Ibn Al-Haitham Journal for Pure and Applied Sciences
Journal homepage: jih.uobaghdad.edu.iq
PISSN: 1609-4042, EISSN: 2521-3407
IHJPAS. 2025, 38(4)

Enhanced Multi-Objective Evolutionary Algorithm for Community Detection Using a Community Strength-Based Mutation Strategy

Asal Jameel Khudhair[1*], Amenah Dahim Abbood[2]

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

Received: 8 April 2025 Accepted: 17 June 2025 Published: 20 October 2025
doi.org/10.30526/38.4.4143

Abstract

Community structures are fundamental in understanding the structure and functionality of complex networks. Different optimization algorithms, including both single-objective and multi-objective approaches, have been employed to address the challenge of community detection. Recently, multi-objective evolutionary algorithms (MOEAs) have attracted many researchers to identify communities in static networks. Many algorithms have been proposed to find a solution that achieves a trade-off between exploring new areas of the solution space and improving the quality of existing solutions. In this trade-off is crucial; whereas exploitation improves existing solutions, it may fail to find better solutions from insufficiently explored regions of the solution space. Therefore, mutation in evolutionary algorithms greatly impacts community detection within social networks. Conventional mutation methods usually tend to apply too much randomness, which results in convergence being less precise about finding a suitable optimum solution. This paper introduces a new mutation called community strength enhancement (CSE) to enhance the search efficiency of the Multi-Objective Evolutionary Algorithm with Decomposition (MOEA/D) and speed up the convergence of the suggested algorithm. Moreover, the proposed algorithm overcomes the limitations of traditional MOEA/D by accurately and effectively identifying communities across a wide range of social networks. The enhanced algorithm was evaluated on two groups of datasets (twenty synthetic and four real-world) using normalized mutual information (NMI) and modularity (Q) across five baseline models. Integrating the CSE mutation strategy led to significant improvements in performance, particularly under high mixing parameters and in large-scale networks, as evidenced by increased NMI and modularity scores.

Keywords: Multi-objective optimization, Evolutionary algorithms, Community detection, Metaheuristic, Hybrid, Social network.

1.Introduction

Networks represent a robust framework for modeling and analyzing various real-world systems, such as social network platforms, biological systems, transportation infrastructure, and information systems (1). These frameworks effectively capture both the components of these systems and their interactions (2). When identifying communities, the number of connections within a community is denser than those outside the communities (3-5). Therefore, this study employs two objective functions in the MOEA/D algorithm: the first objective function aims to maximize the intra connections within a community and the second objective function aims to minimize the inter connections connecting a node to other communities. To build interconnected communities, increasing internal connections and reducing external connections is necessary (6, 7). Evolutionary optimization algorithms inspired by the principles of natural selection, due to the iterative and adaptive exploration of large solution spaces, can carry out this task according to (8). Among the core components of evolutionary algorithms, mutation operators play a crucial role in introducing diversity into the population and preventing premature convergence (9). Many social network analysis studies have aimed to capture the evolution of the community structure (10). For example, (11) unsigned and unweighted networks, (12) with the signed network, and (13) with the positive and negative weight networks. Despite the success of current evolutionary-based identification algorithms, they still exhibit a speed problem and face the challenge of assigning the weak node to the true community. Several researchers have attempted to improve the performance of MOEA/D algorithms by developing mutation strategies. A need for techniques that depend more on the structural properties of the network remains. The study in this context introduces the new mutation strategy Community Strength Enhancement (CSE), which focuses on intra-neighbor characteristics of nodes, thus helping the effectiveness of community detection. The contributions in this paper are listed below.

- We state the problem as a multi-objective community detection algorithm based on the MOEA/D framework. Two conflicting objective functions are employed to solve the problem of single-objective functions, which most existing state-of-the-art methods adopt.
- We introduce a new mutation operator based on the initialization process of neighbor nodes and their relationships to assign nodes to more suitable communities. The latest mutation strategy can improve the efficiency of the mutation process and make the algorithm converge faster.
- We conducted a comparative evaluation by applying the traditional and the proposed algorithms across five models. The results revealed that integrating the proposed strategy consistently enhanced the performance of all models, achieving superior results on real-world networks compared to existing state-of-the-art methods. We organize the paper as follows. Section 2 introduces the problem of community detection; Section 4 presents the original framework of the MOEA/D algorithm and the proposed mutation operator to identify communities. Section 5 shows the results of the experiments on the proposed method and its comparison with other methods; Section 6 covers the paper's conclusion.

1.1. Preliminaries

This section presents the basic concepts of community detection in complex networks. In complex networks, communities present a vital substructure, depicting a set of nodes with significantly greater internal connections than external connections with the rest of the network. The network structure represents the system as a graph (G). For a static, unweighted, and undirected network, $G = (V, E)$, where V is the set of nodes, E is the set of edges connecting these nodes, N is the number of nodes in the network $N = |V|$, k is a number of subgroups and

m is the number of all edges $m = |E|$. An adjacency matrix (A_{NxN}) can also represent the graph; let $A = [A_{ij}]$ where A_{ij} is given by:

$$A_{ij} = \begin{cases} 1, & \text{if there is an edge between nodes } i \text{ and } j \\ 0, & \text{otherwise} \end{cases}$$

You can use the adjacency matrix to calculate a community or a node's internal and external edges.

The primary objective of community detection is to divide the network into subgroups $C = \{C_1, C_2, \dots, C_k\}$ so that each community demonstrates significantly stronger internal connections than external ones. In other words, nodes that belong to the same community are very densely connected, whereas the links between different communities are comparatively less dense. To determine whether a subset $S \subset V$ represents a valid community (Measuring Community Strength), we compute the number of internal edges E_{in} and the number of external edges E_{out} for this subset: $E_{in}(S) = \sum_{i,j \in S} A_{ij}$,$E_{out}(S) = \sum_{i \in S, j \notin S} A_{ij}$. For node e_{in} represents the number of internal edges of a node within the same community and e_{out} represents the number of edges connecting the node to nodes outside the community. If $E_{in}(S) > E_{out}(S)$, the subset S can be considered a well-defined community.

1.2. The Objective Function

The purpose of partitioning a network into groups of vertices is to ensure that the edge density within each group exceeds the edge density between groups. For this purpose, we require an objective function that increases the number of connections within each cluster and another objective function that reduces the number of connections between the other clusters. Evaluate how well the generated communities capture the original structure and properties of the data. Additionally, any problem with a single objective function has a unique solution. At the same time, the Pareto front is the result of multiobjective optimization efforts to find exact solutions under many conflicting objectives simultaneously. This study presents the formulation for identifying communities as a task involving two optimization objectives. It was formulates the community detection problem as a maximization problem with two objectives (14). The first objective is the community score (CS), and the second is the community fitness (CF).

$$CS(\mathcal{C}) = \sum_{k=1}^{K} \frac{1}{|C_k|} \sum_{v \in C_k} \left(\frac{e_{in}(V)}{|C_k|}\right)^r \times E_{in}(C_k) \quad (1)$$

The parameter r controls the size of the communities to increase the weight of the degree of the internal node within a community and community size$|C_k|$. Thus, the CS calculated by the summation of a local score for each community Ck.

$$CF(\mathcal{C}) = \sum_{k=1}^{K} \frac{E_{in}(C_k)}{\left(E_{in}(C_k) + E_{out}(C_k)\right)^{\alpha}} \quad (2)$$

Where α is a positive number that determines the size of communities. If α is significant, the network will be split into small communities; otherwise, large communities will be the most prevalent.

Where α is a positive number that determines the size of communities. If α is significant, the network will be split into small communities; otherwise, large communities will be the most prevalent. For example, in 2020, (15) and (16) incorporated these two objectives into their research as a multiobjective optimization model. It was formulated the community detection problem as a multi-objective minimization problem by (17). They considered modularity (Q) as two conflicting objectives that measure the degree of internal connectivity and interconnectivity.

Therefore, they define two objectives that should be minimized as follows. The first measures the intra-connection

$$\text{Intra}(\mathcal{C}) = 1 - \sum_{k=1}^{K} \frac{E_{in}(C_k)}{m} \quad (3)$$

While the second measures the degree of inter-connections:

$$\text{Inter}(\mathcal{C}) = \sum_{k=1}^{K} \left[\frac{E(C_k)}{2m}\right]^2 \quad (4)$$

They have shown that optimizing these two objectives simultaneously can produce a wide range of possible community structures, with more or less emphasis on connections within and between communities. Since modularity is a weighted sum of two objectives, it is clear that the partition that maximizes modularity must be a member of the Pareto set. The two objectives are also adopted by other researchers. For example, in 2015, (18) and (19) minimize the kernel k-means (KKM) and the ratio cut (RC).

$$KKM(\mathcal{C}) = 2(N - K) - \sum_{k=1}^{K} \frac{E_{in}(C_k)}{|C_k|} \quad (5)$$

$$RC(\mathcal{C}) = \sum_{k=1}^{K} \frac{E_{out}(C_k)}{|C_k|} \quad (6)$$

Which is used additionally in recent literary research (19-22).

