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Discovering Groups of key Potential Customers in Social Networks: A Multi-Objective Optimization Model

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KEYWORDS

Social network analysis, Influence Maximization, Diffusion Speed, Multi-objective optimization.

ABSTRACT

Nowadays, the popularity of social networks as a marketing tool has brought a deal of attention to social networks analysis (SNA). One of the common problems in this field is influence maximization problem which is related to flow of information within networks. Although the problem has been considered by many researchers, the concept behind has been used less in a business context. In this paper, by using a cost-benefits analysis, we propose a multi-objective optimization model which helps to identify the location of the key nodes,that are symbols of potential influential customers in real social networks. The main novelty of this model is that it determines the best nodes by combining two essential and realistic elements simultaneously: diffusion speed and dispersion cost. Also, the performance of the proposed model is validated by detecting key nodes on a real social network.

1. Introduction

In the era of big data, "science of networks" has emerged as one of the fastest growing academic areas[1,2]. It can be seen that a network-based perspective is penetrated in a wide array of different environments such as technological and transformational infrastructures, social phenomena, and biological systems [3]. A network can be defined as a set of relationships, and more formally, it is a a set of nodes (or objects, individuals) and a mapping of the connections between the nodes (or edges) [4]. A snapshot of the studies in this area shows the analytical approach of the networks has drawn substantial attention from the scientific community. Perhaps Identifying influential spreaders in social networks is the most fundamental research problem in this field. It is believed initializing these influential spreaders as diffusion sources can diffuse the information to the large proportion of the network. Motivated by The phenomenon, influence maximization is investigated by as an epidemic-based problem. Based on the literature, the problem of Influence maximization is determining a minimum set of nodes (as seeds) that could maximize the spread influence within a network [5]. The logic behind this problem is that people are likely to follow opinions, attitudes, and behaviors of those to whom they are connected (e.g. friends, colleagues, and family). Such viewpoint can be seen in many real-world applications like viral

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marketing [6-8] and new products diffusion process [9, 10].The following parts deal with those researchers who focused on the concept of social influence in social networks context. Related literature shows that the raw sprouts of the social influence concept have been cultivated in a seminal research which was conducted by Kempe et al.[11]. They proposed a linear threshold model and an independent cascade model which are two basic models for influence maximization problem. Thereafter, many researchers have tried to improve these models in term of greedy algorithmic framework [12-16]. In [12], a competitive environment is simulated. In this study, viral marketing is introduced as an application of the model outputs. Chen et al. [13, 14] proposed a new discount heuristic that improved influence spread. They enhanced the previous model by Kempe et al. [11]. Hao et al. [15] introduced two diffusion models in social networks for dynamic influence maximization. Ma and Ma [17] improved a candidates-Base greedy algorithm which has better performance compared to the static greedy algorithm. Wang et al. [18] formulated the problem of influence maximization in a heterogeneous network and proposed a co-ranking framework to select seed sets with different types simultaneously. Lin and Lui [19] introduced a Competitive Influence Maximization problem and developed a general algorithmic framework to solve the problem. The main contribution of this research is that the model can support different propagations models. Zhang et al. [20] proposed a genetic algorithm that improved the performance of previous models to solve an influence maximization problem. Their algorithm ensured both diversity and optimal solutions. Wu and pan [21] modeled an influence blocking maximization problem aiming at finding a set of influential people initiating good information propagation to maximize the blocking effect on the bad information propagation in online social networks. To solve the model they developed two efficient heuristic algorithms under multi-campaign independent cascade model. Zeng et al. [22] investigated an alternative influence maximization problem which is naturally motivated by the reliability constraint of nodes in social networks. They emphasized that some key nodes may not be as they expected. Han et al. [23]developed an influence maximization problem in dynamic networks. Timeliness, acceptance ratio, and breadth are three important factors that they considered in their model.

