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Abstract: Several organizations in Iraq manufacture similar commodities in this aggressive social trading. The objective of these organizations is diffusing information about their commodities publicly for popularity of the commodities in social media. More returns result in popular commodities and vice versa. The development of a framework incorporating two organizations engaging to broaden the information to the large media has been undertaken. The organizations first identified their initial seed points concurrently and then data was scattered as per the Independent Cascade Model (ICM). The major objective of the organizations is the identification of seed points for the diffusion of data to several points in social media. Significant is also how fast data diffusion can be done. Data effect will arise from either none, one or more nodes in a social interconnection. Evaluation is also accomplished on the number of fraction parts in various sections are affected by the different rates of data diffusion. The simulation result for suggested framework presented better outcomes result for random network 1 and random network 2 comparing with regular network. This framework is used a Hotellingframwork of competition.

Keywords: *social media; marketing; mechanism.*

1. Introduction

An aggressive selling point entails several manufacturers aggressive to meet the wants and needs of various customers. An aggressive market control relies on more than one customer and manufacturer. In a scenario of two organizations F1 and F2 manufacturing similar commodities, boosting their commodities would entail expansion of data 1 for F1 and data 2 for F2. This is for both organizations to outreach several customers. Hence, scattering data is attained by passing out information. Scattering data passes information to outreach persons via connections (Stieglitz, et al.,2018). The result changes in selection characters, diffusion promotion in relation to a commodity prior to its induction or raise seller status.

Today, several companies diffuse their information concurrently (Fu, G., et al. ,2019). Through social media, an understanding is created on the spread of information in real-world cases. (Singh& Singh (2012), (Singh, Kumar & Singh, 2012). Previously, few ways could be applied to obtain relevant audience unlike today there exist, print, face-to-face, Facebook, etc.Spreading of information is a great study area applicable to several fields like physics, biology, among others. The main concern is the specific case for data diffusion in social interconnections, inclusive of strategic arena diffusion, communication pathway, meaning interconnections are significant in diffusion. Contrary to trading procedures, study is done for ascertaining the significance of “word-of-mouth” and “viral trading” to comprehend the spreading approach (Domingos& Richardson, 2001), including the promotion of several procedures in game theory models (Richardson & Domingos, 2002). Through the incorporation of trading procedures, Domingos and Richardson suggested a foundational algorithmic issue (Singh et al. 2018). When deliberating about word-of-mouth trading methods, it is natural to discern that several organizations, political

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groups, or other companies could engage spreading by use of social interconnections for elevating their commodities concurrently. For instance, Samsung may try to elevateitslatest Galaxy phone, while Apple tries to publicizeitslatest iPhone.There exist many frameworks for aggressive spreading that have been suggested and considered (Young, 2001). Initially, an assumption is made that one of the candidates has hitherto selected their procedures and evaluate the algorithmic issues for establishing the most preferred outcome (Singh, et al. 2012). The objective is getting the maximum impact (Fu,et al. 2019) or reducing the influencer effect (Young, 2001). Similarly, modeling of the influencer as a concurrent approach where all organizations select their procedure concurrently (Goldstone, et al. 2005). Facebook dataset was evaluated for a comprehension of the information spreading procedure in the real world. Implementation of the framework was based on two procedures: one, degree centralization [examine node-local factor], two, rank degree procedure [employed instances of the interconnection] for seed picking. The techniques provide selection of various seed areas of significance in the interconnection.

Two companies were taken into consideration in the suggested framework with two engaging data concurrently. Both companies have a fixed starting budget to be used for choosing seed areas. The companies will select their seed areas concurrently and further, information will be spread as per ICM (Easley & Kleinberg, 2010). ICM entails an interconnection employing straight graph, plus a junction can communicate to another junction in the interconnection within its associates. Within the interconnections, areas receiving data are within the same association. For considerations as informed, the impact of the information ought o be higher or same as the entry value. Once a point has received communication, it can pass information to an adjacent point. The process is ongoing, and it implies that a point transforms from non-informed to informed where the reverse is false. In cases where a point receives information from more than one other points, the high impact data is selected from a point. For equal impact, a point is considered to offer support for just one data with equal chance. The suggested model can locate the significant spreader in social interconnections for both companies.

The rest of the research is arranged in parts as section 2, which is comprehensively discussing similar studies of the suggested model, section 3 explains the suggested framework, selecting spreader point and data diffusion by employing Independent Cascade model. In Section 4, Mean-field approximation was described, and Simulation and Results werepresented. Section 5concludes theresearch.