It was proposed a local information-based multiobjective evolutionary algorithm (LMOEA) by (23). A similar framework as MOEA/D is adopted to simultaneously optimize the two conflicting objectives of the negative ratio association (NRA) and ratio cut (RC). In addition, (24, 25) used the same objectives.

$$NRA = -\sum_{i=1}^{k} \frac{E_{in}(C_k)}{|C_i|} \quad (7)$$

It was proposed a new model that is based on the Hidden Markov Model (HMM- MODCD) consisting from f_{intra} and f_{inter} with the Multi-Objective Evolutionary Algorithm and it proved effective in enhancing the performance of dynamic community detection by (7).

$$f_{\text{intra}}(\mathcal{C}) = 2(N - K) - \sum_{k=1}^{K} \frac{1}{|C_k|} \sum_{v \in C_k} \left(\frac{e_{\text{in}}(v)^2}{e_{\text{in}}(v) + e_{\text{out}}(v)}\right) \quad (8)$$

$$f_{\text{inter}}(\mathcal{C}) = \sum_{j=1}^{K} \frac{1}{|C_j|} \sum_{v \in C_j} \frac{\max_{C_f \neq C_j} e_{\text{out}}(v, C_f)}{\max(e_{\text{in}}(v), 1)} \quad (9)$$

1.3 Evolutionary Algorithm with Decomposition for Multiple Objectives (MOEA/D)

The MOEA/D is used for solving multi-objective optimization by maximizing a limited set of scalar optimization sub-problems to get uniformly spread Pareto solutions. MOEA / D algorithm achieves this objective by distributing resources using pre-specified weight vectors (w). The decomposition and selection of the weight vector will collaborate to promote diversity in the population (P), thus improving the quality of the solution. MOEA/D also studies the effect of constraints on mating coordination on the relationship between exploration and exploitation. MOEA/D ensures that solutions are exchanged synchronously through local interactions and safeguards the optimization process against being stopped prematurely. In this, the MOEA/D procedure presents a convenient optimization process where innovation flourishes in complexity (C) and methodological composition delivers solutions (26). Many studies have shown that MOEA / D-based algorithms show a very high level of success in solving MOP (27, 28). Because of this, researchers have applied it to the problem of detecting a community (CD), in which at least two target functions ($f_1, f_2, \ldots, f_n$) either need to be maximized or minimized. The algorithm below briefly describes the principal MOEA/D phases.

Algorithm 1: General framework to MOEA/D Algorithm for Community Detection

Input:

- Number of objectives (Objective Dimension)
- Population size (Pop Size)
- Number of generations (Generations)
- Mutation Probability (pm)
- Crossover Probability (px)
- Initial Ideal Point based on Fitness Model (minimization or maximization)

Output:

- Near Pareto Optimal Sets (Non-dominated solutions)
- All solutions detected

MOEA/D Loop

For *Generation Counter = 1* ***to*** *Generations* **do**

Step 1: Update Reference Points (Ideal Point, IndivPoint);

Step 2: Initialize Results and Near Pareto Optimal Set;

Iteration Loop (ProblemCounter = 1 to PopSize)

Step 3: **Selection Operator** – Choose two parent solutions (Parent1, Parent2);

Step 4: **Crossover Operator** – Generate child solution from parents;

Step 5: **Mutation Operator** – Apply mutation to the child solution;

End loop

Step 6: **Decode Child Population** – Convert child solutions to meaningful representations (Individual2ClusterDecoding);

Step 7: **Evaluate Fitness** – Calculate fitness values for the child population (ComputeFitnessCollectionParallel);

Step 8: **Update Reference Points** – Update IdealPoint and IndivPoint based on child population;

Step 9: **Update Population** – Combine parent and child populations based on fitness (UpdateProblem);

Step 10: **Update Near Pareto Optimal Set** – Add non-dominated solutions from child population (UpdateNearParetoOptimalSet);

Step 11: **Store Results** – Save Near Pareto Optimal Set for current generation;

End for

End loop

1.4. Related work

Various evolutionary algorithms and optimization frameworks have been used to address the problem of community detection in complex networks. Current mutation strategies may fail to adequately explore solution spaces or preserve meaningful community structures, which can negatively impact the quality and efficiency of the detection process. Researchers address this issue by integrating a local search strategy with the evolutionary algorithm, which can make evolutionary algorithms much better at finding communities. Given the importance of mutation, several studies have proposed improvements to mutation operators designed explicitly for community detection. It was presented a new formulation for the intra-neighbor community detection score and the intra-neighbor score, and a migration operator method with MOEA/D (29). It was suggested a new multi-objective generational genetic algorithm (MOGGA+) integrated with three types of mutation operators (30). In each execution, choose a random mutation from one of these. This algorithm optimized two objectives, the modularity and the conductance measure. RAMESH and SRIVATSUN proposed a framework that integrates the MOEA/D algorithm with a new mutation operator that uses community labels of cliques as genes rather than cliques (31). This algorithm optimizes Kernal K-mean (KKM) and Ratio Cut (RC) objectives. It was. suggested a multi-objective community identification method based on a pigeon-inspired optimization algorithm, MOPIO-Net, and this algorithm minimizes two objectives, RC and Negative Ratio Association (NRA). The algorithm was combined with the suggested boundary node variation strategy to enhance the detection effectiveness (25). Despite many approaches that have led to meaningful progress, there are still challenges, particularly in designing mutation strategies that can be deeply aligned with the structural characteristics of the networks. Most existing methods involve general or random mutation mechanisms, which are not conducive to effectively preserving meaningful community structures. Thus, more targeted strategies that consider the local topology of nodes are called for. **Table 9** summarizes the difference between the state-of-the-art and our proposed CSE mutation strategies.

2. Materials and Methods

In this section, we present the framework of our algorithm and introduce a proposed mutation that would improve its efficiency and effectiveness. This mutation encourages the diversity of efficient solutions that contribute positively to the community detection task across different kinds of networks.

2.1. Framework structure

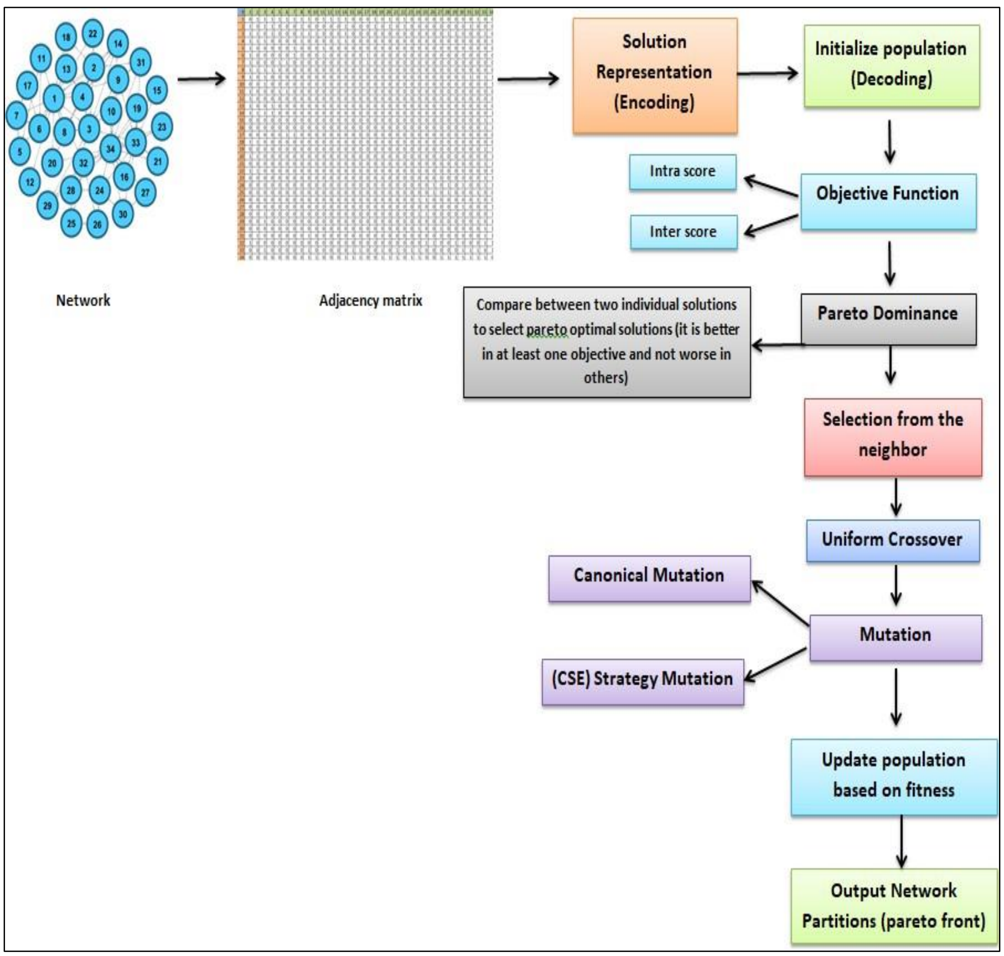


Figure 1. The framework of the proposed Algorithm

In **Figure 1**, the graph is first transformed into an adjacency matrix to represent the relationships between nodes. The next step is the genetic representation. The initialization step in which an initial set of potential solutions is generated to ensure diversity of solutions and a broader exploration of the solution space. It will be attained and evaluated against the chosen objective function, which helps to point out the solution capable of achieving the most initial balance with objects. In the next stage, solutions are selected based on neighborhood relation- ships, and then genetic operations such as cross-over and mutation are performed to introduce new solutions and increase diversity within the population. The population is updated based on fitness evaluations performed over multiple generations, culminating in the final network partition, which can be visualized as a Pareto front of optimal solutions.

2.1.1. Chromosome Representation (chromosome encoding)

The representation of the chromosome is crucial to the effectiveness of evolutionary algorithms (EA). The genotype encoding used here follows a locus-based adjacency representation (14). It is the most commonly used approach and has been proven to be effective in previous research.

