooperative Work, ACM, 2008, pp. 27–36.
[44] Q. Cai, M. Gong, L. Ma, S. Ruan, F. Yuan, L. Jiao, Greedy discrete particle swarm optimization for large-scale social network clustering, Inf. Sci. 316 (2015) 503–516.
[45] Q. Cai, M. Gong, B. Shen, L. Ma, L. Jiao, Discrete particle swarm optimization for identifying community structures in signed social networks, Neural Netw. 58 (2014) 4–13.
[46] Q. Cai, L. Ma, M. Gong, D. Tian, A survey on network community detection based on evolutionary computation, Int. J. Bio-Inspired Comput. 8 (2) (2016) 84–98.
[47] X. Cai, Y. Shi, Y. Zhu, Y. Qiao, F. Hu, An algorithm q-pso for community detection in complex networks, in: Proceedings of the 16th International Symposium on Distributed Computing and Applications to Business, Engineering and Science (DCABES), IEEE, 2017, pp. 76–79.
[48] C. Cao, Q. Ni, Y. Zhai, A novel community detection method based on discrete particle swarm optimization algorithms in complex networks, 2015, pp. 171–178.
[49] A. Cardillo, J. Gómez-Gardenes, M. Zanin, M. Romance, D. Papo, F. Del Pozo, S. Boccaletti, Emergence of network features from multiplexity, Sci. Rep. 3 (1) (2013) 1–6.
[50] Y. Chaabani, J. Akaichi, Bees colonies for meaningfull communities detection in social medias network, in: Proceedings of the 2016 IEEE International Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld), IEEE, 2016, pp. 1052–1057.
[51] B. Chen, L. Chen, Y. Chen, Detecting community structure in networks based on ant colony optimization, in: Proceedings of the International Conference on Information & Knowledge Engineering, 2012, pp. 247–253.
[52] G. Chen, Y. Wang, J. Wei, A new multiobjective evolutionary algorithm for community detection in dynamic complex networks, Math. Probl. Eng. 2013 (2013).
[53] J. Chen, D. Liu, F. Hao, H. Wang, Community detection in dynamic signed network: an intimacy evolutionary clustering algorithm, J. Ambient Intell. Human. Comput. 11 (2) (2020) 891–900.
[54] K. Chen, W. Bi, A new genetic algorithm for community detection using matrix representation method, Physica A: Stat. Mech. Appl. 535 (2019) 122259.
[55] M. Chen, K. Kuzmin, B.K. Szymanski, Community detection via maximization of modularity and its variants, IEEE Trans. Comput. Soc. Syst. 1 (1) (2014) 46–65.
[56] Y. Chen, X. Qiu, Detecting community structures in social networks with particle swarm optimization, in: Frontiers in Internet Technologies, Springer, 2013, pp. 266–275.
[57] F. Cheng, T. Cui, Y. Su, Y. Niu, X. Zhang, A local information based multi-objective evolutionary algorithm for community detection in complex networks, Appl. Soft Comput. 69 (2018) 357–367.
[58] A. Clauset, Finding local community structure in networks, Phys. Rev. E 72 (2) (2005) 026132.
[59] A. Clauset, M.E. Newman, C. Moore, Finding community structure in very large networks, Phys. Rev. E 70 (6) (2004) 066111.
[60] C.A.C. Coello, G.B. Lamont, D.A. Van Veldhuizen, Evolutionary Algorithms for Solving Multi-Objective Problems, 5, Springer, New York, 2007.
[61] D.W. Corne, M.A. Lones, Evolutionary Algorithms, arXiv preprint arXiv:1805.11014(2018).
[62] C. Cotta, M. Sevaux, K. Sörensen, Adaptive and Multilevel Metaheuristics, 136, Springer, 2008.
[63] A. Dahim, Community Detection in ComplexNetworks, University of Exeter, 2018 Ph.D. thesis.
[64] A. Dahim, R. Everson, Detecting dynamic communities in social networks using viterbi and evolutionary algorithms, in: Proceedings of the Book of Abstracts, 2017, p. 344.
[65] L. Danon, A. Díaz-Guilera, A. Arenas, The effect of size heterogeneity on community identification in complex networks, J. Stat. Mech.: Theory Exp. 2006 (11) (2006) P11010.
[66] L. Danon, A. Diaz-Guilera, J. Duch, A. Arenas, Comparing community structure identification, J. Stat. Mech.: Theory Exp. 2005 (09) (2005) P09008.
[67] S. Das, P.N. Suganthan, Differential evolution: a survey of the state-of-the-art, IEEE Trans. Evol. Comput. 15 (1) (2010) 4–31.
[68] A. Davis, B.B. Gardner, M.R. Gardner, Deep South: A Social Anthropological Study of Caste and Class, Univ of South Carolina Press, 2009.
[69] M. De Domenico, A. Lancichinetti, A. Arenas, M. Rosvall, Identifying modular flows on multilayer networks reveals highly overlapping organization in interconnected systems, Phys. Rev. X 5 (1) (2015) 011027.
[70] M. De Domenico, V. Nicosia, A. Arenas, V. Latora, Structural reducibility of multilayer networks, Nat. Commun. 6 (1) (2015) 1–9.
[71] J. Del Ser, E. Osaba, D. Molina, X.-S. Yang, S. Salcedo-Sanz, D. Camacho, S. Das, P.N. Suganthan, C.A.C. Coello, F. Herrera, Bio-inspired computation: Where we stand and what's next, Swarm Evol. Comput. 48 (2019) 220–250.
[72] I.S. Dhillon, Y. Guan, B. Kulis, A Unified View of Kernel K-Means, Spectral Clustering and Graph Cuts, University of Texas, 2004.
[73] P. Doreian, A. Mrvar, A partitioning approach to structural balance, Soc. Netw. 18 (2) (1996) 149–168.
[74] P. Doreian, A. Mrvar, Partitioning signed Soc. Netw., Soc. Netw. 31 (1) (2009) 1–11.
[75] J.H. Drake, A. Kheiri, E. Özcan, E.K. Burke, Recent advances in selection hyper-heuristics, Eur. J. Oper. Res. 285 (2) (2020) 405–428.
[76] R. Eberhart, J. Kennedy, Particle swarm optimization, in: Proceedings of the IEEE International Conference on Neural Networks, 4, Citeseer, 1995, pp. 1942–1948.
[77] J. Eustace, X. Wang, Y. Cui, Overlapping community detection using neighborhood ratio matrix, Physica A: Stat. Mech. Appl. 421 (2015) 510–521.
[78] T.S. Evans, Clique graphs and overlapping communities, J. Stat. Mech.: Theory Exp. 2010 (12) (2010) P12037.
[79] E. Falkenauer, Genetic algorithms and grouping problems, John Wiley & Sons, Inc., 1998.
[80] A. Ferligoj, A. Kramberger, An analysis of the slovene parliamentary parties network, Dev. Stat. Methodol. 12 (1996) 209–216.
