THE VALUE OF A SOCIAL NETWORK

By

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2007

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
December, 2008

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ACKNOWLEDGMENTS

I would like to sincerely thank Dr. Subhash Kak for inspiring me to do this thesis. He has been continuously supportive with his inspirational talks and useful discussions. His tireless effort, commitment, and understanding have made this endeavor possible.

I also thank the members of my graduate committee, Dr.Venkatesh Sarangan and Dr.Nohpill Park for their guidance and suggestions, especially Dr.Sarangan for all his advice and encouragement in completing the research.

I would also like to thank my friends Sumanth Gangasani and Suresh Thippireddy for their friendship during the period of my research. My special thanks to Abhishek Parakh for actively participating in the discussions, and for patiently reviewing the document.

Last but not the least, I would like to thank my family for their encouragement in pursuing the degree. Without their invaluable support, I would not have been able to complete this work.

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CHAPTER I

INTRODUCTION

Social networks are structures consisting of individuals or organizations that create powerful ways of communicating and sharing information. Millions of people use social networking websites like MySpace, Facebook, Bebo, Orkut and Hi5. The question of their value related to size is an important problem in computer science [1, 2], both from the point of view of connectivity and that of business investment.

1.1 Concepts

Social networks connect people and the cost involved in connecting is low, which benefits businesses and institutions. These networks are important in customer relationship management, and they serve as online meeting places for professionals. Virtual communities allow individuals to be easily accessible. People establish their real identity in a verifiable place, these individuals then interact with each other or within groups that share common business interests and goals.

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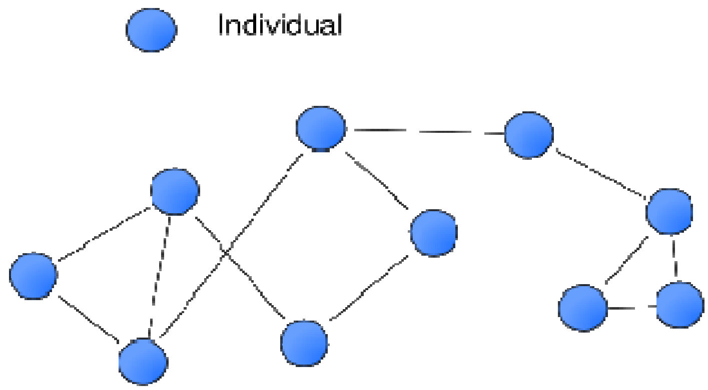


Fig1. Simple Social Network

1.1.1 Need for better estimate of value

False and exaggerated estimates of the value of a social network can have significant implications for technology investors. Until the IT bubble burst in 2001, it had been common to estimate the market value of a social network based on Metcalfe's law which says that a value of a network is proportional to the square of the size of network [1]. Recently Odlyzko and his collaborators have argued against Metcalfe's law saying that it is significantly overestimates value and they have suggested that the value of a general communication network of size *n* grows according to *n log n,* which is Zipf's law [2, 27].

An important claim has been made by anthropologist Robin Dunbar [3, 4] on the extent of connectivity in effective social organizations. He argued that the size of the brain is correlated with the complexity of function and developed an equation, which works for most primates, that relates the neocortex ratio of a particular species - the size of the neocortex relative to the size of the brain – to the largest size of the social group.

For humans, the max group size is 147.8, or about 150. This represents Dunbar's estimate of the maximum number of people who can be part of a close social relationship [4].

Support for Dunbar's ideas come from the community of Hutterites, followers of the sixteenth century Jakob Hutter of Austria, who are pacifists and believe in community property and live in a shared community called colony. Several thousand Hutterites relocated to North America in the late 19th century and their colonies are mostly rural [3,4]. A colony consists of about 10 to 20 families, with a population of around 60 to 150. When the colony's population approaches the upper figure, a *daughter* colony is established.

Dunbar's ideas can be taken to be an indication of the idea that most social networks are "small world" networks [3, 4, 5, and 9]. Small world networks exhibit clustering and small characteristic path lengths that seem to capture many features of social computing networks. We are interested in relating value to size in such networks.

1.2 Problem Formulation

In this thesis we propose to investigate the value of a social network with respect to the probability mechanism underlying its structure. Specifically we introduce new random networks and compute the value for small world networks and scale free networks. We provide evidence in support of the value of such networks to be given by Zipf's law.