2.1.2. Population Initialization (Decoding)

In the first phase of population decoding, the genetic representation of each individual is converted into a community structure. The individual chromosomes represent the relationships between the nodes and should be used to assign the nodes to different clusters.

2.1.3. Uniform Crossover

It generates offspring by exchanging genes between two parents. In this method, each gene in an offspring chromosome is determined with some given prespecified probability of recombination. This operation is repeated for all genes on the chromosome, where, for each position, a random number between 0 and 1 is generated. If it is less than or equal to P_c, the gene in the position copies its allele from Parent1. Otherwise, it copies its allele from Parent2. The genes thus selected are then joined in order of selection itself to form the offspring chromosome.

2.1.4. Enhanced Mutation Operator (Community Strength Enhancement (CSE))

The mutation operator in the traditional version of MOEA/D is employed to enhance the current optimal solution in a random manner. In this case, the exchange of node location between communities occurs randomly, meaning each node of the current solution is replaced by a random selected node from the neighboring nodes. The exchange occurs when the randomly generated value less than the mutation probability (pm). Randomly detecting nodes reduces the effectiveness of the search.

To improve the efficiency of community evaluation solutions in networks, we propose to implement a Community Strength Enhancement (CSE) strategy that provides greater precision in assigning nodes to their actual communities. This strategy illustrates the interconnection of nodes, both within and among communities. The CSE strategy is calculated as follows:

$$\mathrm{CSE}(v, C_k) = V_{\text{neighbour}} * \sum_{i=1}^{V_{\text{neighbour}}} e_{in}(i, C_k) \tag{10}$$

$V_{\text{neighbour}}$, defined by:

$$V_{\text{neighbour}} = \sum_{v \in C_k} |e(v)| \tag{11}$$

$\mathrm{CSE}(\mathrm{v}, \mathrm{C_k})$ refers to the computation of the reassignment rate of the current vulnerable node v in the neighboring community $\mathrm{C_k}$, where $\mathrm{V_{neighbour}}$ represent the neighbor nodes of node v in the community $\mathrm{C_k}$ and $\mathrm{e_{in}}(\mathrm{i}, \mathrm{C_k})$ represents the internal connections of each neighbor nodes of the vulnerable node with each $\mathrm{C_k}$community.

The CSE reassignment strategy is partitioned into three separate scenarios, see **Figure 2.**

- In the first scenario, if the community to which the vulnerable node is assigned has a lower reassignment rate than other communities in its vicinity, the node will be reassigned to the community with the highest reassignment rate.

- In contrast, the second scenario occurs when multiple communities have a shared maximum occupancy rate across all surrounding communities of the vulnerable community. In this circumstance, we assign the node to one of these communities at random based on the probability of mutation (Pm).
- In the third scenario, when a node has equal internal and external connections, it will be reassigned to the community with the highest reassignment rate. This is because the strategy looks at the neighborhood strength and the internal connections of neighborhood, providing a better understanding of the structural context. Thus, even if the internal and external degrees look seemingly equal, this additional information layer enables more accurate and context-aware community assignments.

This study examines the distinction between canonical mutation operators and enhanced mutation operators. The key difference lies in the enhanced mutation strategy ability to potentially migrate a specific node to another suitable cluster according to the above three scenarios. In contrast, the canonical mutation selects and relocates a random node towards a randomly selected cluster. The procedure of the suggested mutation strategy is provided in algorithm 2. In order to enhance the community's local search capability and increase the quality of the network community division, therefore, the (MOEA/D) can be applied to address the challenge of community detection as well as other optimization problems. In this work, we used the canonical and enhanced mutation strategy independently.

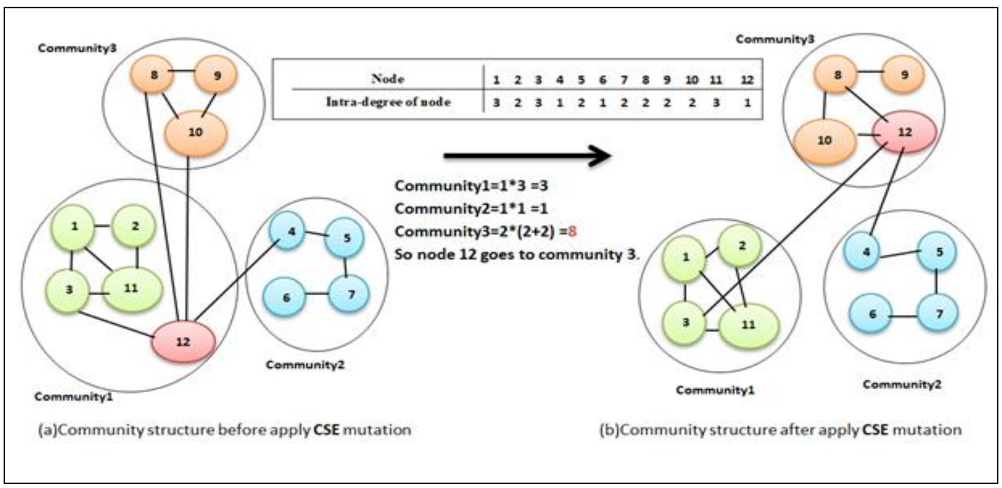


Figure 2. Explain application of Community Strength Enhancement Mutation.

Algorithm 2. The Proposed Community Strength Enhancement Mutation

Input: Number of nodes in the network, degree of each node, mutation probability, individual (partition)
Output: Child (partition)
For *Node i= 1 to N* ***do***
For *Node j = 1 to NumConnectedNodes (Node i)* **do**
Calculate intra-connection for nodes;
End for
End for
For *Node i = 1 to N* **do**
If *NumConnectedNodes (Node i) > 0* ***and*** *rand* $\leq Pm$ **then**
If *k Node i in* $\leq$ *k Node i out* **then**
For *ConnectedNodeCounter = 1 to NumConnectedNodes (Node i)* **do**
Calculate $V_{neighbor}$ from Equation (10) for each community;
Calculate the intra-connection for $V_{neighbor}$ (11) for each community;
End for
End if
temp = 0;
NewCluster = 1;
For k_k = 1: *k do*
Calculate CSE from Equation (10) for each community;
If *temp < CSE* **then**
temp = CSE;
NewCluster = k_k;
Else
Go to canonical mutation;
End if
End for
End for
End for

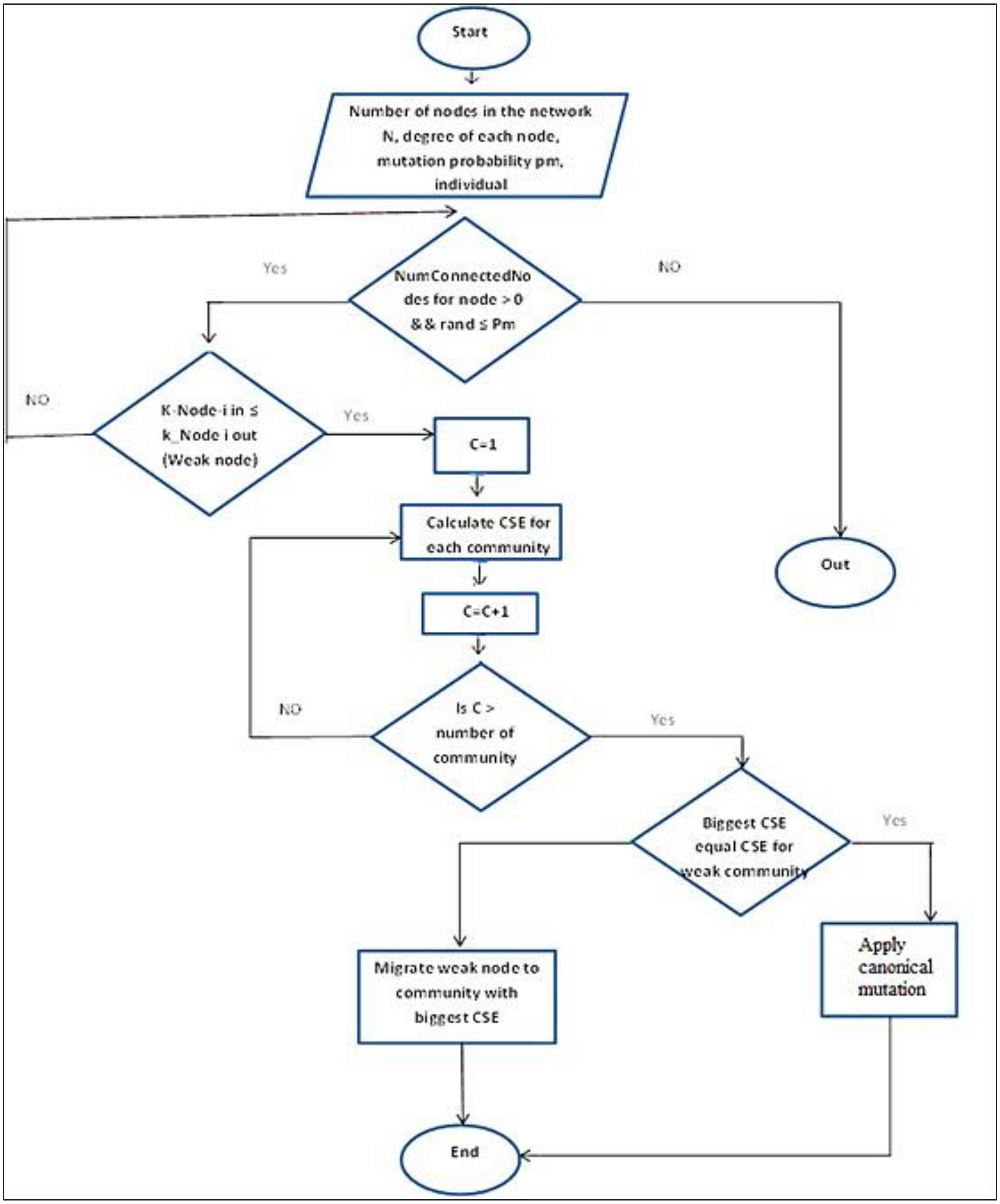


Figure 3. Flowchart for the main steps of the Algorithm 2.