[81] A. Firat, S. Chatterjee, M. Yilmaz, Genetic clustering of social networks using random walks, Comput. Stat. Data Anal. 51 (12) (2007) 6285–6294.
[82] F. Folino, C. Pizzuti, A multiobjective and evolutionary clustering method for dynamic networks, in: Proceedings of the 2010 International Conference on Advances in Social Networks Analysis and Mining (ASONAM), IEEE, 2010, pp. 256–263.
[83] F. Folino, C. Pizzuti, An evolutionary multiobjective approach for community discovery in dynamic networks, IEEE Trans. Knowl. Data Eng. 26 (8) (2014) 1838–1852.
[84] S. Fortunato, Community detection in graphs, Phys. Rep. 486 (3-5) (2010) 75–174.
[85] S. Fortunato, M. Barthelemy, Resolution limit in community detection, Proc. Natl. Acad. Sci. 104 (1) (2007) 36–41.
[86] S. Fortunato, A. Lancichinetti, Community detection algorithms: a comparative analysis: invited presentation, extended abstract, in: Proceedings of the Fourth International ICST Conference on Performance Evaluation Methodologies and Tools, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2009, p. 27.
[87] O. Gach, J.-K. Hao, A memetic algorithm for community detection in complex networks, in: Proceedings of the PPSN, 2012.
[88] O. Gach, J.-K. Hao, Combined neighborhood tabu search for community detection in complex networks, RAIRO-Oper. Res. 50 (2) (2016) 269–283.
[89] C. Gao, Z. Chen, X. Li, Z. Tian, S. Li, Z. Wang, Multiobjective discrete particle swarm optimization for community detection in dynamic networks, EPL (Europhys. Lett.) 122 (2) (2018) 28001.
[90] C. Gao, M. Liang, X. Li, Z. Zhang, Z. Wang, Z. Zhou, Network community detection based on the physarum-inspired computational framework, IEEE/ACM Trans. Comput. Biol. Bioinform. 15 (6) (2016) 1916–1928.
[91] A. Ghasabeh, M.S. Abadeh, Community detection in social networks using a hybrid swarm intelligence approach, Int. J. Knowl.-Based Intell. Eng. Syst. 19 (4) (2015) 255–267.
[92] G.E. Gigerenzer, R.E. Hertwig, T.E. Pachur, Heuristics: The Foundations of Adaptive Behavior., Oxford University Press, 2011.
[93] N. Girdhar, K. Bharadwaj, Community detection in signed social networks using multiobjective genetic algorithm, J. Assoc. Inf. Sci. Technol. 70 (8) (2019) 788–804.
[94] M. Girvan, M.E. Newman, Community structure in social and biological networks, Proc. Natl. Acad. Sci. 99 (12) (2002) 7821–7826.
[95] P.M. Gleiser, L. Danon, Community structure in jazz, Adv. Complex Syst. 6 (04) (2003) 565–573.
[96] F. Glover, M. Samorani, Intensification, diversification and learning in metaheuristic optimization, J. Heurist. 25 (4-5) (2019) 517–520.
[97] H. Gmati, A. Mouakher, I. Hilali-Jaghdam, B-cd: community detection in bipartite networks, Proc. Comput. Sci. 159 (2019) 313–322.
[98] A. Gog, D. Dumitrescu, B. Hirsbrunner, Community detection in complex networks using collaborative evolutionary algorithms, in: Proceedings of the European Conference on Artificial Life, Springer, 2007, pp. 886–894.
[99] D.E. Goldberg, J.H. Holland, Genetic algorithms and machine learning, Mach. Learn. 3 (2) (1988) 95–99.
[100] S. Gómez, P. Jensen, A. Arenas, Analysis of community structure in networks of correlated data, Phys. Rev. E 80 (1) (2009) 016114.
[101] M. Gong, Q. Cai, X. Chen, L. Ma, Complex network clustering by multiobjective discrete particle swarm optimization based on decomposition, IEEE Trans. Evol. Comput. 18 (1) (2014) 82–97.
[102] M. Gong, Q. Cai, Y. Li, J. Ma, An improved memetic algorithm for community detection in complex networks, in: Proceedings of the 2012 IEEE Congress on Evolutionary Computation, 2012, pp. 1–8.
[103] M. Gong, X. Chen, L. Ma, Q. Zhang, L. Jiao, Identification of multi-resolution network structures with multi-objective immune algorithm, Appl. Soft Comput. 13 (4) (2013) 1705–1717.
[104] M. Gong, B. Fu, L. Jiao, H. Du, Memetic algorithm for community detection in networks, Phys. Rev. E 84 (5) (2011) 056101.
[105] M. Gong, L. Ma, Q. Zhang, L. Jiao, Community detection in networks by using multiobjective evolutionary algorithm with decomposition, Physica A: Stat. Mech. Appl. 391 (15) (2012) 4050–4060.
[106] C. Granell, R.K. Darst, A. Arenas, S. Fortunato, S. Gómez, Benchmark model to assess community structure in evolving networks, Phys. Rev. E 92 (1) (2015) 012805.
[107] D. Greene, D. Doyle, P. Cunningham, Tracking the evolution of communities in dynamic social networks, in: Proceedings of the 2010 International Conference

on Advances in Social Networks Analysis and Mining (ASONAM), IEEE, 2010, pp. 176–183.
[108] G. Grinstein, C. Plaisant, S. Laskowski, T. O'Connell, J. Scholtz, M. Whiting, Vast 2008 challenge: introducing mini-challenges, in: Proceedings of the IEEE Symposium on Visual Analytics Science and Technology, VAST'08. 195-196 [published version] hcil-2008-34.
[109] M. Guerrero, F.G. Montoya, R. Baños, A. Alcayde, C. Gil, Community detection in national-scale high voltage transmission networks using genetic algorithms, Adv. Eng. Inf. 38 (2018) 232–241.
[110] R. Guimera, L.A.N. Amaral, Cartography of complex networks: modules and universal roles, J. Stat. Mech.: Theory Exp. 2005 (02) (2005) P02001.
[111] R. Guimera, L. Danon, A. Diaz-Guilera, F. Giralt, A. Arenas, Self-similar community structure in a network of human interactions, Phys. Rev. E 68 (6) (2003) 065103.
[112] R. Guimera, M. Sales-Pardo, L.A.N. Amaral, Modularity from fluctuations in random graphs and complex networks, Phys. Rev. E 70 (2) (2004) 025101.
[113] R. Guimerà, M. Sales-Pardo, L.A.N. Amaral, Module identification in bipartite and directed networks, Phys. Rev. E 76 (3) (2007) 036102.
[114] X. Guo, J. Su, H. Zhou, C. Liu, J. Cao, L. Li, Community detection based on genetic algorithm using local structural similarity, IEEE Access 7 (2019) 134583–134600.
