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Three different modified discrete versions of dynamic arithmetic optimization algorithm for detection of cohesive subgroups in social networks

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ABSTRACT

Many networks in nature, society and technology are represented by the level of organization, where groups of nodes form tightly connected units called communities or modules that are only weakly connected to each other. Social networks can be thought of as a group or community, which are groups of nodes with a large number of connections to each other. Identifying these communities by modularity helps to solve the modularity maximization problem. The modularity value determines the quality of the resulting community. Community detection (CD) helps to uncover potential sub-community structures in the network that play a critical role in various research areas. Since CD problems have NP-hard problem structure, it is very difficult to obtain the optimal modularity value with classical methods. Therefore, metaheuristics are frequently preferred in the literature for solving CD problems. In this study, the DAOA algorithm, which has been recently proposed for solving continuous problems, is adapted to the CD problem. In order to improve the solution quality of the DAOA algorithm, some modifications were made in the core parameters. In addition, global and local search supports were added to the DAOA algorithm and three different modifications were applied to the algorithm in total. According to the results performed under equal conditions, among the three modified algorithms, the algorithm with parameter modification was the best in 2 out of 5 networks. DAOA with global search was the best in 3 networks, while the algorithm with local search was the best in 2 networks. However, the basic DAOA could not achieve the best result in any of the 5 networks. This clearly shows the success of the modifications on the algorithm. On the other hand, when compared with the algorithms in the literature, the proposed DAOA algorithm achieved 80% success out of 10 algorithms in total. This shows that the proposed DAOA algorithm can be used as an alternative for discrete problems.

1. Introduction

Over the past few years, the study of social networks has gained a lot of attention from researchers. Every individual tends to be in a social network. Therefore, the individual has different relationships within the network in accordance with his/her characteristics [1]. Such relationships are revealed through a method known as Social Network Analysis (SNA). SNA is defined as the examination and understanding of the relationships / ties between individuals in a social network [2].

Community detection (CD) in social networks is defined as the process of identifying compatible groups of similar nodes. Detection of these groups helps to find protein interaction networks in biological networks, to find users with similar characteristics for advertisements and recommendations, and to find a common research area in collaborative networks. In addition, this approach is also preferred in many different applications such as analyzing public health, predicting future connections in social networks, and analyzing criminology [3]. CD is one of the main methods of this social network analysis (SNA) [4]. While there are many different techniques, algorithms and approaches to community structure detection, no single CD method can be used effectively in all types of networks due to the wide variety of complex networks [5].

Algorithms that aim to detect all communities on a network can be called global community detection algorithms. Research on CD has mainly focused on such algorithms. The Girvan-Newman (GN) algorithm was the first global CD

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algorithm proposed by Newman et al [6]. Following this work, many algorithms have been developed to address different global CD problems such as hierarchical, dynamic, and overlapping CD [7, 8].

There are two main classification algorithms in the literature for community detection in social networks: The first one is to partition the community according to the dichotomy approach of graph theory; the second one is to partition the community according to the clustering algorithm approach. Modern typical CD algorithms are generally complex and there is some research in the literature based on module optimization algorithms. Cao et al [9] proposed a CD method to explore open and fuzzy communities in unweighted and undirected networks with the help of the weighted modularity maximization method. Xin et al. [10] proposed RWS (Random Walk Sampling) method to find overlapping communities by using random walk method to detect the closest nodes for each node.

Nowadays, many methods and algorithms have been developed for CD on complex networks. However, most of these methods cannot perform community detection on these networks, due to the high dimensionality of the network, which increases the computational complexity. This drawback is one of the major obstacles in performing community detection in such networks. The detection of different communities on the complex network is seen as an optimization problem. Therefore, metaheuristic algorithms can be used to handle the CD problem. Using a predefined objective function, the goal of the metaheuristic algorithm on the CD problem is to find the optimal solution for community detection.

An improved cuckoo search optimization algorithm with genetic algorithm was proposed for community detection in complex networks [11]. Coot bird metaheuristic optimizer was proposed for CD in social networks. This algorithm was compared with the six novel algorithms on small and medium scaled networks [12]. An improved version of Grey Wolves optimization algorithm was proposed for dynamic community detection and data clustering [13]. An improved Harris Hawks optimization algorithm with multi-strategy was developed for community detection in social network [14]. A multi objective Cuckoo Search algorithm was used for community detection in social networks [15]. Genetic algorithm-based community detection was proposed for large-scale social networks [16]. Different metaheuristic algorithms such as Bat, Differential Search, Genetic, Scatter Search was used for CD problem in biological and social networks [17]. Lion and cuckoo search optimization algorithm was proposed for community detection in 2015 and 2017 [18, 19]. The study about interdicting low-diameter cohesive subgroups was carried out in large-scale social networks [20]. Social network analysis and mining studies on a dynamic two-stage community discovery approach were proposed [21]. A review on CD methods and algorithms in social networks was conducted [22]. A systematic review on CD Algorithms were carried out in health applications [23]. A research on malware analysis using community detection algorithms was proposed [24]. A personal privacy protection system from CD with genetic algorithm was proposed [25]. Influence maximization in social networks using effective community detection was proposed [26].

