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Research Article

Opinion Leaders Selection with Grey Wolf Optimizer Algorithm on Social Networks

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Abstract

Digital social network services are same social networks which people call it in their everyday language. Social media platforms and web sites that enable knowledge transfers through social networks are digital tools designed to build social networks and develop them. The interest and the high use of social networks is make these environments available for a variety of activities, including economic, cultural, political, and etc. Opinion leaders one of the significant issues that exists in these environments which have high influence on other users. Opinion leaders in social networks are beneficial and we will be able to use their empowerment and influence by identifying them. In this paper, we have chosen the opinion leaders with Grey Wolf Optimizer (GWO) algorithm. It mimics the leadership hierarchy and hunting mechanism of grey wolves in nature and include 3 main steps of hunting, searching for prey, encircling prey, and attacking prey. Based on the investigations and the results, number of actual opinion leaders identified by this algorithm are significant and the advantage of proposed method is compatibility with different criteria and providing sustainability results in different ways.

Keywords : Opinion Leader, leadership; Grey Wolf Optimizer Algorithm; Virtual Communities; Social Networks.

1 Introduction

Through the use of computers and networks, online forums and social websites have extended people's traditional social contexts and their personal learning networks (PLNs). Online communication has improved the scope of people's interactions and contributed to knowledge sharing, people's learning. People who have similar interests or goals often enjoy interacting and sharing knowledge with each other, and with the help of online forums, their personal relationship networks have expanded into cyberspace and resulted in the formation of different types of virtual communities (VCs). The increasing use of VCs has also attracted considerable attention and created a new educational platform for academic researchers [1]. On social networks, some users have a lot of followers for variety of reasons, such as social popularity, activity, exper-

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tise and etc. This indicates the high penetration of these people, they are often called opinion leaders. In the propagation process of public opinion, opinion leaders have a profound impact on the opinion formation of ordinary agents [2]. An opinion leader is a person or set of persons having more influence on the customers adoption process and decision making [3]. Identification of opinion leader is a two-step procedure in 1- opinion leader analyzes, examine and understand the end users requirements, and 2- opinion leader derives their own opinion from the first step incorporated with their knowledge and skills [4]. The dissemination process of public opinion is a complex system of co-evolution of opinions and networks, and involves many variables, such as network structure, the number of agents involved, and description of opinions. Besides, it is difficult for probability- or statistics-based mathematical models to describe the dynamic evolution of collective opinions. Opinion dynamics models focus on the interaction mechanism between opinions, and assume that agents will decide their own opinions based on those of their opinion neighbors in the network. On that account, an opinion dynamics model is more suitable for the study of the opinion dissemination mechanism on user relationship-based social media platforms [5]. Before making decisions, consumers often seek to reinforce their opinions through gaining consensual validation from certain others [6]. Among these certain others are consumers who can exert an unequal amount of influence on the decisions of others; they are opinion leaders. Opinion leadership refers to the degree to which an individual is able to influence other individuals' attitudes or behavior informally in a desired way with relative frequency. In this light, opinion leaders are those consumers who influence the motivations, attitudes, opinions, beliefs and behaviors of others [7]. Applied bounded confidence theory to construct opinion dynamics models to analyze the influence of opinion leaders in social networks. The results revealed that, as long as the confidence levels of ordinary agents in a social group are sufficiently high, even if the initial opinions of the ordinary agents are dissimilar to those of the opinion leaders, the opinion leaders are eventually able to guide the ordinary agents to accept their desired opinions. Considering that, in some cases, opinion leaders cannot always help spread the desired opinion [8]. In this research we introduce a method for selecting opinion leaders using GWO metaheuristic algorithm and relationships between members. Firstly, we perform a series of pre-processing on the initial data; we are going to choose the primary opinion leaders then map achieved parameters to GWO algorithm and optimize the result. In fact, in this paper we achieve better results by selecting the initial voting leaders with one criterion in the first stage and placing it in the GWO algorithm and optimizing it in the second stage. the advantage of proposed method is compatibility with different criteria and providing sustainability results in different ways. The paper structure is defined as follows: Section 2 is about the previous and related works, section 3 section introduces the GWO algorithm and section 4 introduces the proposed method, section 5 represent results and discussion and section 6 includes the discussion and presentation of suggestions for future work.