The literature review revealed that most researchers have focused only on historic and approximation algorithm to investigate influence maximization problem In addition, they have not paid enough attention to the relationship between social networks' problems and business concepts such as pricing, marketing planning, supply chain and so on. Hence, motivated by proposed model by Kermani et al.[24], we formulate a multi-period multi-objective mathematical model, which make our model different. Here, marketing planning and influence spreading as two important concepts related to social networks are integrated. We formulate it in a multi-objective problem. Two objectives of the problem are the minimization of social marketing expenses and maximization of diffusion speed. This viewpoint is natural because many real problems have contradictory objectives to be fulfilled simultaneously. Generally, our contribution lies in providing a new insight on how to seed key players based on the marketing plan in strategic diffusion models. For further details, the main contributions of this study are summarized as follow:

- We propose a multi-objective mathematical problem to optimize the conflicting goals of maximizing how much the network has been influenced by the seed nodes, and of minimizing the number of such seed nodes which are costly. In fact, our model depicts a tradeoff between effort (the number of nodes that need to be influenced) and effect (the final influence over the whole network). Previous conceptual studies have discussed that marketers need to offer various incentives to overcome customers' negative attitude toward social marketing communications [25, 26]. Nevertheless, previous studies did not consider the cost to persuade the potential user to adopt and spread the information. Hence, unlike previous studies that focused only on diffusion process, we develop a model by considering the cost of inducing user. In addition, we focus on how to choose key players with a given budget to accelerate the speed of diffusion under an influence maximization concept. Definitely, the diffusion speed maximization in an epidemic-based model has more challenges than influence maximization.
- We propose a multi-period model to maximize the final influence over the whole network. Previous studies assumed that the

number of the seed users is a parameter or the seed users should be determined first, and then diffusion process begins. While marketers in these models can determine key players throughout the diffusion process based on their own utility. We believe it is a more realistic approach that a marketer to identify key players in different periods based on the infected nodes in previous periods.

developing an exact model to determine seed nodes locations in social networks can be a special privilege. The accurate identification is a crucial factor because making mistake may create a negative impact on customer attitude [27]. The remainder of the paper is organized as follows. Section 2 presents the problem statement and underlying assumptions for developing the influence maximization model for the problem under consideration. Particularly, Section 2.2 presents a mathematical formulation of the influence maximization model. In section 3, solution approach is introduced. In section 4, the proposed model is illustrated using data which collected by Kermani et al. [1]. Section 5 provides a conclusion and discussion for future research.

2. Problem Definition

Consider a manufacturer who produces a new product/service. Due to changes in the market environment and emerging new technologies, the manufacturer wants to update its marketing strategy. Recent studies in this regard indicate that with the rapid evolution of mobile technology, and an expanding base of mobile phone users, the mobile devices and smartphones offer a great opportunity for the manufacturer to improve its marketing capability and take competitive advantage.

Also, studies indicate that text message (SMS) mobile marketing is one of the most basic and common types of mobile marketing approaches currently available [28, 29]. Any product/ service manufacturer or retailer can send messages to millions of potential customers in the hope that customers might respond to the designated meaning of the message. However, the excess frequency of messages from unknown parties without prior permission can create a negative attitude in customer toward the products or services [30]. Previous studies have suggested the use of motivations such as gifts, discounts, and other incentives as ways of reducing negativity and raising perceived value [25, 26]. It can be inferred that success of marketing in social networks a tool of marketing and branding depends on the strategies that can be employed by the firm. Noteworthy is that mobile users together can create a real social network where individuals communicate with one another using mobile phones [31]. Therefore, the manufacturer, in order to avoid creating a negative attitude in the customers and reduce marketing cost, can apply direct marketing instead of mass marketing. Direct marketing attempts to first select the customers likely to be profitable, and market only to those[32]. In fact, the manufacturer can count them as part of a connected network that can influence other members of the network [32]. Peer influence is one of the concepts that are behind this type of marketing. According to this concept, a person might change her behavior under the influence of others [33]. In reality, a person’s decision to buy a product is often powerfully influenced by her friends, retailers, other users, etc. The main problem that the manufacturer is facing is how to identify the most influential player in the social network.

In another word, the main problem of the manufacturer is finding a small subset of beginning promoters that can influence the largest number of potential customers in the customer network. It can be beneficial and cost-effective because it leverages the customers themselves to carry out most of the promotional effort [32]. Nevertheless, it is self-evident that the manufacturer needs to spend for persuading the key players into influencing other intently. For example, a financial incentive can be allocated to key retailers, who can recommend most potential customers to purchase the specific product/service. Especially, in a mobile network, key players are the active people who communicate with many potential customers by sending the SMS messages in each period of time. Consequently, the manufacturer is facing a multi-objective problem to optimize the conflicting goals of maximizing how much the network has been influenced by the seed nodes, and of minimizing the number of such seed nodes which are costly.

