REVIEW PAPER

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A review: Multi-Objective Algorithm for Community Detection in Complex Social Networks

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ABSTRACT

Recently, research on multi-objective optimization algorithms for community detection in complex networks has grown considerably. Community detection based on multi-objective algorithms (MOAs) in complex social networks is a fundamental scheduler, and it supports knowing the dynamics of a society, finding influential groups, and improving information dissemination. The traditional methodologies often cannot cope with the features that real-world network usually present, related to optimizing various and sometimes conflicting objectives. This paper provides an overview of some recent works on MOAs for community detection in complex social networks. This paper will explore the balance of the reached objectives, such as modularity, community size, and edge density. Which are analyzed by 15 different approaches in order to choose from works published during the period 2019–2024. These strengths and limitations of various MOAs are reviewed with a comparative analysis to provide insights into both the effectiveness and computational efficiency of these methods. The present trends and future research are discussed that underline the need for the development of solutions to be more adaptive and scalable in coping with the gradually increasing complexity of social networks.

Index Terms: Meta-heuristic, Multi-Objective Algorithm, Community Detection, Complex Networks, Optimization and Objective

1. INTRODUCTION

Optimization is a field that combines computer science and mathematics to develop methods for solving complex optimization problems. To solve these issues, one objective or multi-objectives must be maximized or minimized depending on optimization variables. The optimization variables may be real or integer values [1]. There are many optimization algorithms designed for many purposes, such as computer technology, economics, engineering, medicine, and logistics. The aim of these algorithms is to find the best solution to an optimization problem [2]. There are three types of optimization:

1.1. Single Objective Optimization

This type of optimization is used when there is only one objective. Other essential objectives are ignored or even have an impact on them [3].

1.2. Multi-Objective Optimization

Algorithms with a set of objectives (typically consist of two or three objectives) are named by multi-objective algorithms (MOAs). MOAs try to identify an optimal solution or more than one solution to an optimization problem by maximizing or minimizing these objectives [4].

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1.3. Many-Objective Optimization

Multi-objective optimization involving more than three objectives is known as many-objective optimization algorithms [5].

As mentioned previously, the field of optimization is used for solving many different problems; one of them is community detection in complex social networks. There are many real-world complex systems that can be demonstrated as complex networks, such as technology networks, social networks, web networks, and biological networks [6]. First, we need to understand what the meaning of community is. A community is a set of entities that are more strongly connected to each other than the other entities within the network [7]. These communities need some techniques, such as optimization algorithms, to be detected within the network. The techniques of community detection play a crucial role in understanding the functionality of complex networks [8]. This process is used to find hidden structures of communities in complex networks and it can be used to find the topology structures of complex networks and understand what the functions of complex networks are [9]–[12]. In mathematics, complex networks can be demonstrated as graphs, where nodes in a graph are denoted as vertices in the network and links can be used to show the edges of a network [13]. Fig. 1 shows a simple community detection using graph theory.

Nowadays, many optimization algorithms are proposed to address the issue of community detection, such as greedy algorithms and meta-heuristic algorithms. However, the greedy technique is not performing well for detecting communities in large complex networks [14]. However, meta-heuristic algorithms play a crucial role in detecting communities in complex social networks. There are many different meta-heuristic algorithms. The vast majority of meta-heuristics belong to algorithms inspired by nature, such as genetic algorithms (GAs), particle swarm optimization (PSO), and ant colony optimization [15]. A number of them belong to non-nature-inspired algorithms, for example, Tabu Search [16] and Iterated Local Search [17].

This review paper reviews some state-of-the-art algorithms based on multi-objective optimization for detecting communities in complex social networks. Furthermore, some of these approaches enhanced meta-heuristic optimizations to detect high-quality communities. Moreover, another made is a combination of the meta-heuristic algorithms