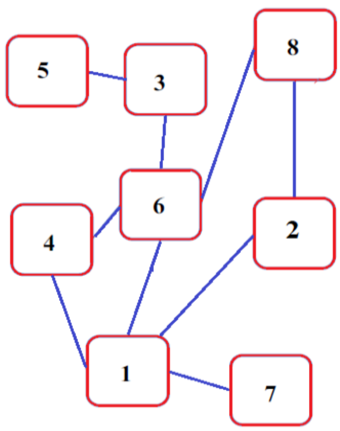
In this study, the effects of the recently developed DAOA algorithm were analyzed on five social networks. For this purpose, the DAOA algorithm is adapted to the CD problem, which is a discrete problem. Then, the DAOA algorithm was modified in three different ways and these versions are also adapted to the CD problem. The obtained solutions were first compared within themselves and then compared with important studies in the literature both in terms of time and solution quality.

The rest of the paper as follow: Section 2 provides an overview of the CD problem. Section 3 introduces the DAOA algorithm and its modified versions. Section 4 presents the experimental studies, while Section 5 and 6 present Discussion and the conclusions of the paper.

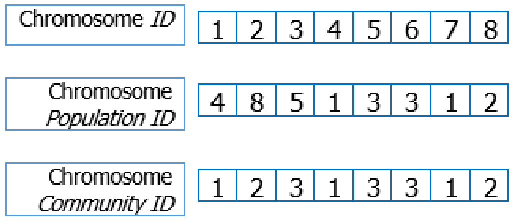
2. Problem

The process of discovering compatible subgroups in a network is defined as community detection and is one of the main tasks of social network analysis [27]. The purpose of the CD problem is to identify subgroups that are more densely connected to each other in the network. Identifying and analyzing the structure of the community of networks has yielded remarkable outputs in fields ranging from biology to the Web.

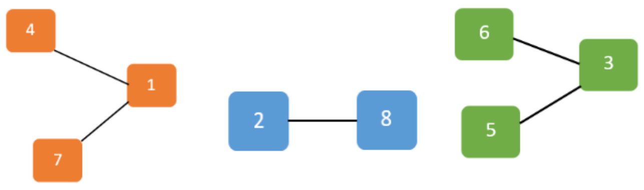
Figure 1 represents a sample network and the obtained subgroups. In this representation, there are eight nodes in the network. Three sub-communities are formed according to the population ID values obtained by considering the edge matrix of each node.



(a) An example of an 8-node network



(b) an example of chromosomes



(c) the subgraphs generated from chromosomes

Figure. 1. A sample network and the obtained subgraphs

Modularity maximization is one of the most well-known methods for finding sub-communities in networks. This approach is realized by dividing a network into different sub-communities and then evaluating the quality of each sub-community. This maximization function allows finding the potential sub-communities of the network of interest and their nodes, the community structure that would generate the highest cost [28]. Modularity-based methods aim to provide the maximization of the modularity value as in Eq. (1).

$$Q_{Basic} = \sum_{i=1}^{n} (e_{ij} - a_i^2) \tag{1}$$

where e_{ij} represents the connection number with one edge in ith subgroup and the other edge in jth subgroup. $\sum_{i=1}(e_{ij})$ expresses the connection number with one edge in the subgroup. Since CD problem is NP-hard such as land readjustment [29] and image thresholding [30], metaheuristic algorithms are often used to find the best value of Q_{Basic} [31].

3. Dynamic Arithmetic Optimization Algorithm (DAOA)

DAOA was proposed in 2022 by adding two dynamic features with a novel accelerator function to the basic arithmetic optimization algorithm proposed [32]. In DAOA, the exploration and exploitation behavior is controlled. This improves the candidate solutions and the search phase throughout the iteration. Figure 2 presents The flowchart of DAOA.