3. Results and Discussion

In this section, we present and discuss the results that demonstrate the effectiveness of our improved MOEA/D algorithm compared to other state-of-the-art algorithms. We applied MOEA/D with canonical mutation and with the proposed mutation for these models (MOGA-NET, MODPSO, LMOEA, HMM-MODCD), all of which are mentioned in Section 3.1. Furthermore, **Table 8** includes the equations used and the period to which they were applied. In each case, a table compares the different mutation strategies and describes the determinants and pathways used in each case.

For fear comparison, we determined the population's size, or an excessive amount of potential solutions, to be 300. We additionally set each solution's size, or number of neighbors, to five. The mutation probability is 0.6, and the crossover probability is 0.8. We settled on 300 generations as the upper limit. The results were set to the mean of 10 simulated trials. The good non-dominated solution from each iteration saved with certain validity conditions into the Near Pareto Optimal Set (PS) archive. It was used to compute the average outcome for ten runs. We first illustrate the (MOEA/D) algorithm on 24 networks divided into two groups of networks (real networks and synthetic networks).

3.1 Dataset description.

This section describes the dataset that was employed in this study. It consists of 24 datasets divided into two groups. The first group examined four real networks. Zachary's network was constructed by examining the friendship connections between 34 club members with 78 relationships within the network (32). The second network consists of 62 bottlenose dolphins from New Zealand and is called the Bottlenose Dolphins Network. This network contains 159 connections with two significant groups (33). Girvan and Newman (34) rated the game of American football (2000) as the third most famous network. The 115 teams that competed in the Football 2000 championship games make up this network. Teams were divided into 12 groups, each representing a different geographic location. The ultimate network consists of the compilation of Krebs' publications on American politics, authored by Krebs himself (35). The 105 books on politics that make up this network from the United States are available on Amazon.com.

The second group consists of synthetic networks. Girvan and Newman (34) introduced a computer-generated benchmark that includes graphs of different levels of complexity. This benchmark was further developed by (36). The initial set of LFR benchmarks consists of a network with 128 nodes, built to accommodate four communities, each with 32 nodes. We evaluated the efficacy of the algorithms on networks produced between 0:05 and 0:5. The networks are referred to as LFR128. The next set of LFR benchmarks has been used to evaluate the four models using larger networks that closely match real-world networks. The benchmarks comprise 10 networks, each containing 1000 nodes. We refer to this set as LFR1000. According to (36), the size of the mixing parameter is between 0.5 and 0.05.

3.2. Experiment on Real Networks.

This section employs four types of real networks to test our algorithm. We show the result and discuss it. **Table 1** shows the results of applying the MOEA/D algorithm to the five models with canonical mutations. These results show how canonical mutations influence the algorithm's performance in different models and serve as a comparison point with the results of applying the proposed CSE strategy in **Table 2.** The results of the tables show that the CSE strategy improves the performance of the MOEA/D algorithm by reassigning nodes to a more appropriate community. Speed up the convergence of the algorithm to the optimum solution. **Table 1.** The maximum and average values of Normalized Mutual Information (NMI) and Modularity (Q) were evaluated for the five models. These models are tested on four real-world networks with canonical mutation.

Table 1. The maximum and average values of Normalized Mutual Information (NMI) and Modularity (Q) were evaluated for the five models. These models are tested on four real-world networks with canonical mutation

Dataset	Measure	MOCD	MOGA-NET	MODPSO	LMOEA	HMM-MODCD
Zachary	$NMI_{\max}$	0.8371	0.8371	0.8371	0.8371	0.8372
	NMI_{av}	0.8371	0.8371	0.8371	0.8371	0.8365
	$Q_{\max}$	0.4188	0.4188	0.4188	0.4188	0.3109
	Q_{av}	0.4188	0.4172	0.4188	0.4188	0.3079
Dolphin	$NMI_{\max}$	0.9065	1	1	1	1
	NMI_{av}	0.8888	1	1	1	1
	$Q_{\max}$	0.5178	0.5052	0.5008	0.5246	0.3339
	Q_{av}	0.5032	0.4931	0.5008	0.4994	0.3339
Football 2000	$NMI_{\max}$	0.7571	0.6838	0.7598	0.7420	0.5493
	NMI_{av}	0.7315	0.6759	0.7292	0.7141	0.3487
	$Q_{\max}$	0.4727	0.4332	0.4713	0.4797	0.2799
	Q_{av}	0.4660	0.4231	0.4538	0.4573	0.2743
Krebs	$NMI_{\max}$	0.6263	0.6285	0.6103	0.6921	0.5934
	NMI_{av}	0.6014	0.6174	0.6019	0.6264	0.5934
	$Q_{\max}$	0.5123	0.5104	0.5189	0.5247	0.3569
	Q_{av}	0.5118	0.5060	0.5135	0.5177	0.3569

Table 2. The maximum and average values of Normalized Mutual Information (NMI) and Modularity (Q) were evaluated for the five models. These models are tested on four real-world networks with community strength enhancement mutation.

Dataset	Measure	MOCD	MOGA-NET	MODPSO	LMOEA	HMM-MODCD
Zachary	NMI_{max}	1	1	1	1	0.8589
	NMI_{av}	0.8372	1	1	1	0.8365
	Q_{max}	0.4188	0.4107	0.4198	0.4174	0.3079
	Q_{av}	0.409	0.4033	0.4126	0.4174	0.3079
Dolphin	NMI_{max}	1	1	1	1	1
	NMI_{av}	1	1	1	1	1
	Q_{max}	0.5178	0.5144	0.5178	0.5163	0.3339
	Q_{av}	0.5032	0.507	0.5172	0.5163	0.3339
Football2000	NMI_{max}	0.9273	0.8599	0.9269	0.9309	0.7961
	NMI_{av}	0.9273	0.8559	0.9177	0.8946	0.7961
	Q_{max}	0.6036	0.5847	0.6044	0.6044	0.3237
	Q_{av}	0.6036	0.5806	0.6044	0.5950	0.3237
Krebs	NMI_{max}	0.6772	0.6314	0.6299	0.6705	0.6313
	NMI_{av}	0.6174	0.594	0.6299	0.6099	0.5979
	Q_{max}	0.5248	0.5249	0.5178	0.5253	0.3539
	Q_{av}	0.5246	0.5211	0.5138	0.5145	0.3539

In the Zachary dataset, all nodes in the actual partition are strong nodes. Two nodes (3 and 10) connect equally within and between the communities. The NMI achieved by all models using traditional mutations was about the same (0.8371), except for the HMM-MODCD model with a slightly better result of 0.8372, indicating that very little diversity was achieved in solution exploration before application of heuristic mutations. Now, the results of the best mutated versions by heuristics are much better, all reaching NMI = 1, which means that the method improves the quality of the results concerning how well the technique achieves community detection. The HMM-MODCD with the traditional mutation method is not the best regarding heuristic mutation. It has now been improved only to 0.8589, possibly due to some inherent weaknesses in its functioning.

In the dolphin dataset, all nodes in the actual partition of the dolphin dataset are strong nodes, except node (40), which has equal connections inside and between communities. All models achieved NMI = 1 for the Dolphin network except the MOCD model, which had 0.9065 with the traditional mutation. However, after applying our custom mutation, all models, including MOCD, reached NMI = 1, demonstrating their effectiveness in enhancing community detection precision.

The football dataset has 15 weak nodes; some of them (12, 25, 51, 59, 60, 64,70, 81, 83, 98) have internal connections smaller than their external connections; on the other hand, nodes (22.93, 43, 91, 111) have internal connections of zero, but there are several external connections. In the football network, the results under traditional mutation produced notable variation, with the HMM-MODCD model having the lowest value of NMI at 0.5493, while MODPSO had the highest at 0.7598. These results show a lack of exploratory diversity in traditional mutation methods. However, after applying the proposed mutation, a significant improvement followed; LMOEA led with the highest value of 0.9309, while HMM-MODCD was 0.7961. This substantial improvement did not raise the NMI to one level, which reflects the complexity of network characteristics, the different responses of models to optimization processes, and the ultimate partitioning conditions that are sensitive and sometimes hard to attain.

The Krebs dataset has 15 weak nodes. For these nodes (8, 19, 29, 51, 78, 86), the number of internal connections is smaller than the number of external connections; on the other hand, in nodes (30, 50), the internal connections of each node are equal to the number of external connections. Thus, the Krebs network was represented the highest by LMOEA with NMI = 0.6921 using a traditional mutation, while its lowest value was recorded at 0.5934 by HMM-MODCD. After its application, some models improved, whereby MOCD achieved the highest value of 0.6772. However, LMOEA dropped to 0.6705 and MODPSO had the least at 0.6299, further underscored by the variation in some models' response towards the optimization strategy.