2. Related work

Many research studies exist on competitive data diffusion (Fotakis, et al. 2014), (He, & Kempe, 2013). Easy apprehension of competitive data spreading is through game-theoretic models. Application areas entail computer science, biology, ecology, sociology, public health, traffic management, economics, and mathematics (Tanimoto,et al., 2014). In other study, the cascade dynamics of multiplex propagation research was undertaken (Centola, et al., 2007), to exhibit the random connections between far nodes highly impact the spread of disease or data giventhe contamination can be conveyed by a soleagile node. Nevertheless, when the dissemination necessitates concurrent exhibition to a variety of sources of actuation, known ascountless dissemination, the impact of random connections makes dissemination attainment harder. Reference (Karsai et al., 2011), evaluated the effects of various artifacts and terrestrial relationships on diffusion in composite disclosure interconnections. The outcomes were, one, the community system and its connectionswith interrelate weights, and two the heterogeneous and explosion task designs on the associations, are significant in spreading speed. (HE et al., 2016), proposed a framework to integrate several techniques including quantitative analysis, text mining, and sentiment analysis to analyze and compare social media content from business competitors. The seed selection techniques and ICM helps highlight theperception of tradingand methods on howfewerbeginningpoints can impact the whole interconnection. The changes of this dispersal can be comprehended by ICM.

3. Proposed method

Let F(X, Y) be an unweighed and aimless interconnection entailing an arrangement of n nodes $V: = \{1, 2, ..., n\}$ and arrangement of connections Y. We designateadjacent of $i \in X$ as $Ni(F) := \{ j|(j, i) \in Y\}$ and the level of i as $di := |Ni(F)|$. A threshold (quantity of information to a node) for node i, designated as Øi is a chancelinking [0, 1]. The area with higher data impact or the same as the threshold is selected as impacted by that data. The impact of data is explained as the impact on the behavior of pointas a result of the data. Its value is about 0 to 1, with, 0 implying no impact and 1 implyingtotal impact of data.

There are two organizations, f1 and f2 and two data 1 and 2, separately. In an interconnection, a point receives information fromnot less than one data, supporter entails point is aiding one of the data, and non-spreader/unknowledgeableimplies lack of information to the point or received data has less influence in comparison to theentry of the point. Points on a social interconnection either reinforce data 1 or data 2 or persist as a non-spreader.

The suggested structure brings out six sections for every point, S, A, B, AB, a and b as shwen in figure 1;where every variable is purposed variables and the total of all the sections is always 1.S signifies a section for the unknowledgeable end, A and B signify sections for knowledgeable ends by data 1 and data 2, separately and AB signifies sections for ends enlightened by both data 1 and 2, while a and b signify sections for supporter of data 1 and 2, separately. Let α1 and α2 be the impact of data 1 and 2, separately ($0 \leq \alpha1 \leq 1$; $0 \leq \alpha2 \leq 1$). The results of α1 and α2 are most likely distinct for separate ends in the internetwork. Various colors are employed for deeper comprehension, green for data 1 and yellow for data 2. For instance, an end in section AB receives information from data 1 with value α1 exhibited in red;likewise, the impact of data 2 with value α2 exhibited in yellow. A point in section a is advocator of data 1. Thus, it is exhibited fully in green color. Likewise, for a point in section b which advocates for data 2 and exhibited in yellow color only, (Note: For a point, if ($\alpha1 == \alpha2$) then, it advocates for both data with a likelihood of 0.5). α1 and α2 signify the rate of diffusion of data1 and data 2.

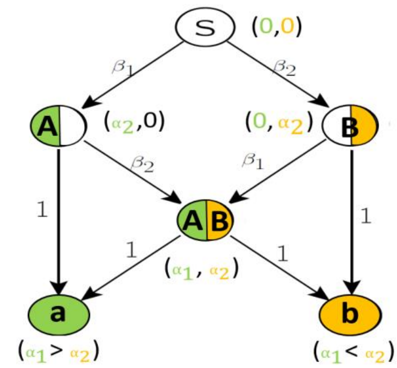

Figure (1): Flowchart for the state of points in a competitive environment.

