KHWARIZMIA
Vol. **(2023)**, 2023, **pp**. 37–45
ISSN: 3078-2694

Review Article

Exploring Signed Social Networks: Algorithms for Community Detection and Structure Analysis

Mayasa M. Abdulrahman [1,*], *Amenah D. Abbood* [2], *Baraa A. Attea* [2]

[1]*Computer Engineering Department, College of Engineering, University of Baghdad, Baghdad, Iraq*.
[2]*Department of Computer Science University of Baghdad, Baghdad, Iraq*

ARTICLE INFO

Article History
Revised: 01 Feb 2023
Accepted 03 Apr 2023
Published 23 Apr 2023

Keywords
Community detection
Structural analysis
Social network analysis
Genetic algorithms
Signed social networks

ABSTRACT

The rapid growth of the internet and social networking platforms has significantly enhanced the way individuals connect and share information, often leading to the formation of complex networks with positive and negative relationships. These signed social networks can be represented as undirected graphs with nodes and edges denoting users and their interactions, respectively. Community detection within these networks has become a prominent research area, as it helps to uncover the underlying structure and instability in relationships, thereby predicting organizational changes. This paper reviews the latest advancements in algorithms for community detection in signed networks, focusing on multi-objective optimization approaches that balance modularity and frustration minimization. We explore various methodologies, including ant colony optimization, genetic algorithms, and memetic algorithms, and their applications in identifying community structures. The study highlights the significance of understanding both positive and negative links in social networks to provide a comprehensive analysis of their structural dynamics.

1. INTRODUCTION

The social network is the most popular type of network and can be defined as a set of nodes that represent users sharing a common interest or exhibiting similar attributes. The networks also have a set of edges that represent the interactions (internal or external). A complex network can be modelled as an undirected graph and can be divided into groups of nodes called communities, modules, or clusters. In each group, there are dense intra-connections and sparse inter-connections with the other communities [1]. The edge distribution in a randomly generated network is mostly uniform with a similar degree of vertices; however, for real networks, the degree of distribution is not uniform, and the edges could be denser among some groups of entities and rarer among the others, which represents the structure of the communities. In the social networks, the entities naturally fall into communities and the internal relationships in such networks are dense while the external relationships are rare [2], [3]. The rapid advancement of the internet and social networking over the past few years has allowed people to connect
and share information and opinions more effectively and the representation of such connections (where people represent the nodes and the link between two persons represents the edge) has been primarily considered positive. Hence, the relationships have been mainly expressed as common interests, collaboration, friendship, and membership to the same group. Since the earlier research efforts on structural balance theory were reported by [4] in relation to the attitude and perception of the social organization of people which was later generalized by [5], the relationships among individuals has been considered either positive or negative, such as friends-enemies, like-dislike, trust-distrust, love-hate. Signed networks refer to an extension to complex unsigned networks while additional positive and negative information is added to the connections; thus, the positive links could represent friendly relations while the negative links could be the antagonistic relations. The determination of the community structure within these kinds of networks has become a trending research area as it allows the determination of the instability within relationships for a better prediction of the changes within an organization. Communities are the major network structures; individuals within a community are more connected with each other compared to their connection with members of another community. Individuals connect with one another because they simply know each other or because they have something in common; so, it can be stated that communities are the major structures in any network [6]. Most of the recently developed approaches for community detection [7], [8], [9] rely on the general definition of the community

*Corresponding author email: rahman@coeng.uobaghdad.edu.iq
DOI: https://doi.org/10.70470/KHWARIZMIA/2023/004

presented by [10]. New extensions have also been suggested for the definition of community in both overlapping and non-overlapping the community structures [11]. However, such definitions of community structure are yet to be well explored for signed networks. Several models have been proposed in the literature for different unsigned community detection models, including modularity is normally applicable for the signed and unsigned community detection [12], [13], [14]. Modularity maximization allows the use of the employed "detection algorithms to partition the networks into various dense partitions that differ greatly from random divisions. Despite the possibility of exploiting such modified unsigned community detection models for the detection of signed communities, they are not suitable enough to address the issue of community detection in signed complex networks [15]. The signed connections between different nodes and their role in community classification into strong and weak communities are yet to be explored in the literature. Considering the relevance of the positive and negative signs over connections between various nodes as the main reason due to their important roles in signed complex networks [16].

2. COMMUNITY DETECTION ALGORITHMS

Various community detection algorithms have been detected over the years for unsigned networks; these algorithms are classified as [12] Graph-based (GBA) and Density-based (DBA) algorithms. The GBAs are further grouped into graph partitioning and graph clustering approaches [17]. The main idea of the graph partitioning algorithms is to partition the graph into several predetermined groups of higher intra-group densities and lower inter-group densities. Signed social networks are associated with scalable dynamic properties and this is a limitation to the use of the common clustering methods as they require the pre-knowledge of the number and size of the communities [18]. The other community detection approach is the DBAs that have been designed to identify arbitrarily shaped communities. The study by [19] developed a DBA called DBSCAN in which only one parameter serves as the input while the object is taken as points to form communities. Another study by [20] proposed a DBA called OC Miner for the identification of overlapping communities in social networks. illustrates and summarizes the classification of CD methods.