3. The Multi-Period Multi-Objective Problem

In this part, the model development procedure, nomenclature, and assumptions are stated. Also, objectives and constraints of the model defined and formulated. The solution technique is explained in detail.

3-1. Nomenclature

The nomenclature presents the notations, parameters, and decision variables of the proposed model (Table 1).

Tab. 1. Notations used for the model

Notations	
$V=(Q,R)$	Social network, its set of vertices Q and edges R
N	The number of nodes in V
i , j	The source and destination nodes
c_i	The cost of choosing i as a seed node
$t_{i,j}$	The Lag Time in sending message from i to j
T	Total number of time periods in the time horizon considered in the problem
M	Big number
B	Total budget
M_c	The maximum message that the manufacturer is allowable to send per unit time
M_n	The maximum message that each potential customer (active node) can forward per unit time
$b_{i,j}$	$b_{i,j}=\begin{cases}1 & \text{The propagation possibility through directed edge <i,j>at } t\ th \text{ period of time}\\ 0 & \text{Otherwise}\end{cases}$
Decision variables:	
$y_i(t)$	$y_i(t)=\begin{cases}1 & \text{If } i\ th \text{ node received a message from the manufacturer at } t\ th \text{ period of time}\\ 0 & \text{Otherwise}\end{cases}$
$x_{i,j}(t)$	$x_{i,j}(t)=\begin{cases}1 & \text{If } i\ th \text{ node forward message toward } j\ th \text{ node at period } t.\\ 0 & \text{Otherwise}\end{cases}$
$z_i(t)$	$z_i(t)=\begin{cases}1 & \text{If } i\ th \text{ node is infected at } t\ th \text{ period of time.}\\ 0 & \text{Otherwise.}\end{cases}$
f_i	The first period of time that i th node has been infected

3-2. Assumptions

- The connection between nodes of the network is directional.
- Each node may influence by either the company or other nodes.
- Time is treated as discrete intervals and the set period of times ($P=\{0,1,2,3,...,m\}$) is defined as a function of a ($m=\left\lfloor \frac{T}{\alpha} \right\rfloor$). Here, a is the period length.
- Each node either has infected (active) or has not (inactive).

3-3. Objectives

As mentioned above the model is formulated as a multi-objective model having two objectives simultaneously. The first objective helps to minimize the total cost for convincing and inducing the seed users while the second objective maximizes the social influence in the customer network.
The objectives are formulated as follow:

- Minimize total social marketing expenses.

$$Min\ cost=\sum_{t\in P}\sum_{i\in N}c_i y_i(t) \tag{1}$$

Maximize the average number of nodes are infected in each period of time.

$$Max\ speed=\frac{\sum_{i\in N} z_i(m)}{T.N} \tag{2}$$

$$\text{Spead of diffusion}=\frac{\text{Influenced network}}{(\text{Passing time}\times\text{Network cardinality})} \tag{3}$$

3-4. Constraints

The manufacturer must also take into consideration some side constraints:

$$z_i(t)\geq z_i(t-1);\quad \forall i\in N, t\in P-\{0\} \tag{4}$$

$$z_i(t)\leq z_i(t-1)+y_i(t-1)+\sum_j x_{j,i}(t-1);\quad \forall i\in N, t\in P-\{0\} \tag{5}$$

$$x_{i,j}(t)\leq b_{i,j}.z_i(t);\forall i,j\in N, t\in P \tag{6}$$

$$M.(1-x_{i,j}(t))+(t-f_i).\alpha\geq t_{i,j};\quad \forall i,j\in N, t\in P \tag{7}$$

$$f_i=\min\{t+(1-z_i(t)).M\ ; t\in P\};\quad \forall\ i\in N \tag{8}$$

$$f_i\leq t+(1-z_i(t)).M\quad \forall t\in P\ , i\in N \tag{8-1}$$

$$f_i=\sum_{t\in P}(t+(1-z_i(t)).M).k_i(t)\ ;\quad \forall\ i\in N \tag{8-2}$$

$$\sum_t k_i(t)=1;\forall\ i\in N \tag{8-3}$$

$$\sum_{i\in N} y_i(t) \le M_c \; ; \forall\, t\in P \tag{9}$$

$$\sum_{j\in N} x_{i,j}(t) \le M_n \; ; \forall\, i\in N, t\in P \tag{10}$$

$$\sum_{t\in P}\sum_{i\in N} c_i y_i(t) \le B \; ; \; \forall\, i\in N, t\in P \tag{11}$$