Let, α_i^{par} be the impact of information i (where, i = 1, 2) on the parent node, α_i^{ch} be the impact of data *i* on child point, d_{ch}be the degree of child point, *k* be the group of children of part, A be the nearest matrix and α_i^{sib} be the impact of data *i* on point sib of parent point only, where, *sib ∈k.* So, the impact of data *i* on point *ch* is revealedin equation 1.

$$\alpha_i^{ch} = \sum_{par \in \kappa} \left(\frac{\alpha_i^{par}}{d_{ch}} .A(ch, par) \right) + \sum_{sib \in \kappa} \left(\frac{\alpha_i^{sib}}{d_{ch}} .A(ch, sib) \right) \tag{1}$$

Where *ch, par, sib ∈ V.*At first, all ends apart from seed ends are in the uninformed section. Companies select seed end concurrently from their data. A company can employ a seed end as a seed on condition it has forecasted for that point.The suggested model is explained in the five subparts with time complexity of O(XY).

1. Calculate the cost for each node in a network.
2. Initialize the budget for each player.
3. Choose seed pointe(s) for each fiem simultaneously.
4. Spread data with independent Cascade model and identify supporter(s) for each data.
5. Repeat steaps 2 to 5 multiple times.

3.1. Cost calculating for each point

Point cost entails the cost of an end to picking seed points. The company caters to the cost of its forecasts. The central tendency idea is employed for determining the value for endpoints. A central tendency (also calledcomputation of central tendency) entails a representative rate for likelihood dissemination (Feingold, 1995). The accepted computations of central tendency include the computation average, the median, and the point.Any data exhibits two types of outliers: Bad outlier and Good outlier. Any inspection falling atan abnormal interval from other figures in a relevant representative from a populace is a bad outlier, and hence median is employed. While any inspection falling at a normal interval from other values in a random sample from apopulation is a good outlier, hence mean is employed. Consideration is on the level of an end for calculation of the cost. Median is chosen in this case as there are bad outliers. Unit cost is allocated to the ends with central tendency and then the cost of the rest of the ends will be based on linear techniques. Algorithm 1 displays the end cost approximation. Time difficulty for establishingthe central tendency valueby employing median takes $O(n)$, with n beingthe sum of number of points in the interconnection.

Algorithm 1: Cost estimation for point
1. Getting the central tendency degree utilizing median
2. Appoint all points with degree equal to central tendency degree as unit cost
3. Calculate the cost for other points utilizing linear method

Let F (X, Y) signify an undirected interconnection with V points and E edges. The level of any pointi is di and the level of central tendencypoint is dct. The cost of the pointi is ci. Hence,The linear method for calculating the cost is:

$$\forall i \quad c_i = \frac{d_i}{d_{ct}}, \qquad i = 1, 2, \ldots \text{ X} \tag{2}$$

3.2. Budget initializing for firm

Every company, *Fi*, is initialized with a unit forecast *Bi*(*Bi* = 1) to be spent for the selection ofthe seed. The concept is that, at the onset, companies ought to select at most the end with the level ofcentral tendency as a seed endand on condition it is good for the seed end, a contender will win or lose from the other company. Improvement can be made over starting forecasts for companies as per our point. An assumption is if there are *f*-number of companies, then,the time difficulty for starting the forecast is $O(f)$, with, $f <<< n$.

3.3. Choosing Spreader Point

There exist a variety of techniques for deciding the benefit of a point.The techniques employed for seed selection entail:

3.3.1 Degree Centrality (DC)

It is a straightforward index for the selection of points influences. For many links, there is greater influence on a point. For influences comparison of points in various interconnections, the normalized degree centrality is explained as:

$$DC(i) = \frac{d_i}{n-1} \tag{3}$$

With $n = |X|$ is the numberof points in G and,n-1 is the highest achievable standard (Tanimoto,et al., 2014). For heavy neighboring matrix constitution of the graph, evaluating the level centrality for all the junctions in a graph takes ɵ(X2). For sparse matrix constitution of the graph, evaluating the degree centrality for all the junctions in a graph takes ɵ (Y).

3.3.2 Rank Degree (RD)

The technique is established on graph illustration of the difficulty in choosing a small subgraph with topological characteristics as per the original graph. A sampling technique successfully selects the influential spreader on condition that (a) the fraction of top-k regular ends in the illustrations and in the graph is averagely adequately huge and (b) the categorization of these ends in the illustrations occur near to the real categorization in the graph (Centola, et al., 2007). The time difficulty of rankinglevel algorithm is $O(n2)$ for scanty matrix.