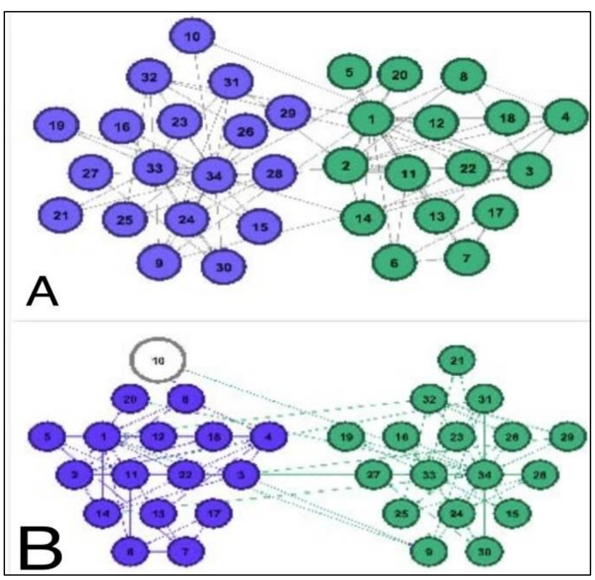


Figure 4. Zachary dataset, **A-** Correct partition and with CSE mutation, **B-** Canonical mutation.

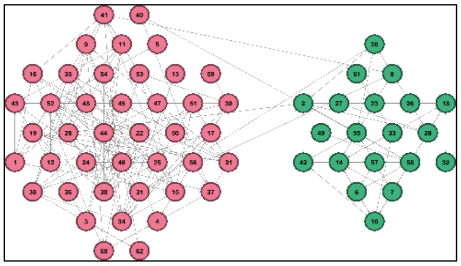


Figure 5. Dolphin dataset with and without Heuristic mutation.

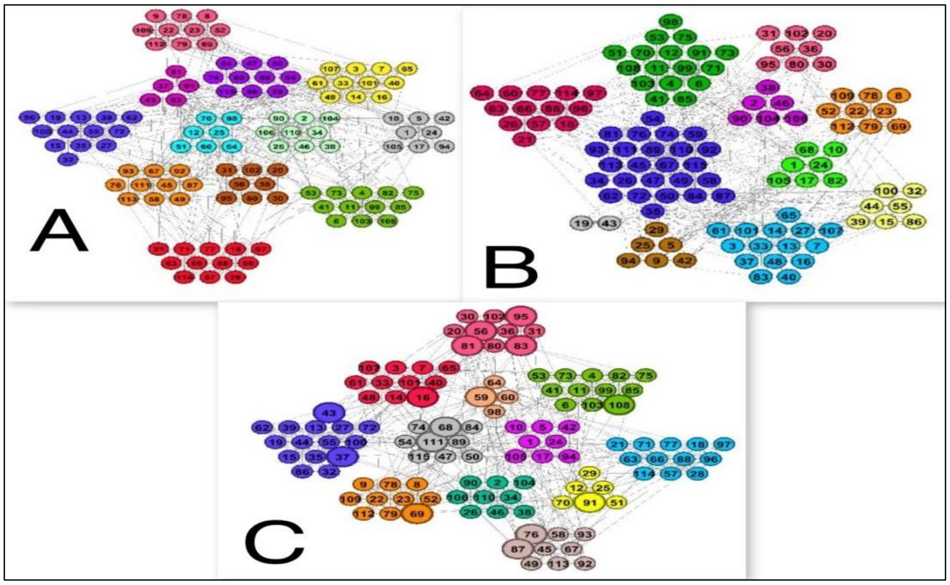


Figure 6. Football dataset, **A-** Correct partition, **B-** Canonical mutation, **C-** Heuristic mutation

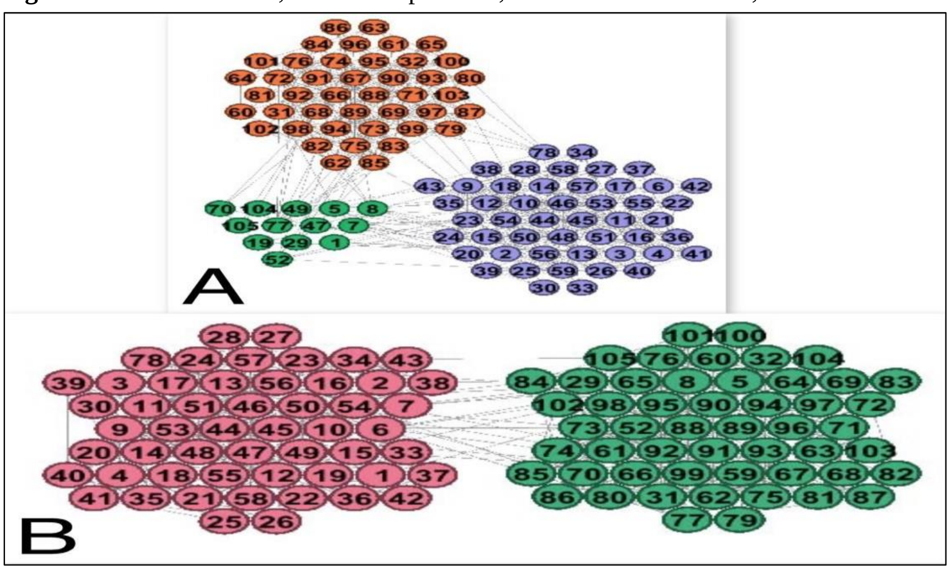


Figure 7. Krebs dataset (A) Canonical mutation (B) Heuristic mutation

The visual representations (**Figures 4, 5, 6 and 7)** present precise comparisons of the performance of the method being considered in the Football and Krebs networks, respectively. The figures portrayed the correct partitions along with the results drawn from the application of the traditional mutation and the CSE strategy, highlighting their effects on quality in community detection. When NMI = 1, the CSE mutation perfectly fits the correct partition.

Table 3. Real world dataset characteristics

Dataset	Nodes	Edges	Communities
Zachary	34	78	2
Dolphin	62	159	2
Football	115	613	12
Krebs	105	440	3

3.3. Experiments on Synthetic Networks

In this paper, we mainly perform experiments on the two groups of Synthetic Networks called the computer-generated benchmark network and the LFR benchmark network. We then displayed and discussed the result. **Table 4** presents the Performance of the five models on synthetic LFR-128 networks without CSE mutation for maximum and average values of NMI and modularity Q, which is shown to gradually decrease as the degree of the mixing parameter μ increases. Thus, it becomes more challenging to correctly recognize the existing community structures within the network as the mixing parameter increases. Throughout the variety of models tested, under all μ levels, it is only at the lowest mixing parameter value that LMOEA outperforms HMM- MODCD in terms of NMI and Q; the value is 0.9498 at $\mu = 0.05$. However, the relative ability of HMM-MODCD to other models is seen to decline significantly, particularly when the level of mixing is increased. It does not seem to perform well when the model has to be applied to very complex networks

Table 5 presents comparison of the models with the suggested mutation strategy CSE. There is a significant improvement in the performance of models due to the incorporation of CSE for nearly all the models and levels of μ. Some models, for example, maintain an NMI of 1.0 up to $\mu = 0.25$, a much more visible enhancement over **Table 4,** whereas the average modularity values over the different runs are more coherent and higher than pre-update runs, showing stronger community quality. These provide evidence that the CSE strategy maintains the quality of the solution as the difficulty increases.

Results of the models on larger-scale synthetic networks (LFR-1000) using canonical mutation are shown in **Table 6.** There is a notable decrease in NMI and modularity as network size and μ increase, validating the scalability challenge faced by evolutionary models in community detection compared to the smaller networks. However, LMOEA maintains a relatively strong performance, compare to other models. The Q values drop significantly when μ exceeds 0.3, showing more pain in preserving meaningful community partitions.

Table 7 shows the impact of the CSE strategy on the same large-scale networks. A clear improvement is observed across most models, especially in NMI scores, where many models keep high values (close to or equal to 1.0) up to $\mu = 0.3$. LMOEA, in particular, maintains both high accuracy and modularity in challenging settings, thus confirming the fact that the strategy is scalable and robust. Moreover, the performance gap between the models is reduced, which means that CSE helps equalize their exploration-exploitation balance and make them work towards optimal solutions.

Table 4. Performance metrics including maximum NMI, average NMI, maximum Q, and aver- age Q for synthetic networks were presented for all models, excluding CSE.