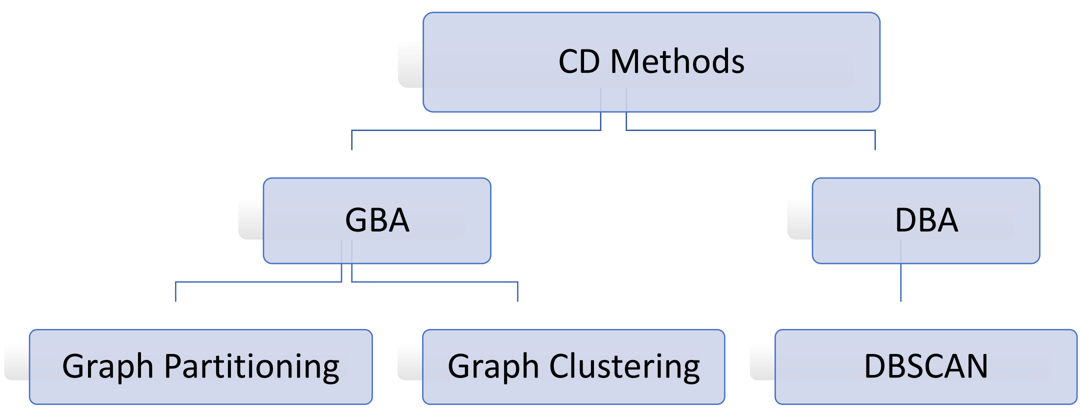


Fig. 1. Classification of Community Detection Methods

Even though community detection has received much research attention over the years, most of the devoted studies were based on unsigned complex networks while few studies have investigated the signed community structures for the co-existence of positive and negative relationships. This section provides a systematic review of the important recent works related to this research. Amelio and Pizzuti [21] focused on the detection of community in signed networks using multi-objective optimization models. They proposed an optimization framework that relies on the maximization of signed modularity (Q_s) introduced by [22] and frustration minimization as define by Doreian and Mrvar [23]. The proposed model emphasized more on identifying the partitioning solutions ($\mathcal{C} \in \Omega$) with low frustration and high modularity structures. The study proposed a Genetic Algorithm for handling the above explained multi-objective model, and attained a good performance in terms of NMI, and signed Modularity.
Liu et al. [24] proposed a multi-objective community detection model for a given graph. Their work depended mainly on the definition provided by Huang et. al. [25] of the structural similarity between vertices in a given graph. The main key point of their method is the structural similarities between two neighbouring nodes in undirected graphs or networks. The performance of the multi-objective maximization model proposed by Liu et al. was compared against Forward Error Corrections (FEC) method proposed by Yang, Cheung, and Liu [26], and the extension provided by Blondel et al. [27]. The results showed the effectiveness of the model by Liu et al. [24] compared to the other models.

Amelio and Pizzuti [28], which is an extension of their initial work, aimed at improving the final solutions achieved by their model in terms of its signed modularity (Q_s). This improvement involves the movement of the positive inter-links from their communities to the adjacent communities while sustaining the increase in their Q_s value. From the experimental and simulation studies on real-life networks, the proposed model was found more effective than the state-of-the-art approaches, including those proposed by [29] and [24]. Recently, several studies have been published based on the work of Amelio and Pizzuti, such as Sani et. al. [30], and Li et al. [31].

Bara'a et al. [32] focused on the community structure in both weak and strong connections. They proposed a novel model for community detection based on weak and strong connections in signed networks. This model was evaluated in terms of its performance against the other existing methods. The study introduced a novel multi-objective model with an anti-frustration heuristic operator for signed community detection. The experiments showed that the proposed model performed better than the other models.

Nancy and Bharadwaj [12] presented an evolutionary-based multi-objective framework for community detection in signed networks which considered both the link density and the link information type. The study also designed a matrix representation of a chromosome with the appropriate mutation and crossover operators. Three basic network properties (Modularity, Frustration, and Social Balance) were considered as the optimization criteria. From the analysis of the results, the efficiency and effectiveness of the proposed model were established.

Liu et al. [33] have proposed a Multi-objective Ant Colony Optimization with Decomposition (MACOD) for community detection problems. Two main contributions were suggested in MACOD, first, two objective functions were divided into a set of sub problems, where each ant handled a single objective sub problem. Second, proposing a problem specific individual encoding strategy based on the graph. In addition, to enhance the stability of MACOD, a local search mechanism was designed. The performance of MACOD has been evaluated based on nine networks. Although it performed well in terms of Normalized Mutual Information (NMI) and Modularity (Q), the performance was similar to another community detection algorithm which was Multi-Objectives Particle Swarm Optimization with Decomposition (MODPSO).