Algorithm 2. Rank Degree	
1.	Adjust parameters: (a) number of initial seeds, (b) f, (c) target sample size x
2.	Input: Undirect graph F (X, Y)
3.	Initialization: (Seed) ← s random points selected uniformly
4.	Sample ← φ

5.	While sample size < target size x do
	(New Seed) ← φ
	For ∀w ∈ (Seeds) do
	Rank w' s friends based on their degree values
	Selection Rule:
	(a) RD (max) ∈ select the max degree (top – 1) friends of w
	(b) RD (f) ∈ select the top – k friends of w, where k = f. (#friend (w)), 0 <f ≤ 1

6.	Update the current sample with the selected edges (w, friend (w) on the top – k) with the symmetric ones
7.	Add to (New Seeds) the top-k friends of w
8.	End for
9.	Update graph G: delete from the graph all the currently selected edges
10.	(Seeds) ← (new Seeds)
11.	If (New Seeds) = φ then repeat step – 4 (random jump)
12.	End if
13.	End while

3.3.3 Eigenvector Centrality (EC)

Assume the eigenvector centrality which the influence of a points is not only set by its neighbors, but also set by the influence of every neighbor (Singh& Singh, 2012).The centrality of a points is commensurate to the summation of the centralities of points to that it is connected. The importance of a point i, indicatevia Xi is :

$$\chi_i = c \sum_{j=1}^{n} a_{ij} \chi_j, \tag{4}$$

That can written in the matrix below

$$\chi = cA\overrightarrow{\chi} \tag{5}$$

So, c is a proportion constant. Time complication for EC is O(V3).

3.4. Data Spreading

Points selected to be starter spreaders are allocated values of α1 and α2 as 1. After the selection of the seed point(s), independent cascade is employed for viewing the number of ends informed by every data. The distribution procedure entails three basic components: transmitter, Receiver, and Medium.

3.4.1. Cascade Model

During cascade distribution, the interconnection is changed into the directed tree(s) by employing seed points as the source forever data. Employing these trees, the outcome is the impact of every data on points part by part. The influence of siblings and points with similar parents at every part is also regarded if there is a border between siblings in the actual interconnection.The dispersal procedure is factored by two features: its design, i.e., the dispersal graph that “who impacted who”, and its time-relatedchanges, i.e., severalpoints that employ the piece of datawith time. The easiest method to explain the diffusion technique is in consideration of a datato be either spreader (i.e., is in possession of the datawith dissemination attempts) or non-spreader. The illustration interconnection exhibited in Figure 2- A describes the data dissemination technique by employing ICM. Here, point 2 is the seed point for data 1 and point 5 is the seed point for data 2.

The illustrations internetwork is viewed as a tree by every seed disseminating data concurrently. Seed ends are beginning areas for data, and therefore are initial points for data. Figure 2-B illustrates the tree-like design of the illustrative einternetwork by taking point 2 as a seed point for data 1. Likewise, for similar sample interconnection, the tree-like structure by taking point 5 as the seed point for data 2 is illustratedin Figure 2- D.

Data is diffused concurrently after seed point selection takes place. Data will be diffused section by section as per the tree-like figure in relation to seed point in the data. The sibling’s association is illustrated by 2-way colored arrows. This means data will be disseminated across siblings causing an impact on both siblings.

Figure 2 – B illustratesthe tree-like anatomy for seed (point 2) of the data 1 and this data won’t disseminate beyond seed (point 5) of the data 2; so, elimination is done for seed 2 data and unreachable points to point 2. The outcome tree is exhibited in Figure2- C. next, evaluation of the influence of data 1 disseminated by seed (point 2) on each point of the interconnections is done. Likewise, the influenceof data 2 spread by seed (point 5) on each pointof the similar interconnection is exhibited in Figure 2- D and E. Finally,from Figure 2-C and E,it is easy to examinethe impact of data 1 and data 2 on the sample interconnection as exhibited in Figure 3-A.

