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Hybrid optimization algorithm for analysis of influence propagation in social network

Akshata Sandeep Bhayyar[1,2], Kiran Purushotham[2]
[1]Department of Computer Science and Engineering, Ramaiah Institute of Technology, affiliated to Visvesvaraya Technological University, Belagavi, India
[2]Department of Computer Science and Engineering, RNS Institute of Technology, Bengaluru, affiliated to Visvesvaraya Technological University, Belagavi, India

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ABSTRACT

Influence maximization (IM) is defined as the problem of identifying a node subset in a social network which increases the spread of influence. IM plays a crucial role in social networks by catalyzing the dissemination of influence, resulting in an augmented count of influenced nodes following the propagation process. The existing researches mainly concentrated on increasing the spread of influence, but did not consider the running time of the network. In this manuscript, the salp swarm algorithm (SSA) and bi-adaptive strategy particle swarm optimization (BiAS-PSO) algorithms are integrated and named as SS-BiAS-PSO algorithm to increase the spread of influence based on the IM problem to minimize the running time of the network. The datasets utilized for the research are Ego-Facebook, Epinions, Gowalla, and HepTh, while linear threshold (LT) is utilized as a diffusion method. Then, the proposed SS-BiAS-PSO algorithm is deployed for the analysis of influence propagation. The proposed algorithm reaches a high influence spread of 645, 680, 715, and 750 with less running times respectively for 10, 20, 30, and 40 seed set sizes in Ego-Facebook. The proposed algorithm proves more effective than the existing techniques like traditional SSA and particle swarm optimization (PSO).

Corresponding Author:

Akshata Sandeep Bhayyar
Department of Computer Science and Engineering, Ramaiah Institute of Technology, affiliated to Visvesvaraya Technological University
Belagavi, India
Department of Computer Science and Engineering, RNS Institute of Technology Bengaluru, affiliated to Visvesvaraya Technological University
Belagavi, India
Email: akshataphd@gmail.com

1. INTRODUCTION

With the quick development of social networks, many people are using WeChat, Twitter, Facebook, and various social software to carry out data exchange, promotion of products, opinion of the public, and for various other activities that bring convenience for the productive life of people [1], [2]. The interaction among individuals can influence the spread in social networks [3], and the evidence confirms that data or distribution of influence is efficient in certain practical applications like fresh product promotion [4]. The main problem is to identify a target set with better communication characteristics with the support of a relationship network developed between users receiving the product while attaining high promotion of the product, and this procedure is an influence on the maximization problem [5], [6]. Hence, analysis of behavior and social network structure characteristics provides a theoretical base for solutions to various social and economic issues [7]. Influence maximization (IM) threats are a vital part of the analysis of social networks and are one of the crucial issues in social networks [8], [9]. IM problem is defined as choosing of a group of users from social network to increase the predictable number of affected users [10]. Recently, many algorithms for the problem of influence maximization research have abstracted social networks as static structures, avoiding the fact that interaction among users changes over time [11], [12]. In the previous researches, the amount paid for message spreading in the process of influence maximization was considered as rare [13]. Hence, the selection of a minimum-cost seed node group to acquire influence maximization of a node is a major issue yet to be solved. The time utilized for influence propagation in social networks is maximum in the previous methods, which also needs to be resolved [14], [15]. To overcome these limitations and solve IM problems, it is required to develop new swarm intelligence-based algorithms for this problem. These algorithms leverage diversity and local development capabilities of an algorithm, efficiently addressing IM problem while minimizing the running time. There are two ways in swarm intelligence-based algorithms for solving IM problems which are developing of an objective function, and rendering of an enhanced performance by the optimization algorithm. In this research, the salp swarm algorithm (SSA) and bi-adaptive strategy particle swarm optimization (BiAS-PSO) algorithms are integrated to increase the spread of influence based on the IM problem and minimize the running time of the network.