Ji et al. [34] proposed an optimization algorithm for handling the problem of community detection based on Ant Colony Optimizer (ACO), the proposed algorithm which was called "Multi-Objective Community Detection-Ant Colony Optimizer (MOCD-ACO)", consisted of two main components: MOEA/D for dividing the problem into M sub problems, and multi-objective ACO (MACO) which was responsible for handling these sub problems. Moreover, weight simulated annealing local search operator was employed for improving the quality of the solutions and escape the local optima. MOCD-ACO was evaluated based on four real-world case studies, in terms of NMI and Q. The results showed that MOCD-ACO has attained better performance because of the combination between the decomposition process of MOEA/D and MACO.

Che et al. [35] have proposed a community detection based on Memetic Algorithm (MA) for signed networks, their algorithm was called "MACD-SN". The signed modularity (Qs) represented the main objective function. In order to enhance the performance of MA, they have proposed novel crossover and variation operators and proposed a new local search method for helping the algorithm escaping from the current local best and search for better solutions. The results were evaluated based on five different synthetic signed networks, the types of these networks were different in terms of balancing, one network was balanced while the rest were unbalanced. Although MACD-SN was better than the other competitors in most experiments, it suffered when detecting the overlapping communities in signed networks.

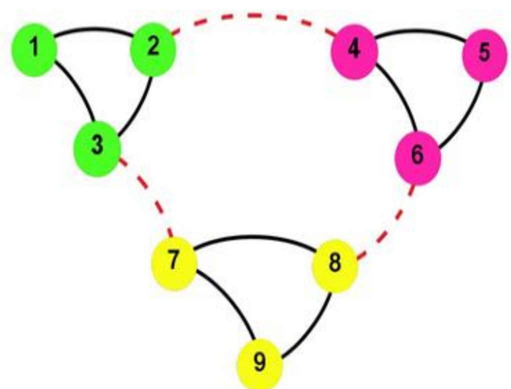
3. COMMUNITY DETECTION ALGORITHMS

3.1 Networks and Communities

Networks (graphs) are one of the most fundamental data structures in computer science. A network can be represented as an adjacency matrix $A \in R^{N \times N}$, where N denotes the number of nodes in the network. Here, the entry A_{ij} is one if there is a connection between node i and j, and zero otherwise. A graph is used to represent the relationships of objects in a certain network. An object in a network represents a single node or vertex and the relationship between two objects is called edge or link.

The network can be used to describe the connection between humans and their relationship in social life, countries in the world trading commodities, cities in a delivery problem, train stations or bus stops in some transportation system, connected computers on the Internet, airports in-flight data set, interactions between proteins in biological systems, and so for. Analysing such types of networks has become an immensely promising research area, and there is a lot of active research in network science, including community detection.

A static network is modelled as a graph $G = (V, E)$, where V represents the set of nodes or vertices, $V(G) = \left\{v_1, v_2, .. v_N\right\}$ with $N = |V|$ and $E(G)$ represents a set of L links or edges between nodes; $L = |E(G)|$.This definition is extended for singed networks as $G = (V, E, W)$, where W represents the type of the connections, W can be formulated as $W: V \times V \rightarrow \{-1,0,+1\}$, where A_{ij}= +1 if there is a link positive connection between v_i and v_j where i,j ∈{1,2,…, N }, A_{ij}= -1 if there is a negative connection between v_i and v_j while A_{ij}= 0 otherwise. Therefore, the graph is considered undirected and unweighted; each node has some connections to other nodes, and this number of connections is the degree (deg) of the node. The adjacency matrix contains all the important information about the graph. Each row and column is indexed by a node's number, and all elements on the main diagonal in the adjacency matrix are zero as there are no connections between a node and itself. Figure 2 illustrates a graph partitionedinto three communities in different colours. It also displays the matrix representationof the graph. The objective of community detection is to partition th e graph, or equivalently, into a set of K clusters or communities $\mathcal{C} = \{C_1, C_2, \dots, C_k\}$. The number of nodes in the cluster can be denoted $|C_k|$.



0	1	1	0	0	0	0	0	0
1	0	1	-1	0	0	0	0	0
1	1	0	0	0	0	-1	0	0
0	-1		0	1	1	0	0	0
0	0	0	1	0	1	0	0	0
0	0	0	1	1	0	0	-1	0
0	0	-1	0	0	0	0	1	1
0	0	0	0	0	-1	1	0	1
0	0	0	0	0	0	1	1	0

Fig. 2. Graph and Adjacency matrix representation of a network, the values 0 if no connection between two nodes, 1 if there is a positive connection and -1 if there is a negative connection between two nodes as shown in red colour

It is important to mention all the important mathematical formulation as follows:

- Degree of a node in a network (N) $deg(n_i, N)$: represents the number of edges between the nodes.

$$deg(n_i, N) = \sum_{j=1}^{N} A_{ij} \tag{1}$$

while the Degree for the connection of all nodes in a Network (N) is represented by $Deg(N) = \sum_{i=1}^{N} deg(n_i, N)$.