2 RELATED WORKS

The study on opinion leaders are compared with gather information from mass communications, most of the voters get their information from other part of voters who pay more attention to information from media. Thus, more influential voters are called opinion leaders [8, 9, 10]. The two-step flow theory proposed that opinion leaders connected to the public through mass media, play a huge role in filtering and re-disseminating information. Earlier studies about opinion leaders concentrated on the field of communication, and after that many studies identified the relationship between opinion leaders and followers exists in many other fields [9]. The studies on opinion leader identification can be divided into two parts: (1) link-based opinion leader identification methods, this type of approach focuses on analyzing social influence and connectivity feature via the structure of graph and information flow. The representative approaches, namely PageRank and HITS use the hyperlink structure of web pages to calculate page importance [11, 12]. These approaches have been adapted to identify opinion

Table 1: Side By Side Comparison of the Reviewed Methods.

Title	Author and year
Influence Rank algorithm [13]	X. Song et al-2007
Top centrality [36]	F. Bodendorf et al.-2009
Domain-specific opinion leadership hypothesis [37]	F. Li et al.-2011
BARR [19]	R. Van der Merwe et al.-2009
A social network approach and threshold model based on distance [23]	Y. Cho et al.-2012
Extended Advogato trust Algorithm [20]	S. Al-Oufi et al.-2012
Top in and out-degree [24]	Y. S. Kim et al.-2013
Hybrid IO-degree [24]	Y. S. Kim-2013
Super edge rank algorithm [22]	N. Ma et al.- 2014
Total trust value [21]	S. M. Aghdam et al.-2016
A new opinion leaders detecting algorithm [25]	G. Sun et al.-2018
firefly search algorithm [12]	L. Jain et al.-2019
Opinion leader detection using whale optimization algorithm [9]	L. Jain, et al.-2020

Table 1. Continue

Positive point	Negative point	How is work
Simple and uses coverage, diversity, and distortion metrics	Only applicable in the blogosphere; does not describe the method to remove extraneous content	Identify the leader based on the content posted by the user in the blogosphere. The algorithm also ranked the blogs according to the contribution in the network
Simplicity	Insufficient accuracy	Analyze users relationships and users connections
Useful for marketing strategies and the diffusion of new product	Limited only for marketing area and few centrality measures used	Link the leadership phenomenon with the social network theory and proposed that opinion leader are more domain specific rather than topic specific
Useful for marketing strategies	Only consider the blogs	Include blog material, lovers, and their relationship to find the lighted area. Opinion leaders selected based on the material placed by them
Almost optimal identification	Need a lot of computing	Analyze sociality, distance and centrality
Control access permission in the network; Useful in the recommended system	Used only the binary link structure of the network; Trust metric is not useful for explicit global relationships	Enhance the Advogato trust metric that assists with the finding of Trustworthy users related to each entity. Also used capacity-first maximum flow method to find the most reliable user
Simplicity	Insufficient accuracy	Use social network method with analyze users relationships
Simplicity	Insufficient accuracy and threshold set	Use social network method with analyze users relationships and threshold
Accuracy and optimal identification	Need a lot of computing	hybrids the network topology analysis and text mining
Almost optimal identification	Need a lot of computing	trust relationship evaluating
Introduce multi-relation concept; less iteration time; improve performance	Compared only with page-rank; High complexity	Node importance matrix in multi-relational social network proposed based on signal spreading to identify the opinion leade
Almost optimal identification	Need a lot of computing	used the modified firefly algorithm and analyze users relationships
Accuracyand efficiency of the algorithm is also increases because more information about the other users vector position accumulated	Difficult to set some parameters	proposed a social network based nature-inspired algorithms with different standard benchmark optimization functions