1.3 Layout of Thesis

We first review articles that lead to the proposal for new random networks. Chapter 2 presents review of literature, Chapter 3 presents our methodology, and chapter 4 provides results on value of different kinds of social networks. These chapters also discuss the theory of the networks and issues related to simulation.

CHAPTER II

REVIEW OF LITERATURE

2.1 Background

Odlyzko *et al* claimed [2] the reason for failure of the dot-com and telecom booms that was based on Metcalfe's law, according to which value of a communication network is proportional to the square of the size of the network. There is also the Reed's law [7] saying that the value is exponentially related to the size. Odlyzko *et al* argued that the Metcalfe's rule is a significant overestimate and Reed's law is even more of an overestimate. It should be noted that Metcalfe actually meant to establish the existence of a cost-value crossover point (critical mass) before which networks don't pay; the trick is to get past that point, to establish critical mass.

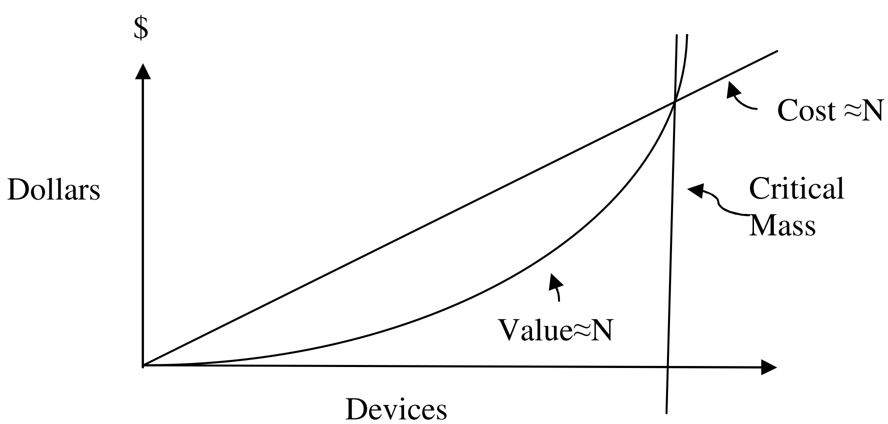


Fig. 2 Robert Metcalfe's original circa-1980 slide

Consider a network of 100 000 members that we know brings in $1 million, if the network doubles its membership to 200 000, by Metcalfe's law the value grows by ($200\ 000^2/100\ 000^2$) times, quadrupling to $4 million, whereas the *n log n* law says its value grows by (200 000 log (200 000))/ (100 000 log (100 000)) times to only $2.1 million. In both the cases, the network's growth in value more than doubles, still outpacing the growth in members, but one is much more modest growth than the other. Much of the difference between the artificial values of the dot-com era and the genuine value created by the internet can be explained by the difference between the Metcalfe-fueled optimism of n^2 and the more sober reality of *n log n*.

Odlyzko *et al* developed several quantitative justifications for their *n log n* rule of thumb valuation of a general communications network of size *n*. One of them is Zipf's law which states that if we order some large collection by size or popularity, the second element in the collection will be about half the measure of the first one, the third one will be about one-third the measure of the first one, and so on. In other words, the *kth* ranked item will measure about 1/*k* of the first one. As example of this popularity is a rough measure of value to booksellers like Amazon. If we have a million books, then the most popular 100 will contribute a third of the total value, the next 10,000 another third, and the remaining 989,900 the final third. The value of the collection of *n* items is proportional to *log n*. For this reason we choose to call the proposal of Odlyzko and associates also as the Zipf's law.

2.2 Small World Phenomenon

The small world phenomenon is the empirical fact that we are all linked by short chains of acquaintances, which was first pointed in pioneering work of Stanley Milgram. Kleinberg [5] argues that the framework developed by Watts and Strogatz provided a compelling evidence that the small world phenomenon is pervasive in a range of networks arising in nature and technology. But he believes that the existing models are insufficient to explain the striking algorithmic component of Milgram's original findings that individuals using local information are collectively very effective at actually constructing shorts paths between two points in a social network. Kleinberg proves that no decentralized algorithm, operating with local information only, can construct short paths in these networks with non-negligible probability. He defines an infinite family of network models that generalizes the Watts-Strogatz model, and shows that for one of these models, there is a decentralized algorithm capable of finding short paths with high probability.

Kleinberg says that social network exhibits small world phenomenon adding that recent work has suggested that the phenomenon is pervasive in networks arising in nature and technology, and a fundamental ingredient in the structural evolution of the World Wide Web.