NETWORK	MEASURE	MOCD	MOGA-NET	MODPSO	LMOEA	HMM-MODCD
LFR-128-0.05	NMmax	1	1	1	1	1
	Qmax	0.7012	0.7012	0.7012	0.7012	0.4131
	NMlav	1	0.9874	1	0.9975	1
	Qav	0.7012	0.7012	0.6945	0.6999	0.4131
LFR-128-0.1	NMImax	0.9076	0.8868	0.9431	0.9498	0.9076
	Qmax	0.6014	0.5669	0.618	0.6307	0.3662
	NMlav	0.8837	0.8478	0.9182	0.8982	0.8451
	Qav	0.5837	0.5419	0.5987	0.5935	0.3528
LFR-128-0.15	NMImax	0.7862	0.729	0.873	0.8435	0.7565
	Qmax	0.453	0.4441	0.4985	0.5	0.3037
	NMlav	0.7587	0.7104	0.8125	0.7636	0.5295
	Qav	0.4431	0.4199	0.4778	0.4545	0.2887
LFR-128-0.2	NMImax	0.6502	0.6316	0.7139	0.6961	0.5356
	Qmax	0.3634	0.3281	0.4012	0.3827	0.2929
	NMlav	0.6288	0.5656	0.6638	0.6254	0.4239
	Qav	0.3521	0.3177	0.3658	0.3343	0.2657
LFR-128-0.25	NMImax	0.5629	0.462	0.5894	0.5682	0.4188
	Qmax	0.2764	0.2491	0.3019	0.2875	0.25
	NMlav	0.5239	0,405	0.5568	0.523	0.354
	Qav	0.2666	0.1965	0.2713	0.259	0.25
LFR-128-0.3	NMImax	0.5054	0.3653	0.5331	0.5189	0.3955
	Qmax	0.2322	0.1766	0.2413	0.2498	0.25
	NMlav	0.4641	0.3428	0.4558	0.4448	0.3119
	Qav	0.215	0.1398	0.2176	0.2068	0.25
LFR-128-0.35	NMImax	0.4514	0.087	0.4062	0.3949	0.29
	Qmax	0.1846	0.0229	0.1949	0.1852	0.25
	NMlav	0.3812	0.0087	0.3779	0.3677	0.239
	Qav	0.1759	0.0023	0.17010	0.1654	0.25
LFR-128-0.4	NMImax	0.3593	0.087	0.3444	0.4063	0.2525
	Qmax	0.1636	0.021	0.1613	0.1613	0.25
	NMlav	0.3151	0.0087	0.32	0.3167	0.2065
	Qav	0.1462	0.0021	0.1446	0.1432	0.25
LFR-128-0.45	NMImax	0.2878	0.03	0.3198	0.307	0.208
	Qmax	0.1339	0.0015	0.1333	0.1324	0.25
	NMlav	0.264	0.02	0.2344	0.2415	0.171
	Qav	0.1287	0.001	0.1274	0.1245	0.25
LFR-128-0.5	NMImax	0.2585	0.03	0.26	0.2418	0.2445
	Qmax	0.1349	0.0015	0.1262	0.135	0.25
	NMlav	0.2214	0.02	0.2132	0.1891	0.161
	Qav	0.1215	0.001	0.1165	0.1169	0.25

Table 5. Performance metrics including maximum NMI, average NMI, maximum Q, and aver- age Q for synthetic networks were presented for all models, including the CSE heuristic.

NETWORK	MEASURE	MOCD	MOGA-NET	MODPSO	LMOEA	HMM-MODCD
LFR-128-0.05	NMmax	1	1	1	1	1
	Qmax	0.7012	0.7012	0.7012	0.7012	0.1431
	NMlav	1	1	1	1	1
	Qav	0.7012	0.7012	0.7012	0.7012	0.1431
LFR-128-0.1	NMmax	1	1	1	1	1
	Qmax	0.6533	0.6533	0.6533	0.6533	0.3892
	NMlav	1	1	1	1	1
	Qav	0.6533	0.6533	0.6533	0.6533	0.3892
LFR-128-0.15	NMmax	1	1	1	1	0.8679
	Qmax	0.5995	0.5995	0.5995	0.5996	0.3447
	NMlav	1	1	1	0.9707	0.8571
	Qav	0.5995	0.5931	0.5995	0.583	0.3447
LFR-128-0.2	NMmax	1	1	1	0.9748	1
	Qmax	0.5508	0.5508	0.5508	0.5389	0.3379
	NMlav	0.9666	0.95	1	0.8622	0.8622
	Qav	0.5355	0.5292	0.5508	0.4726	0.3252
LFR-128-0.25	NMmax	1	0.9325	1	0.9247	0.8571
	Qmax	0.5	0.4728	0.5	0.4713	0.3027
	NMlav	0.922	0.8974	1	0.7601	0.651
	Qav	0.4669	0.4574	0.5	0.3851	0.2871
LFR-128-0.3	NMmax	0.9452	0.9247	1	0.7999	0.5911
	Qmax	0.4149	0.4247	0.4502	0.3719	0.2705
	NMlav	0.8408	0.8791	1	0.5704	0.4947
	Qav	0.3738	0.4046	0.4502	0.2567	0.2594
LFR-128-0.35	NMmax	0.9248	0.8682	1	0.5819	0.5002
	Qmax	0.3212	0.3556	0.4023	0.2554	0.25
	NMlav	0.6842	0.7584	0.9422	0.4691	0.3238
	Qav	0.2883	0.3129	0.382	0.2049	0.25
LFR-128-0.4	NMmax	0.5531	0.686	0.6667	0.436	0.3017
	Qmax	0.2118	0.2638	0.2441	0.1843	0.25
	NMlav	0.4323	0.5665	0.6085	0.338	0.2319
	Qav	0.1777	0.2227	0.2227	0.1537	0.25
LFR-128-0.45	NMmax	0.42	0.3	0.6667	0.3475	0.2375
	Qmax	0.1615	0.0015	0.1973	0.1531	0.25
	NMlav	0.2939	0	0.395	0.2582	0.1734
	Qav	0.1396	0	0.1703	0.1319	0.25
LFR-128-0.5	NMmax	0.2585	0.03	0.3868	0.2978	0.1636
	Qmax	0.1707	0.0015	0.1692	0.1255	0.25
	NMlav	0.2133	0	0.2609	0.1891	0.13281
	Qav	0.1327	0	0.1474	0.1169	0.25

Table 6. Performance metrics including maximum NMI, average NMI, maximum Q, and average Q for synthetic networks were presented for all models, with canonical mutation.

NETWORK	MEASURE	MOCD	MOGA-NET	MODPSO	LMOEA	HMM-MODCD
LFR-1000-0.05	NMmax	0.9321	0.9259	0.931	0.9367	0.9369
	Qmax	0.7353	0.7501	0.7709	0.7605	0.3907
	NMlav	0.7353	0.7501	0.7709	0.7605	0.3907
	Qav	0.9221	0.9147	0.9274	0.936	0.6261
LFR-1000-0.1	NMmax	0.8624	0.8506	0.8726	0.8635	0.8411
	Qmax	0.6353	0.5897	0.64	0.6237	0.3288
	NMlav	0.8577	0.8402	0.8657	0.8635	0.8307
	Qav	0.6257	0.5875	0.6277	0.6175	0.3288
LFR-1000-0.15	NMmax	0.7915	0.7613	0.78	0.7709	0.7203
	Qmax	0.5	0.4828	0.4909	0.4813	0.2554
	NMlav	0.7736	0.7509	0.7771	0.7672	0.645
	Qav	0.4846	0.4675	0.4726	0.4726	0.2497
LFR-1000-0.2	NMmax	0.709	0.692	0.7033	0.7017	0.6221
	Qmax	0.3966	0.384	0.3831	0.3865	0.2186
	NMlav	0.7018	0.6829	0,7012	0.7017	0.5486
	Qav	0.3909	0.3712	0.38	0.3865	0.214
LFR-1000-0.25	NMmax	0.6314	0.6053	0.646	0.6316	0.4753
	Qmax	0.3293	0.3046	0.3209	0.3181	0.2056
	NMlav	0.6265	0.5981	0.6408	0.6316	0.39
	Qav	0.3213	0.2928	0.3135	0.3181	0.2049
LFR-1000-0.3	NMmax	0.5801	0.5738	0.593	0.5769	0.4332
	Qmax	0.2617	0.2562	0.2608	0.2553	0.2051
	NMlav	0.5747	0.5397	0.5839	0.5638	0.3577
	Qav	0.2614	0.2418	0.2566	0.2529	0.2051
LFR-1000-0.35	NMmax	0.5211	0.4945	0.5313	0.5151	0.3464
	Qmax	0.2182	0.1997	0.2055	0.206	0.2072
	NMlav	0.5132	0.4815	0.519	0.5136	0.3105
	Qav	0.2122	0.1907	0.2018	0.2029	0.2072
LFR-1000-0.4	NMmax	0.474	0.4336	0.464	0.467	0.3048
	Qmax	0.1716	0.1581	0.1714	0.1673	0.2174
	NMlav	0.4585	0.3955	0.4653	0.467	0.2344
	Qav	0.1705	0.1389	0.1684	0.1665	0.2125
LFR-1000-0.45	NMmax	0.4185	0.3772	0.4296	0.4285	0.2442
	Qmax	0.1475	0.1233	0.143	0.1375	0.2204
	NMlav	0.4073	0.3219	0.4147	0.3973	0.1852
	Qav	0.1468	0.0982	0.1408	0.1466	0.2204
LFR-1000-0.5	NMmax	0.4003	0.2858	0.3857	0.3703	0.2443
	Qmax	0.1305	0.0709	0.1281	0.1285	0.2287
	NMlav	0.3747	0.2141	0.3787	0.3727	0.1426
	Qav	0.1285	0.0428	0.1235	0.1205	0.2287

Table 7. Performance metrics including maximum NMI, average NMI, maximum Q, and aver- age Q for synthetic networks were presented for all models, with the CSE heuristic.