procedure DAOA
Initial the core parameter such as α and μ
Create randomly initial population
while (t < Max_Iter)
Calculate fitness values for all the population
Get the best solution
Update the DAF value according to Equation (2)
Update the DCS value according to Equation (6)
for i =1: Population size
for j = 1: Position size
Create ***r***1, ***r***2, ***r***3 values between 0 and 1
if r1 > DAF
if r2 > 0.5
Update positions of the solutions with first rule in Equation (3)
else
Update positions of the solutions with second rule in Equation (3)
end if
if r1 < DAF
if r3 > 0.5
Update positions of the solutions with first rule in Equation (4)
else
Update positions of the solutions with second rule in Equation (4)
end if
end if
end for
end for
$t = t + 1$
end while
Report best solution
end procedure

Figure 2. The flowchart of DAOA

$$\mathrm{DAF} = \left(\frac{\mathrm{Iter}_{\max}}{\mathrm{Iter}}\right)^{\propto} \tag{2}$$

$$X_{i,j}(C_{iter+1}) = \begin{cases} \mathrm{best}(x_j)/(\mathrm{DCS}+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & r2 < 0.5 \\ \mathrm{best}(x_j) \times (\mathrm{DCS}+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & \text{otherwise} \end{cases} \tag{3}$$

$$X_{i,j}(C_{iter+1}) = \begin{cases} \mathrm{best}(x_j) - \mathrm{DCS} \times ((UB_j - LB_j) \times \mu + LB_j) & r3 < 0.5 \\ \mathrm{best}(x_j) + \mathrm{DCS} \times ((UB_j - LB_j) \times \mu + LB_j) & \text{otherwise} \end{cases} \tag{4}$$

$$\mathrm{DCS}\ (0) = 1 - \sqrt{\frac{\mathrm{Iter}}{\mathrm{Iter}_{\max}}} \tag{5}$$

$$\mathrm{DCS}\ (t+1) = \mathrm{DCS}\ (t) \times 0.99 \tag{6}$$

In original DAOA, μ was taken 0.001, alpha was determined as -25. In this paper, three modification were applied to DAOA. While original DAOA adapted to the problem is expressed DisDAOA1, modified versions are named as DisDAOA2, DisDAOA3 and DisDAOA4, respectively.

3.1. Parameter Tuning: DisDAOA2

In this modified version of DAOA, some core parameters were changed experimentally. To strengthen the local search, μ was set as 0.01 and alpha was taken as -5. In In addition, DAF value was taken as between 0 and 1 randomly. These parameters were also equally used for DisDAOA3 and DisDAOA4. The rest of the algorithm is faithful to the original DAOA.

3.2. DAOA with global search: DisDAOA3

In this version, to see the contribution of global search to the algorithm, the scout bee of artificial bee colony (ABC) was applied to the algorithm. The scout bee phase is used to generate new solutions in regions where there is a lack of new food sources in the search space [33, 34]. In this paper, limit value of the scout bee phase was determined as 10.

3.3. DAOA with local search: DisDAOA4

In this modification, Instead of using only the best value ($best(x_j)$), the second best value ($best2(x_j)$) was also used in order to generated fitter solutions in the search space. For this, four decision variables named *a*, *b*, *c* and *d* were added to the algorithm. These variables were used to generate random values between [0, 1]. The way they are adapted to the algorithm is given in the equations below. In case r1 is greater than DAF, Equations (7) and (8) are used. In case r2 > 0.5, Equation (7) is used, otherwise Equation (8) is run. Depending on the parameter *a* in Equation (7) and *b* in Equation (8), the first and second rules are run respectively.

$$X_{i,j}(C_{iter+1}) = \begin{cases} best(x_j)/(DCS+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & a < 0.5 \\ best(x_j)/(DCS+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & otherwise \end{cases} \quad (7)$$

$$X_{i,j}(C_{iter+1}) = \begin{cases} best(x_j) \times (DCS+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & b < 0.5 \\ best2(x_j) \times (DCS+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & otherwise \end{cases} \quad (8)$$

In case r1 is smaller than DAF, Equations (9) and (10) are run. In case r3 > 0.5, Equation (9) is used, otherwise Equation (10) is operated. According to the parameter *c* and *d* in Equation (7) and (8), the first and second rules are operated to produce new solutions respectively.

$$X_{i,j}(C_{iter+1}) = \begin{cases} best(x_j) - DCS \times ((UB_j - LB_j) \times \mu + LB_j) & c < 0.5 \\ best2(x_j) - DCS \times ((UB_j - LB_j) \times \mu + LB_j) & otherwise \end{cases} \quad (9)$$

$$X_{i,j}(C_{iter+1}) = \begin{cases} best(x_j) + DCS \times ((UB_j - LB_j) \times \mu + LB_j) & d < 0.5 \\ best2(x_j) + DCS \times ((UB_j - LB_j) \times \mu + LB_j) & otherwise \end{cases} \quad (10)$$

4. Experimental Studies

In this study, DAOA algorithm, which has been recently introduced to the literature, was used for community detection in social networks. In the experimental studies, five different social networks, which are preferred for CD analysis in many different studies, were used as input data set and are given in Table 1. All experimental works were carried out in Matlab R2021a code development platform with Intel Core i7 2.80 GHz CPU, 16 GB RAM and Windows 10 64-bit operating system.