The Watts and Strogatz proposed model [21] for the small world phenomenon is based on a class of random networks that interpolates between two extremes, in which the edges of the network are divided into local and long range contacts. Watts and Strogatz argue that such a model captures two crucial parameters of social networks:

there is a simple underlying structure that explains the presence of most edges, but a few edges are produced by a random process that does not respect this structure. Kleinberg raises two important questions regarding the small world phenomenon. " Why should arbitrary pairs of strangers be able to find short chains of acquaintances that link them together?" and "Why should there exist short chains of acquaintances linking together arbitrary pairs of strangers?" [17, 21]

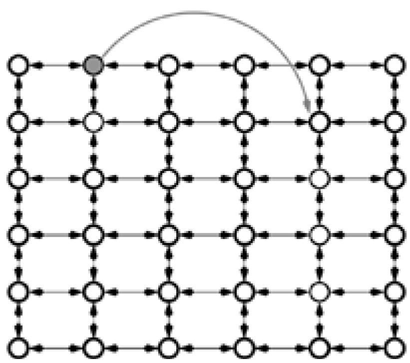


Fig .3 Two –dimensional grid with a single random shortcut superimposed [5]

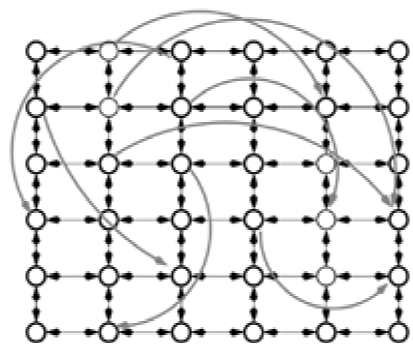


Fig. 4 Two dimensional grid with many random shortcuts superimposed (Watts-Strogatz model) [5]

Kleinberg studied decentralized algorithms by which individuals, knowing only the locations of their direct acquaintances, attempt to transmit a message from a source to a target along a short path. Firstly it is shown that the existing models are insufficient to explain the success of such decentralized algorithms in finding short paths through a social network. In a class of networks generated according to the model of Watts and Strogatz, it was proved that there is no decentralized algorithm capable of constructing paths of small expected length.

Kleinberg defines an infinite family of random network models that naturally generalizes the Watts-Strogatz model and showed for one of these models, there is a decentralized algorithm capable of finding short paths with high probability. Finally he proves the stronger statement that there exist a unique model within the family for which decentralized algorithms are effective. Avinash Kak [23] presents an extensive discussion of the small world phenomenon together with simulations.

Subhash Kak in his proposal [4] on the future of social computing networks has proposed the envisioning of new social computing networks where the physical connectivity provided to the participants is bootstrapped in new ways so that we can speak of creativity enhancing digital ecosystem.

2.3 Different Networks

Based on the topological characteristics online social networks can be modeled into three major types. They are

1) Random networks

2) Scale free networks

3) Small world networks.

2.3.1 Random Networks

Intorduced by Erdos and Renyi in 1959 [19], such networks can be easily constructed by connecting each pair of nodes in the network with a probability p. A graph can be represented as $G(n,p)$ where n is the number of actors and p being the probability of having an edge between any two actors. If an actor in the graph is connected to all other (*n-1*) actors with the same probability as *p* and *n* being the total number of actors in the graph, the probability that *P(k)* that an actor has a degree equivalent to *k* is given by the binomial distribution

$$P(k)= C_k^{n-1} p^k (1-p)^{N-1-k}$$

The average degree of an actor in the network is $x=(n-1)\,p$ so we can rewrite the above equation as

$$P(k)= C_k^{n-1} \left[\frac{x}{(n-1-x)}\right]^k [1-x/(n-1)]^{n-1} \approx x^k/k!\ \ e^{-x}$$

From the above equation we can say that degree of connectivity of actors follows the Poisson distribution. Random networks are extensively studied and are usually used as refrences in robustness tests of networks and how a rumor or virus spreads around the network. Bernoulli random networks random network is created in which edges are generated independently from a Bernoulli distribution. A random number between 0 and 1 is generated for each cell in an adjacency matrix. If this number is less than the specified probability then an edge is created. We specify a single probability for the whole matrix, or different probabilities for each row, column or cell. The whole procedure can be repeated for a number of trials to create an integer valued network

2.3.2 Scale Free Networks

Scale free networks were introdued by Barabasi and his team [11, 25]. They have the characteristics of continous growth and preferential attachement. In random networks the degree distribution follows Poisson distribution but in scale free network the degree distribution follows the power law which says that $P(k) \approx k^{-\lambda}$ where λ is a constant and is within the range $2<\lambda<3$.