[115] Y. Guo, X. Li, Y. Tang, J. Li, Heuristic artificial bee colony algorithm for uncovering community in complex networks, Math. Probl. Eng. 2017 (2017).
[116] A.I. Hafez, H.M. Zawbaa, A.E. Hassanien, A.A. Fahmy, Networks community detection using artificial bee colony swarm optimization, in: Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014, Springer, 2014, pp. 229–239.
[117] R. Halalai, C. Lemnaru, R. Potolea, Distributed community detection in social networks with genetic algorithms, in: Proceedings of the 2010 IEEE International Conference on Intelligent Computer Communication and Processing (ICCP), IEEE, 2010, pp. 35–41.
[118] J. Handl, J. Knowles, An evolutionary approach to multiobjective clustering, IEEE Trans. Evol. Comput. 11 (1) (2007) 56–76.
[119] M.N. Haque, L. Mathieson, P. Moscato, A memetic algorithm for community detection by maximising the connected cohesion, in: Proceedings of the 2017 IEEE Symposium Series on Computational Intelligence (SSCI), 2017, pp. 1–8.
[120] D. He, J. Liu, D. Liu, D. Jin, Z. Jia, Ant colony optimization for community detection in large-scale complex networks, in: Proceedings of the Seventh International Conference on Natural Computation (ICNC), 2, IEEE, 2011, pp. 1151–1155.
[121] D. He, J. Liu, B. Yang, Y. Huang, D. Liu, D. Jin, An ant-based algorithm with local optimization for community detection in large-scale networks, Adv. Complex Syst. 15 (08) (2012) 1250036.
[122] D. He, Z. Wang, B. Yang, C. Zhou, Genetic algorithm with ensemble learning for detecting community structure in complex networks, in: Proceedings of the Fourth International Conference on Computer Sciences and Convergence Information Technology, ICCIT'09, IEEE, 2009, pp. 702–707.
[123] J.M. Hofman, C.H. Wiggins, Bayesian approach to network modularity, Phys. Rev. Lett. 100 (25) (2008) 258701.
[124] J.H. Holland, Adaptation in Natural and Artificial Systems: An Introductory Analysis With Applications to Biology, Control, and Artificial Intelligence, University of Michigan Press Ann Arbor, 1975.
[125] P.W. Holland, K.B. Laskey, S. Leinhardt, Stochastic blockmodels: first steps, Soc. Netw. 5 (2) (1983) 109–137.
[126] C. Honghao, F. Zuren, R. Zhigang, Community detection using ant colony optimization, in: Proceedings of the 2013 IEEE Congress on Evolutionary Computation(CEC), IEEE, 2013, pp. 3072–3078.
[127] E.R. Hruschka, R.J. Campello, A.A. Freitas, et al., A survey of evolutionary algorithms for clustering, IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) 39 (2) (2009) 133–155.
[128] Y. Hu, Z. Zhou, K. Hu, H. Li, Detecting overlapping communities from micro blog network by additive spectral decomposition, J. Intell. Fuzzy Syst. 38 (1) (2020) 409–416.
[129] J. Huang, H. Sun, Y. Liu, Q. Song, T. Weninger, Towards online multiresolution community detection in large-scale networks, PLoS One 6 (8) (2011) e23829.
[130] Q. Huang, T. White, G. Jia, M. Musolesi, N. Turan, K. Tang, S. He, J.K. Heath, X. Yao, Community detection using cooperative co-evolutionary differential evolution, in: Proceedings of the International Conference on Parallel Problem Solving from Nature, Springer, 2012, pp. 235–244.
[131] X. Huang, D. Chen, T. Ren, D. Wang, A survey of community detection methods in multilayer networks, Data Min. Knowl. Discov. (2020) 1–45.
[132] R. Interdonato, A. Tagarelli, D. Ienco, A. Sallaberry, P. Poncelet, Node-centric community detection in multilayer networks with layer-coverage diversification bias, in: Proceedings of the International Workshop on Complex Networks, Springer, 2017, pp. 57–66.
[133] P. Jaccard, Nouvelles recherches sur la distribution florale, Bull. Soc. Vaud. Sci. Nat. 44 (1908) 223–270.
[134] A.K. Jain, M.N. Murty, P.J. Flynn, Data clustering: a review, ACM Comput. Surv. (CSUR) 31 (3) (1999) 264–323.
[135] R. Jäschke, L. Marinho, A. Hotho, L. Schmidt-Thieme, G. Stumme, Tag recommendations in social bookmarking systems, AI Commun. 21 (4) (2008) 231–247.
[136] S.H. Javadi, S. Khadivi, M.E. Shiri, J. Xu, An ant colony optimization method to detect communities in social networks, in: Proceedings of the 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, IEEE Press, 2014, pp. 200–203.
[137] L.G. Jeub, M.W. Mahoney, P.J. Mucha, M.A. Porter, A local perspective on community structure in multilayer networks, arXiv preprint arXiv:1510.05185(2015).
[138] L.G. Jeub, O. Sporns, S. Fortunato, Multiresolution consensus clustering in networks, Sci. Rep. 8 (1) (2018) 1–16.
[139] J. Ji, X. Song, C. Liu, X. Zhang, Ant colony clustering with fitness perception and pheromone diffusion for community detection in complex networks, Physica A: Stat. Mech. Appl. 392 (15) (2013) 3260–3272.
[140] G. Jia, Z. Cai, M. Musolesi, Y. Wang, D.A. Tennant, R.J. Weber, J.K. Heath, S. He, Community detection in social and biological networks using differential evolution, in: Proceedings of the Learning and Intelligent Optimization, Springer, 2012, pp. 71–85.
[141] D. Jin, D. He, D. Liu, C. Baquero, Genetic algorithm with local search for community mining in complex networks, in: Proceedings of the 22nd IEEE International Conference on Tools with Artificial Intelligence (ICTAI), 1, IEEE, 2010, pp. 105–112.
[142] I. Jutla, L. Jeub, P. Mucha, A generalized Louvain method for community detection implemented in Matlab, 2011, URL http://netwiki.amath.unc.edu/GenLouvain
[143] N.J. Kadhim, H.H. Saleh, Improving extractive multi-document text summarization through multi-objective optimization, Iraqi J. Sci. (2018) 2135–2149.
[144] F. Karimi, S. Lotfi, H. Izadkhah, Multiplex community detection in complex networks using an evolutionary approach, Exp. Syst. Appl. (2020) 113184.
[145] A.-M. Karimi-Majd, M. Fathian, B. Amiri, A hybrid artificial immune network for detecting communities in complex networks, Computing 97 (5) (2015) 483–507.
[146] B. Karrer, E. Levina, M.E. Newman, Robustness of community structure in networks, Phys. Rev. E 77 (4) (2008) 046119.
[147] B. Karrer, M.E. Newman, Stochastic blockmodels and community structure in networks, Phys. Rev. E 83 (1) (2011) 016107.