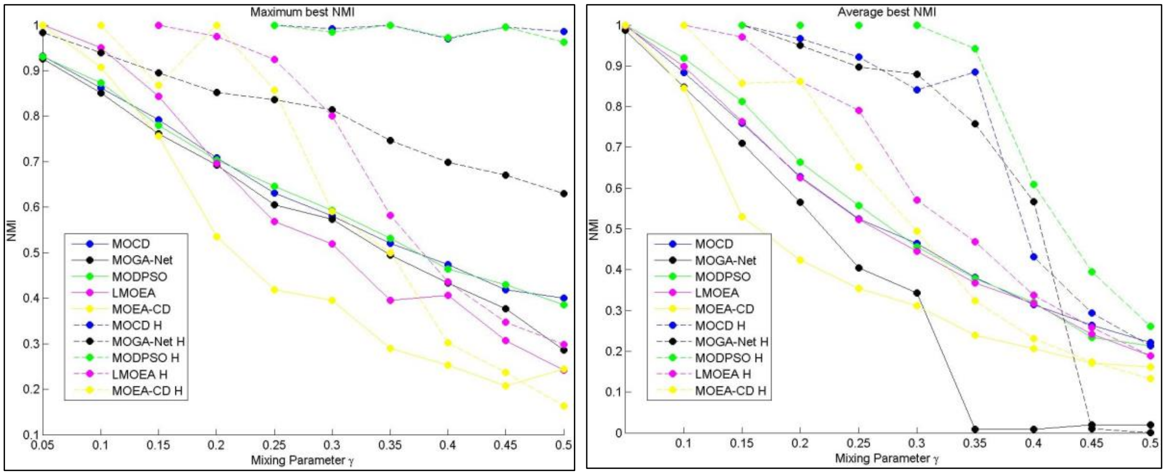
NETWORK	MEASURE	MOCD	MOGA-NET	MODPSO	LMOEA	HMM-MODCD
LFR-1000-0.05	NMmax	1	0.9839	1	1	0.9942
	Qmax	0.8602	0.8942	0.9101	0.9101	0.4645
	NMlav	0.9992	0.9784	1	0.9977	0.9934
	Qav	0.8587	0.8896	0.9101	0.9098	0.4645
LFR-1000-0.1	NMmax	1	0.9392	1	0.9857	0.9832
	Qmax	0.8602	0.8602	0.8602	0.8542	0.4382
	NMlav	0.9992	0.938	1	0.9823	0.9832
	Qav	0.8602	0.8022	0.8602	0.8533	0.4382
LFR-1000-0.15	NMmax	1	0.8953	1	0.9727	0.9878
	Qmax	0.8099	0.7234	0.8098	0.7959	0.4138
	NMlav	1	0.8892	1	0.9727	0.9878
	Qav	0.8098	0.7098	0.8098	0.7959	0.4138
LFR-1000-0.2	NMmax	1	0.8519	1	0.9652	0.9522
	Qmax	0.7624	0.6486	0.7624	0.7419	0.387
	NMlav	1	0.8448	1	0.9652	0.9522
	Qav	0.7624	0.63337	0.7624	0.7419	0.387
LFR-1000-0.25	NMmax	1	0.8364	1	0.9202	0.9359
	Qmax	0.7131	0.5768	0.7131	0.687	0.3618
	NMlav	1	0.8364	1	0.9202	0.9359
	Qav	0.7131	0.5706	0.7131	0.687	0.3618
LFR-1000-0.3	NMmax	0.992	0.8137	0.9843	0.9259	0.9145
	Qmax	0.6661	0.5327	0.6661	0.6194	0.3371
	NMlav	0.9901	0.7969	0.9917	0.9119	0.8716
	Qav	0.6661	0.5258	0.6661	0.6031	0.3358
LFR-1000-0.35	NMmax	1	0.7466	1	0.9802	0.4994
	Qmax	0.6154	0.4582	0.6153	0.6089	0.2812
	NMlav	0.9988	0.7281	0.9939	0.9802	0.4994
	Qav	0.6153	0.4421	0.6153	0.6089	0.2812
LFR-1000-0.4	NMmax	0.9699	0.699	0.9723	0.8246	0.292
	Qmax	0.5619	0.414	0.5614	0.4919	0.2548
	NMlav	0.9661	0.6861	0.9675	0.8021	0.1568
	Qav	0.5614	0.4051	0.5614	0.4619	0.25483
LFR-1000-0.45	NMmax	0.9962	0.6705	0.9955	0.6474	0.2809
	Qmax	0.5151	0.348	0.5152	0.3498	0.253
	NMlav	0.9933	0.6611	0.9836	0.6474	0.2809
	Qav	0.5149	0.344	0.5142	0.3498	0.253
LFR-1000-0.5	NMmax	0.9855	0.6294	0.9626	0.492	0.2206
	Qmax	0.467	0.3117	0.4671	0.251	0.25
	NMlav	0.95	0.5891	0.967	0.492	0.1108
	Qav	0.4665	0.3007	0.4665	0.251	0.25

Table 8. A comprehensive overview of the applied model: its name, formula and when it is applied

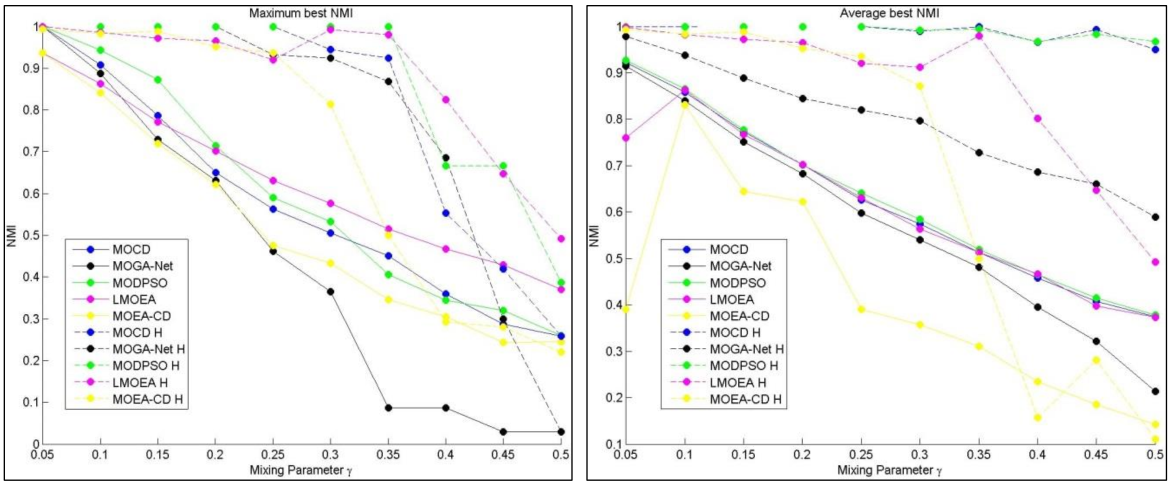
Name	Model functions	References used the model
MOCD	CS Eq1 and CF Eq2	(14, 15, 16)
MOGA-Net	Intra Eq3 and Inter Eq4	(28, 18)
MODPSO	KKM Eq5 and RC Eq6	(19, 22, 21)
LMOEA	RC 6 and NRA 7	(23, 24, 25)
HMM-MODCD	f_{intra} 8 and f_{inter} 9	(7)

Table 9. Comparative table summarizing the difference between state-of-the-art mutation strategies mentioned in Section l and our CSE proposed mutation strategy.

Reference	Name of mutation strategy	The role of the proposed strategy to improve the evolutionary algorithm	The limitation of the mutation method
(11, 30)	Migration mutation operator	This method shows that a weak node joins the community to which most of its neighbors belong.	1. Focusing on binary relationships only may lead to ignoring network complexities and an imbalanced distribution of information. 2. Difficulty in handling highly interconnected networks, thereby reducing the accuracy of community detection.
(31)	Community Based mutation operator	This method modifies a whole community. One community is selected at random and its cohesion is assessed. If it is weak, a small group is transferred to the highly cohesive neighboring community as identified by Weighted Roulette Selection.	1. Unexpected changes in community structure influence solution stability. 2. May lead to lower diversity and lower-quality outcomes. 3. Strengthening a community is not a guarantee of the best solution for all scenarios.
(25)	Mutation strategy	This Mutation occurs where nodes at the boundary of different communities have connectivity with multiple communities, irrespective of the number of internal connections. They are assigned to the majority community among their neighbors to improve clustering accuracy in complex networks	1. Based on boundary node identification and mutation, it increases the complexity of the algorithm. 2. Reclassification of nodes can be done wrongly in cases where the conditions for mutation are not accurately defined.
Our mutation strategy	Community strength enhancement (CSE)	Our strategy is to measure the proximity of each node to different communities within the network. This proximity is defined by assessing the structural relationships between nodes, such as common neighbors, and the strength of their connections. Therefore, each node gets signed to the community for which such relatedness is at its maximum, that is, optimally assigning communities, based on relational proximity.	1. The increase in the number of communities makes identification more difficult. 2. The complexity of the process comes from the comparison of proximity between communities.



(a) LFR-128-maximum NMI (b) LFR-128-average NMI



(c) LFR-1000-maximum NMI (d) LFR-1000-average NMI

Figure 8. Overall performance of all models based on their maximum and average NMI. The results with the community strength enhancement (CSE) are shown by dashed lines, whereas the results without it are represented by solid lines.

4. Conclusion

This work presents a new mutation operation called community strength-based enhancement (CSE) to be incorporated into the MOEA/D algorithm to improve its efficiency, stability, and convergence rate during evolution. This strategy uses information about community structure and explores neighboring node-internal and node-external links, guiding mutation operations with more structural awareness. Results show that the modified MOEA/D algorithm with CSE performs better regarding normalized mutual information (NMI) and modularity (Q) than the unmodified MOEA/D algorithm and other state-of-the-art community detection methods. These results justify the promise of enriching advanced multi-objective evolutionary optimization algorithms with the present strategy. In principle, it can be applied to design better algorithms for community detection in complex networks. This paper is an optimistic move in the design of detection strategies.