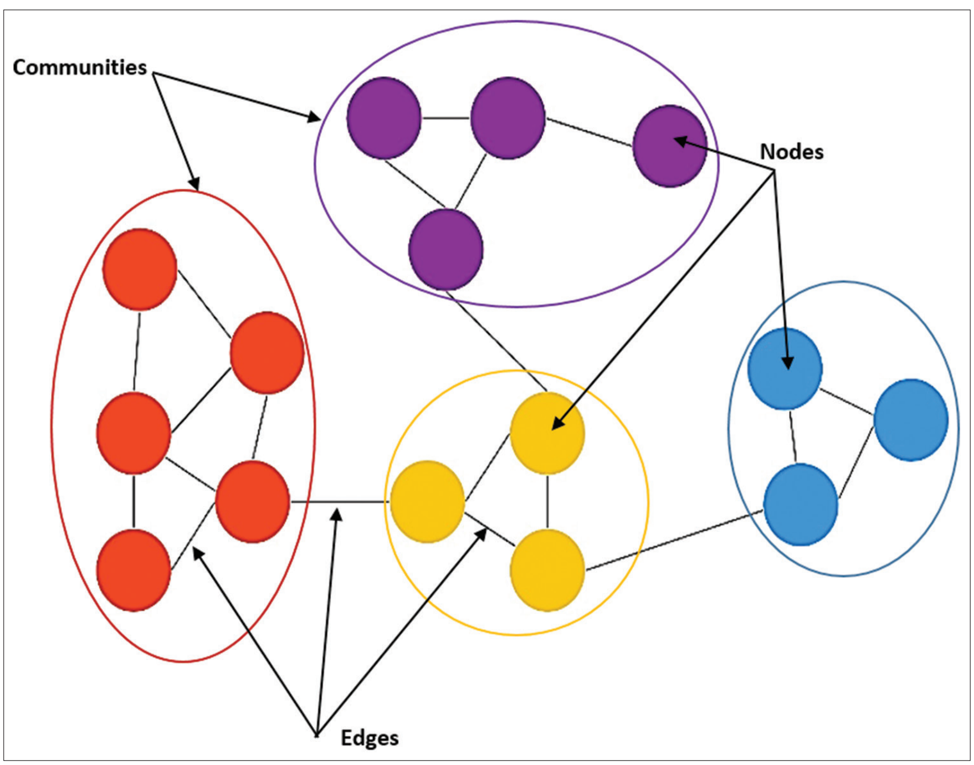

Fig. 1. Example of showing community structure by a graph theory.

to perform better quality of detection. The detail is presented in Section 3.

The rest of the paper is organized as follows: Section 2 is a research strategy; the strategy of the research is explained here. Section 3 presents a literature review; in this section, we discuss the contributions of 15 different researchers. Section 4 is methodology; in this section, the common datasets and evaluation metrics are explained. Section 5 is a comparison and discussion; this section is about the comparison between approaches in terms of objectives, some popular problems of algorithms, solutions, challenges, and future work based on gaps in the reviewed algorithms. The final section is a conclusion; the paper is concluded here.

2. RESEARCH STRATEGY

This paper presents a review of the available literature on MOAs for community detection in a complex social network. Hence, a few different multi-objective strategies that work for community detection in different complex networks are presented. The approaches selected for consideration in supporting the goals of our research have been based on originality and thorough coverage of significant subjects related to MOAs for community detection. In this review paper, fifteen different approaches have been selected from the range of 2019–2024. Moreover, most of the research in our paper is from well-renowned conferences and journals. Furthermore, this literature presents and discusses methodologies and improvements for each selected approach. Table 1 shows the characteristics of fifteen different papers related to community detection in a complex social network by a MOA.

All of these papers are classified into 6 categories. Each category shows the number of papers that were published in the mentioned year that are presented in Fig. 2.

Furthermore, each of those researchers used more than one complex network to test and compare their algorithm with previous algorithms. Table 2 shows the number and names of the networks used by each paper to test the result.

TABLE 1: Presents the characteristics of all 15 papers in our literature

References	Title	Year of publication
[18]	A multi-objective multi-agent optimization algorithm for the community detection problem	2019
[19]	An Enhanced Multi-Objective Evolutionary Algorithm with Decomposition for Signed Community Detection Problem	2020
[20]	A Compression Based Multi-Objective Evolutionary Algorithm for Community Detection in Social Networks	2020
[21]	Evolutionary Multi-Objective Optimization Algorithm for Community Detection in Complex Social Networks	2021
[22]	A Parallel multi-objective evolutionary algorithm for community detection in large-scale complex networks	2021
[23]	Multi-objective NSGA-II-based community detection using dynamical evolution social network	2021
[24]	A fast variable neighborhood search approach for multi-objective community detection	2021
[25]	A Multi-Objective Evolutionary Algorithm with Neighbor Node Centrality for Community Detection in Complex Networks	2022
[26]	A Multi-Objective Evolutionary Algorithm Based on Mixed Encoding for Community Detection	2023
[27]	A Two-Stage Multi-Objective Evolutionary Algorithm for Community Detection in Complex Networks	2023
[28]	A Macro-Micro Population-Based Co-Evolutionary Multi-Objective Algorithm for Community Detection in Complex Networks	2023
[29]	Multi-objective Optimization Overlapping Community Detection Algorithm based on Subgraph Structure	2023
[30]	A Multi-Objective Pigeon-Inspired Optimization Algorithm for Community Detection in Complex Networks	2024
[31]	Two-stage multi-objective evolutionary algorithm for overlapping community discovery	2024
[32]	Community Detection in Social Networks Using a Local Approach based on Node Ranking	2024