leaders in online communities [13, 14]. (2) Hybrid the social link information with semantic-based information embodied in documents [15, 11, 12]. In fact, both social links and textual information associated with persons are important for opinion leader identification. A number of studies have hydrides text mining and social interaction to identify opinion leaders [16, 17]. Song, X., et al. in their work Identify the leader based on the content posted by the user in the blogosphere. The algorithm also ranked the blogs according to the contribution in the network [13]. Li et al. in [18] introduce a framework which validated by an experimental study. The framework analyzes textual content, user behavior, and time, this study ranked opinion leaders based on expertise, novelty, influence, and activity. In another work Van der Merwe, R. and G. Van Heerden Link the leadership phenomenon with the social network theory and proposed that opinion leader are more domain specific rather than topic specific [19]. Al-Oufi, S., H.-N. Kim, and A. El Saddik for identify opinion leaders Enhance the Advogato trust metric that assists with the finding of Trustworthy users related to each entity. Also used capacity-first maximum flow method to find the most reliable user [20]. Aghdam and Navimipour in [21] propose a new way to identifying the opinion leaders in online communities. That study uses the trust relationship between the users and evaluates the total trust value of primary opinion leaders then chose that users which have top total trust value as opinion leaders. In [22], Ma and Liu to selecting opinion leaders introduce SuperedgeRank algorithm which hybrids the network topology analysis and text mining. First, the study established a super network model with multidimensional sub networks, which are social, psychological, environmental and viewpoint sub networks. Then, the study proposed four super network indexes: node super degree, super edge degree, super edgesuper edge distance, and super edge overlap. then study applied SuperedgeRank algorithm to rank super edges, and used the result to select opinion leaders. In [23] those users who have high sociality and high emission speeds choices with using a social network method and threshold model as opinion leaders and [24] select those users' with top-in degree, top- out degree and hybrid mix of in-degree and out-degree with varying weights as influential opinion leaders. Sun, G. and S. Bin in 2018 introduce a new approach which act by Node importance matrix in multi-relational social network based on signal spreading to identify the opinion leaders [25]. [12] Introduced an approach to discover the local and global opinion leader in the social network communities using a modified Louvain method to find out the communities in the social network built on the modularity gain of the network heuristic and firefly search algorithm. One of the latest works about opinion leaders is [9] which propose a new social network based nature-inspired whale optimization algorithms with different standard benchmark optimization functions to identify the top-n opinion leaders in the social network. Also in Table 1, some works about opinion leaders compared with each other. Meta-heuristics may be classified into three main classes: evolutionary, physics-based, and SI algorithms (SI is The emergent collective intelligence of groups of simple agents). Evolutionary algorithms (EAs) are usually inspired by the concepts of evolution in nature. The most popular algorithm in this branch is GA. This algorithm was proposed by Holland in 1992 and simulates Darwinian evolution concepts. [26] used this algorithm for redundancy allocation problem (RAP). The engineering applications of GA were extensively investigated by Goldberg. The optimization is done by evolving an initial random solution in EAs. Each new population is created by the hybridization and mutation of the individuals in the previous generation. Since the best individuals have higher probability of participating in generating the new population, the new population is likely to be better than the previous generation(s). This can guarantee that the initial random population is optimized over the course of generations. Some of the EAs are GWO [27], Farmland Fertility Algorithm [28], Symbiotic Organisms Search Algorithm[29, 30], Whale Optimization Algorithm [31, 32] and etc. GWO inspired by grey wolves (Canis lupus). It mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented. Table 1 show the comparison of related works.

3 GWO ALGORITHM

Grey wolf (Canis lupus) belongs to Canidae family. Grey wolves are considered as apex predators, meaning that they are at the top of the food chain. Grey wolves mostly prefer to live in a pack. The group size is 512 on average. Of particular interest is that they have a very strict social dominant hierarchy as shown in fig. 1. The leaders are a male and a female, called alpha. The alpha is mostly responsible for making decisions about hunting, sleeping place, time to wake, and so on. The alphas decisions are dictated to the pack. In gatherings, the entire pack acknowledges the alpha by holding their tails down. The alpha wolf is also called the dominant wolf since his/her orders should be followed by the pack [33, 27]. (fig 1). The second level in the hierarchy of grey wolves is