Li *et al.* [16] implemented an agent-based evolutionary model (ABEM) for influencing maximization in social networks. Initially, the model used a distributed method through an enhanced genetic algorithm (GA) to address IM in social networks. The implemented model was integrated with GA and activity-based model (ABM) for optimizing seeds selection from two stages at the individual and global levels. The implemented method not only performed well but also handled huge-scale social networks by distributing the execution cost. However, the implemented method did not consider the effect of overlapping caused by the chosen high central nodes in the seed group that degrade the methods efficient. Zhang *et al.* [17] introduced an overlapping community-based particle swarm optimization (OCPSO) algorithm for the maximization of influence in social networks. The introduced method utilized overlapping, non-overlapping and interactive data nodes. Particularly, an algorithm of overlapping community detection was utilized to acquire data of overlapping community structures. Further, depending on three strategies of evolutionary initialization, mutation and local search developed in OCPSO, the influential nodes were superiorly identified. However, the introduced algorithm did not control the solution accuracy well, and increased the network’s running time. Kuikka *et al.* [18] presented two programming methods and their corresponding pseudo-algorithms to analyze complex networks for influence maximization in social networks. Both methods represented the network structure on a detailed level. These two algorithms depended on similar influence spreading methods represented to be combined to measure the spreading probabilities among the nodes pair. The methods contained multiple unique and actual features, but were ineffective for most real-world network sizes. The presented algorithm showed superior scalability and performance by the identification of influence nodes. However, the network size and count of individuals were maximized, because measuring the cost of central value was huge and the method was highly time-consuming. Duan *et al.* [19] suggested a multi-hop remove (MHR) algorithm for maximization of influence in social networks. The suggested algorithm determined a hop range under various probabilities of propagation. The complexity of time can be highly minimized if nodes meet the requirements of directly chosen. The suggested algorithm enhanced influence spread and minimized the rich clubs’ interference. However, the suggested algorithm consumed a high running time for high-scale networks. He *et al.* [20] developed dynamic opinion maximization algorithm with the hybrid model for maximization of influence in social networks. The developed algorithm chose seed nodes that included community detection, and determination of nodes in candidate seed, alongside a seeding algorithm with discrete particle swarm optimization. The developed algorithm had an advantage over the selected benchmarks on the mean opinions of activated nodes. Nonetheless, when a huge number of nodes were identified in the search process of the developed method, it resulted in huge computational costs.

Kumar *et al.* [21] implemented a modified degree with exclusion ratio (MDER) method for influence maximization in social networks. The implemented method identified an influential node in social networks by modified degree centrality concept and exclusion of mutual. The implemented algorithm utilized ten real-life networks of different applications, complexity and size. The implemented method provided superior and highly diverse solutions. However, the method did not test huge-scale networks and lacked theoretical resistance to the relationship between influence and fairness. Fan *et al.* [22] introduced a discretizes the Harris Hawka optimization (DHHO) algorithm for IM in social networks. Depending on the six degrees of separation theory in social networks, huge accurate and common objective functions were developed to measure the seed nodes' influence. The introduced method utilized discrete coding and energy, wherein the position presentation rules were redefined and then given to influence the maximization problem. The introduced method covered influence quickly with huge accuracy. However, the influence spread of the introduced algorithm was small. Tang *et al.* [23] suggested a discrete scheduled particle swarm optimization

(DSPSO) algorithm for the maximization of influence in social networks. The suggested algorithm chose an optimum size of nodes to seed the group in every round to ensure the continuation of the spreading procedure. To make the whole exploration of the solution space, the strategy of local search, particularly for discrete network topology was developed on the best swarm individuals. The suggested algorithm had a high influence spread. Yet, repeated selection of nodes consumed more time in the suggested algorithm. The existing algorithms have limitations noted as: no consideration of the effect of overlapping caused by chosen huge central nodes in the seed set, thereby affecting its efficiency. The algorithms were not able to control the solution accuracy efficiently, resulting in increased network running time with small influence spread. Additionally, many existing algorithms have drawbacks in balancing efficiency and effectiveness to various extents. In this research, the proposed SS-BiAS-PSO algorithm has a global search ability to escape local optimal in influence maximization propagation (IMP). Moreover, the algorithm provides an advantage in optimum accuracy and time cost. This hybrid method takes benefit of the optimization process and efficiency of time that enables the features of network dynamics to address IMP in huge-scale social networks. The main contributions of the research are given below:

a. Based on the activation status with linear threshold (LT) model, an activated opinion model is developed. The four real-time datasets utilized for the analysis of influence propagation in social networks are: Ego-Facebook, Epinions, Gowalla and HepTh.
b. SSA and BiAS-PSO algorithms are integrated to increase the spread of influence based on IM problem to identify influential nodes in social networks through modifying the seed set values.
c. The performance of the proposed algorithms is analyzed by influence spread and running time of the network in terms of various iterations.

The rest of the research is organized in the following format: section 2 explains the details of the proposed algorithm. Section 3 designates the results and discussion of the proposed algorithm. Finally, section 4 presents the conclusion.

2. PROPOSED METHOD

In this section, the dataset utilized for research and the problem of IM in social networks is described. This research focuses on the LT method, one of the two primary influence diffusion methods, with the other being the independent cascade method. At last, the process of the proposed hybrid SS-BiAS-PSO algorithm is described.