- Degree of a community $Deg(C_k, N)$: represents the number of edges between the nodes in a single community.

$$Deg(C_k, N) = \sum_{i \in C_k} \sum_{j=1}^{N} A_{ij} \tag{2}$$

- Internal degree of a node $deg_{in}(n_i, C_k)$: represents the number of edges for a single node in a single community.

$$deg_{in}(n_i, C_k) = \sum_{j \in C_k} A_{ij} \tag{3}$$

- Internal degree of a community $Deg_{in}(C_k, N)$: represents the number of edges between the nodes in a single community.

$$Deg_{in}(C_k, N) = \sum_{i \in C_k} \sum_{j \in C_k}^{N} A_{ij} \tag{4}$$

- External degree of a node $deg_{out}(n_i, C_k)$: represents the number of edges for a single node and other communities.

$$deg_{out}(n_i, C_k) = \sum_{j \in C_k} A_{ij} \tag{5}$$

- External degree of a community $Deg_{out}(C_k, N)$: represents the number of edges between the nodes in two different communities.

$$Deg_{out}(C_k, N) = \sum_{i \in C_k} \sum_{j \notin C_k}^{N} A_{ij} \tag{6}$$

- Strong nodes: A node is called "Strong" when its internal degree is larger than the external degree.

$$deg_{in}(n_i, C_k) > deg_{out}(n_i, C_k) \quad (7)$$

- Strong community: represents the count of the strong nodes within a single community.

$$Deg_{in}(C_k, N) > Deg_{out}(C_k, N) \quad (8)$$

- Weak node: A node is called "Weak" when its internal degree is lower than the external degree.

$$deg_{in}(n_i, C_k) < deg_{out}(n_i, C_k) \quad (9)$$

- Weak community: represents the count of the weak nodes within a single community.

$$Deg_{in}(C_k, N) < Deg_{out}(C_k, N) \quad (10)$$

- Cardinality of a community $|C_k|$: represents the number of nodes within a single community.

Generally, the graphs of the networks can be classified into two different types (classes) based on the type of connections between the nodes. These classes are unsigned and signed graphs. Signed networks or graphs can be divided into two adjacency matrices A^+ and A^- where $A = A^+ + A^-$. The connection between the nodes is positive when n_i^+ and n_j^+ (i.e., the value in A^+ is equal 1) while the connection is considered negative when n_i^- and n_j^- are connected (i.e., the value in A^- is equal 1), as follows:

$$Positive\ (n_i^+, n_j^+) = \begin{cases} 1\ if\ n_i and\ n_j is\ a\ positive\ tie\ in\ E \\ 0\ Otherwise \end{cases}$$

$$Negitive\ (n_i^-, n_j^-) = \begin{cases} 1\ if\ n_i and\ n_j is\ a\ negitive\ tie\ in\ E \\ 0\ Otherwise \end{cases} \quad (11)$$

3.2 Evaluation Scores

Each generated candidate solution can be evaluated based on the following evaluation measures:

- Normalized Mutual Information (NMI):
  This is the most widely used similarity measure to assess the accuracy of community detection algorithms. The NMI has been proven to be reliable. The NMI value increases gradually when the two partitions become more similar and vice versa. In addition, NMI is symmetric and unbiased in terms of cluster distribution [36], [37].
  Let P and $\mathcal{C}$ be two partitions of a network with K_p and K_c communities, respectively. Also, let Z be the confusion matrix whose elements Z_{ij} are defined as the number of nodes in the community i of partition P that is also in the community j of the partition $\mathcal{C}$. If $Z_i^P = \sum_j^{K_c} Z_{ij}$ is the number of nodes in the community i of the partition P and similarly for Z_j^c, then, the NMI is defined as follows:

$$NMI(P, \mathcal{C}) = \frac{-2\sum_{i=1}^{K_p}\sum_{j=1}^{K_\mathcal{C}} Z_{ij} log\ (Z_{ij}N/Z_i^P Z_j^C)}{\sum_{i=1}^{K_P} Z_i^P log\ (Z_i^P/N) + \sum_{j=1}^{K_\mathcal{C}} Z_j^C log\ (Z_j^C/N)} \quad (12)$$

The NMI is non-negative and equal to zero if and only if the joint distribution Z_{ij}/N can be written as a product of distribution Z_i^P/N and Z_j^C, that is if knowledge of partition $\mathcal{C}$ provides no information about membership of partition $\mathcal{C}$. The NMI $(P, \mathcal{C}) = 1$ when P and $\mathcal{C}$ are identical up to relabeling of the communities.

Therefore, NMI is considered a measure of the similarity between the known correct partition and a detected one as it can overcome the problem of comparing different community structures.

Later, the NMI was developed by [38], to Weighted NMI (WNMI) as follows:

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

The resulted value of the first part in equation 13 represents the weight, which effect on the NMI. If the difference between the correct partition ($\mathcal{C}^*$) and the predicted partition ($\mathcal{C}$), i.e., both solutions have the same exact number of clusters, then the exponential function generates 1. Then, the results of $WNMI$ and NMI are identical. Otherwise, as the difference between these two solutions in terms of the number of clusters increases, then the value of $WNMI$ decreases, because of the exponential function.