NSGA: Non-dominated sorting genetic algorithm

TABLE 2: Presents a number and name of networks used to evaluate the algorithm by each paper in the literature

References	Number of networks used by each paper	Network's formal name
[18]	5	Karate, Les Misérables, Bernard, Grevy's zebra, Facebook
[19]	5	Karate, Dolphins, Football 2000, Football 2001, Krebs
[20]	11	Karate, Dolphins, Football, Polbooks, Co-authors, Email, Netscientist, Facebook, GR_QC, GC_Hep_TH, GC_Hep_PH.
[21]	4	Karate, Dolphin, Football, Books about US Politics.
[22]	10	Football, Net-science, blogs, ca-GrQc, ca-HepTh1, ca-HepTh2, ca-AstroPh, ca-CondMat, loc-Brightkite, loc-Gowalla.
[23]	3	Last.fm, Douban, SYNFIX.
[24]	10	Karate, Dolphins, Football, netscience, jazz, musae_DE_edgesnetwork, musae_ENGB_edgesnetwork, musae_ES_edgesnetwork, musae_FR_edgesnetwork, musae_RU_edgesnetwork.
[25]	9	Karate, Dolphin, Football 2000, Football 2001, Kreb's books, SFI, Jazz, Netscience, Power grid.
[26]	4	Karate, Dolphins, Books, Football.
[27]	4	Karate, Dolphin, Football, Polbooks
[28]	14	Karate, Dolphin, football, the Books about US politics, the Yeast PPI dataset, the Blogs network, the PGP network, Ca-GrQc, Ca-HepTh1, Ca-HepTh2, Ca-AstroPh, Ca-CondMat, Epinions, and Enron-large.
[29]	4	Karate, dolphin, football, American political books network.
[30]	3	Karate, Dolphin, Football
[31]	9	Karate, Dolphin, Football, Polbook, Email, Jazz, SFI, Y2H, Yeast-D2.
[32]	18	Karate, Dolphins, PolBooks, Football, SFI, NetScience, Email, PowerGrid, PGP, GrQc, ca-AstroPh, ca-HepTh, ca-HepPh, Condmat-2003, Condmat-2005, Email Enron, Collaboration, Internet.

3. LITERATURE REVIEW

In this section, we discussed the methodology and contribution for each selected paper. The algorithms are categorized into three categories (modified evolutionary algorithms, hybrid evolutionary algorithms, and swarm intelligence algorithms).

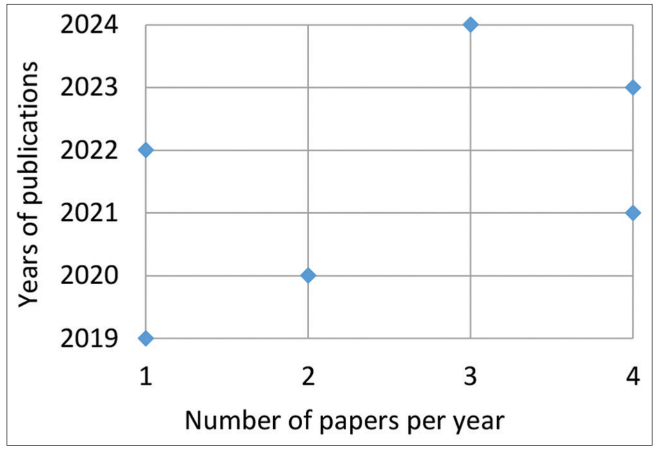

Fig. 2. Demonstrates the number of selected paper per year.