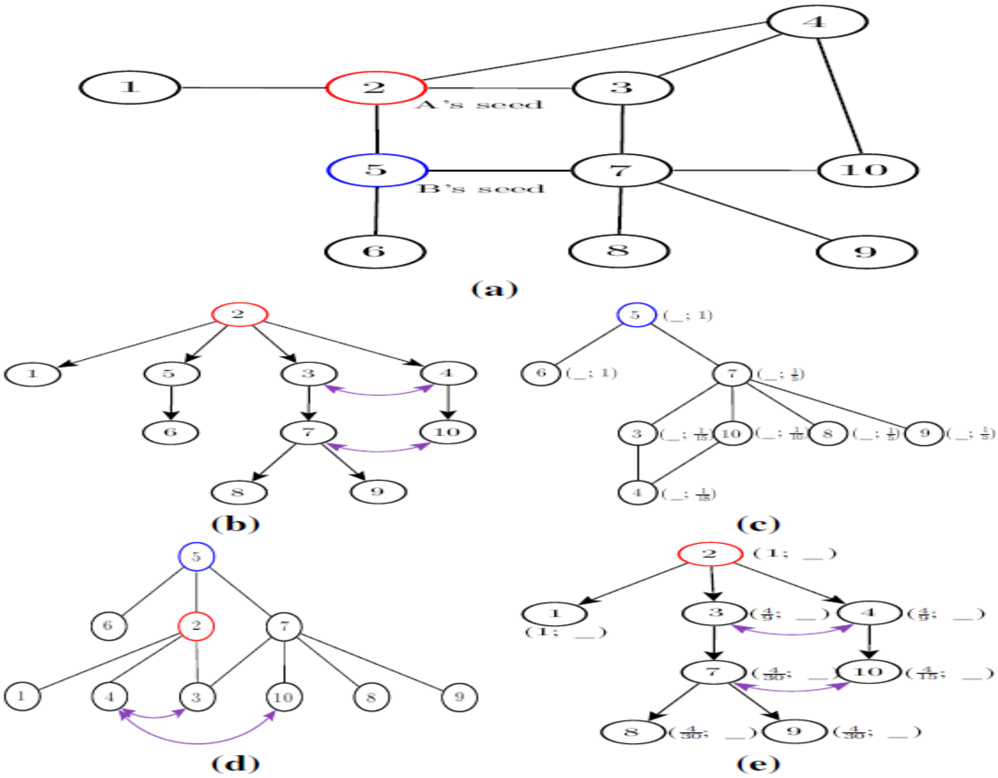

Figure (2): Point 2 and point 5 as the seed of data 1 and 2, respectively.

In an aggressive domain with two companies $F1$ and $F2$, three cases can arise, one, company $F1$ wins, two, company $F2$ wins, threea tie. As we can see in Figure 3-A, point 2 is the seed for data 1 and point 5 is the seed for data 2. The influence of data 1 on points 1, 2, 3, 4 and 10 is greater in comparison todata 2;thus, support fordata 1. Likewise, the impact of data 2 on points 5, 6, 7, 8 and 9 is greater than data 1;thus, reinforcement for data 2. This is a tie case because of the same supporter number for each.

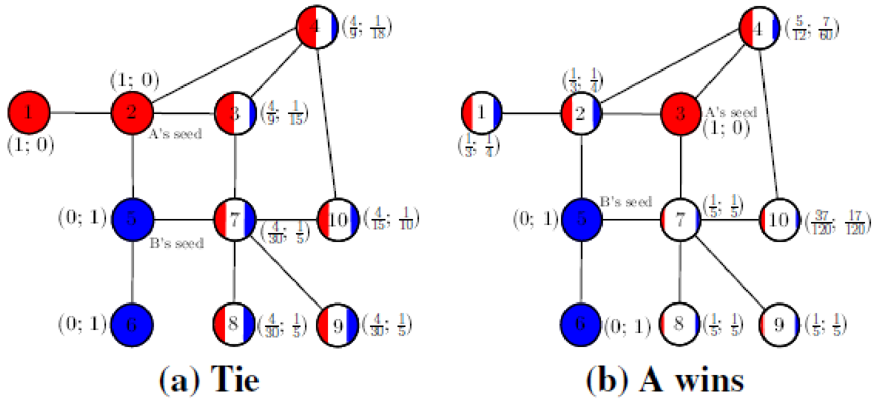

Figure (3): Data spreading in the network environment.

The procedure can moreover be expanded to several participants or organizations. Figure 3-B illustrates a company *F*1 winning. Point 3 is the seed and points 1, 2, 3, 4 and 10 are supporters for data 1. Point 5 is the seed and points 5 and 6 are supporters for data 2. Here, points 7, 8 and 9 are similarly impacted by both data; thus, support for each data with same likelihood. The decision is arrived at after comparison is made onthe values of the impact of data at every end. The time difficulty for disseminating data is $O(XY)$.

4. Simulation and Outcomes (Data Sets employed)

The Facebook dataset was considered for setting statistics as exhibited in Table 1. It entails'circles' (or 'Friends lists') and it is an easy (undirected and unweighted) graph with people beingpoints and their friendship beingat the border. By employing the datasets specified , simulation is affected by the suggested framework detailed in section 3. The post data dissemination is evaluating the number of fraction pints impacted by the data with the number of informed fractions supporting the data. There is possibility of points evenly impacted by both data under the same probability. During the simulation using MATLAB 10 program on Windows 10, the points are allocated to provide support for one data sporadically.