[148] S. Kaur, S. Singh, S. Kaushal, A. Sangaiah, Comparative analysis of quality metrics for community detection in social networks using genetic algorithm, Neural Netw. World 26 (6) (2016) 625.
[149] H.-J. Kim, Y.-H. Kim, Recent progress on graph partitioning problems using evolutionary computation, arXiv preprint arXiv:1805.01623(2018).
[150] J. Kim, J.-G. Lee, S. Lim, Differential flattening: a novel framework for community detection in multi-layer graphs, ACM Trans. Intell. Syst. Technol. (TIST) 8 (2) (2016) 1–23.
[151] M.-S. Kim, J. Han, A particle-and-density based evolutionary clustering method for dynamic networks, Proc. VLDB Endow. 2 (1) (2009) 622–633.
[152] Z. Kuncheva, G. Montana, Community detection in multiplex networks using locally adaptive random walks, in: Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015, 2015, pp. 1308–1315.
[153] H. Kuo, C. Lin, Cultural evolution algorithm for global optimizations and its applications, J. Appl. Res. Technol. 11 (4) (2013) 510–522.
[154] A. Lancichinetti, S. Fortunato, J. Kertés, Community Spectroscopy in Complex Networks, Technical Report, technical report, 2008.
[155] A. Lancichinetti, S. Fortunato, Benchmarks for testing community detection algorithms on directed and weighted graphs with overlapping communities, Phys. Rev. E 80 (1) (2009) 016118.
[156] A. Lancichinetti, S. Fortunato, Community detection algorithms: a comparative analysis, Phys. Rev. E 80 (5) (2009) 056117.
[157] A. Lancichinetti, S. Fortunato, Limits of modularity maximization in community detection, Phys. Rev. E 84 (6) (2011) 066122.
[158] A. Lancichinetti, S. Fortunato, Consensus clustering in complex networks, Sci. Rep. 2 (2012) 336.
[159] A. Lancichinetti, S. Fortunato, J. Kertész, Detecting the overlapping and hierarchical community structure in complex networks, New J. Phys. 11 (3) (2009) 033015.
[160] A. Lancichinetti, S. Fortunato, F. Radicchi, Benchmark graphs for testing community detection algorithms, Phys. Rev. E 78 (4) (2008) 046110.
[161] K. Lang, Newsweeder: learning to filter NetNews, in: Proceedings of the 1995 Machine Learning, Elsevier, 1995, pp. 331–339.
[162] S. Lehmann, M. Schwartz, L.K. Hansen, Biclique communities, Phys. Rev. E 78 (1) (2008) 016108.
[163] E.A. Leicht, M.E. Newman, Community structure in directed networks, Phys. Rev. Lett. 100 (11) (2008) 118703.
[164] J. Leskovec, K.J. Lang, M. Mahoney, Empirical Comparison of Algorithms for Network Community Detection (2010) 631–640.
[165] J. Li, Y. Song, Community detection in complex networks using extended compact genetic algorithm, Soft Comput. 17 (6) (2013) 925–937.
[166] L. Li, L. Jiao, J. Zhao, R. Shang, M. Gong, Quantum-behaved discrete multi-objective particle swarm optimization for complex network clustering, Pattern Recognit. 63 (2017) 1–14.
[167] M. Li, J. Liu, A link clustering based memetic algorithm for overlapping community detection, Physica A: Stat. Mech. Appl. 503 (2018) 410–423.
[168] Q. Li, Z. Cao, W. Ding, Q. Li, A multi-objective adaptive evolutionary algorithm to extract communities in networks, Swarm Evol. Comput. 52 (2020) 100629.
[169] S. Li, Y. Chen, H. Du, M.W. Feldman, A genetic algorithm with local search strategy for improved detection of community structure, Complexity 15 (2010) 53–60.
[170] X. Li, X. Wu, S. Xu, S. Qing, P.-C. Chang, A novel complex network community detection approach using discrete particle swarm optimization with particle diversity and mutation, Appl. Soft Comput. 81 (2019) 105476.
[171] Y. Li, G. Liu, S.-y. Lao, A genetic algorithm for community detection in complex networks, J. Cent. South Univ. 20 (5) (2013) 1269–1276.
[172] Y. Li, J. Liu, C. Liu, A comparative analysis of evolutionary and memetic algorithms for community detection from signed social networks, Soft Comput. 18 (2) (2014) 329–348.
[173] Y. Li, Y. Wang, J. Chen, L. Jiao, R. Shang, Overlapping community detection through an improved multi-objective quantum-behaved particle swarm optimization, J. Heurist. 21 (4) (2015) 549–575.
[174] Y.-H. Li, J.-Q. Wang, X.-J. Wang, Y.-L. Zhao, X.-H. Lu, D.-L. Liu, Community detection based on differential evolution using social spider optimization, Symmetry 9 (9) (2017) 183.

[175] Z. Li, L. He, Y. Li, A novel multiobjective particle swarm optimization algorithm for signed network community detection, Appl. Intell. 44 (3) (2016) 621–633.
[176] Z. Li, J. Liu, K. Wu, A multiobjective evolutionary algorithm based on structural and attribute similarities for community detection in attributed networks, IEEE Trans. Cybern. 48 (7) (2017) 1963–1976.
[177] Z. Li, S. Zhang, R.-S. Wang, X.-S. Zhang, L. Chen, Quantitative function for community detection, Phys. Rev. E 77 (3) (2008) 036109.
[178] M. Liang, C. Gao, X. Li, Z. Zhang, A physarum-inspired ant colony optimization for community mining, in: Pacific-Asia Conference on Knowledge Discovery and Data Mining, Springer, 2017, pp. 737–749.
[179] D. Liben-Nowell, J. Kleinberg, The link-prediction problem for social networks, J. Am. Soc. Inf. Sci. Technol. 58 (7) (2007) 1019–1031.
[180] Y.-R. Lin, Y. Chi, S. Zhu, H. Sundaram, B.L. Tseng, Analyzing communities and their evolutions in dynamic social networks, ACM Trans. Knowl. Discov. Data (TKDD) 3 (2) (2009) 8.
[181] M. Lipczak, E. Milios, Agglomerative genetic algorithm for clustering in social networks, in: Proceedings of the 11th Annual Conference on Genetic and Evolutionary Computation, ACM, 2009, pp. 1243–1250.
[182] C. Liu, J. Liu, Z. Jiang, A multiobjective evolutionary algorithm based on similarity for community detection from signed social networks, IEEE Trans. Cybern. 44 (12) (2014) 2274–2287.
[183] C. Liu, Q. Liu, Community detection based on differential evolution using modularity density, Information 9 (9) (2018) 218.
[184] F. Liu, G. Xie, A fast algorithm for community detection of network systems in smart city, IEEE Access 7 (2019) 51856–51865.