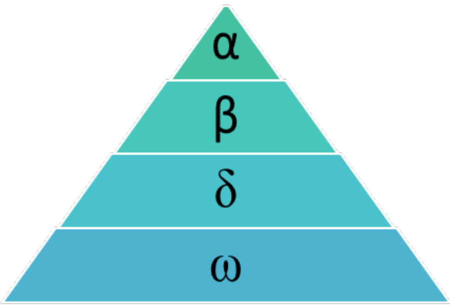

Figure 1: Hierarchy of grey wolf (dominance decreases from top down.

beta[27]. The betas are subordinate wolves that help the alpha in decision-making or other pack activities. The beta wolf can be either male or female, and he/she is probably the best candidate to be the alpha in case one of the alpha wolves passes away or becomes very old. The beta wolf should respect the alpha, but commands the other lower-level wolves as well. It plays the role of an advisor to the alpha and discipliner for the pack. Delta wolves have to submit to alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category. Scouts are responsible for watching the boundaries of the territory and warning the pack in case of any danger. Sentinels protect and guarantee the safety of the pack. Elders are the experienced wolves who used to be alpha or beta. Hunters help the alphas and betas when hunting prey and providing food for the pack. Finally, the caretakers are responsible for caring for the weak, ill, and wounded wolves in the pack. The omega plays the role of scapegoat. Omega wolves always have to submit to all the other dominant wolves. They are the last wolves that are allowed to eat. It may seem the omega is not an important individual in the pack, but it has been observed that the whole pack faces internal fighting and problems in case of losing the omega. This is due to the venting of violence and frustration of all wolves by the omega(s). This assist satisfying the entire pack and maintaining the dominance structure. In some cases, the omega is also the babysitters in the pack. If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). The main phases of grey wolf hunting are Tracking, chasing, and approaching the prey. Pursuing, encircling, and harassing the prey until it stops moving. Attack towards the prey [34]. These steps are shown in fig. 2. In order to mathematically

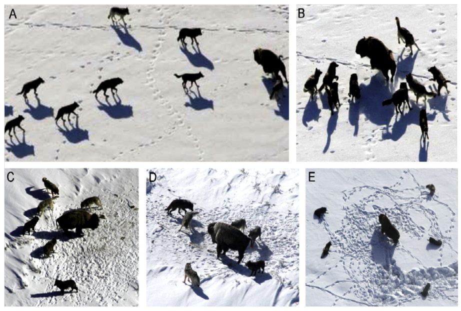

Figure 2: Hunting behavior of grey wolves: (A) chasing, approaching, and tracking prey (BD) pursuing, harassing, and encircling (E) stationary situation and attack [34].

model the social hierarchy of wolves when designing GWO, the fittest solution consider as the alpha (a). Consequently, the second and third best solutions are named beta (b) and delta (d) respectively. The rest of the candidate solutions are assumed to be omega (x). In the GWO algorithm the hunting (optimization) is guided by a, b, and d. The x wolves follow these three wolves. As mentioned above, grey wolves encircle prey during the hunt (In other sense, $\overrightarrow{D}$ is the distance between the wolf and the prey). In order to mathematically model encircling behavior the 3.1 and 3.2 are used:

$$\overrightarrow{D} = |\overrightarrow{C} \times \overrightarrow{X}p(t) - \overrightarrow{X}(t)| \tag{3.1}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X}p(t) - \overrightarrow{A} \times \overrightarrow{D} \tag{3.2}$$

Where t indicates the current iteration, $\vec{A}$ and $\overrightarrow{C}$ are coefficient vectors, $\overrightarrow{X}p$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf. The vectors $\overrightarrow{\mathrm{A}}$ and $\vec{C}$ are calculated as follows:

$$\overrightarrow{\mathrm{A}} = 2\overrightarrow{\mathrm{a}} \times \overrightarrow{\mathrm{r}}1 - \overrightarrow{\mathrm{a}} \tag{3.3}$$

$$\overrightarrow{\mathrm{C}} = 2 \times \overrightarrow{\mathrm{r}}2 \tag{3.4}$$