- Modularity (Q):

  If the ground-truth partition for the network is unknown, then modularity is often used as the internal measure to assess the network partitions. However, it has a resolution limitation; it does not detect small communities well and tends to be skewed by the size of the whole network. Modularity measures the strength of partitioning a network into communities. Network partitions that have high values of modularity have dense connections within the community and sparse connections with the others. It is widely accepted as a score that has been used in optimization methods for community detection in the networks. Modularity has been introduced by [39] is defined as:

$$Q(\mathcal{C}) = \sum_{k=1}^{K} \frac{|Deg_{in}(C_k)|}{2Deg(N)} - \left(\frac{Deg(C_k,N)}{2Deg(N)}\right)^2 \qquad (14)$$

where $2Deg(N)$ represents the volume of the network. $Q(C_k)$ shown to be the summed difference between the fraction of links within a community minus the expected fraction of links within the community if the graph were rearranged at random but preserving the degree distribution. The range values for the modularity falls in the range of [-0.5,1], where 1 implies accurate community structures. The modularity value is positive if the number of connections within the community is more than the number of expected connections from a random arrangement in which the degree distribution is preserved. It is negative when each node is in one community or sometimes when the network is partitioned into very small communities; 0 implies that all nodes are in one community.
It should be noted that increasing network cardinality causes an exponential increase in the possible partition space. Therefore, modularity optimization is considered a non-deterministic polynomial-time (NP-hard) problem. Gomez et al [22] reformulated the definition of modularity as modularity signed (Q_s) that aims at reflecting the strength of the correlations (both positive and negative) in signed networks while ensuring the probabilistic semantics of Q are preserved :

$$Q_s(\mathcal{C}) = \frac{1}{2Deg^{+}(N) + 2Deg^{-}(N)}$$

$$\sum_{v_i \in V} \sum_{v_j \in V} \left[\left(A_{i,j} - \frac{\deg^{+}(v_i,A)}{2Deg^{+}(N)} - \frac{\deg^{-}(v_i,A)}{2Deg^{-}(N)}\right)\right] \delta(C_i, C_j) \qquad (15)$$

where $\delta(C_i, C_j)$ in equation 13 is the Kronecker delta function, which is defined as follows:

$$\delta(C_i, C_j) = \begin{cases} 1 \; if \; n_i and \; n_j \; belong \; to \; the \; same \; cluster \\ 0 \; Otherwise \end{cases} \qquad (16)$$

- Error Rate (Error):

  The error represents the impact of the negative-internal connections and positive-external on the total number of nodes [26], as follows:

$$Error(\mathcal{C}) = \frac{\sum_{k=1}^{K}(Deg_{in}^{-}(\mathcal{C}) + Deg_{out}^{+}(\mathcal{C}))}{2Deg(N)} \qquad (17)$$

where $Deg_{in}^{-}(\mathcal{C})$ and $Deg_{out}^{+}(\mathcal{C})$ denote the negative-internal connections, and the positive-external connections for a specific cluster (C_k) respectively.

4. MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

A multi-objective optimization problem is an optimization problem that involves multiple objective functions, in mathematical terms while trying to either minimize or maximize the mathematical function of several variables with respect to certain constraints. This general framework can be used to model several problems, both theoretical and real-world. The structure of mathematical models (mathematical programming model) can generally be represented as follows [40], [41], [42]:

$$\begin{aligned} &Max \; or \; Min \; f(x_i), && (i = 1,2,3,\dots,D) \\ &subject \; to \;\; h_j(x_i) = 0, && (j = 1,2,3,\dots,J), \\ &g_k(x_i) \le 0, \;\; (k = 1,2,3,\dots,K) && \qquad (18) \end{aligned}$$

where x is the decision variables, and $f_i(x), h_j(x),$ and $g_k(x)$ are functions of the design vector.
One of the main components of an optimization problem is the objective function which needs to be minimized or maximized. If the optimization problem consists of only one objective function, then, it is called a "Single-Objective Optimization Problem (SOOP)". Otherwise, it is called a "Multi-Objective Optimization Problem (MOOP)". The general mathematical formula for any MOOP is given same as equation 16.
The problem of identifying the communities in any given network is considered as MOOP, as there are two main objectives which must be handled; (i) maximizing the internal connection between the nodes inside the communities, and (ii) minimizing the external connections between the nodes with the other nodes in different communities.
Regarding MOO, the term domination is commonly used for this purpose. Here, our discussion is restricted to the concept of unconstrained optimization problems (problems without any form of equality, bound constraints, or inequality). Considering two solutions, the domination between them is defined thus:
Solution S_1 is considered to have dominated by Solution S_2 only when the following conditions are met:

1- In all objectives, solution S_2 is never worse than solution S_1; hence, the comparison between the solutions is only based on the values of their Objective Functions (OFs) or the position of the related points z^1 and z^2 in the OF set Z.
2- In at least one objective, Solution S_2 must be better than Solution S_1.
A pairwise comparison is possible for a given pair of solutions or the related points in the OF set Z using the above-stated definition and the dominance of a point on the other can be proven. The non-dominated points of a class are all the points that are not dominated by any other set member, shows the generated illustration of Pareto Optimality and Dominated/Non-Dominated Solutions.