$$z_i(0) = 0 \; ; \forall i \tag{12}$$

$$z_i(t), y_i(t), x_{i,j}(t), k_i(t) \in \{0,1\}, f_i \in \Re^+ \; ; \; \forall i, j\in N, t\in P \tag{13}$$

Constraint (4) implies that the number of the nodes which are acted at *t th* period of time should not be less than the number of the nodes which will at *t+1th* time period. Constraint (5) shows that the active nodes at *t th* period of time cannot be more than all nodes which were acted by the manufacturer and another node at *t-1 th* period of time.

Constraint (6) indicates that *i th* node can send information to *j th* node when it is active ($z_i(t)=1$) and also has a link with *j th* node ($b_{i,j}=1$). Constraint (7) take into account the fact that *i th* node does not forward the information to *j th* node until he/she makes sure about the authenticity of the information, so there are some time lags. The constraint (8) is included for calculating the first period that *i th* node is infected. Because of nonlinear relationship in the constraint (8), it can be replaced by constraints 8-1, 8-2 and 8-3. Constraint (9) indicates that the manufacturer's plan for sending advertised message is limited in each period. Constraint (10) states that members of the network have a limited information propagation capacity. Constraint (11) pertains to the manufacturer's marketing budget. Constraint (12) shows that the information or idea that the manufacturer wants to spread in the network is novel. So, in the first period, all network members are unaware of the information. Finally, constraint (13) indicates non-negative and 0-1 decision variables.

4. Solution Method

The above model is a multi- objective mathematical program. Therefore, in order to find the optimal solution to the problem the utility concept which is embedded in the multi-objective is used (see [34]). Consider a multi-objective of the following form:

$$\begin{cases} \max F(x) = (f_1(x), f_2(x), \dots f_n(x)) \\ s.t \\ x \in S \end{cases} \tag{14}$$
$$i = 1,2,\dots,n$$

Where $F(x)$ is the vector of objectives; $n \ge 2$ is the number of objective functions; $x = (x_1, x_2, \dots, x_r)$ is the vector of decision variables, and S is the feasible solution space.

In this form problem, we can find the best and the worst values for each objective as the following function:

$$\begin{cases} \overline{f_i} = \max f_i(x) \\ s.t \\ x \in S \end{cases} \quad i = 1,2,\dots,n \tag{15}$$

$$\begin{cases} \underline{f_i} = \min f_i(x) \\ s.t \\ x \in S \end{cases} \quad i = 1,2,\dots,n \tag{16}$$

Then, according to Eq. (17), we evaluate all these *n* objectives function utility by the normalized function of U_i:

$$U_i(x) = \frac{f_i(x) - \underline{f_i}}{\overline{f_i} - \underline{f_i}} \qquad i = 1,2,\dots,n \tag{17}$$

Where $0 \le U_i(x) \le 1$ for all $x \in S$

Obviously, the difficulty of identifying an optimal solution for a multi-objective decision problem lies in the possible conflicts that may exist between the optimal solutions (utility) for the separate objectives. According to this fact, a Max-Min approach is used to create a balance between conflict utilities. Following is an expression of Max-Min function:

$$\begin{cases} Max\ Min\{U_i(x); i = 1,2,\dots,n\} \\ s.t \\ x \in S \end{cases} \tag{18}$$
$$i = 1,2,\dots,n$$

The equation of (18) can be converted to the following form:

$$\begin{cases} Max\ \lambda & i=1,2,\dots,n \\ s.t & \\ \lambda \le U_i(x)\ \ i=1,2,\dots,n & \\ x \in S & \end{cases} \quad (19)$$

In the above equations, it is assumed that all the objectives are equally important. If we have a different view, we must consider different utility for each objective by definition different weight ($\frac{1}{\theta_i}$).

4-1. Solution to the problem

As mentioned above our model is a multi-objective optimization problem. Based on the above solution method, the following steps should be taken to solve the model.