Table 1. The social networks in the experimental studies

Networks	*#Node*	*#Edge*
Zachary's karate club **[35, 36]**	*34*	*78*
Bottlenose dolphins **[37]**	*62*	*159*
American college football **[38]**	*115*	*615*
Books about US politics	*105*	*441*
Grevy's zebras **[39]**	*27*	*111*

In this paper, the DAOA algorithm is modified in three different ways. These algorithms, adapted to the CD problem and named as DisDAOA1, DisDAOA2, DisDAOA3 and DisDAOA4 were run under equal conditions in 30 independent runs. The best values for each comparison are presented in bold. In each run, the number of population, maximum iteration and maxFEs were used as 20, 500 and 10,000.

Table 2 presents comparative results of the modified DAOA algorithms within themselves according to solution quality. For the Karate network, DisDAOA3 produced the best results in terms of Mean, Std and Worst. In terms of Best, three modified versions including the original DAOA algorithm achieved the best value.

For the Dolphins network, DisDAOA2 was the best algorithm in terms of Mean and Best, while DisDAOA4 was the most successful algorithm in terms of Std and Worst. For the Football network, DisDAOA4 produced the best result according to Mean and Best, while DisDAOA3 was the most successful algorithm according to Std and Worst. When the Books social network is analyzed, while DisDAOA3 performed the best in all the metrics except Best, DisDAOA4 was the most effective algorithm in terms of Best. According to the Zebras network results, all modifications produced the best result in terms of Mean, Std, Worst and Best, while the original version of DAOA, DisDAOA1, produced the best value only in terms of Best. According to all these results, it is seen that the modifications made in different aspects improve the basic algorithm in terms of solution quality.

Table 2. Comparison of the modified algorithms in terms of solution quality

Dataset		DisDAOA1 (original)	DisDAOA2 (parameter)	DisDAOA3 (global)	DisDAOA4 (local)
Karate	*Mean*	0.4151	0.4173	**0.4196**	0.4194
	Std	0.0065	0.0051	**0.0009**	0.0016
	Worst	0.3993	0.4020	**0.4156**	0.4112
	Best	**0.4198**	**0.4198**	**0.4198**	**0.4198**
Dolphins	*Mean*	0.5090	**0.5239**	0.5225	0.5239
	Std	0.0123	0.0045	0.0062	**0.0042**
	Worst	0.4717	0.5079	0.5031	**0.5123**
	Best	0.5268	**0.5285**	0.5285	0.5285
Football	*Mean*	0.5276	0.5600	0.5627	**0.5644**
	Std	0.0301	0.0187	**0.0150**	0.0215

	Worst	0.4707	0.5163	**0.5252**	0.4922
	Best	0.5908	0.5837	0.5838	**0.6019**
Books	*Mean*	0.5101	0.5194	**0.5202**	0.5185
	Std	0.0130	0.0066	**0.0057**	0.0088
	Worst	0.4763	0.4969	**0.5007**	0.4986
	Best	0.5267	0.5268	0.5266	**0.5269**
Zebras	*Mean*	0.2748	**0.2768**	**0.2768**	**0.2768**
	Std	0.0031	**0.0000**	**0.0000**	**0.0000**
	Worst	0.2702	**0.2768**	**0.2768**	**0.2768**
	Best	**0.2768**	**0.2768**	**0.2768**	**0.2768**

Table 3 shows the comparative results of the DAOA algorithms in terms of time. According to these results, for Karate, DisDAOA2 produces the best result for Mean and Max, while DisDAOA4 is the best for Std and Min.

For the Dolphin network, DisDAOA2 performed the best except for Min. DisDAOA1 performed the best for Min. For the Football network, it produced DisDAOA1 for Min, DisDAOA3 for Std and DisDAOA4 for Mean and Max values. In the Books social network, DisDAOA1 produced the best results in terms of all the metrics. For Zebras, DisDAOA3 performed the best in all benchmarks. However, with the exception of DisDAOA1, all the modified algorithms performed very well in terms of Min, achieving 0.00, which is less than 1/100th of a second.