2.1. Dataset

The datasets utilized for research are four real-world social networks with distinct characteristics. The four real-world datasets are: Ego-Facebook, Epinions, Gowalla, and HepTh [24]. Ego-Facebook, Gowalla and HepTh are referred to as "collaboration networks," while Epinions is referred to as a "trust network." Table 1 gives the statistical data of four datasets including the type of network, number of nodes, number of edges in the network, and the description of network.

Table 1. Dataset description

Datasets	Nodes	Edges	Types	Description
Ego-Facebook	4,039	88,234	Undirected	Social circles on Facebook
Epinions	75,879	508,837	Directed	Who trusts whom a network of Ep.com
Gowalla	196,591	950,327	Undirected, Geo-location	Gowalla location-based online social network
HepTh	27,770	352,807	Directed, Temporal labeled	ArXiv high energy physics paper citation network

2.2. Influence maximization (IM)

IM is the process of selecting a group of nodes in a social network so the major individuals are influenced by them [25]. The social network is described as a weighted graph $G = (V, E, W)$, the V represents a group of nodes, E represents a group of edges among nodes in G that express relationship among two users $W(u, v)$ is integrated with weight (u, v) edge and that represents influence of u on v. Considering the social network $G = (V, E, W)$ and k is positive integer, the IM issue aims to identify the seed set S^* with k nodes through V set as S to increase the speed of influence $\sigma(s)$ below a given diffusion method. The mathematical formula for IM is given as (1). In (1), S represents the chosen seed set, S^* represents the optimum set of seed nodes for IM, and $\sigma(s)$ represents the predictable count of influenced nodes.

$$S^* = \underset{S \subseteq V, |S| = k}{argmax\ \sigma(s)} \tag{1}$$

2.3. Methods for diffusion

The spread methods utilized for IM problems majorly include independent cascade (IC) and linear threshold (LT) methods. In a LT method, every directed edge $(u, v) \in E$ of social network G is integrated with the respective weight $W(u, v) \in [0,1]$. Here, $W(u, v)$ describes the ratio of user u's influence on v user between their neighbors. Additionally, every node is integrated with threshold $\theta(v) \in [0,1]$. This threshold is determined, with no ability to modify the process of spreading, meaning that the node v is activated while the weighted sum of whole activated nodes in the neighbor is higher than or equal to threshold $\theta(v)$. Initially, the seed node is active and various nodes are inactive. Afterward, the node v is stimulated to disturb the neighbor nodes, and the aforementioned process is repeated. The process of spread is stopped when the influence, sum the active nodes in the previous active nodes of the network that can not activate the inactive neighbor nodes.

In LT method, node v threshold is node acceptance to object propagating in the present network. The object includes information, products, where a single node is not enough to activate the v node, but the whole influence of various nodes activates v. While new objects are propagated in the social networks, users require a significant count of friends and relatives to accept objects. Hence, node v is activated through the general influence of receiving neighbors. This general influence transformation is a set behavior that frequently occurs in the society while facing difficult selections.

2.4. Proposed Bi-adaptive strategy-particle swarm optimization (BiAS-PSO) algorithm

In this research, including GA mutation strategy and metropolis criteria of simulated annealing (SA), a BiAS-PSO is proposed for improving the ability of global and local search of PSO. In PSO, a new strategy known as bi-adaptive is created among swarm and individuals, where every particle belongs to a bi-adaptive strategy. The detailed explanation of bi-adaptive strategy is described in the below sections.

2.5. Bi-adaptive strategy

In biological behavior, the individuals learned the experience through population, that tended to create experience from restricted count of graph nodes, as an outcome, population become much diverse. In PSO, a new strategy known as the bi-adaptive created among swarm and individuals is proposed. Here, every particle belongs to a bi-adaptive strategy. The mathematical formula for particle speed of PSO is given as (2).

$$v_i^{t+1} = wv_i^t + c_1r_1(pbest_i^t - x_i^t) + c_2r_2(gbest_i^t - x_i^t) + c_3r_3\left(Tbest_{bi(i)}^t - x_i^t\right) \tag{2}$$

Where, $bi(i)$ represents which two adaptive strategies the i^{th} particle belonged to, and $Tbest_{bi(i)}^t$ represents the optimum location of bi-adaptive strategy. The (c_3r_3) is same as (c_1r_1) and (c_2r_2). With bi-adaptive strategy added, the population maintained a characteristic of every bi-strategy on the process of iteration updation which maximizes the diversity of population and early convergence of PSO in resolving the huge-dimensional issues. The mathematical formula of inertia weight improves the local search performance, as given in (3). In (3), w_{max} and w_{min} denotes the maximum and minimum scores. t_{max} denotes the highest number of iterations.