Scale free networks are noteworthy because many empirically observed networks such as the world wide web, protein networks, citation networks and some social networks have this property. The scale free network has the characteristic of adding new nodes over time and there is a continuous growth. Preferential attachment is other characteristic by which new node is added. Each time each step will have higher probability of attaching itself or having an edge to the node which is well connected . Hence older nodes have more probability of establishing an edge with the new node that is joined into the network. Even the clustering coefficeint of nodes also follows the power law. The probability for a node attaching itself to a new node is given by

$$P(K_i) = \frac{K_i}{\sum_j K_j}$$

where K_i is degree of node i.

Since the network follows power law, the topology of network formed is different from other models.

2.3.3 Small World Networks

Stanley Milgram in his [26] paper presented the experiment of passing documents from a person to his acquaintance and then to immdeiate accquaintance could linkup two starangers in different parts of the country. It was found that to link up two strangers in an average case would take six people in between. This phenomenon is widely known as the six degrees of separation. The small world propety usually mean that network exhibiting short linking path between individuals. The Watts and Strogatz model [21] is used to generate small world networks is, given the number of nodes *N*, the mean degree K, and parameter β, satisfying $0 \leq \beta \leq 1$ and $N >> ln(n) >> 1$; the model constructs an undirected graph with N nodes and $(NK)/2$ edges . A regular ring lattice is constructed with N nodes and K neighbours, $K/2$ on each side i.e. if the nodes are labeled $n_0 \ldots n_{N-1}$, there is an edge (n_i, n_j) if and only if $| i-j | \cong k \ (mod\ N)$ for some $| k | \ \varepsilon (1, K/2)$. For every node $n = n_0 \ldots n_{N-1}$ take every edge (n_i, n_j) with $i<j$, and reire it with probability β. Small world network is created by rewiring the basic network, rewiring at each node consists of redirecting one of the outgoing arcs at the node to some other destination node.The extent of rewiring is controlled by a probability β and is done by replacing (n_i, n_i) with (n_i, n_k) where k is chosen with uniform probability from all possible values that avoid loops $(k \neq i)$ and link duplication with $k' = k$ at this point.

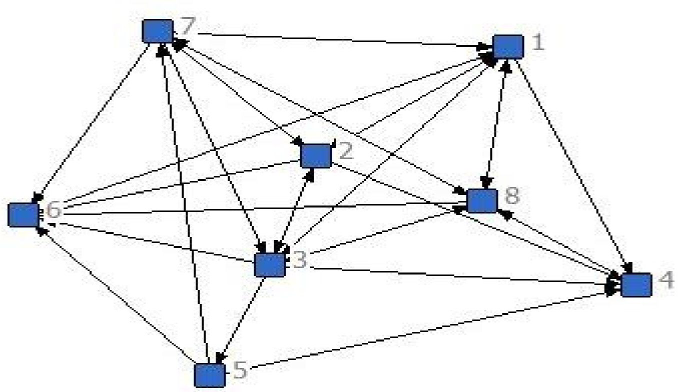
2.4 Zipf's Law

Zipf's law is an empirical law originally proposed for words in a large text and it states that given some corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the frequency table. The most frequent word will occur approximately twice as often as the second most frequent word, which occurs twice as often as the fourth most frequent word etc. In the network context, if the value of the most important member to user *A* is taken to be proportional to 1; that of the second most important member is proportional to ½, and so on. For a network that has n members, this value to the user *A* will be proportional to $1 + 1/2 + 1/3 + \ldots + 1 / (n-1)$, which approximates to $log\ n$. Given that the number of users is n, the total value of the network is proportional to $n\ log\ n$.

Metcalfe's law took the value of the network to be proportional to its connectivity, since the total number of connections in a network of n users is $n\ (n-1)$ or about n^2. In practice many users will be connected socially only to a fraction of all the users though the networks provide a full connectivity of n^2. Reeds law [7] is based on the insight that in a communication network as flexible as internet, in addition to linking pairs of members. With n participants, there are 2^n possible groups, and if they are all equally valuable, the value of the network grows like 2^n.

2.5 Sample Random Networks

We examined different random networks, and estimate the total number of connections and connectivity and compare them with the values $n \log n$ and $n^{2.}$ A few sample graphs with small number of nodes 8, 9, 10, 11 are given in Figures 5 to 7.