Table (1): Facebook data set statistics

1.	Edges	88233
2.	Points	4039
3.	Edges in largest WCC	88233
4.	Points in largest WCC	4039
5.	Edges in largest SCC	88233
6.	Points in largest SCC	4039
7.	Arvrage clustring coefficient	0.6055
8.	Number of triangles	1612011
9.	Fraction of closed triangles	0.2648
10.	Diameter	8

The benefit is achievement of the required fraction of supporter or every data for the allocated seed point pairs. For simplicity of a tie between the organizations, a boundary of 5 % is contemplated. If the contrast is lower to this boundary, then balance is attained.

4.1. Results for Facebook data

An illustration is made for the outcomes from the three techniques (DC, EC, and RD) on Facebook data. Being that there is existence of two aggressivedata (i.e., *info 'm'*1 and *info 'm'* 2), and three techniques for seed determination; thus, better evaluation entails further classification of the outcomes into fractions of impacted points (μ *influenced*) and a fraction of supporter points (μ *supporter*) for everydata. For further evaluation, various interconnections both random and regular, apart from the Facebook dataset were also produced. More explanations are detailed in subsequent sections for the interconnection characteristics.

Here, the *x*-axis represents the quantity of levels '*L*' and *y*-axis constitutes a fraction of the impacted nodes, μ *influenced* or fraction of the supporter nodes, μ *supporter.* Figure 5-A, for Facebook interconnection, there is an illustration of the influence of μ with *L* for techniques. For Facebook dataset,there is a higher influence for μ *on* DC in comparison with EC but like RD. The reason being the method used for choosing theseed selection earlier explainedin Section 1. In observation was less variance for DC, EC butgreater variance for RD, which is as a result of target size earlier described in Algorithm 4, allocated to 10%. Figure 5- B exhibitsrise of µ*supporter* over *L* for various techniques.

The key focus of any company is the maximization of supporters. However, it is indicated that DC µ *supporter* for both companies was similar at the endpoint. Accordingly, balance was attained. There was a higher population in favor of the information, hence DC on Facebook interconnection is recommended. RD was satisfactory although with maximum variance. On the contrary, EC attained balance with a lower populace in comparison to DC and RD, due to the method for choosing the seed. There is a high reduction of information during the commencement of the distribution procedure for EC. Figure 5-A reveals the integratedoutcomes for all the three techniques for the fraction of influenced points (µ *influenced*) on the Facebook interconnections. From observations, for the Facebook dataset, DC and RD reveal the same characteristics with EC behaving contrary. In the end, all the techniques achieved the influence of the whole interconnections for a dataset. Figure 5-B reveals the unified outcomes for the fraction of supporter points (µ *supporter*) in the interconnections. For the Facebook interconnections, RD exhibited satisfactory outcomes in comparison to DC and EC. Also, DC outcomes were higher to EC.

4.2. Random Network 1 (Result)

This is an interconnection with the characteristic of having similar ends as the Facebook interconnection and nearly the same moderate degree. The clustering coefficient (CC) of the random interconnection 1 is issued for contrasting with the main interconnection. CC is an estimate of the level to which ends in a graph tend to group together. It is of benefit to for data dissemination process. For random interconnection 1 with the same characteristics to Facebook interconnection, Figure 6-A exhibits thatwith few levels,the entire interconnection was influenced by datain comparison to the main network. In conclusion, the diameter of the random interconnection 1 was minimal in comparison tothe actual interconnection. µ *supporter* for data was exhibited in Figure 6-B For DC, low variance was seen, and balance was attained. A similar characteristic was also exhibited by EC (Figure 6- B). In Figure 6-B, the supporter for data 1 was exhibited. For DC, a higher contrast of more than 5% margin was exhibited between the µ *supporter* for data. There was a greater change in EC fraction of supporter for data in comparison to the actual interconnection, because of better network diameter. This is also as a result of an adjacent seed point selected earlier by EC. The rise in level numbers results in lower support for data which is equally lower in comparison with the margin. Equilibrium attainment was due to the fewer support data in comparison to margin. The RD technique performed better for µ *supporter* further attaining balance. This signifies lesser number of loops in the interconnections. From Figure 6- A for DC, there are 5 levels for influence of information, likewise for EC and RD. In summary, there was a lower diameter for random interconnection 1 in comparison to the actual Facebook interconnection. Figure 6- B shows data supporters. The balance was attained in DC; however average variance was seen. Comparably, balance was attained for EC and RD.