$$w(t) = w_{max} - \frac{w_{max} - w_{min}}{t_{max}} t \tag{3}$$

2.5.1. Mutation strategy

The gene mutation is performed while the parent produced next generation for allowing children generation that has high search ability. Mutation operation is implemented in PSO algorithm through the mutation possibility operator $p_{mu} = e^{-\beta t / t_{max}}$. After the conventional update of PSO, a random number among 0 and 1 is produced and compared to p_{mu} for every particle. When the random number is lesser than p_{mu}, 2 dimensions are randomly chosen for every particle and random initialization is performed. At last, the fitness score of mutation particle is measured. If improved, the mutation operation is kept; or else, the particle is cached and mutation is maintained, or else determined through assigning the metropolis criteria.

2.5.2. Metropolis criteria

The Metropolis criteria is the main strategy of SA algorithm. As a new solution is produced from the previous one, the criteria are accepted depending on the fitness variance among the new and previous solutions. Metropolis criteria have an additional parameter temperature T. At high temperature, greater the accepted possibility, the particle is allowed to have the high ability of global search at initial search. The mathematical formula for measuring the possibility of accepting mutation is given as (4). In (4), $fit(x)$ denotes an assessment function and p_a denotes the possibility.

$$p_a = \begin{cases} 1, fit(x_i^{t,n}) < fit(x_i^{t,n+1}) \\ e^{\frac{fit(x_i^{t,n+1}) - fit(x_i^{t,n})}{T}}, fit(x_i^{t,n}) < fit(x_i^{t,n+1}) \end{cases} \quad (4)$$

2.6. Proposed salp swarm-bi-adaptive strategy particle swarm optimization (SS-BiAS-PSO) algorithm

The hybridization of the SSA and BiAS-PSO is used for the analysis of influence propagation in social networks. The SSA is more able of gaining the accuracy in different presented metaheuristics. The drawback of SSA is which gets trapped to a global or local optimal, which is unfit for high difficulties and has a low convergence rate, diversity and pre-convergence. To reduce these weaknesses and improve the searchability of SSA algorithm, the benefits of the PSO algorithm [26], [27] are combined and a new algorithm, SS-BiAS-PSO is proposed. The exploitation and exploration of SSA are improved through BiAS-PSO to develop a hybrid SSA-BiAS-PSO algorithm. The current algorithm finds the effective value of difficult optimization process. The BiAS-PSO algorithm phase is processed in exploring the optimum solution vectors. Therefore, SS-BiAS-PSO algorithm is elevated as a local search technique for enhancing the dominance of optimal solution. The proposed method is helpful in quickly trapping solution of the global optima and ignoring a local optimum in search area during the search procedure. Therefore, the proposed algorithm supports the capability to search and obtain correct convergences by accelerating search.

2.6.1. Initialization

In the searching process of an algorithm, the search stage randomly initializes the crowd following the given criteria, wherein the algorithm employs a random vector of n dimensions for i^{th} salp $X = x_i \sim (i = 1,2,3,\dots,n)$. The parameters utilized for initialization are population size (m), inertia weight (ω), learning parameters (c_1, c_2) and maximum velocity (V_{max}). Table 2 shows the parameters and their range of optimization algorithms.

Table 2. Parameters

Parameters	Range
Population size	[100, 500]
Inertia weight	[0.1, 1.0]
Learning parameters	[0, 2]
Maximum velocity	[0, 3]

2.6.2. Evaluation of fitness function

Fitness value of each search agent is evaluated through an objective function, while each search agent further considers new locations by fitness values in a search space. The optimization algorithm is initialized with a group of random particles (*i.e.*, solutions), then searching for an optimum solution through updating generations. In every iteration, all particles are updated with the next best values. The initial one is a good solution (*i.e.*, fitness), and is represented as p_{best}. Next, its value is then obtained through the optimizer by any particle in the population, signified as g_{best}.

2.6.3. Updating leader position

The location of a main search agent like a leader is represented by (5) and (6) for the search process in the search space. The leader location is utilized by the mathematical (2),

$$x_j^l = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) c_3 \ \geq 0.5 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) c_3 < 0.5 \end{cases} \quad (5)$$

where, x_j^l describes the location of superior and probable solutions, ub_j describes the upper bound of dimension j, ib_j describes the lower bound of dimension j, F_j describes the position of the food source, c_2 and c_3 describe the 2 random numbers in a range [0,1], c_1 describes the important variable in the algorithm that gradually minimizes over generations, allowing a vast exploration at an initial stage of the optimization procedure. The numerical expression of c_1 is mentioned (6). Here, L describes the maximum iterations and l represents the current iterations.