Table 3. Comparison of the modified algorithms in terms of time (second)

Dataset		DisDAOA1	DisDAOA2	DisDAOA3	DisDAOA4
Karate	*Mean*	1.47	**1.44**	1.63	1.57
	Std	1.01	0.88	1.03	**0.78**
	Min	0.06	0.02	0.15	**0.02**
	Max	4.34	**2.72**	3.72	3.12
Dolphins	*Mean*	4.93	**4.65**	7.86	6.40
	Std	0.50	**0.35**	0.62	1.16
	Min	**4.19**	4.43	7.17	4.50
	Max	6.56	**6.41**	9.09	8.90
Football	*Mean*	17.70	**16.30**	23.20	19.08
	Std	1.68	**0.91**	1.29	1.32
	Min	15.03	**14.55**	21.76	15.40
	Max	21.36	**18.24**	28.61	21.91
Books	*Mean*	18.69	18.31	21.48	**17.72**
	Std	3.37	1.78	**0.76**	0.77
	Min	**15.46**	15.91	19.94	16.61
	Max	28.85	24.16	23.09	**19.06**
Zebras	*Mean*	0.78	0.19	**0.06**	0.10
	Std	1.57	0.35	**0.05**	0.15
	Min	0.01	**0.00**	**0.00**	**0.00**
	Max	8.21	1.82	**0.16**	0.64

Figure 3-7 shows the convergence graphs of social networks. When Figure 3 is analysed, DisDAOA2 achieved the fastest convergence. DisDAOA3 was the slowest. According to Figure 4 convergence results, DisDAOA1 showed the fastest convergence in the first 300 iterations. When Figure 5 is analysed, it is seen that all algorithms show improvement throughout the iterations in terms of convergence. At the end of the iteration, DisDAOA4 seems to be more successful. When the convergence curves are analysed in Figure 6, DisDAOA1-2 was more successful during the first 250 iterations, while DisDAOA3-4 was more effective in the following iterations. Finally, when the convergence graphs of the algorithms in Figure 7 are analysed, all algorithms achieved the optimum value within the first 50 iterations. The slowest algorithm was DisDAOA3.