3.1. Modified Evolutionary Algorithms

Hosseinian and Baradaran [18] proposed a new approach named a multi-objective multi-agent optimization algorithm (MAOA) for detecting community problems in social networks. This algorithm optimizes each objective simultaneously to obtain enhanced accuracy and efficiency in the detection of communities in the networks. This algorithm introduces an agent-based multi-objective for detecting communities. The agents are organized into groups of leaders and active agents. By having this, the algorithm used a grouped structure. By enhancing the agent's environment and behaviors, the algorithm effectively facilitated the solution space exploration. Another contribution in this approach is integrating the concept of Pareto dominance to ensure the algorithm can approximate the Pareto optimal front and identify solution efficiency. Experimentally, there are two main contributions: Performance improved by using a multi-agent strategy and providing better initialization to make more applicability in large and more complex networks. Experimental results were tested on some real-world networks and compared with three meta-heuristic algorithms. The result demonstrates that the MAOA performs better in terms of accuracy and efficiency.

Another approach based on a multi-objective evolutionary algorithm with decomposition (MOEA/D) is proposed by Abdulrahman *et al.* [19]. It is decomposing the multi-objective optimization problem into several sub-problems efficiently. The aim of this method is to balance the quality of detecting communities with the distribution of solutions through the Pareto front and find a different set of Pareto optimal solutions. MOEA/D focused on enhancing mutation operators to improve performance. Unlike the traditional mutation operator, this randomly selects a node for mutation. In this approach, the internal and external connections between nodes have been calculated. Nodes with low internal and high external connections are called positive connections and nodes with high internal and low external connections are called negative connections. The mutation operator has been applied over the positive connections. Having positive and negative connections helps the efficiency of the algorithm. A variety of real-world networks were selected to evaluate the performance of MOEA/D. The result of this approach is outperformed compared with the traditional methods. It provides a better structure for community detection in dynamic networks.

In the same year of [19], Liu *et al.* [20] designed an enhanced algorithm using a multi-objective evolutionary algorithm (MOEA). To optimize the process of community detection, the proposed algorithm performed a compression-based method to optimize two objectives, such as maximizing the modularity and minimizing the number of communities. The compression process was applied over the network topologies to obtain smaller networks. The main purpose of this approach is improving efficiency by compressing networks because the majority of algorithms for community detection have a problem of computational time. Furthermore, to prefer a better community structure, both initialization and mutation processes have been improved. The approach conducts extensive experiments on some datasets and the result outperforms some existing methods in terms of computational efficiency and accuracy. The proposed algorithm has the ability to exploit in the search of an optimal solution and make a balance between exploration and exploitation. The results are tested on some different datasets and compared with some state-of-the-art algorithms. The proposed algorithm obtained higher accuracy and performance.

Another paper by Shaik *et al.* [21] presents a novel algorithm to detect communities in complex social networks using three objectives. Optimizing three objectives is a main novelty because traditional approaches primarily focused on single or two objectives. There are two variants of a non-dominated sorting GA (NSGA) III introduced. The first is NSGA-III-KRM (kernel k-means, ratio cut, and modularity) and the second variant is NSGA-III-CCM (community score, community fitness, and modularity). Moreover, a new measurement of the ranking mechanism for Pareto solutions by using a ratio of hyper-volume to inverted generational distance is produced to enhance the Pareto set evaluation. This research addresses some limitations and improves the performance metrics of previous approaches. To evaluate the result of this algorithm, four network datasets are selected and compared with some existing state-of-the-art methods. The algorithm achieved a good result compared with other algorithms.

A new parallel MOEA (PMOEA) was proposed by Su *et al.* [22]. It is designed to detect communities in large-scale complex networks. The first operation performed by PMOEA is to identify communities based on specific nodes (key nodes) rather than the entire network. After that, it executes multiple copies of a MOEA to detect communities linked to each key node using a parallel mechanism. Another contribution in this approach is enhancing the mutation and crossover operators to capture a better community in the network. Through performing the parallel process, the computational efficiency and quality of detection are enhanced. Experiments of this algorithm indicate that it works better than other evolutionary and non-evolutionary algorithms, showing that it can handle networks with up to 200,000 nodes.