12345678
----
1 01110001
2 10110110
3 11011101
4 00100001
5 00010110
6 10000000
7 11100101
8 10100110

Fig.5 Random Graph with 8 nodes and value 27.

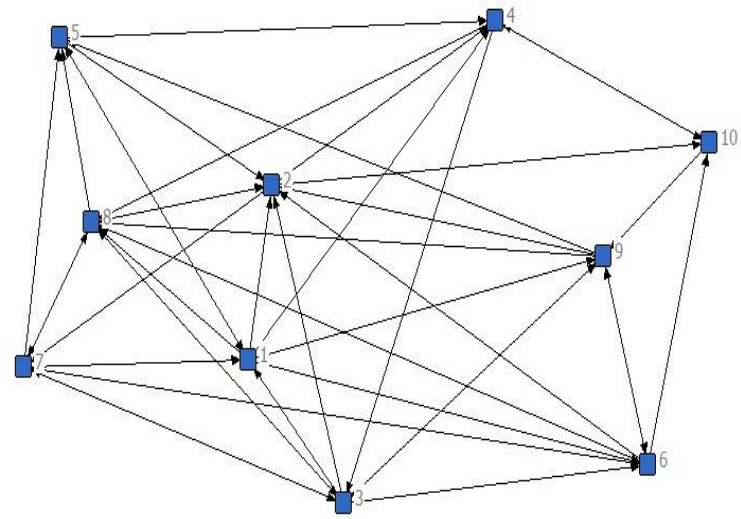


Fig .6 Random Bernoulli graph with 10 nodes, and value 44

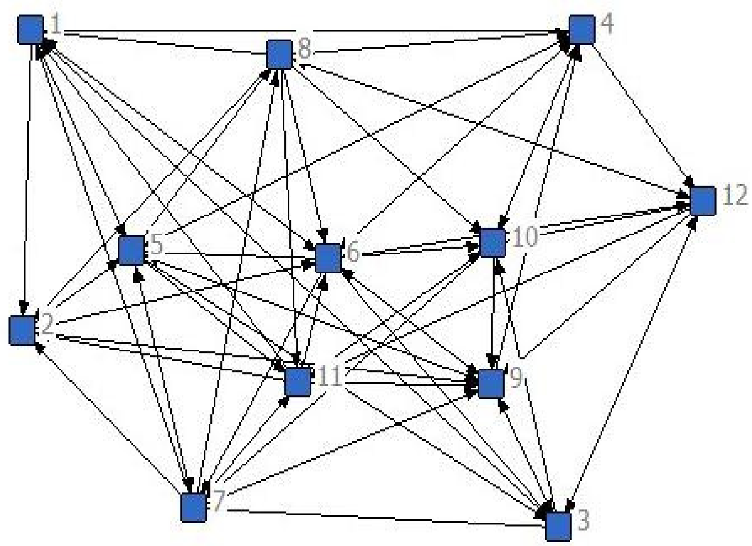


Fig. 7 Random Bernoulli graph with 12 nodes, 62 connections

2.5.1 Value of Random Networks

For randomly generated graphs with Bernoulli distribution and for a probability of tie being 0.5, the connectivity values for different network are as follows:

No. of nodes	Actual Value	n^2 (Metcalfe's)	n log n (Zipf's)
8	33	64	7
9	39	81	9
10	44	100	10
11	59	121	11
12	62	144	13
13	75	169	14
14	83	196	16
15	96	225	18