[185] J. Liu, T. Liu, Detecting community structure in complex networks using simulated annealing with k-means algorithms, Physica A: Stat. Mech. Appl. 389 (11) (2010) 2300–2309.
[186] J. Liu, J. Zeng, Community detection based on modularity density and genetic algorithm, in: Proceedings of the 2010 International Conference on Computational Aspects of Social Networks (CASoN)„ IEEE, 2010, pp. 29–32.
[187] J. Liu, W. Zhong, H.A. Abbass, D.G. Green, Separated and overlapping community detection in complex networks using multiobjective evolutionary algorithms, in: Proceedings of the 2010 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2010, pp. 1–7.
[188] Z. Lixiao, X. Tingrong, L. Jie, L. Haiyan, An overlapping community detection algorithm based on multistep greedy strategy, in: Proceedings of the 2013 Fourth International Conference on Intelligent Systems Design and Engineering Applications, IEEE, 2013, pp. 103–106.
[189] F. Lobo, C.F. Lima, Z. Michalewicz, Parameter Setting in Evolutionary Algorithms, 54, Springer Science & Business Media, 2007.
[190] Z. Lü, W. Huang, Iterated tabu search for identifying community structure in complex networks, Phys. Rev. E 80 (2) (2009) 026130.
[191] D. Lusseau, The emergent properties of a Dolphin social network, Proc. R. Soc. Lond. B: Biol. Sci. 270 (Suppl 2) (2003) S186–S188.
[192] V. Lyzinski, M. Tang, A. Athreya, Y. Park, C.E. Priebe, Community detection and classification in hierarchical stochastic blockmodels, IEEE Trans. Netw. Sci. Eng. 4 (1) (2016) 13–26.
[193] J. Ma, J. Liu, W. Ma, M. Gong, L. Jiao, Decomposition-based multiobjective evolutionary algorithm for community detection in dynamic social networks, Sci. World J. 2014 (2014).
[194] L. Ma, M. Gong, J. Liu, Q. Cai, L. Jiao, Multi-level learning based memetic algorithm for community detection, Appl. Soft Comput. 19 (2014) 121–133.
[195] A. Maas, R.E. Daly, P.T. Pham, D. Huang, A.Y. Ng, C. Potts, Learning word vectors for sentiment analysis, in: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, 2011, pp. 142–150.
[196] M. Maashi, E. Özcan, G. Kendall, A multi-objective hyper-heuristic based on choice function, Exp. Syst. Appl. 41 (9) (2014) 4475–4493.
[197] M. Magnani, O. Hanteer, R. Interdonato, L. Rossi, A. Tagarelli, Community detection in multiplex networks, arXiv preprint arXiv:1910.07646(2019).
[198] P. Mazur, K. Zmarzlowski, A. Orlowski, Genetic algorithms approach to community detection, Acta Phys. Polonica-Ser. A Gen. Phys. 117 (4) (2010) 703.
[199] M. Meilă, Comparing clusteringsan information based distance, J. Multivar. Anal. 98 (5) (2007) 873–895.
[200] H.-W. Mewes, D. Frishman, C. Gruber, B. Geier, D. Haase, A. Kaps, K. Lemcke, G. Mannhaupt, F. Pfeiffer, C. Schüller, et al., Mips: a database for genomes and protein sequences, Nucleic Acids Res. 28 (1) (2000) 37–40.
[201] H.-W. Mewes, D. Frishman, U. Güldener, G. Mannhaupt, K. Mayer, M. Mokrejs, B. Morgenstern, M. Münsterkötter, S. Rudd, B. Weil, Mips: a database for genomes and protein sequences, Nucleic Acids Res. 30 (1) (2002) 31–34.
[202] H.-W. Mewes, K. Heumann, A. Kaps, K. Mayer, F. Pfeiffer, S. Stocker, D. Frishman, Mips: a database for genomes and protein sequences, Nucleic Acids Res. 27 (1) (1999) 44–48.
[203] A. Mislove, M. Marcon, K.P. Gummadi, P. Druschel, B. Bhattacharjee, Measurement and analysis of online social networks, in: Proceedings of the 7th ACM SIGCOMM Conference on Internet Measurement, 2007, pp. 29–42.
[204] P. Moscato, et al., On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms, Caltech Concurrent Comput. Program, C3P Rep. 826 (1989) 1989.
[205] C. Mu, J. Xie, Y. Liu, F. Chen, Y. Liu, L. Jiao, Memetic algorithm with simulated annealing strategy and tightness greedy optimization for community detection in networks, Appl. Soft Comput. 34 (2015) 485–501.
[206] C.-H. Mu, J. Xie, Y. Liu, F. Chen, Y. Liu, L.-C. Jiao, Memetic algorithm with simulated annealing strategy and tightness greedy optimization for community detection in networks, Appl. Soft Comput. 34 (2015) 485–501.
[207] P.J. Mucha, M.A. Porter, Communities in multislice voting networks, Chaos: Interdiscip. J. Nonlinear Sci. 20 (4) (2010) 041108.
[208] M.C. Nascimento, L. Pitsoulis, Community detection by modularity maximization using grasp with path relinking, Comput. Oper. Res. 40 (12) (2013) 3121–3131.
[209] F. Neri, C. Cotta, Memetic algorithms and memetic computing optimization: a literature review, Swarm Evol. Comput. 2 (2012) 1–14.
[210] M.E. Newman, The structure and function of complex networks, SIAM Rev. 45 (2) (2003) 167–256.
[211] M.E. Newman, Finding community structure in networks using the eigenvectors of matrices, Phys. Rev. E 74 (3) (2006) 036104.
[212] M.E. Newman, Modularity and community structure in networks, Proc. Natl. Acad. Sci. 103 (23) (2006) 8577–8582.
[213] M.E. Newman, M. Girvan, Finding and evaluating community structure in networks, Phys. Rev. E 69 (2) (2004) 026113.
[214] M.E. Newman, E.A. Leicht, Mixture models and exploratory analysis in networks, Proc. Natl. Acad. Sci. 104 (23) (2007) 9564–9569.
[215] M. Nicholson, Genetic algorithms and grouping problems, 1998,
[216] V. Nicosia, G. Mangioni, V. Carchiolo, M. Malgeri, Extending the definition of modularity to directed graphs with overlapping communities, J. Stat. Mech.: Theory Exp. 2009 (03) (2009) P03024.
[217] P. Novoa-Hernández, C.C. Corona, D.A. Pelta, Self-adaptation in dynamic environments-a survey and open issues., IJBIC 8 (1) (2016) 1–13.
[218] T.B.S. d. Oliveira, L. Zhao, Complex network community detection based on swarm aggregation, in: Proceedings of the Fourth International Conference on Natural Computation, 7, 2008, pp. 604–608.
[219] J.H. Ong, J. Teo, Emperical analysis of hyper-heuristic search algorithms in expensive numerical optimzation, in: Proceedings of the 2017 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), IEEE, 2017, pp. 117–121.