Based on the NSGA II algorithm, the dynamic community detection (DCD) system proposed by Alkhalec Tharwat *et al.* [23]. The proposed algorithm explains the growing need for community detection methods effectively in dynamic social networks. DCD is the main goal of this algorithm, while networks change over time. It utilizes a multi-objective optimization framework by using the specialty of NSGA-II and involves formulating the community detection problems in social networks where the state of networks changes over time. While the network is dynamic, the proposed algorithm identified communities at different time points. This algorithm is able to be used in various applications, such as recommender systems, analysis of social media, and retrieving information. The result of this algorithm obtained better performance compared with classical GAs.

Another approach, using a multi-objective GA (MOGA-Net), is proposed by Abbood *et al.* [25] for community detection in complex networks. The proposed approach uses the NSGA-II for finding globally non-dominated solutions, which guarantees that no other possible partition is superior for both objectives. The proposed algorithm introduced a novel scoring model (intra-score and inter-score). They assist the algorithm to capture better community structure. A new contribution of this approach is identifying the healthy and infected communities during COVID-19. This study compares MOGA-Net's performance with other state-of-the-art methods using some real networks, showing how efficiently it creates accurate community structures. This algorithm also introduces a new scoring model that quantifies the density of internal connections (intra-score) and the sparsity of inter-community connections (inter-score).

There is an additional contribution by Zhu *et al.* [27] is a fundamental task that aids the comprehension of complex networks. The proposed approach implements a two-stage MOEA that strengthens community detection through optimizing multiple objectives simultaneously. First, in the initial stage, the individual similarity parameters are targeted to find possible communities; then, in the second stage, distinct crossover operators are employed with respect to the characteristics of the detected communities. The algorithm is developed to handle challenges arising in traditional community-detection methods, which face the complexity and dynamics of real-world networks. Furthermore, it enhanced the boundary-independent nodes by applying the second-stage strategy. They further validate their approach through extensive experiments on many datasets, showing that their algorithm performs better than the state-of-the-art approaches in both accuracy and computational efficiency.

In the study of Zhang *et al.* [28], a new algorithm named MMCoMO (Macro-Micro Population-Based Co-Evolutionary Multi-Objective) algorithm was proposed and it's different than the traditional MOEAs. They worked with a single population at the first steps, which lead to a limiting balance between exploration and exploitation. On the other hand, the MMCoMO employs macro-population and micro-population as two types of population. The main contribution in this approach identified the macro and micro populations. The macro-population emphasizes exploration. During this process, the network quickly portioned to detect the approximate community structure. Meanwhile, the micro-population focuses on exploitation to achieve more precise community configurations the structures of the network through local search are refined. In addition to quality enhancement, the MMCoMO improves the computational efficiency of detecting communities compared with existing MOEAs.

After that, Cai *et al.* [31] provide a fast two-stage MOEA for the identification of the overlapping community in networks. The main goal of this algorithm is to discover overlapping communities using a two-stage MOEA. The first stage aims at identifying the high-quality non-overlapping communities by using the population initialization technique using the degree central nodes. It also increases the robustness of community division with respect to the existing methods. In the second stage, the algorithm picks out additional nodes from the networks that have previously been categorized in non-overlapping communities as central nodes. An information feedback model is used to adjust a fuzzy scale for thresholding to improve the identification of overlapping nodes. Another contribution in this approach is identifying a new initialization of the population using central nodes based on node degree for better partitioning. The proposed algorithm's efficiency is tested through experiments on some different networks and compared with other algorithms based on the modularity and accuracy value of community structure and achieved higher results.

Sheykhzadeh *et al.* [32] proposed a novel local community detection algorithm based on node ranking in social networks. It is referred to as LCD-SN local method community detection algorithm in social networks and is designed to overcome the limitations of previous approaches that usually have low accuracy and high computational time. Node ranking means how nodes interact and are ranked relative to community nodes and their connectivity. The algorithm has been designed to look for communities of densely connected nodes and relatively scattered nodes in between communities. First-degree and second-degree neighbor nodes are used by LCD-SN to build the communities, as a result of which accuracy and determinism are improved while seed nodes are not required. The algorithm starts with node scaling and defining the important nodes with the help of local characteristics and then it creates the primary groups with the node and its first-order neighbors. Communities are identified in the last step in the process known as post-processing. The paper also presents a new measure for ranking the nodes in the network, which makes community detection even better. Experimental analysis shows that LCD-SN is useful for finding communities with a flexible approach to the trade-off between time and solution quality.