One major feature of any two of such points is that a point-wise gain can only be made in an objective at the expense of at least one other objective. With this balance between the properties of the non-dominated points, practitioners can focus on establishing a wide range of them prior to taking a final decision. These points somehow constitute a front which may be disconnected in some cases when considered collectively on the objective space. Therefore, it is always considered that the non-dominated points often represent a non-dominated front.
Considering the above concept, the Pareto-optimal solutions in MOOP can now be easily defined. For the above task, if the given set of points contain all points in a feasible decision variable space, then, the points which, by definition, lie on the non-domination front, are not dominated by any other point within the objective space; thus, they are considered Pareto-optimal points which collectively make up the Pareto Optimal Front. while the related decision variable vectors are the Pareto-optimal solutions. illustrates the Pareto Optimality concept; Optimization algorithms such as multi objective evolutionary algorithm (MOEA) and multi objective genetic algorithms (MOGA) are used to obtain a Pareto Optimal Front curve or surface.

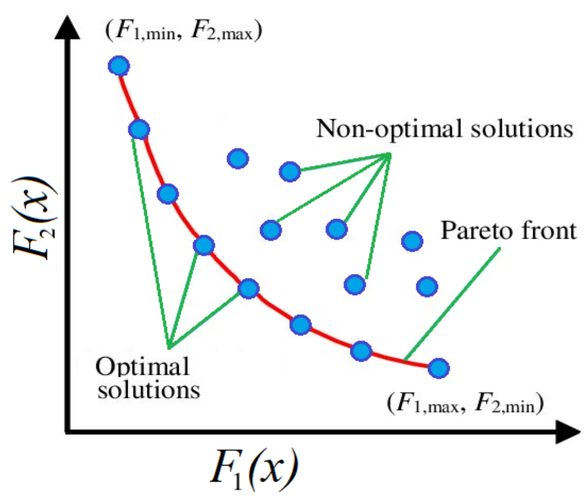


Fig. 3. The concepts of Pareto Optimality

Although the optimal solution in a SOOP is normally defined, it is not the same for MOOP as the objectives in MOOP are sometimes conflicting and a single solution may not represent the best solution for all the objectives. Hence, rather than a single optimum, a set of trade-off solutions generally called Pareto-optimal Solutions is established. Being that no other solutions are better than these solutions in the design space and can never be dominated, they are considered optimal solutions. From the mathematical perspective, the definition of the dominance between two solutions can be expressed as x_1 dominates x_2 if :

$$f_i(x_1) \leq f_i(x_2) \forall i \in \{1,2, \ldots m\} \; and \; \exists j \in \{1,2, \ldots, m\} \mid f_j(x_1) < f_j(x_2) \qquad (19)$$

5. CONCLUSION

In this paper, we explored the complexities of signed social networks and the challenges associated with community detection within these networks. We reviewed and compared several advanced algorithms, including ant colony optimization, genetic algorithms, and memetic algorithms, focusing on their application to multi-objective optimization problems in signed networks. Our findings indicate that these algorithms effectively balance modularity and frustration minimization, crucial for accurately identifying community structures in networks with both positive and negative relationships. Our analysis demonstrated that multi-objective approaches, particularly those incorporating local search mechanisms, significantly enhance the stability and performance of community detection algorithms. The results from various case studies and synthetic datasets showed that the integration of decomposition processes and innovative local search methods led to superior performance in terms of Normalized Mutual Information (NMI) and modularity (Q). Future research could further refine these algorithms and explore their application in more diverse and dynamic signed network environments. Additionally, investigating the impact of different objective functions and developing more sophisticated hybrid approaches could provide deeper insights into the structural dynamics of complex social networks.

Conflicts Of Interest

The authors should pledge that they don't have any conflict of interest in regards of their research. If there are no conflict of interest then authors can declare the following "The authors declare no conflicts of interest".

Funding

The funding section of your journal paper template should provide a concise and transparent declaration of the financial support received to carry out the research presented in your paper.

Acknowledgment

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks ...". Instead, try "R. B. G. thanks...". Put sponsor acknowledgments in the unnumbered footnote on the first page.