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad (6)$$

2.6.4. Velocity initialization

The velocity initialization is a significant part of population-based algorithms and with the help of the developed algorithm, it is possible to minimize the efforts of search agent on the search procedure in search space, and avoid incorrect positions. Many times, in a search process, these search agents leave the projected boundary of the search area which obstructs the identifying energy and provides less algorithm accuracy to find a global optimum, and therefore, the proposed algorithm plays a significant role in trapping an effective global optimal solution and avoiding local optimal in search space. The initialization of velocity is processed in 3 different ways, *i.e.*, i) small random value is initialized, ii) random values near to zero are initialized and at last, and iii) zero is initialized. Various initialization stages impact the algorithm accuracy in several ways.

2.6.5. Position updating of follower

The follower position in the search space of the search process is changed by mathematical (7).

$$v_i^{k+1} = w \times v_i^k + c_1 \times \left(salp_j^{fitness} - food_j^{position}\right) \tag{7}$$

where, v velocity plays a significant part in trapping the global optimum quickly and avoiding incorrect positions on the search procedure.

2.6.6. Stopping criteria

At last, the stopping criteria are given to search the global optimum for every kind of issue such as falling into the local optimal, slow convergence rate, and so on. Here, the criteria are utilized for estimating every search agent used in the procedure and replacing the superior position of the search agent, and this is repeated until the stopping criteria are satisfied. The remaining process is similar to the salp swarm algorithm. Figure 1 represents the process of the proposed SS-BiAS-PSO algorithm.

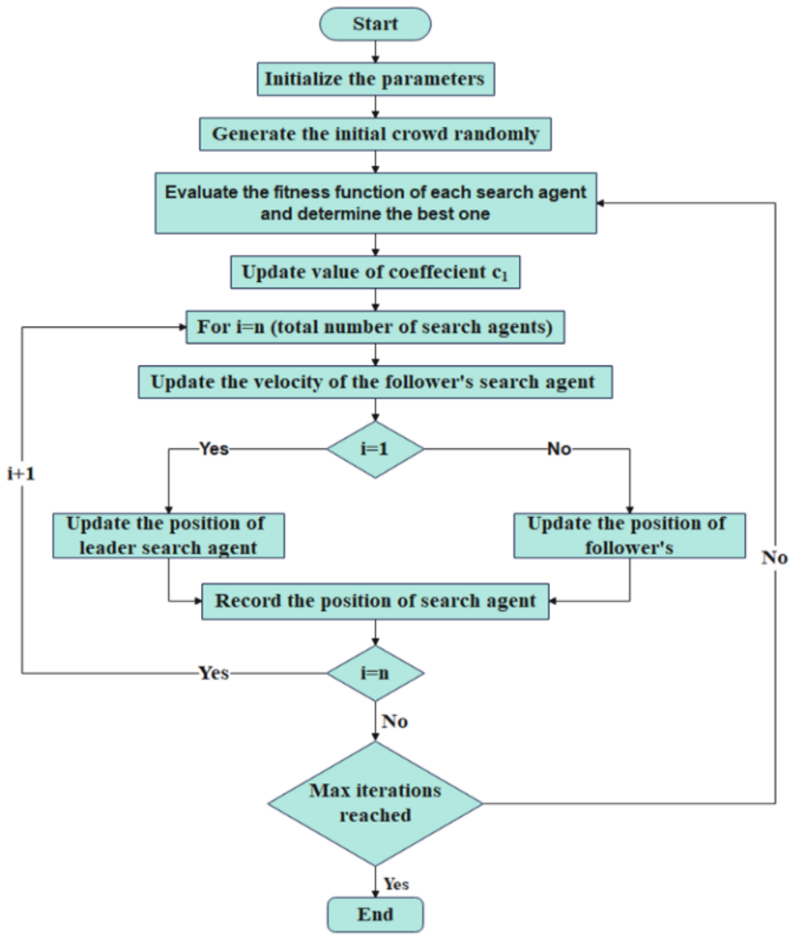

Figure 1. Process of proposed SS-TSAPSO algorithm

The proposed SS-BiAS-PSO algorithm plays a significant role in trapping a solution in the search space during the process of search and the benefits are given below:

a. The proposed SS-BiAS-PSO algorithm holds a superior optimum solution after every iteration.
b. The proposed SS-BiAS-PSO updates the position of every search agent in the search space with the aim of the search agent being to exploit and explore in the search space for a better optimal solution.
c. The SS-BiAS-PSO algorithm updates a position of the follower's agent with a support of velocity. This plays a significant role in avoiding an incorrect location and quick trapping of global optimum in the search space. It also improves balance among exploitation and exploration.
d. The deliberate use of slow movements by the follower search agent during search in the search space serves to safeguard the SS-BiAS-PSO algorithm against descending to local optima.
e. The significant parameter of the SSA algorithm supports the SS-BiAS-PSO algorithm in minimizing the complexity, making it effortless for execution.