3.2. Hybrid Evolutionary Algorithms

Pérez-Peló *et al.* [24] present a hybrid meta-heuristic approach for detecting communities in networks by combining variable neighborhood search (VNS) and Greedy randomized adaptive search procedure (GRASP). The main contribution in this approach is improving the efficiency of search by combining VNS and GRASP. Moreover, the limitations of traditional community detection algorithms are highlighted, especially these challenges that are associated with high modularity that suffers from the limitation of resolution. Based on bi-objective community detection problems, this algorithm aims to optimize multiple objectives simultaneously, which leads to a reliable community structure. As a result, the algorithm shows effectiveness compared with the existing approaches and is good for these applications that are used for analyzing complex networks.

In this direction, Yang *et al.* [26] have proposed a hybrid approach to community detection in complex networks. The main contribution in this algorithm is identifying a mixed encoding strategy by combining locus-based and label-based representation. Having this combination helps the algorithm to represent a valid community structure and is more flexible. Furthermore, this study has recognized the difficulties that were posed by methods based on traditional modularity maximization, especially with regard to network topology issues and invalid solution generation. To improve these issues, this paper proposes a MOEA based on the integration of label-based and locus-based representations. The experimental results have shown that this approach outperforms existing algorithms concerning effectiveness and efficiency. These results confirm that this algorithm is a competitive approach when compared with traditional methods of community detection and consequently.

3.3. Swarm Intelligence Algorithms

As a part of swarm intelligence, Li [29], proposed a new overlapping community detection algorithm based on subgraph structures and multiple objective optimization techniques. The main contribution in this approach is transforming overlapping nodes into clique nodes. Due to the possible overlap in real-world communities, the algorithm herein proposed employs the k-core decomposition to find maximum cliques, which form the building blocks for the weighted graph. Instead of randomly initializing the population, the proposed algorithm leverages the k-core decomposition for better initial community partitioning. The algorithm integrates a PSO to improve search accuracy and convergence speed. The result of this algorithm compared with similar community detection algorithms on some real-world networks and demonstrated a decent performance.

Then, Yu *et al.* [30] introduced a new algorithm named multi-objective pigeon-inspired optimization (MOPIO). This algorithm performed three main steps: Initialization, search, and mutation methods. It starts by constructing a solution representation of the community structure to evaluate two objective functions to assess community quality. The main contribution of this research is integrating pigeon-inspired optimization for community detection. It enhanced the applicability of the algorithm for complex networks. Furthermore, to address the problem of misclassification of boundary nodes, they proposed a novel strategy through the mutation process. The result of this work is evaluated based on different networks and it performs better for detecting community structures compared with other existing approaches. This algorithm not only enhanced the accuracy of community detection but also offered a framework compactable with various networks.

4. METHODOLOGY

This review paper explains the methodologies and contributions of fifteen studies based on a MOA for detecting communities in social networks. Each paper used the number of networks that were shown in Table 2 and commonly evaluated the performance of their algorithm using two metrics. This section demonstrates the detailed information of the common networks and explains metrics that are used to evaluate algorithms.

4.1. Common Networks

The networks that are used by each study consist of a different number of nodes and edges. Each node is strongly connected with others in the same community and weakly with other nodes in the different community. The connections between nodes are called edges [7]. This number of edges and nodes defines the size of the networks. Furthermore, in some of these networks, the number of communities was detected using a ground truth [33]. Table 3 shows the properties of some common networks that are used by the papers.

4.2. Metrics for Evaluating the Results

Q modularity and normalized mutual information (NMI) are two main metrics that are used to evaluate community detection in social networks. All of the studies in this review paper used these two metrics to evaluate the result of detecting communities for each network that was used in their paper.

TABLE 3: Some different size of common real-world networks

Networks	Number of nodes	Number of edges	Number of communities
Karate [34]	34	78	2
Dolphin [35]	62	159	2
Polbooks [36]	105	441	3
Football [37]	115	613	12
Citeseer [38]	3,327	4,676	6
Ca-GrQc [39]	5,242	14,496	-
CA-HelpTh [39]	9,877	25,998	-
Facebook [12]	4,039	88,234	-
Ca-HepTh2 [39]	12,008	118,521	-
Ca-AstroPh [39]	18,772	198,110	-
ca-CondMat [40]	23,133	93,497	-
Email-Enron [41]	36,692	183,831	-

The modularity Q, which can be computed without knowledge of the actual community labels of a network, was chosen as a measure of quality for the communities; a higher Q value indicates better performance in community detection [42]. The formula of modularity Q was defined as below.

$$Q = \sum_{i=1}^{k} \left[\frac{l_s}{M} - \left(\frac{d_s}{2M} \right)^2 \right]$$

k and M show the number of detected communities and edge's number in a network, respectively. Then, l_s is a number of edges for each node in the community i, and d_s is a total degree of nodes in the same community [42].