References

[1] S. Papadopoulos, Y. Kompatsiaris, A. Vakali, and P. Spyridonos, "Community detection in Social Media," Data Mining and Knowledge Discovery, vol. 24, no. 3, pp. 515–554, May 2012, doi: 10.1007/s10618-011-0224-z.
[2] S. Fortunato, "Community detection in graphs," Physics Reports, vol. 486, no. 3–5, pp. 75–174, Feb. 2010, doi: 10.1016/j.physrep.2009.11.002.
[3] M. Girvan and M. E. J. Newman, "Community structure in social and biological networks," Proc. Natl. Acad. Sci., vol. 99, no. 12, pp. 7821–7826, Jun. 2002, doi: 10.1073/pnas.122653799.
[4] F. Heider, "Attitudes and Cognitive Organization," J. Psychol., vol. 21, no. 1, pp. 107–112, Jan. 1946, doi: 10.1080/00223980.1946.9917275.
[5] D. Cartwright and F. Harary, "Structural balance: a generalization of Heider's theory," Psychol. Rev., vol. 63, no. 5, pp. 277–293, 1956, doi: 10.1037/h0046049.
[6] W. Lin, X. Kong, P. S. Yu, Q. Wu, Y. Jia, and C. Li, "Community detection in incomplete information networks," in Proc. 21st Int. Conf. World Wide Web (WWW), New York, NY, USA: ACM Press, 2012, pp. 341–350, doi: 10.1145/2187836.2187883.
[7] C. Shi, Z. Yan, Y. Cai, and B. Wu, "Multi-objective community detection in complex networks," Appl. Soft Comput., vol. 12, no. 2, pp. 850–859, Feb. 2012, doi: 10.1016/j.asoc.2011.10.005.
[8] C. Shi, P. S. Yu, Z. Yan, Y. Huang, and B. Wang, "Comparison and selection of objective functions in multiobjective community detection," Computational Intelligence, vol. 30, no. 3, pp. 562–582, Aug. 2014, doi: 10.1111/coin.12007.
[9] J. Yang and J. Leskovec, "Defining and evaluating network communities based on ground-truth," Knowl. Inf. Syst., vol. 42, no. 1, pp. 181–213, Jan. 2015, doi: 10.1007/s10115-013-0693-z.
[10] F. Radicchi, C. Castellano, F. Cecconi, V. Loreto, and D. Parisi, "Defining and identifying communities in networks," Proc. Natl. Acad. Sci. U. S. A., Sep. 2003, doi: 10.1073/pnas.0400054101.
[11] J. Eustace, X. Wang, and Y. Cui, "Community detection using local neighborhood in complex networks," Physica A: Stat. Mech. Appl., vol. 436, pp. 665–677, Oct. 2015, doi: 10.1016/j.physa.2015.05.044.
[12] N. Girdhar and K. K. Bharadwaj, "Community Detection in Signed Social Networks Using Multiobjective Genetic Algorithm," J. Assoc. Inf. Sci. Technol., vol. 70, no. 8, pp. 788–804, Aug. 2019, doi: 10.1002/asi.24164.
[13] M. E. J. Newman, "Modularity and community structure in networks," Proc. Natl. Acad. Sci., vol. 103, no. 23, pp. 8577–8582, Jun. 2006, doi: 10.1073/pnas.0601602103.
[14] D. Mehrle, A. Strosser, and A. Harkin, "Walk-modularity and community structure in networks," Netw. Sci., vol. 3, no. 3, pp. 348–360, Sep. 2015, doi: 10.1017/nws.2015.20.
[15] Y. Niu, "Coordinated Optimization of Parameters of PSS and UPFC-PODCs to Improve Small-Signal Stability of a Power System with Renewable Energy Generation," in Proc. 11th Int. Conf. Power, Energy and Electr. Eng. (CPEEE), Feb. 2021, pp. 249–254, doi: 10.1109/CPEEE51686.2021.9383370.
[16] Y. Niu et al., "Energy-Saving Analysis of Wireless Body Area Network Based on Structural Analysis," in 2022 Int. Congr. Human-Computer Interact., Optim. Robot. Appl. (HORA), Jun. 2022, pp. 1–6, doi: 10.1109/HORA55278.2022.9799972.

[17] Y. Niu et al., "A Photovoltaic Electric Vehicle Automatic Charging and Monitoring System," in 2022 Int. Symp. Multidisciplinary Studies Innov. Technol. (ISMSIT), Oct. 2022, pp. 241–246, doi: 10.1109/ISMSIT56059.2022.9932813.

[18] Y. Niu and A. Korneev, "Application Study of Intelligent Agricultural Photovoltaic Power Generation Tracking System," in 2021 IEEE Bombay Sect. Signature Conf. (IBSSC), Nov. 2021, pp. 1–4, doi: 10.1109/IBSSC53889.2021.9673430.

[19] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise," in Proc. 2nd Int. Conf. Knowl. Discovery Data Mining, vol. 96, no. 34, pp. 226–231, 1996.

[20] S. Y. Bhat and M. Abulais, "OCMiner: A density-based overlapping community detection method for social networks," Intell. Data Anal., vol. 19, no. 4, pp. 917–947, Jul. 2015, doi: 10.3233/IDA-150751.

[21] A. Amelio and C. Pizzuti, "Community mining in signed networks," in Proc. 2013 IEEE/ACM Int. Conf. Adv. Soc. Netw. Anal. Min. (ASONAM), New York, NY, USA: ACM Press, 2013, pp. 95–99, doi: 10.1145/2492517.2492641.

[22] S. Gómez, P. Jensen, and A. Arenas, "Analysis of community structure in networks of correlated data," Phys. Rev. E Stat. Nonlinear Soft Matter Phys., vol. 80, p. 016114, 2009, doi: 10.1103/PhysRevE.80.016114.

[23] P. Doreian and A. Mrvar, "A partitioning approach to structural balance," Soc. Netw., 1996, doi: 10.1016/0378-8733(95)00259-6.