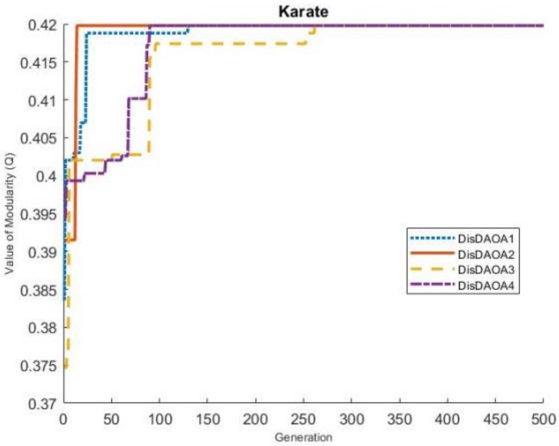


Figure 3. Convergence curves of the global best modularity values for Karate

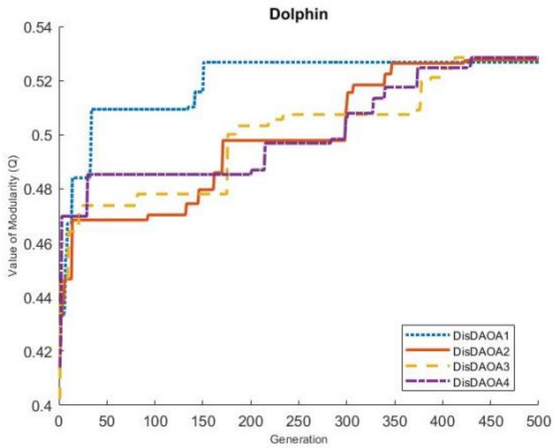


Figure 4. Convergence curves of the global best modularity values for Dolphins

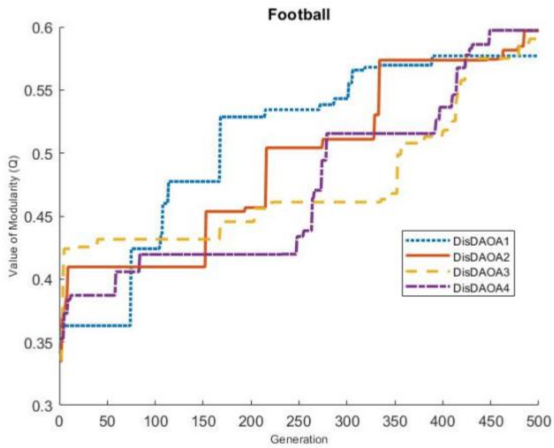


Figure 5. Convergence curves of the global best modularity values for Football

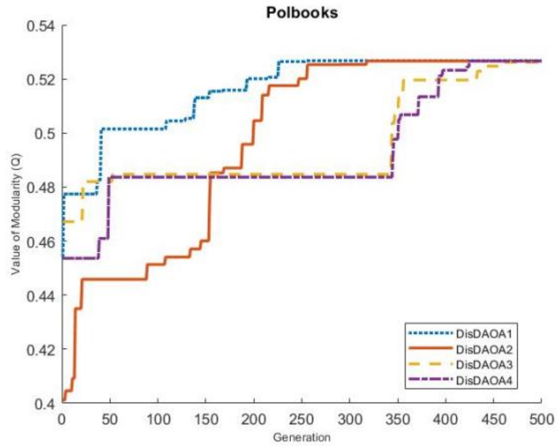


Figure 6. Convergence curves of the global best modularity values for Polbooks

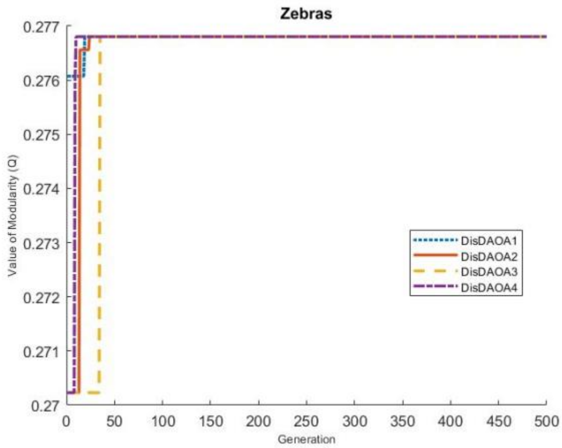


Figure 7. Convergence curves of the global best modularity values for Zebras

In Table 4, the comparative results are presented for the DisDAOA algorithm with five algorithms called Slime Mould Algorithm (SMA), Atom search optimization (ASO), Arithmetic Optimization Algorithm (AROA) Archimedes optimization algorithm (AOA), and Harris Hawks Optimization (HHO) in study of [12] in terms of solution quality. Besides, DisDAOA represents the best results obtained from four different DAOA algorithms. According to the results in this table, for the Karate network, all the algorithms obtained the best result according to the Best value. While HHO was the best in terms of Mean and Worst, AOA algorithm was the most successful in terms of *Std* For the Dolphins network, the proposed algorithm seems to produce the best result in all cases. In the Football network, the proposed algorithm was the most successful in all other metrics except for Std, it produced a result close to the best value produced by SMA, which is the most successful algorithm for this network. In the Books network, similar to the Dolphins network, DisDAOA produced the best value in terms of Mean, Std, Worst, and Best. In the Zebras network, it is seen that all algorithms produced the best results in terms of Best. However, SMA and AOA algorithms seem to be more unsuccessful in terms of Worst.

Table 4. Comparison of the proposed algorithm with the algorithms in study of [12] in terms of solution quality

Dataset		**DisDAOA**	**AOA**	**ASO**	**HHO**	**SMA**	**AROA**
Karate	*Mean*	0.4196	0.4185	0.4180	**0.4197**	0.3829	0.4108
	Std	0.0009	0.0032	**0.0020**	0.0005	0.0110	0.0079
	Worst	0.4156	0.4060	0.4102	**0.4174**	0.3752	0.3909
	Best	**0.4198**	**0.4198**	**0.4198**	**0.4198**	0.4174	**0.4198**
Dolphins	*Mean*	**0.5239**	0.4915	0.4803	0.5054	0.4351	0.5055
	Std	**0.0042**	0.0119	0.0132	0.0119	0.0144	0.0113
	Worst	**0.5123**	0.4687	0.4581	0.4688	0.4100	0.4865
	Best	**0.5285**	0.5116	0.5140	0.5265	0.4656	0.5268
Football	*Mean*	**0.5644**	0.4673	0.4333	0.4780	0.4308	0.4998
	Std	0.0150	0.0213	0.0255	0.0277	**0.0049**	0.0138
	Worst	**0.5252**	0.4372	0.3981	0.4280	0.4225	0.4722
	Best	**0.6019**	0.5141	0.5181	0.5458	0.4440	0.5268
Books	*Mean*	**0.5202**	0.5081	0.4943	0.5121	0.4752	0.4773
	Std	**0.0057**	0.0103	0.0112	0.0104	0.0103	0.0099
	Worst	**0.5007**	0.4886	0.4705	0.4908	0.4540	0.4633
	Best	**0.5269**	0.5248	0.5113	0.5264	0.5003	0.4963
Zebras	*Mean*	**0.2768**	**0.2768**	**0.2768**	**0.2768**	0.2761	**0.2768**
	Std	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.0020	**0.0000**
	Worst	**0.2768**	0.2766	**0.2768**	**0.2768**	0.2702	**0.2768**
	Best	**0.2768**	**0.2768**	**0.2768**	**0.2768**	**0.2768**	**0.2768**