Table 1 Values for different random networks

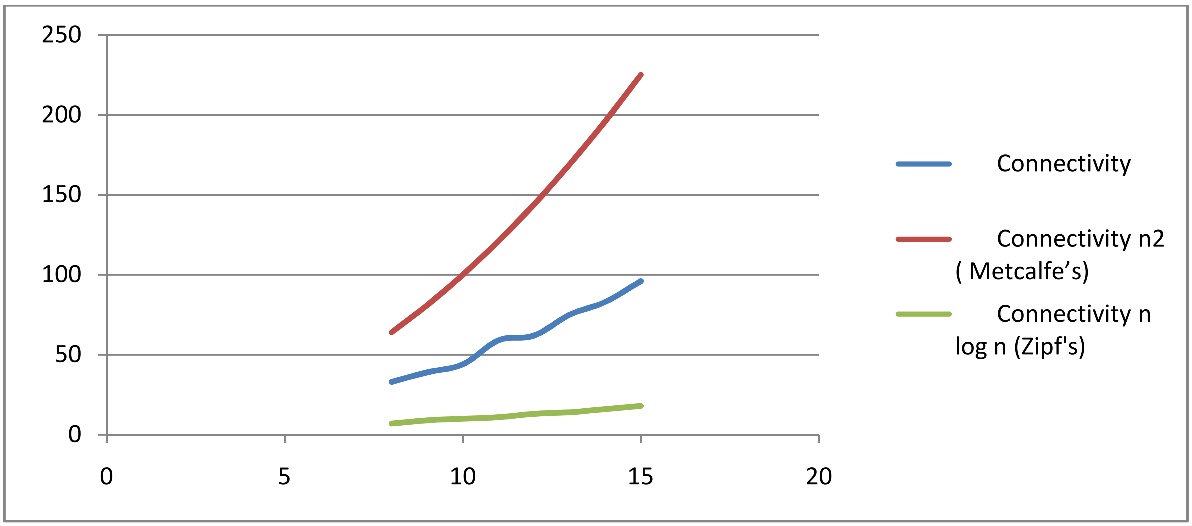


Fig. 8 Sample graph showing different values for different networks

It may be seen that from this example the graph fits Zipf's model better than Metcalfe's law.

CHAPTER III

PROBABILISTIC NETWORKS

3.1 Probabilistic Random Networks

We consider probabilistically generated social networks. These networks are based on the variable binomial distribution in which sets of nodes are connected to other nodes with different probability distributions.. Several networks are considered and the average samples are considered for calculating the bin values. The histogram for such values is given in Fig. 9. This histogram is a consequence of the examples that contributed to our simulation, which explains the bump for the bin 16.35. The main point here is the frequency increases as we increase the bin value. The bin values are the average number of connections for nodes labeled 1 through 100, where the probability mechanism for generating nodes varies in group of 10.

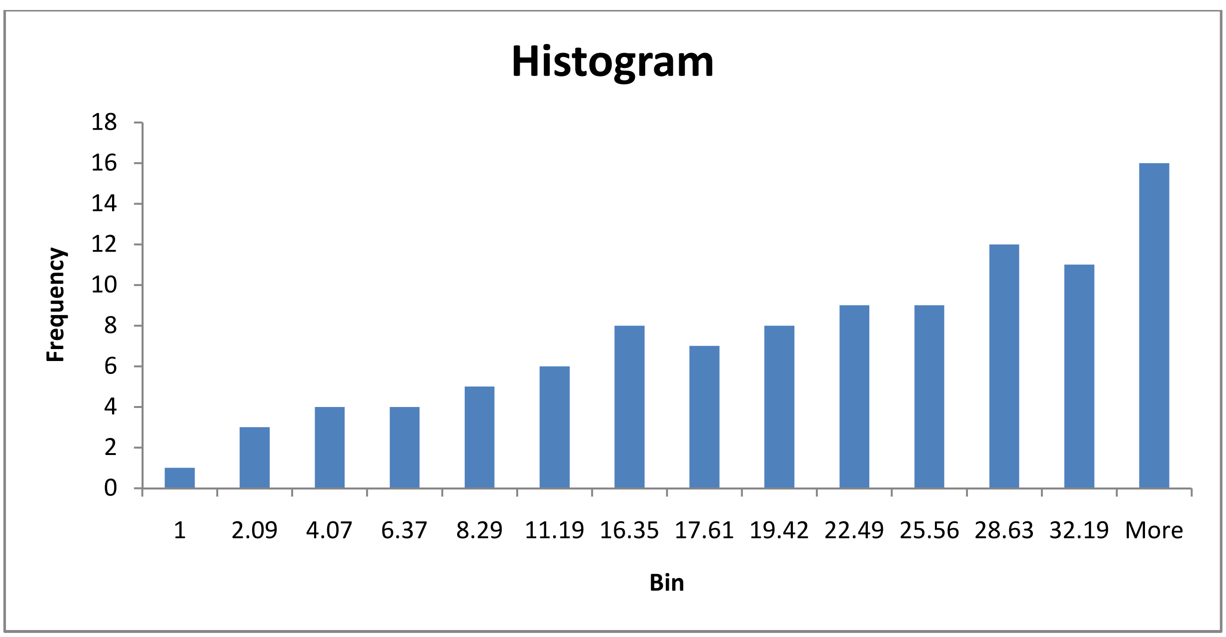


Fig.9 Histogram showing the new random networks

3.1.1 Value of Networks

With the above experiment results we calculated the value for the networks generated and compared them with the values n^2 and *n log n.* We generated networks with variable number of nodes like 100, 90, 80, 70 etc. and we calculated the values obtained with Metcalfe's law and the heuristic *n log n* Zipf's law.