[24] C. Liu, J. Liu, and Z. Jiang, "A Multiobjective Evolutionary Algorithm Based on Similarity for Community Detection From Signed Social Networks," IEEE Trans. Cybern., vol. 44, no. 12, pp. 2274–2287, Dec. 2014, doi: 10.1109/TCYB.2014.2305974.

[25] B. Yang, J. Huang, D. Liu, and J. Liu, "A Multi-agent based decentralized algorithm for social network community mining," in Proc. 2009 Int. Conf. Adv. Soc. Netw. Anal. Min. (ASONAM), 2009, doi: 10.1109/ASONAM.2009.23.

[26] B. Yang, W. Cheung, and J. Liu, "Community Mining from Signed Social Networks," IEEE Trans. Knowl. Data Eng., vol. 19, no. 10, pp. 1333–1348, Oct. 2007, doi: 10.1109/TKDE.2007.1061.

[27] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, "Fast unfolding of communities in large networks," J. Stat. Mech. Theory Exp., vol. 2008, no. 10, p. P10008, Oct. 2008, doi: 10.1088/1742-5468/2008/10/P10008.

[28] A. Amelio and C. Pizzuti, "An evolutionary and local refinement approach for community detection in signed networks," Int. J. Artif. Intell. Tools, 2016, doi: 10.1142/S0218213016500214.

[29] M. Gong, Q. Cai, X. Chen, and L. Ma, "Complex network clustering by multiobjective discrete particle swarm optimization based on decomposition," IEEE Trans. Evol. Comput., 2014, doi: 10.1109/TEVC.2013.2260862.

[30] N. Shahabi Sani, M. Manthouri, and F. Farivar, "A multi-objective ant colony optimization algorithm for community detection in complex networks," J. Ambient Intell. Humaniz. Comput., vol. 11, no. 1, pp. 173–188, Jan. 2020, doi: 10.1007/s12652-018-1159-7.

[31] Q. Li, Z. Cao, W. Ding, and Q. Li, "A multi-objective adaptive evolutionary algorithm to extract communities in networks," Swarm Evol. Comput., vol. 52, p. 100629, Feb. 2020, doi: 10.1016/j.swevo.2019.100629.

[32] B. A. Attea, H. M. Rada, M. N. Abbas, and S. Özdemir, "A new evolutionary multi-objective community mining algorithm for signed networks," Appl. Soft Comput., vol. 85, p. 105817, Dec. 2019, doi: 10.1016/j.asoc.2019.105817.

[33] R. Liu, J. Liu, and M. He, "A multi-objective ant colony optimization with decomposition for community detection in complex networks," Trans. Inst. Meas. Control, vol. 41, no. 9, pp. 2521–2534, Jun. 2019, doi: 10.1177/0142331218804002.

[34] P. Ji, S. Zhang, and Z. Zhou, "A decomposition-based ant colony optimization algorithm for the multi-objective community detection," J. Ambient Intell. Humaniz. Comput., vol. 11, no. 1, pp. 173–188, Jan. 2020, doi: 10.1007/s12652-019-01241-1.

[35] S. Che, W. Yang, and W. Wang, "A Memetic Algorithm for Community Detection in Signed Networks," IEEE Access, vol. 8, pp. 123585–123602, 2020, doi: 10.1109/ACCESS.2020.3006108.

[36] L. Danon, A. Díaz-Guilera, J. Duch, and A. Arenas, "Comparing community structure identification," J. Stat. Mech. Theory Exp., vol. 2005, no. 09, pp. P09008–P09008, Sep. 2005, doi: 10.1088/1742-5468/2005/09/P09008.

[37] A. Lancichinetti, S. Fortunato, and J. Kertész, "Detecting the overlapping and hierarchical community structure in complex networks," New J. Phys., vol. 11, no. 3, p. 033015, Mar. 2009, doi: 10.1088/1367-2630/11/3/033015.

[38] S. Romano, J. Bailey, N. X. Vinh, and K. Verspoor, "Standardized mutual information for clustering comparisons: One step further in adjustment for chance," in Proc. 31st Int. Conf. Mach. Learn. (ICML), 2014.

[39] M. E. J. Newman and M. Girvan, "Finding and evaluating community structure in networks," Phys. Rev. E, vol. 69, no. 2, p. 026113, Feb. 2004, doi: 10.1103/PhysRevE.69.026113.

[40] S. Koziel and X. S. Yang, Computational Optimization, Methods and Algorithms, 2011, doi: 10.1007/978-3-642-20859-1.

[41] T. Weise, M. Zapf, R. Chiong, and A. J. Nebro, "Why is optimization difficult?," in Nature-Inspired Algorithms for Optimization, R. Chiong, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 1–50, doi: 10.1007/978-3-642-00267-0_1.

[42] S. Mirjalili, "SCA: A sine cosine algorithm for solving optimization problems," Knowl.-Based Syst., vol. 96, pp. 120–133, 2016, doi: 10.1016/j.knosys.2015.12.022.