[220] E. Osaba, J. Del Ser, D. Camacho, M.N. Bilbao, X.-S. Yang, Community detection in networks using bio-inspired optimization: latest developments, new results and perspectives with a selection of recent meta-heuristics, Appl. Soft Comput. 87 (2020) 106010.
[221] M. Oti, B. Snel, M.A. Huynen, H.G. Brunner, Predicting disease genes using protein–protein interactions, J. Med. Genet. 43 (8) (2006) 691–698.
[222] G. Palla, I. Derényi, I. Farkas, T. Vicsek, Uncovering the overlapping community structure of complex networks in nature and society, Nature 435 (7043) (2005) 814–818.
[223] S. Pérez-Peló, J. Sánchez-Oro, A. Duarte, On the analysis of the influence of the evaluation metric in community detection using grasp.
[224] N. Pillay, R. Qu, Hyper-Heuristics: Theory and Applications, Springer, 2018.
[225] C. Pizzuti, Community detection in social networks with genetic algorithms, in: Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation, ACM, 2008, pp. 1137–1138.
[226] C. Pizzuti, GA-Net: a genetic algorithm for community detection in social networks, in: Proceedings of the International Conference on Parallel Problem Solving from Nature, Springer, 2008, pp. 1081–1090.
[227] C. Pizzuti, A multi-objective genetic algorithm for community detection in networks, in: Proceedings of the 21st International Conference on Tools with Artificial Intelligence, ICTAI'09, IEEE, 2009, pp. 379–386.
[228] C. Pizzuti, Overlapped community detection in complex networks, in: Proceedings of the 11th Annual Conference on Genetic and Evolutionary Computation, ACM, 2009, pp. 859–866.
[229] C. Pizzuti, A multiobjective genetic algorithm to find communities in complex networks, IEEE Trans. Evol. Comput. 16 (3) (2012) 418–430.
[230] C. Pizzuti, Boosting the detection of modular community structure with genetic algorithms and local search, in: Proceedings of the 27th Annual ACM Symposium on Applied Computing, 2012, pp. 226–231.
[231] C. Pizzuti, Evol. Comput. for community detection in networks: a review, IEEE Trans. Evol. Comput. 22 (3) (2018) 464–483.
[232] P. Pons, M. Latapy, Computing Communities in Large Networks using Random walks., J. Graph Algorithms Appl. 10 (2) (2006) 191–218.
[233] M. Pourkazemi, M.R. Keyvanpour, Community detection in social network by using a multi-objective evolutionary algorithm, Intell. Data Anal. 21 (2) (2017) 385–409.
[234] H.M. Rada, B.A. Attea, Understanding the role of positive and negative relations for community detection problem in signed networks: a new perspective, Iraqi J. Sci. 58 (4B) (2017) 2222–2235.
[235] F. Radicchi, C. Castellano, F. Cecconi, V. Loreto, D. Parisi, Defining and identifying communities in networks, Proc. Natl. Acad. Sci. 101 (9) (2004) 2658–2663.
[236] U.N. Raghavan, R. Albert, S. Kumara, Near linear time algorithm to detect community structures in large-scale networks, Phys. Rev. E 76 (3) (2007) 036106.
[237] S. Rahimi, A. Abdollahpouri, P. Moradi, A multi-objective particle swarm optimization algorithm for community detection in complex networks, Swarm Evol. Comput. 39 (2018) 297–309.
[238] D.A. Rashid, et al., Multi-layer multi-objective evolutionary algorithm for adjustable range set covers problem in wireless sensor networks, Iraqi J. Sci. 57 (1C) (2016) 755–767.
[239] S. Ray, M. De, A. Mukhopadhyay, A multiobjective go based approach to protein complex detection, Proc. Technol. 4 (2012) 555–560.
[240] K.E. Read, Cultures of the central highlands, new guinea, Southwestern J. Anthropol. 10 (1) (1954) 1–43.
[241] B.S. Rees, K.B. Gallagher, Overlapping community detection using a community optimized graph swarm, Soc. Netw. Anal. Min. 2 (4) (2012) 405–417.
[242] J. Reichardt, M. Leone, (Un)detectable cluster structure in sparse networks, Phys. Rev. Lett. 101 (7) (2008) 078701.

[243] R.G. Reynolds, An introduction to cultural algorithms, in: Proceedings of the Third Annual Conference on Evolutionary Programming, World Scientific, 1994, pp. 131–139.
[244] S. Romano, J. Bailey, V. Nguyen, K. Verspoor, Standardized mutual information for clustering comparisons: one step further in adjustment for chance, in: Proceedings of the International Conference on Machine Learning, 2014, pp. 1143–1151.
[245] P. Ronhovde, Z. Nussinov, Multiresolution community detection for megascale networks by information-based replica correlations, Phys. Rev. E 80 (1) (2009) 016109.
[246] M. Rosvall, C.T. Bergstrom, An information-theoretic framework for resolving community structure in complex networks, Proc. Natl. Acad. Sci. 104 (18) (2007) 7327–7331.
[247] S. Sadi, S. Etaner-Uyar, Ş. Gündüz-Öğüdücü, Community detection using ant colony optimization techniques, in: Proceedings of the 15th International Conference on Soft Computing, 2009.
[248] J. Sánchez-Oro, A. Duarte, Iterated greedy algorithm for performing community detection in social networks, Fut. Gen. Comput. Syst. 88 (2018) 785–791.
[249] N.S. Sani, M. Manthouri, F. Farivar, A multi-objective ant colony optimization algorithm for community detection in complex networks, J. Ambient Intell. Human. Comput. 11 (1) (2020) 5–21.
[250] M. Shahmoradi, M. Ebrahimi, Z. Heshmati, M. Salehi, Multilayer overlapping community detection using multi-objective optimization, Fut. Gen. Comput. Syst. 101 (2019) 221–235.
[251] H. Shen, X. Cheng, K. Cai, M.-B. Hu, Detect overlapping and hierarchical community structure in networks, Physica A: Stat. Mech. Appl. 388 (8) (2009) 1706–1712.
[252] J. Shetty, J. Adibi, The Enron Email Dataset Database Schema and Brief Statistical Report, 4, University of Southern California, 2004, pp. 120–128.
[253] C. Shi, Y. Wang, B. Wu, C. Zhong, A new genetic algorithm for community detection, in: Proceedings of the International Conference on Complex Sciences, Springer, 2009, pp. 1298–1309.
[254] C. Shi, Z. Yan, Y. Cai, B. Wu, Multi-objective community detection in complex networks, Appl. Soft Comput. 12 (2) (2012) 850–859.
[255] C. Shi, Z. Yan, X. Pan, Y. Cai, B. Wu, Multi-objective decision making in the detection of comprehensive community structures, in: Proceedings of the 2011 IEEE Congress on Evolutionary Computation (CEC, 2011, pp. 1489–1495.