$$\overrightarrow{\mathrm{a}} = 2 \times 2(iterations/maxiterations) \tag{3.5}$$

Where components of $\overrightarrow{\mathrm{a}}$ are linearly decreased from 2 to 0 over the course of iterations(To shrink the hunting ring.) and r1, r2 are random vectors in [0, 1]. To see the effects of Eqs. 3.1 and 3.2, a two-dimensional position vector and some of the possible neighbors are illustrated in Figure 3(a). As can be seen in this figure, a grey wolf in the position of (X, Y) can update its position according to the position of the prey (X*, Y*). Different places around the best agent can be reached with respect to the current position by adjusting the value of $\overrightarrow{\mathrm{A}}$ and $\vec{C}$ vectors. For instance, (X*X, Y*) can be reached by setting $\overrightarrow{\mathrm{A}}$ =(1,0) and $\overrightarrow{\mathrm{A}}$ =(1,1). The possible updated positions of a grey wolf in 3D space are depicted in Figure 3(b). Note that the random vectors r1 and r2 allow wolves to reach any position between the points illustrated in 3. So a grey wolf can update its position inside the space around the prey in any random location by using 3.1 and 3.2.

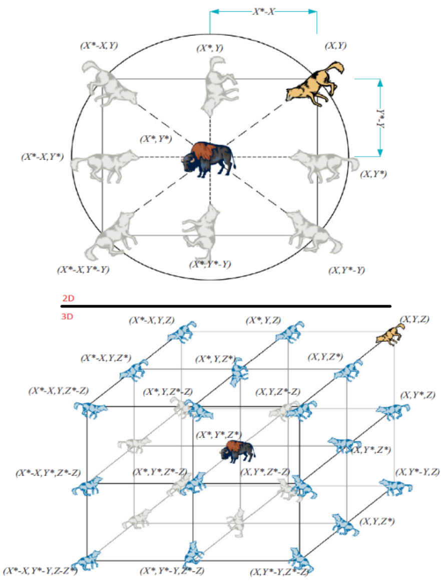

Figure 3: 3. 2D and 3D position vectors and their possible next locations [27].

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution) beta, and delta have better knowledge about the potential location of prey. Therefore, three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The following formulas are used [27].

$$\overrightarrow{\mathrm{D}}\alpha = |\overrightarrow{\mathrm{c}}1 \times \overrightarrow{\mathrm{X}}\alpha - \overrightarrow{\mathrm{x}}|, \overrightarrow{\mathrm{D}}\beta = |\overrightarrow{\mathrm{C}}2 \times \overrightarrow{\mathrm{X}}\beta - \overrightarrow{\mathrm{X}}|, \overrightarrow{\mathrm{D}}\delta = |\overrightarrow{\mathrm{C}}3 \times \overrightarrow{\mathrm{X}}\delta - \overrightarrow{\mathrm{X}}| \tag{3.6}$$

$$\overrightarrow{\mathrm{X}}1 = \overrightarrow{\mathrm{X}}\alpha - \overrightarrow{\mathrm{A1}} \times (\overrightarrow{\mathrm{D}}\alpha), \overrightarrow{\mathrm{X}}2 = \overrightarrow{\mathrm{X}}\beta - \overrightarrow{\mathrm{A}}2 \times (\overrightarrow{\mathrm{D}}\beta), \overrightarrow{\mathrm{X}}3 = \overrightarrow{\mathrm{X}}\delta - \overrightarrow{\mathrm{A}}3 \times (\overrightarrow{\mathrm{D}}\delta) \tag{3.7}$$

$$\overrightarrow{\mathrm{X}}(\mathrm{t}+1) = \frac{\overrightarrow{\mathrm{x}}1 + \overrightarrow{\mathrm{x}}2 + \overrightarrow{\mathrm{x}}3}{3} \tag{3.8}$$

Figure 4. represent pseudo code and 5 represent flowchart of the GWO algorithm and 6 represent flowchart of the proposed approach.

```
Initialize the GWO population X_i(i=1,2,...,n)
Initialize a, A, and C (with equations 5, 3 and 4)
Calculate the fitness of each search agent
X_α= the best search agent
X_β= the second best search agent
X_δ= the third best search agent
While (t<Max number of iterations)
 For each search agent
     Update the position of the current search agent (with
equation 8)
End for
Update a,A, and C (A,C are updated according to a and a
updating according equation 5)
Calculate the fitness of all search agents
Update X_α, X_β, and X_δ, t=t+1;
End while
Return X_α
```

Figure 4: Pseudo code of the GWO algorithm.