Table 5 presents the comparison of the proposed algorithm with the algorithms named Improved Bat based on the Scatter Search based on Big Bang–Big Crunch (BB–BC), Genetic (SSGA), Differential Evolutionary (BADE), Bat (BA), and Gravitational Search (GSA) algorithm in the studies of [17] in terms of solution quality. According to the results in this table, BB-BC was the most successful algorithm in the Karate network. In terms of Best, all the algorithms produced the best value. It is also seen that the proposed algorithm is the best in terms of Mean. For the Dolphin network, DisDAOA clearly performed the best in all metrics. According to the results for the Football social network, the proposed algorithm produced the best results in terms of Best and Mean, BB-BC for Std and BADE for Worst. In the Books social network, as in the Dolphins network, the proposed algorithm performed the best in all values. In the Zebras network, the BB-BC algorithm did not find the optimal value except Best. All the other algorithms produced the best value in terms of Mean, Std, Worst and Best.

Table 5. Comparison of the proposed algorithm with the algorithms in studies of [17] in terms of solution quality

Dataset		DisDAOA	BADE	BB–BC	BA	GSA
Karate	*Mean*	**0.4196**	0.4188	**0.4196**	0.4133	0.417
	Std	0.0009	0.0018	**0.0004**	0.0105	0.0037
	Worst	0.4156	0.4156	**0.4188**	0.3946	0.4107
	Best	**0.4198**	**0.4198**	**0.4198**	**0.4198**	**0.4198**
Dolphins	*Mean*	**0.5239**	0.5129	0.5141	0.4919	0.4677
	Std	**0.0042**	0.0120	0.0068	0.0289	0.0155
	Worst	**0.5123**	0.4940	0.5049	0.4427	0.4517
	Best	**0.5285**	0.5268	0.522	0.5157	0.4891
Football	*Mean*	**0.5644**	0.5513	0.5061	0.5272	0.4032
	Std	0.0150	0.0085	**0.0069**	0.0325	0.0109
	Worst	0.5252	**0.5430**	0.4986	0.4742	0.3905

	Best	**0.6019**	0.5646	0.5171	0.5523	0.4175
Books	*Mean*	**0.5202**	0.5178	0.4914	0.502	0.4661
	Std	**0.0057**	0.0042	0.0084	0.0149	0.0079
	Worst	**0.5007**	0.5137	0.4799	0.4815	0.4558
	Best	**0.5269**	0.5239	0.4992	0.5211	0.4775
Zebras	*Mean*	**0.2768**	**0.2768**	0.2766	**0.2768**	**0.2768**
	Std	**0.0000**	**0.0000**	0.0003	**0.0000**	**0.0000**
	Worst	**0.2768**	**0.2768**	0.2761	**0.2768**	**0.2768**
	Best	**0.2768**	**0.2768**	**0.2768**	**0.2768**	**0.2768**

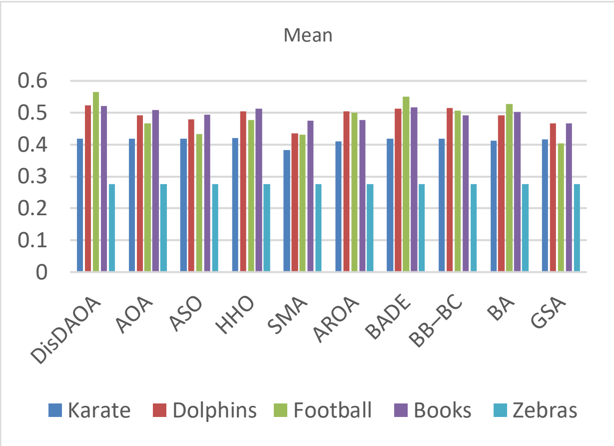


Figure 8. Comparison of DAOA with all the other studies in terms of mean

Figure 8 presents the comparison of DAOA with all the other studies in terms of mean. According to these results, It is seen that the proposed algorithm is superior especially in Dolphins and Football networks.

Table 6 shows the comparison of the proposed algorithm with the algorithms in study of [12] in terms of time. According to these results, it is clear that the proposed algorithm is the most successful for all problems without exception. In addition to Table 6, Table 7 presents the comparison of the proposed algorithm with the algorithms in studies of [17] in terms of time. It is obviously clear that the proposed algorithm is again the most successful in terms of time in all social networks without exception.