[256] C. Shi, Z. Yan, Y. Wang, Y. Cai, B. Wu, A genetic algorithm for detecting communities in large-scale complex networks, Adv. Complex Syst. 13 (2010) 3–17.
[257] C. Shi, P.S. Yu, Y. Cai, Z. Yan, B. Wu, On selection of objective functions in multi-objective community detection, in: Proceedings of the 20th ACM International Conference on Information and Knowledge Management, 2011, pp. 2301–2304.
[258] C. Shi, P.S. Yu, Z. Yan, Y. Huang, B. Wang, Comparison and selection of objective functions in multiobjective community detection, Comput. Intell. 30 (3) (2014) 562–582.
[259] C. Shi, C. Zhong, Z. Yan, Y. Cai, B. Wu, A multi-objective approach for community detection in complex network, in: Proceedings of the 2010 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2010, pp. 1–8.
[260] J. Shi, J. Malik, Normalized cuts and image segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 22 (8) (2000) 888–905.
[261] Z. Shi, Y. Liu, J. Liang, PSO-based community detection in complex networks, in: Proceedings of the Second International Symposium on Knowledge Acquisition and Modeling, IEEE, 2009, pp. 114–119.
[262] M.F. Shirjini, S. Farzi, A. Nikanjam, Mdpcluster: a swarm-based community detection algorithm in large-scale graphs, Computing (2020) 1–30.
[263] D. Shizuka, D.R. Farine, Measuring the robustness of network community structure using assortativity, Anim. Behav. 112 (2016) 237–246.
[264] A. Sinclair, M. Jerrum, Approximate counting, uniform generation and rapidly mixing Markov chains, Inf. Comput. 82 (1) (1989) 93–133.
[265] X. Song, J. Ji, C. Yang, X. Zhang, Ant colony clustering based on sampling for community detection, in: Proceedings of the 2014 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2014, pp. 687–692.
[266] F. Souam, A. Aïtelhadj, R. Baba-Ali, Dual modularity optimization for detecting overlapping communities in bipartite networks, Knowl. Inf. Syst. 40 (2) (2014) 455–488.
[267] N. Srinivas, K. Deb, Muiltiobjective optimization using nondominated sorting in genetic algorithms, Evol. Comput. 2 (3) (1994) 221–248.
[268] C. Stark, B.-J. Breitkreutz, T. Reguly, L. Boucher, A. Breitkreutz, M. Tyers, Biogrid: a general repository for interaction datasets, Nucleic Acids Res. 34 (suppl_1) (2006) D535–D539.
[269] R. Storn, On the usage of differential evolution for function optimization, in: Proceedings of the North American Fuzzy Information Processing, IEEE, 1996, pp. 519–523.
[270] R. Storn, K. Price, Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces, J. Glob. Optim. 11 (4) (1997) 341–359.
[271] P. Suganthan, S. Das, S. Mukherjee, S. Chatterjee, Adaptation methods in differential evolution: a review, in: Proceedings of the 20th International Conference on Soft Computing MENDEL, 2014, 2014, pp. 131–140.
[272] A. Swiercz, Hyper-heuristics and metaheuristics for selected bio–inspired combinatorial optimization problems, Heuristics and Hyper-Heuristics–Principles and Applications, InTech, 2017.
[273] R. Tackx, F. Tarissan, J.-L. Guillaume, Comsim: a bipartite community detection algorithm using cycle and nodes similarity, in: Proceedings of the International Conference on Complex Networks and their Applications, Springer, 2017, pp. 278–289.
[274] A. Tagarelli, A. Amelio, F. Gullo, Ensemble-based community detection in multilayer networks, Data Min. Knowl. Discov. 31 (5) (2017) 1506–1543.
[275] E.-G. Talbi, A taxonomy of hybrid metaheuristics, J. Heurist. 8 (5) (2002) 541–564.
[276] L. Tang, X. Wang, H. Liu, Uncovering groups via heterogeneous interaction analysis, in: Proceedings of the Ninth IEEE International Conference on Data Mining, IEEE, 2009, pp. 503–512.
[277] M. Tasgin, A. Bingol, Communities detection in complex networks using genetic algorithms, in: Proceedings of the European Conference on Complex Systems (ECSS06), 2006.
[278] M. Tasgin, A. Herdagdelen, H. Bingol, Community detection in complex networks using genetic algorithms, arXiv preprint arXiv:0711.0491(2007).
[279] C.P. Tautenhain, M.C. Nascimento, An ensemble based on a bi-objective evolutionary spectral algorithm for graph clustering, Exp. Syst. Appl. 141 (2020) 112911.
[280] X. Teng, J. Liu, M. Li, Overlapping community detection in directed and undirected attributed networks using a multiobjective evolutionary algorithm, IEEE Trans. Cybern. 51 (1) (2019) 138–150.
[281] D. Teodorović, Bee colony optimization (BCO), in: Innovations in Swarm Intelligence, Springer, 2009, pp. 39–60.
[282] C.-W. Tsai, W.-C. Huang, M.-H. Chiang, M.-C. Chiang, C.-S. Yang, A hyper-heuristic scheduling algorithm for cloud, IEEE Trans. Cloud Comput. 2 (2) (2014) 236–250.
[283] C.J. Van Rijsbergen, Information Retrieval, (, Butterworth, London, 1979.
[284] U. Von Luxburg, A tutorial on spectral clustering, Stat. Comput. 17 (4) (2007) 395–416.
[285] C. Von Mering, R. Krause, B. Snel, M. Cornell, S.G. Oliver, S. Fields, P. Bork, Comparative assessment of large-scale data sets of protein–protein interactions, Nature 417 (6887) (2002) 399.
[286] X. Wan, X. Zuo, F. Song, Solving dynamic overlapping community detection problem by a multiobjective evolutionary algorithm based on decomposition, Swarm Evol. Comput. (2020) 100668.
[287] D. Wang, Y. Zhao, Network community detection from the perspective of time series, Physica A: Stat. Mech. Appl. 522 (2019) 205–214.
[288] S. Wang, M. Gong, W. Liu, Y. Wu, Preventing epidemic spreading in networks by community detection and memetic algorithm, Appl. Soft Comput. (2020) 106118.
[289] S. Wang, M. Gong, B. Shen, Z. Wang, Q. Cai, L. Jiao, Deep community detection based on memetic algorithm, in: Proceedings of the 2015 IEEE Congress on Evolutionary Computation (CEC), 2015, pp. 648–655.
[290] S. Wang, J. Liu, Community robustness and its enhancement in interdependent networks, Appl. Soft Comput. 77 (2019) 665–677.
[291] S. Wang, J. Liu, X. Wang, Mitigation of attacks and errors on community structure in complex networks, J. Stat. Mech.: Theory Exp. 2017 (4) (2017) 043405.