4 PROPOSED METHOD

The act of selecting opinion leaders is use data of relationships between users. This initial data

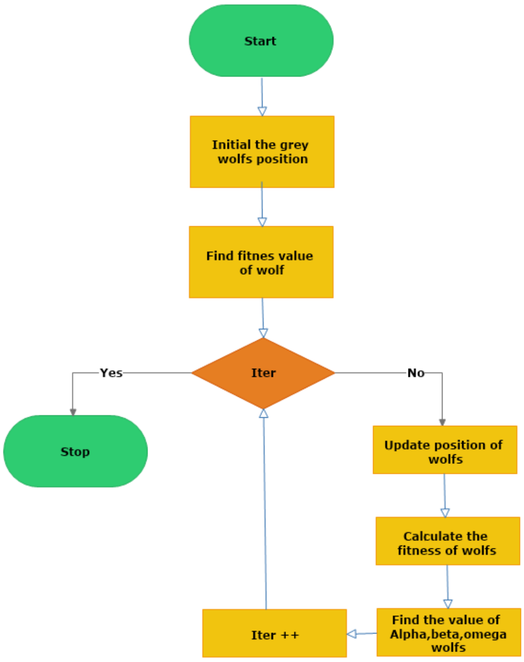

Figure 5: Flowchart of the GWO algorithm.

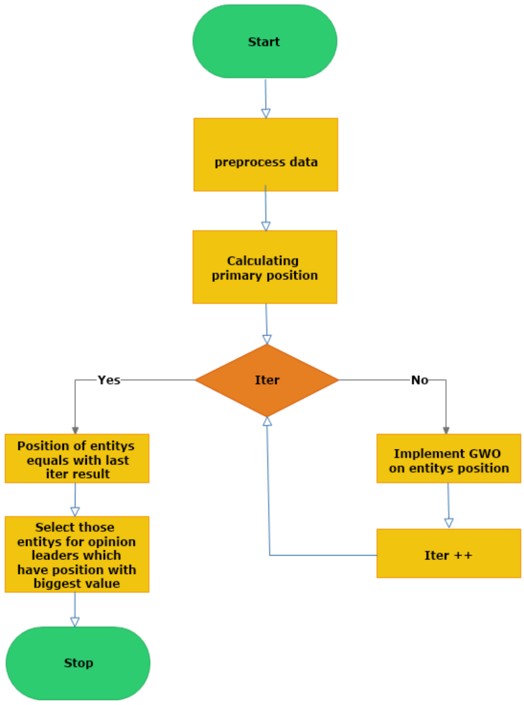

Figure 6: flowchart of the proposed approach.

requires a series of pre-processing. In order to achieve optimal and accurate results, primary data are pre processed, then at the second step users mapped to vector, in three step we identified alpha, beta and omega and at the last we apply the GWO algorithm and select opinion leaders.

4.1 Opinion Leader Selecting

4.1.1 Data Filtering

In this study, we have used opinions website data sets to test the proposed method which includes users ' vote to reviews which written by other users. Data sets are publicly available at [35] To avoid of error causes and losing of accuracy self-trust statements and duplicate comments are removed.

4.1.2 Mapping Users to Vector Space

The GWO algorithm works based on population and particles. In this optimization method, we need to display the entities in a vector space to available calculate the distance between particles and optimize their position. In this paper, we will display users position in vector spaces based on user opinions. This means that users on social networks have a number of positive and negative votes for their content and also gave positive and negative comments to other users. Here, the hybridization of positive and negative comments taken by users as a point x and positive and negative comments given as y is considered. The reason for choosing the gray wolf optimization algorithm to selecting opinion leaders is the similarity of its nature and its entities to the structure of social networks and opinion leaders. Some other reasons are as follows: - The social hierarchy assists GWO to save the best solutions obtained so far over the course of iteration. - The encircling mechanism defines a circle-shaped neighborhood around the solutions which can be extended to higher dimensions as a hyper-sphere. - The GWO has only two main parameters to be adjusted (a and C).