In the diffusion process, the propagated data is adopted through certain nodes in the network. The nodes' obtained data is propagated further at some rate defined by their popularity. The obtained parameter represents the extent to which data spreads in the network.

3. RESULTS AND DISCUSSION

The performance of the proposed SS-BiAS-PSO algorithm is implemented by Python environment with the following system requirements: RAM: 16 GB, processor: Intel core i7, and operating system: Windows 10 (64 bit). The performance of the proposed algorithm is estimated in terms of the performance measures of influence spread and running time of the network with different iterations. Various tables and graphs are described to show the effectiveness of proposed algorithm.

3.1. Quantitative and qualitative analysis

The performance of the proposed algorithm is analyzed with influence spread and running time of a network on four datasets utilized for research. The existing algorithms considered for evaluation are the whale optimization algorithm (WOA), grey wolf optimization (GWO), salp swarm algorithm (SSA), and particle swarm optimization (PSO) algorithms. Various tables and figures are represented below to show that the proposed algorithm is performed superiorly.

Table 3 and Figure 2 show the performance of the proposed algorithm, which is analyzed by influence spread with Ego-Facebook dataset at seed size k, ranging from 10 to 40. The proposed algorithm reaches a high influence spread of 645, 680, 705, and 725 for iterations of 100, 200, 300 and 400, respectively. The proposed algorithm performs superiorly when compared with other existing algorithms like WOA, GWO, SSA, and PSO algorithms.

Table 3. Influence spread of proposed method for Ego-Facebook dataset

Seed set size (k)	Influence spread for Ego-Facebook				
	WOA	GWO	SSA	PSO	SS-BiAS-PSO
10	572	584	603	620	645
20	589	606	620	644	680
30	597	618	647	695	715
40	627	658	684	702	750

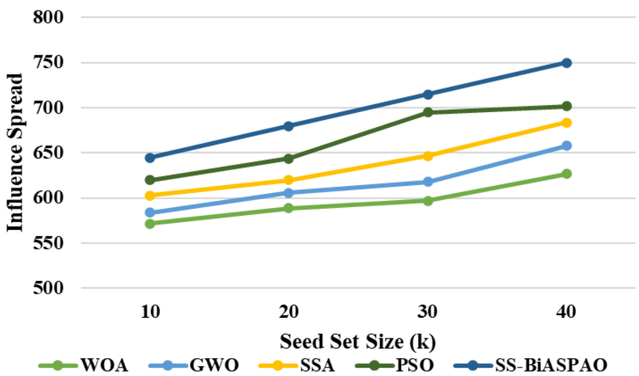

Figure 2. Influence spread of proposed method for Ego-Facebook dataset

Table 4 and Figure 3 display the performance of the suggested algorithm which is analyzed by influence spread with Epinions dataset at seed size k ranging from 10 to 40. The proposed algorithm reaches a high influence spread of 70, 95, 107 and 128 for iterations of 100, 200, 300, and 400, respectively. The proposed algorithm performs commendably, as opposed to other existing algorithms.

Table 4. Influence spread of proposed method for Epinions dataset

Seed set size (k)	Influence spread for Epinions				
	WOA	GWO	SSA	PSO	SS-BiASPSO
10	40	47	65	80	100
20	49	55	90	110	150
30	57	63	76	115	190
40	69	74	88	147	220

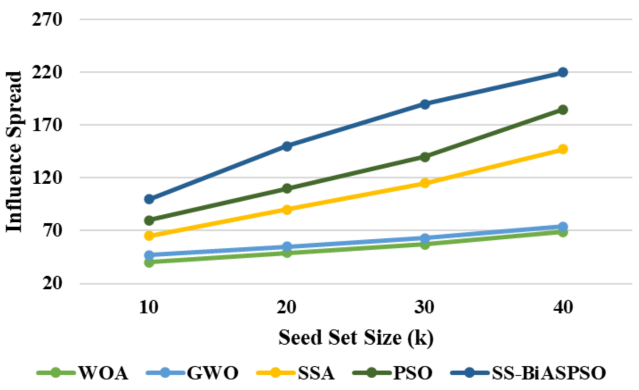

Figure 3. Influence spread of proposed method for Epinions dataset

Table 5 and Figure 4 demonstrate the performance of the suggested algorithm, which is analyzed by the influence spread with Gowalla dataset at seed size k ranging from 10 to 40. The SS-BiAS-PSO algorithm reaches a high influence spread of 2090, 2200, 2350, and 2500 for corresponding iterations of 100, 200, 300, and 400, thereby outperforming the previous algorithms.