For the fraction of influenced nodes (µ *influenced*) in the random network 1,it was observed that DC, EC, and RD showed similar behaviors as they succeeded in impacting the whole network. For the fraction of supporter points (µ *supporter*), RD and EC gave improved outcomes than DC on random network 1 with similar properties to Facebook interconnections.

4.3. Random Network 2 (Result)

Random network 2 similarly entails characteristics like the random interconnection 1. For random interconnection 2 similar characteristics were for the Facebook interconnection. Exhibited in Figure 7-A is that for DC, the whole interconnection was impacted by data in four parts. Five levels were undertaken by EC while four for RD. In conclusion, Facebook's interconnection had greater diameter in comparison to RD. Figure 7-B exhibits µ *supporter* for data. For DC, there was low variance,with balance achievement. Similar behavior was seen in EC. For RD, there was average variance with achievement of symmetry.

4.4 Regular Network (Result)

This is a random interconnection having about the same moderate level of the actual interconnection (Facebook). It helps in bringing out the benefit of level dissemination of points in an interconnection. For a regular interconnection possessing equivalent factors to Facebook interconnection, the fraction of impacted points are revealed in figure 8-A. There was lower influence of the total populace impacted by data for DC. This was the same for EC and RD as in figure 8- A. On the other hand, figure 8-B highlights the fraction of supporter ends. Less µ *supporter* and moderate variance were exhibited for DC yet balance was attained. Generally, satisfactory outcomes were revealed by RD in comparison to Dc and EC. Providing better explanation. For the benefit of topological loops (an interconnection factor). Differentiating Facebook internetwork outcomes with outcome 2 gave the benefit of topological loops. There were few supporters for random normal interconnection showing the benefit of network disseminations for diffusion.