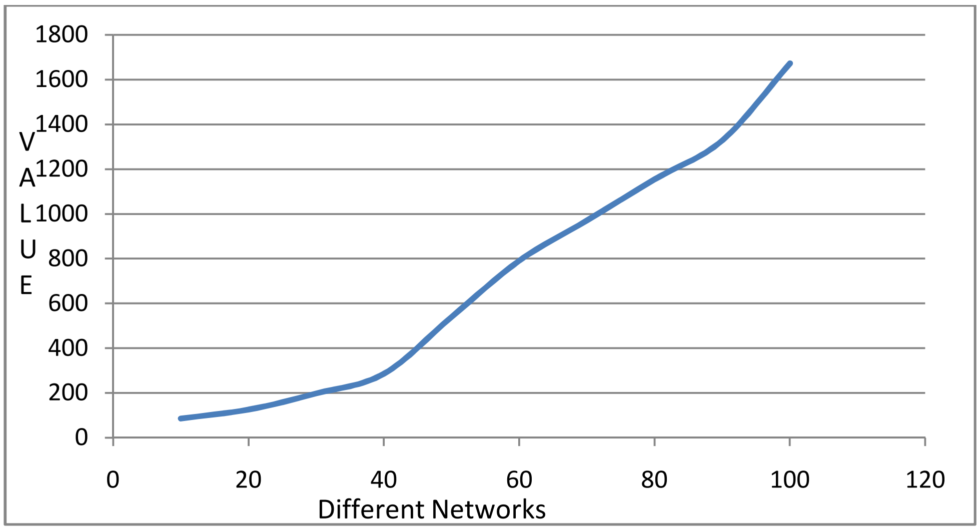


Fig. 10 Graph showing the values for new random networks

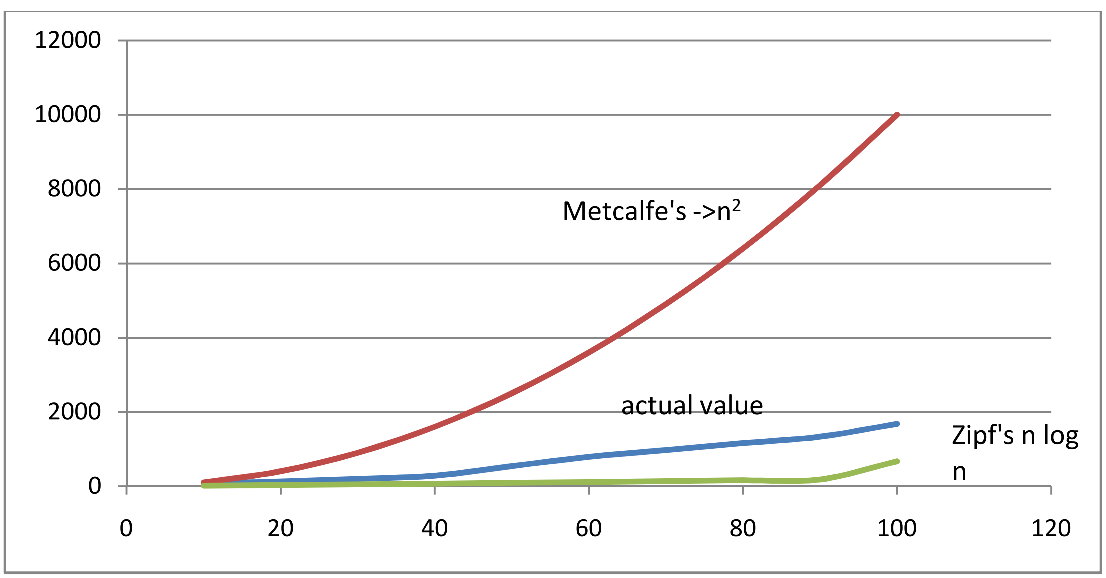


Fig. 11 Comparison of values between the n^2, *n log n* for example networks

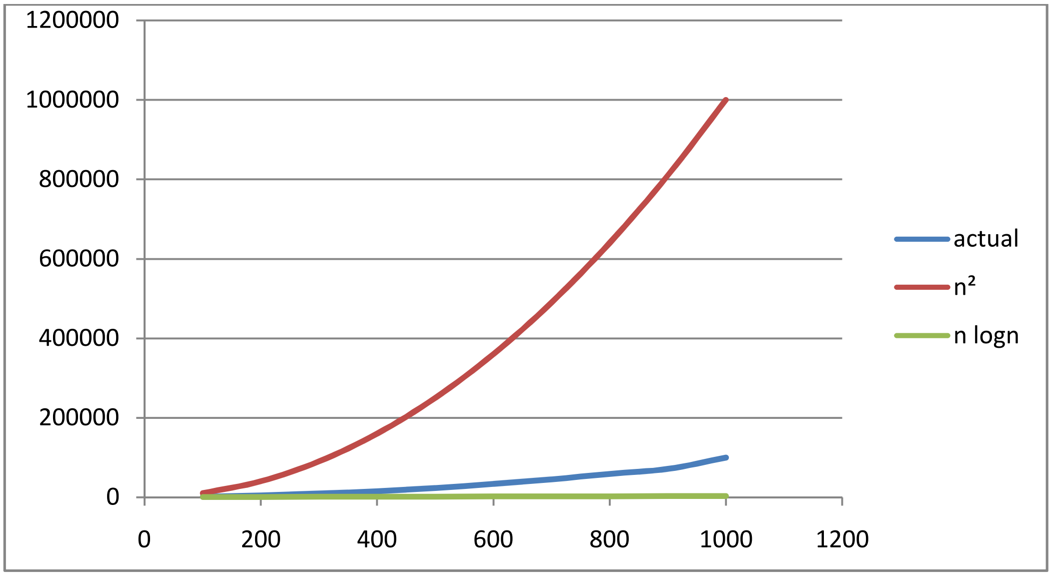


Fig.12 Graph showing the values of example networks compared with n^2 and *n log n*

Figures 11 and 12 show the values of the network in comparsion with other values n^2 and *n log n*. The number of nodes in the network is the X-axis and the associated value for each node is in the Y-axis. From this observation we clearly understand that the actual value of the network lies somewhere in between the values n^2 and *n log n*.

3.2 Small World Networks

We have simulated small world networks and and the value associated to coressponding graphs are observed on an average case. We generated a Watts-Strogatz small world network consisting of *N* nodes [17, 18, 21]. Each node is directly connected to *k* immediate neighbours that are located symmetrically in the ring lattice on two sides of the node.