4.1.3 Identifying Alpha, Beta and Omega

The GWO algorithm solves the problem by calculating and updating the angular position based on the position of the alpha, beta and omega wolfs. So, we need to identify them, we use a hybrid method to recognize alpha, beta, and omega wolfs that is obtained from 4.9. In fact, this relationship acts as a fitness function and the values obtained by this equation are considered as input to the gray wolf algorithm.

$P = X + Y$

X =
$\alpha \times$ (in-degree positive - in-degree negative)

Y =

$$1-\alpha\times(out-degreepositive+out-degreenegative) \tag{4.9}$$

Where p is the node's position and in and out-degree is positive or negative feedbacks which a user gave or taken that, and $\alpha = 0.7$, where α increases the value of input comments toward output comments. So, we consider the sum of x and y for each nod and a node with the largest value it is in the best position and holds a high ranking. in truly we select three best opinion leaders with 4.9 and map them to primary alpha, beta and omega values and with this parameter run GWO algorithm to the specified number of repetitions for all nods in papulation. So, at this step, with a loop which is repeat to a certain number (300 iterations in this paper) we apply GWO algorithm on the initial population. After applying the algorithm on the population, we sort the results and select those users as opinion leaders which have big value of x and y, in fact, we choose those users as opinion leaders that are near to alpha beta and omega, and this similarity is optimized in the repetition of the algorithm cycle.

5 RESULTS AND DISCUSSION

Based on the stated structure for this study, data pre-processing is applied to data set, then for all methods used in this test, the percentage of real opinion leaders (repeated in 2 or more methods) is calculated and presented in the diagram. The implementation and verification of the proposed method in this study use Visual Studio software and C#.net programming language environment. The results of the experiment of the real opinion leaders are visible in 7. 7 indicates that, GWO method returns a good percentage of real opinion leaders. So, we calculate the number of real opinion leaders and expressed the ratio of each method to that. We use Matching coefficient (MC) and Jacard coefficient (JC)[24] for extracting similarity between tow users.

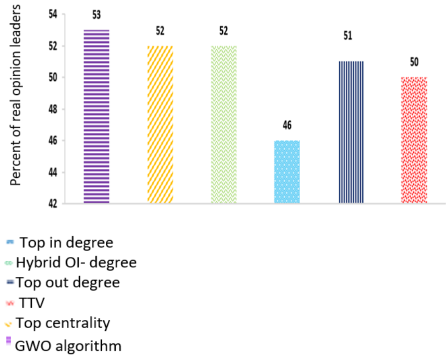

Figure 7: The percentage of correct opinion leaders for all methods from 50 selected items.

$$\text{MC} = \frac{1}{1 + \mathrm{e}^{-\alpha(\text{ | out-digree(i) nout-digree(j) |}-\mu)}} \tag{5.10}$$

where $\alpha = 1$ and $\mu = \frac{1}{n}\sum_{k=1}^{n} \text{math}_k = 9.5$ and $|out - degree(i) \cap$ out-degree(j) represents the number of users that are trusted by both users i and j.

$$\text{JC} = \frac{|\text{ out-digree (i) nout-digree(j) }|}{|\text{ out-digree (i) u out-digree (j) }|} \tag{5.11}$$

Where $|out-digree(i) \bigcap out-digree(j)|$ represents the number of users who are trusted by both users i and j and $|out-digree(i) \bigcup out-digree(j)|$ represents the number of users who are trusted by either a user i or a user j, but not both. To test the proposed method, our method with the other five methods expressed in the test of real pinion leaders choose 60 opinion leaders with their own way and then Percent of returned confiding users with (JC and MC) methods are calculated. When the trust value between user A and user B (can be calculated by criteria of jc, mc and) is more than a certain amount (0.09) user B is confiding user. This method is used in SNM (social network marketing) to identify users who follow the opinion leaders commands.