[292] X. Wang, P. Cui, J. Wang, J. Pei, W. Zhu, S. Yang, Community preserving network embedding., in: Proceedings of the AAAI, 17, 2017, pp. 3298239–3298270.
[293] Z. Wang, C. Wang, C. Gao, X. Li, X. Li, An evolutionary autoencoder for dynamic community detection, Sci. China Inf. Sci. 63 (11) (2020) 1–16.
[294] Z. Wang, X. Zhao, P. Wen, J. Xue, C. Hu, Community detection in complex networks using improved artificial bee colony algorithm (2016).
[295] D.J. Watts, Networks, dynamics, and the small-world phenomenon, Am. J. Sociol. 105 (2) (1999) 493–527.
[296] I.S. Weaver, H. Williams, I. Cioroianu, M. Williams, T. Coan, S. Banducci, Dynamic social media affiliations among UK politicians, Soc. Netw. 54 (2018) 132–144.
[297] X. Wen, W.-N. Chen, Y. Lin, T. Gu, H. Zhang, Y. Li, Y. Yin, J. Zhang, A maximal clique based multiobjective evolutionary algorithm for overlapping community detection, IEEE Trans. Evol. Comput. 21 (3) (2017) 363–377.
[298] D.H. Wolpert, W.G. Macready, No free lunch theorems for optimization, IEEE Trans. Evol. Comput. 1 (1) (1997) 67–82.
[299] P. Wu, L. Pan, Multi-objective community detection based on memetic algorithm, PloS One 10 (5) (2015).
[300] I. Xenarios, L. Salwinski, X.J. Duan, P. Higney, S.-M. Kim, D. Eisenberg, Dip, the database of interacting proteins: a research tool for studying cellular networks of protein interactions, Nucleic Acids Res. 30 (1) (2002) 303–305.
[301] J. Xiang, X.-G. Hu, X.-Y. Zhang, J.-F. Fan, X.-L. Zeng, G.-Y. Fu, K. Deng, K. Hu, Multi-resolution modularity methods and their limitations in community detection, Eur. Phys. J. B 85 (10) (2012) 352.
[302] D. Xiaodong, W. Cunrui, L. Xiangdong, L. Yanping, Web community detection model using particle swarm optimization, in: Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2008 (IEEE World Congress on Computational Intelligence)., IEEE, 2008, pp. 1074–1079.
[303] X. Yan, L.G. Jeub, A. Flammini, F. Radicchi, S. Fortunato, Weight thresholding on complex networks, Phys. Rev. E 98 (4) (2018) 042304.
[304] B. Yang, W. Cheung, J. Liu, Community mining from signed social networks, IEEE Trans. Knowl. Data Eng. 19 (10) (2007) 1333–1348.
[305] J. Yang, J. Leskovec, Defining and evaluating network communities based on ground-truth, Knowl. Inf. Syst. 42 (1) (2015) 181–213.
[306] F. Ye, C. Chen, Z. Zheng, Deep autoencoder-like nonnegative matrix factorization for community detection, in: Proceedings of the 27th ACM International Conference on Information and Knowledge Management, 2018, pp. 1393–1402.
[307] W.W. Zachary, An information flow model for conflict and fission in small groups, J. Anthropol. Res. (1977) 452–473.
[308] P.M. Zadeh, Z. Kobti, A multi-population cultural algorithm for community detection in social networks, Proc. Comput. Sci. 52 (2015) 342–349.
[309] K.R. Zalik, B. Zalik, Memetic algorithm using node entropy and partition entropy for community detection in networks, Inf. Sci. 445-446 (2018) 38–49.
[310] C. Zhang, X. Hei, D. Yang, L. Wang, A memetic particle swarm optimization algorithm for community detection in complex networks, Int. J. Pattern Recognit. Artif. Intell. 30 (02) (2016) 1659003.
[311] J. Zhang, A.C. Sanderson, Jade: adaptive differential evolution with optional external archive, IEEE Trans. Evol. Comput. 13 (5) (2009) 945–958.
[312] L. Zhang, H. Pan, Y. Su, X. Zhang, Y. Niu, A mixed representation-based multiobjective evolutionary algorithm for overlapping community detection, IEEE Trans. Cybern. 47 (9) (2017) 2703–2716.

[313] Q. Zhang, H. Li, MOEA/D: a multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (6) (2007) 712–731.
[314] S. Zhang, R.-S. Wang, X.-S. Zhang, Identification of overlapping community structure in complex networks using fuzzy c-means clustering, Physica A: Stat. Mech. Appl. 374 (1) (2007) 483–490.
[315] W. Zhang, R. Zhang, R. Shang, J. Li, L. Jiao, Application of natural computation inspired method in community detection, Physica A: Stat. Mech. Appl. 515 (2019) 130–150.
[316] X. Zhang, K. Zhou, H. Pan, L. Zhang, X. Zeng, Y. Jin, A network reduction-based multiobjective evolutionary algorithm for community detection in large-scale complex networks, IEEE Trans. Cybern. 50 (2018) 703–716.
[317] Z.-Y. Zhang, Y. Wang, Y.-Y. Ahn, Overlapping community detection in complex networks using symmetric binary matrix factorization, Phys. Rev. E 87 (6) (2013) 062803.
[318] X. Zhao, B. Yang, X. Liu, H. Chen, Statistical inference for community detection in signed networks, Phys. Rev. E 95 (4) (2017) 042313.
[319] Y. Zhao, G. Karypis, Criterion Functions for Document Clustering: Experiments and Analysis, Technical Report TR 01-40, Department of Computer Science, University of Minnesota., 2001.
[320] A. Zhou, B.-Y. Qu, H. Li, S.-Z. Zhao, P.N. Suganthan, Q. Zhang, Multiobjective evolutionary algorithms: a survey of the state of the art, Swarm Evol. Comput. 1 (1) (2011) 32–49.
[321] H. Zhou, Distance, dissimilarity index, and network community structure, Phys. Rev. E 67 (6) (2003) 061901.
[322] K. Zhou, A. Martin, Q. Pan, Z. Liu, Selp: semi-supervised evidential label propagation algorithm for graph data clustering, Int. J. Approx. Reason. 92 (2018) 139–154.
[323] X. Zhou, Y. Liu, J. Zhang, T. Liu, D. Zhang, An ant colony based algorithm for overlapping community detection in complex networks, Physica A: Stat. Mech. Appl. 427 (2015) 289–301.
[324] J. Zhu, B. Chen, Y. Zeng, Community detection based on modularity and k-plexes, Inf. Sci. 513 (2020) 127–142.
[325] W. Zhu, Y. Tang, J.-A. Fang, W. Zhang, Adaptive population tuning scheme for differential evolution, Inf. Sci. 223 (2013) 164–191.
[326] X. Zhu, Y. Ma, Z. Liu, A novel evolutionary algorithm on communities detection in signed networks, Phys. A: Stat. Mech. Appl. 503 (2018) 938–946.