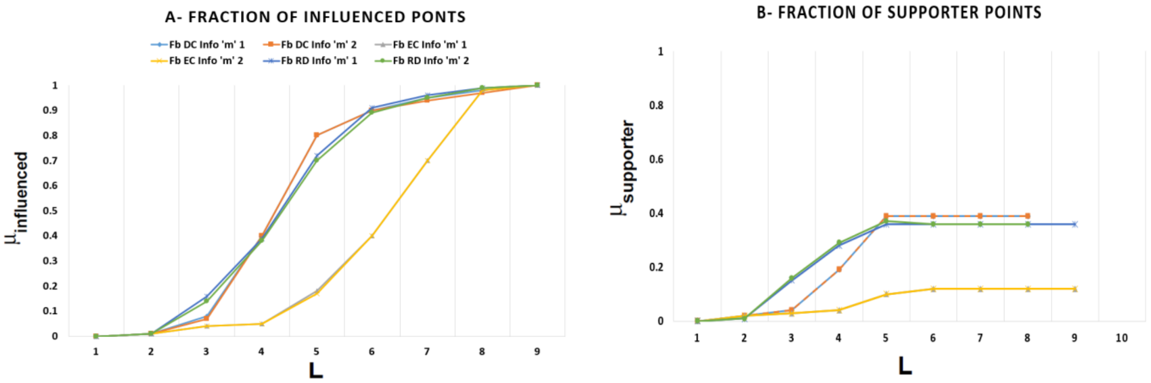

Figure (4): Facebook Network

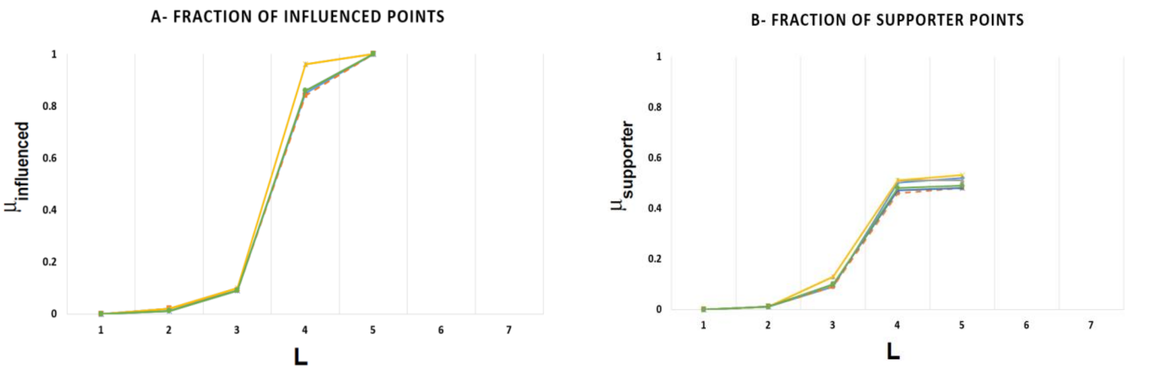

Figure (5): Random Network 1

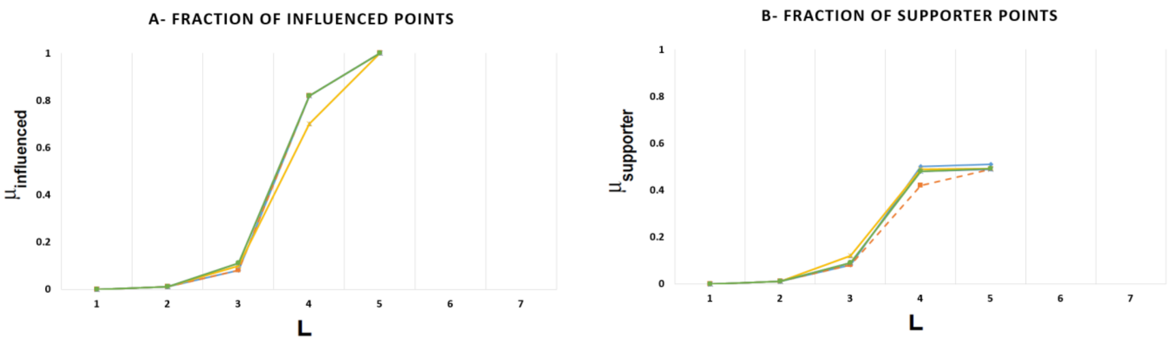

Figure (6): Random Network 2

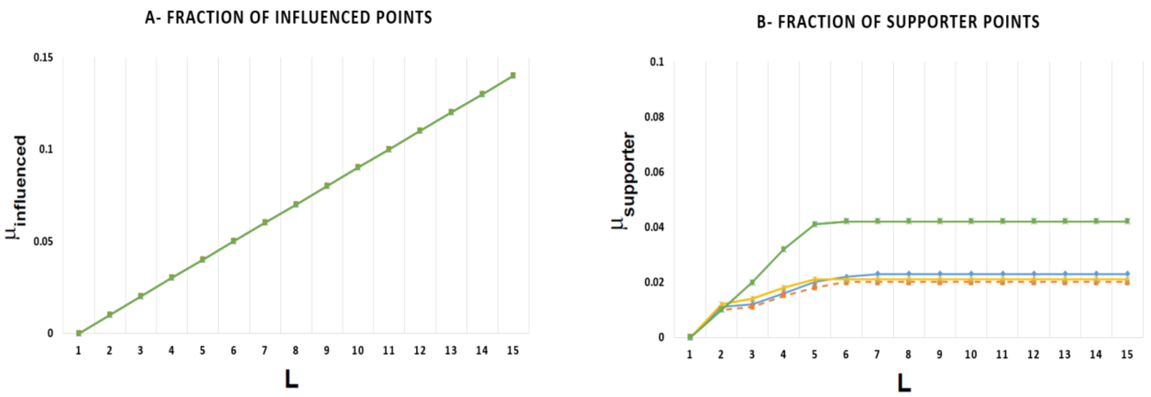

Figure (7): Regular Network

5. Conclusions

Cascade model: For comparison outcomes, two parameters are selected (1) Clustering Coefficient, and (2) Degree distribution of points. All the techniques(DC, EC, and RD)vary from one other. The distinguishing factor was on the seed point determination technique, directly dependent on the interconnection structure. Thus, the distinctness was as a result ofone, seed picking technique, and two, interconnection structure values i.e., clustering coefficient and degree distribution of point. From the comparison, topological loops are beneficial for changes, however seed determination techniques may fail to perform. The degree of distribution arising from comparison of random and random normal interconnections proved significant for changes. Data sets outcomes distinction revealed good outcomes for total fraction points support. Moreover, symmetry was obtained for the fraction of point support. DC exhibited this factor because of its priority for point level for seed choosing.The Rank degree technique gives priority for the interconnection splitting for seed determination. The benefit is the selection of an end for easy achievement of the interconnection from the required size. The technique performed uniformly well and exhibited preferred outcomes in comparison with the other two techniques.

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