To demonstrate the effect of variation in the number of opinion leaders, we conducted the experiment with a different number of opinion leaders. 10 and 11 represents results in the deference size of opinion leaders to (JC and MC) methods.

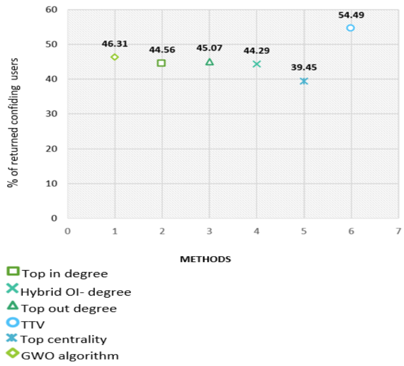

Figure 8: Percentage of returned confiding users with JC method.

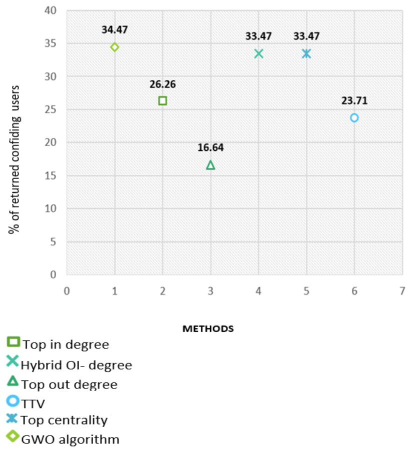

Figure 9: Percentage of returned confiding users with MC method.

Our method GWO base approach has achieved good results and the advantage of proposed method is Compatibility with different criteria and providing sustainability results in different ways and this is a significant point.

6 CONCLUSIONS AND FUTURE WORKS

In this study, a method proposed for identifying opinion leaders based on GWO algorithm. In our method at the first step preliminary data filtered to obtain accurate results then at the second step users mapped to vector, in three step we identified primary alpha, beta and omega and at the last we apply the GWO algorithm and select opinion leaders. After implementing the proposed method, we have compared and evaluated it with

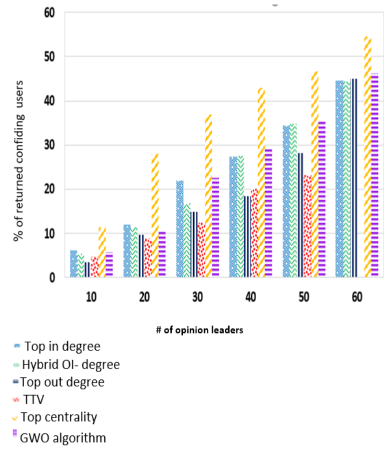

Figure 10: Percentage of returned confiding users in the deference size of opinion leaders with JC method.

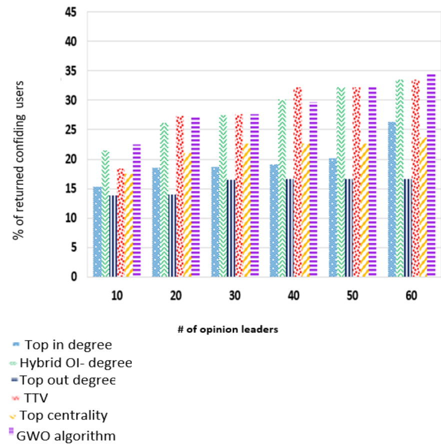

Figure 11: Percentage of returned confiding users in the deference size of opinion leaders with MC method.

Percent of real opinion leaders and SNM campaigns. The proposed method has achieved good results and the advantage of proposed method is compatibility with different criteria and providing sustainability results in different ways. It should be noted that the reason for good performance for TTV method is that this method is based on the JC Criterion. The proposed method takes only the opinions of users to each other to process relationship. So to cover different environments and also increase the accuracy of the algorithm, it is necessary to consider other factors such as topological parameters, similarity, expertise, and so on.

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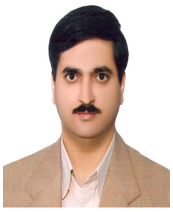

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