Step 1, Determine the maximum and minimum value of the first objective (Speed) regardless the second objective (Cost):

- Maximum speed = $\overline{Speed}$
- Minimum speed = $\underline{Speed}$

Step 2, Determine the maximum and minimum value of the second objective (Cost) regardless the first objective (Speed):

Maximum cost = $\overline{Cost}$

- Minimum cost = $\underline{Cost}$

Step 3, Definition of the utility function of first objective (Speed) based on the Eq. (3):

- $$U(Speed) = \frac{Speed - \underline{Speed}}{\overline{Speed} - \underline{Speed}}$$

Step 4, Definition of the utility function of second objective (Cost) based on the Eq. (2):

- $$U(Cost) = \frac{\overline{Cost} - Cost}{\overline{Cost} - \underline{Cost}}$$

Step 5, Convert the proposed bi-objective model to Max-Min Model (maximize the minimum utility):

- $$\begin{cases} Max\ \lambda \\ s.t \\ \lambda \le U(Speed) \\ \lambda \le U(Cost) \\ Eqs(4)-(7)\ ,Eq(8-1),Eq(8-2), \\ Eq(8-3),Eqs(9)-(13) \end{cases}$$

Finally, Solve the single objective optimization model obtained from "*Step 5*" in which the minimum utility of first objective ($U(Speed)$) and second objective ($U(Cost)$) is maximized.

5- Experiment

In this section, to illustrate the validity of the proposed model and the usefulness of the proposed solution method, a simple experiment is presented. For this purpose, we conduct an experiment on a real-world mobile network dataset created by Kermani et al.[1]. This dataset was collected from Abrar University students in Tehran, Iran (fig.1.) Moreover, we suppose that the other required information is obtained by the marketing department (Table 2).

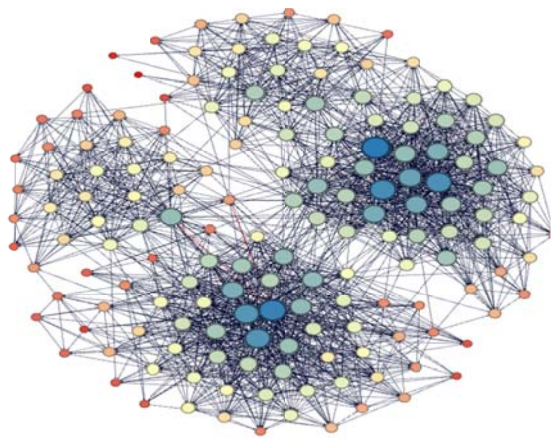

Fig. 1. Abrar University Dataset

Tab. 2. Data Associated with the network

Input	Value	Input	Value
N	163	$t_{i,j}$	$Random\_Uniform(0,4)$
c_i	1	T	10
$b_{i,j}$	Fig. 1	B	20
M_c	3	M_n	5
α	2	$m = \left\lfloor \frac{T}{\alpha} \right\rfloor$	5

According to the solution approach that mentioned above, Table 3 illustrates utility values of both objectives.

Tab. 3. Utility of objectives

	Maximum	Minimum	Utility
Speed	0.1	0	$\frac{Speed}{0.1}$
Cost	20	0	$\frac{20-Cost}{20}$

6. Results and Discussion

Using these data, the problem is solved by CPLEX solver 24.1.2 version. Results of implementing the proposed model on the sample network are shown in Table 4.

In addition, Fig. 2 represents demographic information of the network in the optimal scenario. The results were illustrated by using Gephi software[35]. As it can be seen from Fig. 2, seed nodes, infected nodes and non-infected nodes are highlighted with different colors. Also, Fig. 3 shows how many nodes is infected in each period.