Table 5. Influence spread of proposed method for Gowalla dataset

Seed set size (k)	Influence spread for Gowalla				
	WOA	GWO	SSA	PSO	SS-BiAS-PSO
10	1538	1610	1720	1950	2090
20	1605	1728	1944	2070	2200
30	1748	1869	2015	2160	2350
40	1874	1983	2103	2340	2500

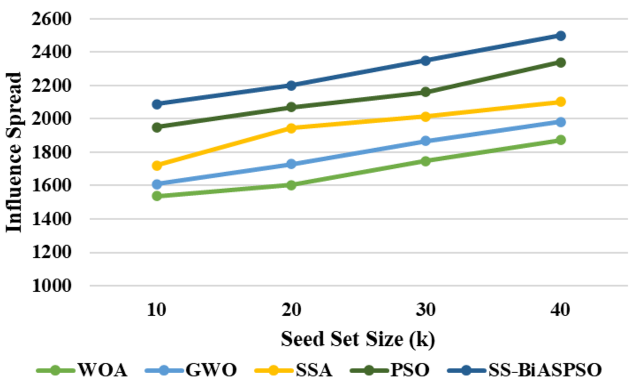

Figure 4. Influence spread of proposed method for Gowalla dataset

Table 6 and Figure 5 demonstrate the outcomes of the proposed algorithm analyzed by means of influence spread with the HepTh dataset at seed size k ranging from 10 to 40. The SS-BiAS-PSO algorithm attains a high influence spread of 438, 460, 472, and 493 correspondingly for iterations of 100, 200, 300 and 400, as opposed to the previous algorithms.

In Table 7, the performance of the proposed algorithm is evaluated by running time for four different datasets. The proposed method utilizes the running time of 0.2×102, 0.5×102, 0.7×102, and 103 for 100, 200, 300, and 400 iterations in the Ego-Facebook dataset. The proposed method consumes a running time of 102, 0.2×102, 0.6×102, and 103 simultaneously for 100, 200, 300, and 400 iterations on the Epinions dataset. The suggested method consumes a running time of 0.3×103, 0.5×103, 0.8×103, and 104 simultaneously for 100, 200, 300, and 400 iterations on the Gowalla dataset. On the other hand, on the HepTh dataset, it consumes a running time of 0.7×103, 104, 0.5×104, and 0.8×104 individually for 100, 200, 300, and 400 iterations.

Table 6. Influence spread of proposed method for HepTh dataset

Seed Set Size (k)	Influence Spread for HepTh				
	WOA	GWO	SSA	PSO	SS-BiAS-PSO
10	364	387	402	417	438
20	383	404	424	442	460
30	401	417	439	460	472
40	419	438	467	480	493

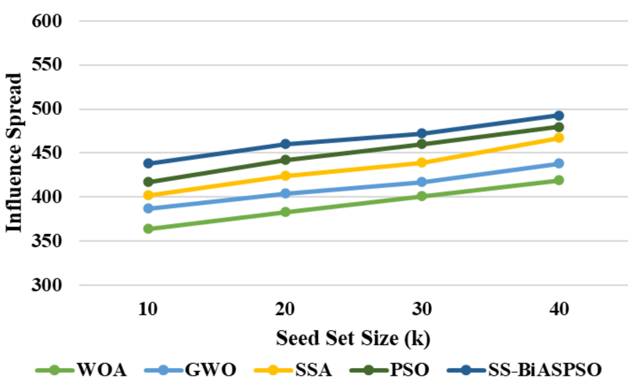

Figure 5. Influence spread of proposed method for HepTh dataset

Table 7. Running time for a proposed method with four datasets

Seed Set Size (k)	Running time for various datasets (sec)			
	Ego-Facebook	Epinions	Gowalla	HepTh
10	0.2×102	102	0.3×103	0.7×103
20	0.5×102	0.2×102	0.5×103	104
30	0.7×102	0.6×102	0.8×103	0.5×104
40	103	103	104	0.8×104

3.2. Comparative analysis

The performance of the proposed SS-BiASPSO algorithm is compared with other existing techniques like ABEM [16], OCPSO [17] and DHHO [22] at seed size k ranging from 10 to 40. The SS-BiAS-PSO algorithm is compared in terms of influence spread and running time of the network on the Ego-Facebook, Epinions and Gowalla datasets. Table 8 represents the comparative analysis of the proposed algorithm.