However, using truth grounds, the NMI was used in order to measure how similar the detected and real communities were. Greater value of NMI shows better performance in detecting communities [43]. The following is the definition of the NMI formula.

$$NMI(A,B) = \frac{\sum_{i=1}^{C^A} \sum_{j=1}^{C^B} C_{i,j} \, Log\left(\frac{C_{i,j} N}{C_{i.} C_{.j}} \right)}{\sum_{i=1}^{C^A} C_{i.} \log(C_{i.}/n) + \sum_{j=1}^{C^B} C_{.j} \log(C_{.j}/n)}$$

In partitions A and B, CA and C^B present the number of communities, C shows the confusion matrix, and $C_{i,j}$ is a shared node between community i of A and community j of B. $C_{i.}$ or $C_{.j}$ determines the total elements of C in row i or column j, while the number of nodes in the network is n [43].

5. COMPARISON AND DISCUSSION

5.1. Compare Objectives used by Algorithms

All of the studies that were selected in this review paper used a MOA for detecting communities in the networks. Moreover, most of them used the MOA for optimizing two objectives instead of one that optimized three objectives. The number of objectives and their types are explained in Table 4. Furthermore, Fig. 3 explains the most frequent objectives used by the algorithms.

According to Fig. 3, modularity is the most frequently used by the algorithms. Then RC comes as the most commonly used after modularity. The modularity is used to measure the quality of network partitions and a RC is a solution to achieve as few as possible connections between the communities [21].

5.2. Problem Definition of Community Detection and Limitations

5.2.1. Overlapping communities

Refer to a problem in which one node simultaneously belongs to multiple communities [44]. Most of the studies in this review paper solved the mentioned problem. Fig. 4 shows the overlapping communities in the network.

TABLE 4: Demonstrates the number and type of objectives that optimized by the papers in the literature

Paper references	Number of objectives used by each paper		
	Objective 1	Objective 2	Objective 3
[18]	Optimize modularity	Optimize community score	
[19]	Maximizing modularity	Optimizing of frustration function	
[20]	Minimize KKM	Minimize RC	
[21]	Maximizing community score	Maximizing community fitness	Maximizing modularity
[22]	Minimizing the conductance of a community	Maximizing the number of key nodes in a community	
[23]	Optimize modularity	NMI	
[24]	Optimize NRA	Optimize RC	
[25]	Optimize community structure	Optimize community fitness	
[26]	Minimize KKM	Minimize RC	
[27]	Maximizing modularity	Minimizing the number of misclassified nodes	
[28]	Optimize KKM	Optimize RC	
[29]	Maximal clique detection	Community structure optimization	
[30]	Minimize community score	Minimize community fitness	
[31]	Modularity optimization	NMI	
[32]	Accuracy of community detection	Computational efficiency	

KKM: Kernel K-means, RC: Ratio cut, NMI: Normalized mutual information

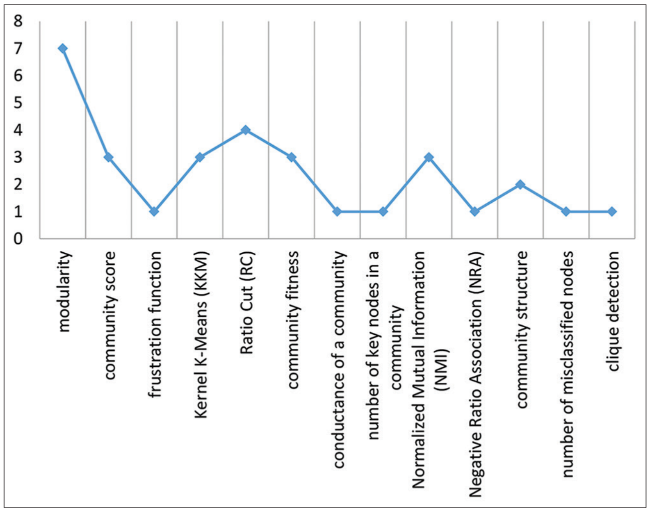

Fig. 3. The most frequent objectives used by the algorithms.