Tab. 4. Solution results

Diffusion speed	Number of Seed nodes	Number of infected nodes	Consumed cost	Speed utility	Cost-utility	Min-Max utility (λ)
0.086	6	140	6	0.859	0.850	0.850

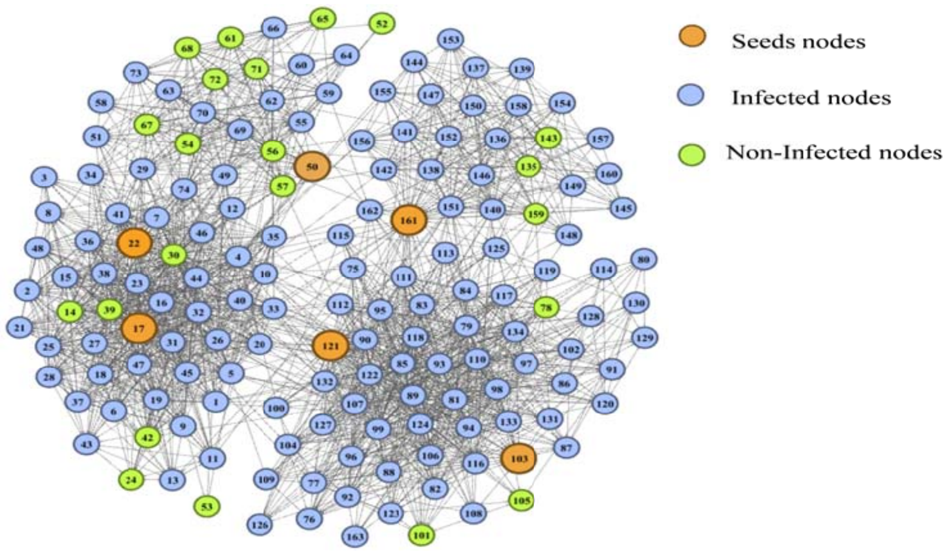

Fig. 2. represents demographic information of the network

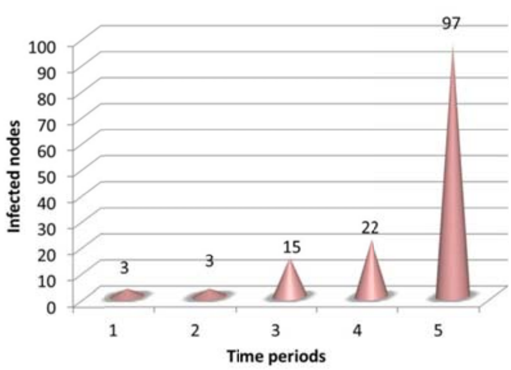

Fig. 3. The number of infected nodes in different periods of time

To give a more qualitative sense of the results, the distribution of infected nodes at different periods is shown in Fig. 4. The optimization results are also listed in Table.5. From the table, the achievement level of the single objective is found as 0.85. The solution shows that the company can inform 140 potential customers by spending 6 fractions of the total defined budget for selecting 6 key players in the network. In this point, the company obtains the best utility. The findings also indicate that the company can cost more to inform all members of the network, although may reduces its utility.