From Table 8, it is clear that the proposed algorithm performs preferably in relation to the existing algorithms like ABEM [16], OCPSO [17] and DHHO [22]. The SS-BiAS-PSO algorithm attains a high influence spread of 680 with a minimized time of 0.5×102 for the Ego-Facebook dataset, alongside a high influence spread of 100 with a minimized time of 0.2×102 for the Epinions dataset, and a commendable influence spread of 2,200 with minimized time of 0.5×103 on the Gowalla dataset at seed size k=10, thereby outperrming the preexisting techniques.

Table 8. Comparative analysis

Dataset	Methods	Influence Spread			
		k=10	k=20	k=30	k=40
Ego-Facebook	ABEM [16]	540	650	700	740
	OCPSO [17]	320	340	360	N/A
	DHHO [22]	320	350	370	400
	Proposed SS-BiAS-PSO	645	680	715	750
Epinions	OCPSO [17]	80	140	170	N/A
	Proposed SS-BiAS-PSO	100	150	190	220
Gowalla	OCPSO [17]	2060	2100	2160	N/A
	Proposed SS-BiAS-PSO	2090	2200	2350	2500

3.3. Discussion

In this section, the benefits of the proposed algorithm and drawbacks of existing algorithms is explained. The ABEM [16] method has the limitations noted as follows: no consideration of the effect of overlapping caused by the chosen high central nodes in seed set that affect the efficiency. The OCPSO [17] algorithm cannot control the solution accuracy well, whereby the network's running time is increased. Hence, the selection of a minimum-cost seed node group to acquire the influence maximization of a node is a major issue to be solved. The time utilized for influence propagation in the social networks is the maximum in the previous method that needs to be resolved. In this manuscript, the SSA and BiAS-PSO algorithms are integrated to increase the spread of influence based on the IM problem and minimize the running time of the network. The SS-BiAS-PSO algorithm is evaluated with four datasets: Ego-Facebook, Epinions, Gowalla, and HepTh. This algorithm attains a noteworthy spread of influence with less running time of social network, proving superior to the existing algorithms.

4. CONCLUSION

The existing research is mainly concentrated only on increasing the spread of influence and does not consider the running time of the network. In this research, the SSA and BiAS-PSO algorithms are integrated and named as SSPSO algorithm to increase the spread of influence based on the IM problem with minimized network running time. The datasets utilized for the research are Ego-Facebook, Epinions, Gowalla and HepTh datasets, while and LT is deployed as a diffusion method. Then, the proposed SS-PSO algorithm is utilized for the analysis of influence propagation. The proposed algorithm is analysed in terms of performance measures of influence spread and running time of the network. The SS-BiAS-PSO algorithm reaches a high influence spread of 645, 680, 715, and 750 with less running time at seed size k ranging from 10 to 40 in Ego-Facebook. It also accomplishes a high influence spread of 2090, 2200, 2350 and 2500 with less running time at seed size k ranging from 10 to 40 in Gowalla. Moreover, a high influence spread of 100, 150, 190 and 220 with less running time is obtained at seed size k ranging from 10 to 40 in Ego-Epinions, while an influence spread of 438, 460, 472, and 493 with less running time is witnessed at seed size k ranging from 10 to 40 in HepTh. The proposed algorithm performs commendably in relation to other existing algorithms such as WOA, GWO, SSA, and PSO. In the future, various metaheuristic optimization algorithms can be used to further enhance the performance of influence propagation. The proposed method can be used for various purposes like identifying the spread of disease, crime rate prediction, and identifying social movements. The analysis of social networks is used as a tool to understand and predict human behavior.

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BIOGRAPHIES OF AUTHORS

Akshata Sandeep Bhayyar is currently working as assistant professor, Department of Computer Science and Engineering, RIT. Having teaching experience of 11 years and areas of interest are data mining, sentimental analysis, cognitive psychology in online social network. She can be contacted at email: akshataphd@gmail.com.

Kiran Purushotham working as HoD, professor in Computer Science and Engineering Department, RNSIT, Bengaluru from past 24 years. His research interests include cryptography, big data analytics, data mining, privacy preserving data mining and privacy preserving data publishing. He can be contacted at email: kiranpmys@gmail.com.