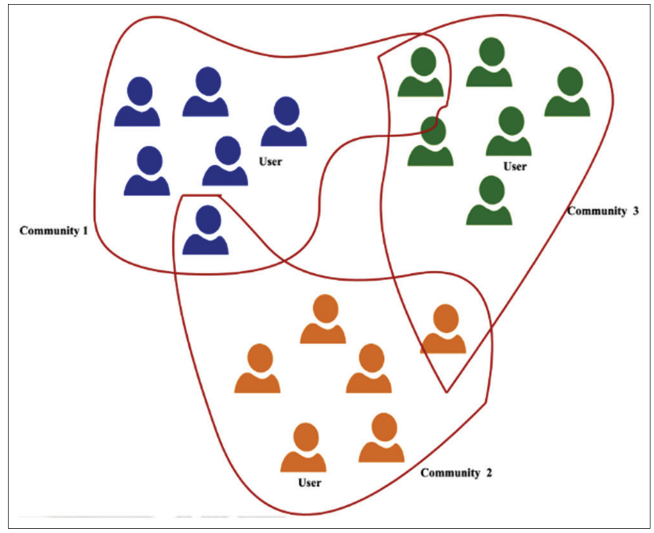

Fig. 4. Overlapping communities [45].

5.2.2. Dynamic networks

Is a network that changes structure over time. Either through the addition, removal, or change of nodes, edges, or both, dynamic networks differ from static networks with fixed nodes and edges [46]. Today, detecting communities in dynamic networks is the most popular challenge especially in terms of real-time community detection or recommender systems. Some algorithms try to solve this problem but not completely. It's a main gap in today's approaches. Any changes in the network the algorithm needs to execute again and it's a main limitation in the community detection algorithms.

5.2.3. Computational complexity

One of the most popular problems in MOAs for detecting communities is computational complexity because they must optimize two or three objectives simultaneously. This problem appears more while the network becomes larger over time. Furthermore, it's the main limitation in the majority of algorithms. Some algorithms simplified the complexity but the quality of the detection decreased and vice versa.

5.3. Addressing Limitations

5.3.1. Overlapping communities

Nowadays, the majority of algorithms prevent this problem by:

1. Evaluating the algorithm by robust functions Q modularity and NMI
2. Use high-accurate objectives, such as K-means [47], RC [48] and normalized cut [49]
3. Using evolutionary algorithms, such as NSGAII.

5.3.2. Dynamic networks problem

1. Where a new node is added, try to update only the nearby community instead of the entire network
2. Integrating graph neural network [50] to predict how communities in the network will change in the future.

5.3.3. Computational complexity

1. Instead of using random partitioning in the initialization process, you can use smart partitioning, such as Louvain [51] or Kernighan and Lin [52]
2. Develop a robust hybrid algorithm to reduce computational time
3. Improve mutation and crossover operators
4. Can be used early stopping to terminate the algorithm when no significant improvement is obtained over the generations
5. Used the compression technique over large-size networks.

5.4. Challenges and Future Work

According to the limitations that were explained in the previous sub-section, there are many challenges and future works.

1. Prepare a robust hybrid algorithm by using the specialty of the previous algorithms. That cover both the quality of detection and simplifies the complexity
2. Applied the algorithm to perform real-time community detection of the huge networks

3. Applied the algorithm for recommendation using the recommender system.

6. CONCLUSION

Nowadays, the MOA is the most widespread study for detecting communities in complex networks. The researchers have proposed various algorithms to achieve the highest accuracy and efficiency in detecting communities among different networks. Those approaches used MOAs to solve two or three conflict problems in the structure of the network. This research establishes a foundational understanding of various aspects of a MOA for community detection in complex networks by providing a detailed overview of the published literature. Our review paper focuses on novelties, development, processing, and published literature reviews, with the aim of identifying research gaps in the MOAs for detecting communities in complex networks. This survey summarized 15 different studies that were published in the years between 2019 and 2024. Furthermore, the methodology and contribution for each study have been demonstrated. After that, the datasets and evaluation metrics that were used by each approach have been presented. Then, discussion about the limitation and solution has been made.

The future work is developing a hybrid algorithm based on the gaps in the recent algorithms to detect more accurate community detection in complex networks.

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