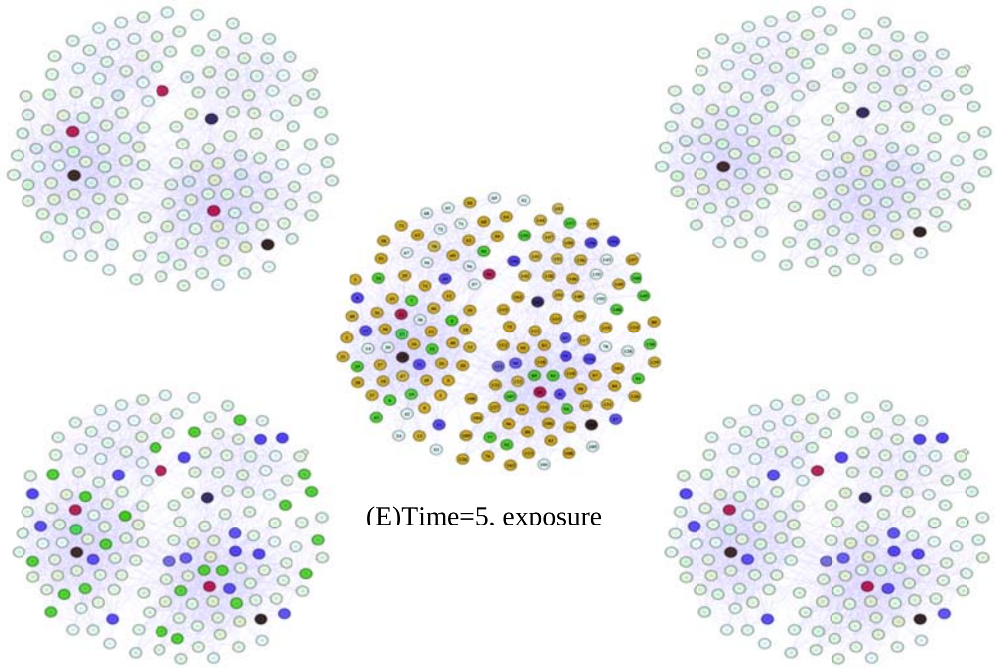

Fig.4. Customers network exposure to the product/ service for the manufacture

Tab. 5. Effects of changes in the consumed- budget

Consumed-Budget	Diffusion speed	Infected nodes	Max-Min utility
1	0.054	88	0.54
2	0.060	98	0.60
3	0.066	108	0.66
4	0.073	119	0.73
5	0.082	133	0.82
6	0.086	140	0.85
7	0.089	146	0.825
8	0.093	152	0.800
9	0.096	157	0.775
10	0.1	163	0.75

Altogether, as oppose to some recent contributions in computer science, which only focus on social networks, we believe researchers, in order to achieve a practical knowledge, should focus on connections between different fields of scientific knowledge. Hence, we develop a model that considered two problems together: (1) diffusion speed maximization and (2) marketing planning in social networks. As mentioned above, the proliferation of social networks has allowed companies to collect information about their own customers and their social relationships. They get to focus on profitable customers and markets only to those. By doing so, they can reduce their own expenses and avoid harmful side effects of social marketing. In fact, they should be aware that any attempt at attracting customer's attraction is not suitable because it may create a negative impact on customer's attitude. So, they have to choose target more exactly and pay more attention to their motivation and hedonic enjoyment [25, 27, 36]. It can be deduced that selecting and persuading key players is costly for companies.

Furthermore, they should make a decision based on what has happened in the past. Having a multi-period marketing plan can satisfy the concern. They can select those customers as a seed in each period that would have the greatest impact on remaining customers who still have not informed.

Regarding these facts, in this paper, we proposed a multi-period multi-objective model to discover key players in social networks. The proposed model is then applied to typical personal network collected from Abrar university students who communicate with each other. We assume that it is a network of a manufacture's potential customers. In addition, we assume the manufacturer have a limited budget and a multi-period marketing plan. Fig.4 (a) shows the personal network in the first period when the three key players who have the greatest impact on the members of the network are targeted by the manufacture. Now the potential customers are exposed to the product/service through their personal network members. The degree of exposure is computed by dividing the degree of exposure, 3, by total size of the personal network, 163. Therefore, the degree of exposure to the product/service is 0.0184 for this sample network at time-period 1. In Fig.4 (d), the key players who are infected in the first two periods start to inform potential customers. Clearly, information provided by friends is more acceptable and trustable than that from marketers [37]. Thus, it is no wonder that in this time members of the network become infected at a faster rate than the first 2 periods. In this period the degree of exposure is 0.086. Fig.4 (E) represents the total number of informed potential customers after five periods. As it is seen from Fig.4 (E), exposure rate would increase exponentially as more people in the personal network are active to spread information related to the product/service. Also, As seen in Figs. 2 and 4, the tradeoff between effort (the number of nodes that need to be influenced) and effect (the final influence over the whole network) results in 6 seeds customers during 5 periods which three of them in the first period, two of them in the second period, and one of them in the third period are selected. As mentioned above, in each period the marketer can analyze infected nodes, and then select new seed nodes again.

7. Conclusion

In this paper, we develop a mathematical model for diffusion speed maximization problem which relies on finding strategic nodes in social networks. Our main contribution in this paper is summarized in two parts: (1) we introduce a new insight that marketing plan should be integrated with influence spreading concept. According to this fact, we model the influence propagation as a multi-period process. (2) Several studies have suggested that spreading information among seed nodes and persuading them to adopt the information is costly. So, as a new view on the issue, we propose an exact multi- objective mathematical model to identify the location the seed users exactly. The model is solved by a solution procedure that ensures a Pareto solution with maximum utility and examined on a real-world dataset. There is much scope in extending the present work. For example, when the size of the network is large, our model has not a suitable performance. Therefore, one logical extension of the current research is developing a compatible algorithm with large- scale networks which considers other factor s such as product price.

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