Acknowledgment

I appreciate all of those who assisted me, guided me, and supported me during the research's preparation.

Conflict of Interest

There are no conflicts of interest.

Funding

There is no finding for the article.

References

1. Farrokhpour Dizaj Y, Lotfi S, Hajipour J. A Multi-Objective Social-Based Algorithm for Community Detection. Multimedia Tools Appl. 2025;1–30. https://doi.org/10.1007/s11042-024-20555-7.
2. Abduljabbar DA. Community Detection in Modular Complex Networks Using an Improved Particle Swarm Optimization Algorithm. Iraqi J Sci. 2023;64(8):4228–43. https://doi.org/10.24996/ijs.2023.64.8.
3. Bara'a AA, Abbood AD, Hasan AA, Pizzuti C, Al-Ani M, Özdemir S, Al-Dabbagh RD. A Review of Heuristics and Metaheuristics for Community Detection in Complex Networks: Current Usage, Emerging Development and Future Directions. Swarm Evol Comput. 2021;63:100885. https://doi.org/10.1016/j.swevo.2021.100885.
4. Abbood AD, Attea BA, Hasan AA, Everson RM, Pizzuti C. Community Detection Model for Dynamic Networks Based on Hidden Markov Model and Evolutionary Algorithm. Artif Intell Rev. 2023;56(9):9665–97. https://doi.org/10.1007/s10462-022-10383-2.
5. Abed IH, Bahadori S. Using Density Criterion and Increasing Modularity to Detect Communities in Complex Networks. InfoTech Spectrum: Iraqi J Data Sci. 2025;2(1):1–15. https://doi.org/10.51173/ijds.v2i1.12.
6. Nan D-Y, Yu W, Liu X, Zhang Y-P, Dai W-D. A Framework of Community Detection Based on Individual Labels in Attribute Networks. Physica A Stat Mech Appl. 2018;512:523–36. https://doi.org/10.1016/j.physa.2018.08.100.
7. Abbood AD, Hasan AA, Bara'a AA. Pearson Coefficient Matrix for Studying the Correlation of Community Detection Scores in Multi-Objective Evolutionary Algorithm. Period Eng Nat Sci. 2021;9(3):796–807.
8. Sani NS, Manthouri M, Farivar F. A Multi-Objective Ant Colony Optimization Algorithm for Community Detection in Complex Networks. J Ambient Intell Human Comput. 2020;11(1):5–21. https://doi.org/10.1007/s12652-018-1159-7.
9. Ghafori S, Gharehchopogh FS. A Multiobjective Cuckoo Search Algorithm for Community Detection in Social Networks. In: Multi-Objective Combinatorial Optimization Problems and Solution Methods. Amsterdam: Elsevier; 2022. p. 177–93. https://doi.org/10.1016/B978-0-12-823799-1.00007-3.
10. Ahmad H, Sajid M, Mazhar F, Fuzail M. Mapping Unseen Connections: Graph Clustering to Expose User Interaction Patterns. J Future Artif Intell Technol. 2025;1(4):474–96. https://doi.org/10.62411/faith.3048-3719-77.
11. Attea B, Hariz W. A Heuristic Multi-Objective Community Detection Algorithm for Complex Social Networks. Iraqi J Sci. 2015;56(4):3533–45.
12. Abdulrahman MM, Abbood AD, Bara'a AA. The Influence of NMI Against Modularity in Community Detection Problem: A Case Study for Unsigned and Signed Networks. Iraqi J Sci. 2021;62(6):2064–81. https://doi.org/10.24996/ijs.2021.62.6.32.
13. Sulistianingsih N, Winarko E, Sari AK. GN-PPN: Parallel Girvan-Newman-Based Algorithm to Detect Communities in Graph with Positive and Negative Weights. Int J Intell Eng Syst. 2022;15(6). https://doi.org/10.22266/ijies2022.1231.26.
14. Pizzuti C. A Multiobjective Genetic Algorithm to Find Communities in Complex Networks. IEEE Trans Evol Comput. 2011;16(3):418–30. https://doi.org/10.1109/TEVC.2011.2161090.
15. Li Q, Cao Z, Ding W, Li Q. A Multi-Objective Adaptive Evolutionary Algorithm to Extract Communities in Networks. Swarm Evol Comput. 2020;52:100629.

https://doi.org/10.1016/j.swevo.2019.100629.

16. Shahabi Sani N, Manthouri M, Farivar F. A Multi-Objective Ant Colony Optimization Algorithm for Community Detection in Complex Networks. J Ambient Intell Human Comput. 2020;11(1):5–21. https://doi.org/10.1007/s12652-018-1159-7.
17. Shi C, Yan Z, Cai Y, Wu B. Multi-Objective Community Detection in Complex Networks. Appl Soft Comput. 2012;12(2):850–59. https://doi.org/10.1016/j.asoc.2011.10.005.
18. Wu P, Pan L. Multi-Objective Community Detection Based on Memetic Algorithm. PLoS One. 2015;10(5):e0126845.
19. Gong M, Cai Q, Chen X, Ma L. Complex Network Clustering by Multiobjective Discrete Particle Swarm Optimization Based on Decomposition. IEEE Trans Evol Comput. 2013;18(1):82–97. https://doi.org/10.1109/TEVC.2013.2260862.
20. Zhu W, Li H, Wei W. A Two-Stage Multi-Objective Evolutionary Algorithm for Community Detection in Complex Networks. Mathematics. 2023;11(12):2702. https://doi.org/10.3390/math11122702.
21. Zhou H, Chen G. A Multiobjective Optimization Whale Optimization Based Community Detection Algorithm. In: 2022 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA). IEEE; 2022. p. 1–4. https://doi.org/10.1109/CVIDLICCEA56201.2022.9824328.
22. Zhang X, Zhou K, Pan H, Zhang L, Zeng X, Jin Y. A Network Reduction-Based Multiobjective Evolutionary Algorithm for Community Detection in Large-Scale Complex Networks. IEEE Trans Cybern. 2018;50(2):703–16. https://doi.org/10.1109/TCYB.2018.2871673.
23. Cheng F, Cui T, Su Y, Niu Y, Zhang X. A Local Information Based Multi-Objective Evolutionary Algorithm for Community Detection in Complex Networks. Appl Soft Comput. 2018;69:357–67. https://doi.org/10.1016/j.asoc.2018.04.037.
24. Ji P, Zhang S, Zhou Z. A Decomposition-Based Ant Colony Optimization Algorithm for the Multi-Objective Community Detection. J Ambient Intell Human Comput. 2020;11:173–88. https://doi.org/10.1007/s12652-019-01241-1.
25. Yu L, Guo X, Zhou D, Zhang J. A Multi-Objective Pigeon-Inspired Optimization Algorithm for Community Detection in Complex Networks. Mathematics. 2024;12(10):1486. https://doi.org/10.3390/math12101486.
26. Zhang Q, Li H. MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. IEEE Trans Evol Comput. 2007;11(6):712–31. https://doi.org/10.1109/CEC.2012.6252954.
27. Aslani B, Mohebbi S. Learn to Decompose Multiobjective Optimization Models for Large-Scale Networks. Int Trans Oper Res. 2024;31(2):949–78. https://doi.org/10.1111/itor.13169.
28. Abdulrahman MM, Abood AD, Attea BA. An Enhanced Multi-Objective Evolutionary Algorithm with Decomposition for Signed Community Detection Problem. In: 2020 2nd Annual International Conference on Information and Sciences (AiCIS). IEEE; 2020. p. 45–50. https://doi.org/10.1109/AiCIS51645.2020.00017.
29. Attea BA, Hariz WA, Abdulhalim MF. Improving the Performance of Evolutionary Multi-Objective Co-Clustering Models for Community Detection in Complex Social Networks. Swarm Evol Comput. 2016;26:137–56. https://doi.org/10.1016/j.swevo.2015.09.003.
30. Guerrero M, Gil C, Montoya FG, Alcayde A, Banõs R. Multi-Objective Evolutionary Algorithms to Find Community Structures in Large Networks. Mathematics. 2020;8(11):2048. https://doi.org/10.3390/math8112048.
31. Ramesh A, Srivatsun G. A Multiobjective Evolutionary Algorithm with a Novel Mutation Operator for Overlapping Community Detection. J Theor Appl Inf Technol. 2024;102(5).
32. Zachary WW. An Information Flow Model for Conflict and Fission in Small Groups. J Anthropol Res. 1977;33(4):452–73..

33. Lusseau D. The Emergent Properties of a Dolphin Social Network. Proc R Soc Lond B Biol Sci. 2003;270(Suppl 2):S186–8. https://doi.org/10.1098/rsbl.2003.0057.
34. Girvan M, Newman ME. Community Structure in Social and Biological Networks. Proc Natl Acad Sci U S A. 2002;99(12):7821–6. https://doi.org/10.1073/pnas.122653799.
35. Newman ME. Modularity and Community Structure in Networks. Proc Natl Acad Sci U S A. 2006;103(23):8577–82. https://doi.org/10.1073/pnas.0601602103.
36. Lancichinetti A, Fortunato S, Radicchi F. Benchmark Graphs for Testing Community Detection Algorithms. Phys Rev E. 2008;78(4):046110.