Table 6. Comparison of the proposed algorithm with the algorithms in study of [12] in terms of time (second)

Dataset		DisDAOA	AOA	ASO	HHO	SMA	AROA
Karate	*Mean*	**1.44**	2.35	4.29	5.28	6.80	5.67
	Std	**0.78**	2.44	2.15	3.50	1.75	2.87
	Min	**0.02**	0.04	0.03	0.22	4.21	0.51
	Max	**2.72**	8.76	9.45	13.30	12.00	13.07
Dolphins	*Mean*	**4.65**	9.72	10.60	23.21	8.61	13.14
	Std	**0.35**	1.19	2.05	1.78	1.26	0.59
	Min	**4.19**	7.56	8.13	20.35	6.87	12.16
	Max	**6.41**	12.59	16.44	28.54	11.46	15.46
Football	*Mean*	**16.30**	31.28	29.12	81.50	40.42	46.63
	Std	**0.91**	2.64	3.53	7.50	5.16	1.62
	Min	**14.55**	26.94	20.72	67.95	34.42	43.46
	Max	**18.24**	36.36	34.99	97.08	62.09	50.15
Books	*Mean*	**17.72**	32.83	29.33	89.65	52.51	41.11
	Std	**0.76**	2.56	5.25	3.19	3.89	1.95
	Min	**15.46**	26.56	20.51	83.57	43.12	36.33
	Max	**19.06**	38.44	41.25	94.92	59.79	44.84
Zebras	*Mean*	**0.06**	2.35	1.73	3.37	5.12	1.47
	Std	**0.05**	0.22	0.12	0.07	0.14	0.07
	Min	**0.00**	1.72	1.57	3.23	4.87	1.34
	Max	**0.16**	2.68	2.00	3.51	5.46	1.61

Table 7. Comparison of the proposed algorithm with the algorithms in studies of [17] in terms of time

Network/Algoritma	DisDAOA	BADE	SSGA	BB–BC	BA	GSA
Karate	**1.44**	48.00	57.40	46.22	37.22	39.88
Dolphins	**4.65**	135.86	139.96	128.68	105.72	104.17
Football	**16.30**	433.54	521.48	450.71	333.43	337.89
Books	**17.72**	372.28	469.04	373.51	279.34	309.82
Zebras	**0.06**	30.85	38.52	30.75	23.42	28.50
Average running time	**8.034**	*204.11*	*245.28*	*205.97*	*155.83*	*164.05*

5. Discussion

Three different modifications were used in this study. Firstly, the DAOA algorithm was discretised by keeping its original values (DisDAOA1). Then, the core parameters of the algorithm were modified (DisDAOA2). Then, the parameters of the DisDAOA2 algorithm were used and global search support was added (DisDAOA3). In addition, local search capability was added to the DisDAOA2 algorithm (DisDAOA4). When the results are analysed, it is seen that the modifications made in a very small network such as Zebras are very appropriate. In the Karate network, global search was found to be more effective. When we look at larger scale networks such as Football and Books, the effect of global search is again seen. As a result, it can be said that global search supported algorithms will give more successful results as the structure of the algorithm grows. In terms of time, since the local and global search phases create extra cost to the algorithm, these algorithms produce results in a slightly longer time.

6. Conclusions

In this study, five different networks were used for community detection on social networks. The newly proposed DAOA algorithm was used to solve the CD problem. In addition to the basic version called DisDAOA1, three modified versions was also utilized to solve the CD problem. The modifications are parameter tuning, global and local search and these algorithms were named as DisDAOA2, DisDAOA3 and DisDAOA4. Firstly, the DAOA approaches were compared within each other. According to the results of this comparison, it can be said that DisDAOA3 version is better than the other one. However, all modified versions were found to be better in terms of solution quality. However, in terms of time, the new decision mechanisms in the modified versions slowed down the algorithm relatively. However, this slowdown is negligible when the results are carefully analyzed.

In comparisons with important studies in the literature, the DisDAOA algorithm was almost the best algorithm in 4 out of 5 social networks. When analyzed in terms of time, it was clearly seen that the DisDAOA algorithm performed very well. Especially when analyzed with the results of Atay's study, it is clear that the proposed algorithm is very successful in terms of time.

For future studies, the algorithm can be strengthened with different modification methods. In addition, the proposed algorithm can be applied to different discrete problems other than the CD problem.

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Author contributions

Conceptualization: Methodology, Formal analysis and investigation, Writing - original draft preparation, Writing - review and editing, Funding acquisition, Resources, Supervision: [Ismail Koc]

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Authors are requested to disclose interests that are directly or indirectly related to the work submitted for publication.

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