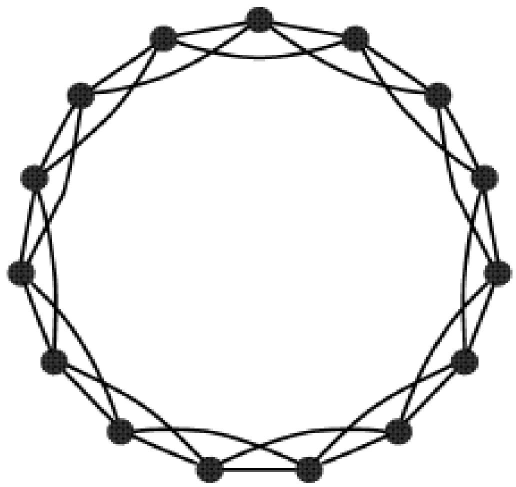


Fig. 13 Watts Strogatz ring lattice for a small world networks with 15 Nodes and 4 local contacts for each node

A small world network is generated by "rewiring" the basic network i.e. ring lattice. Rewiring at each node consists of redirecting one of the outgoing arcs at the node to some other destination node. The extent of rewiring is controlled by probability *p*. We generate a random number which is uniformly distributed and check whether the generated random number is less than or greater than the given probability. If the random number generated is less than the assumed probability we rewire an arc, otherwise the arc is left unchanged.

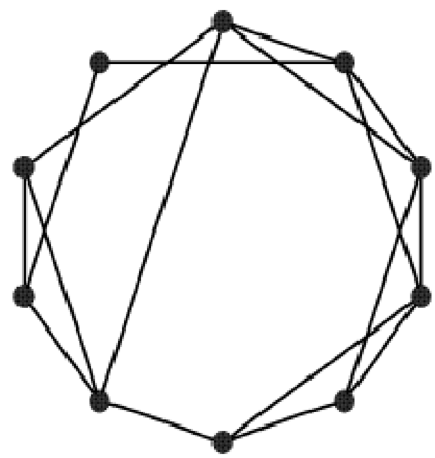


Fig.14 Small world network with the probability of rewiring is p=0.08

As we increase the value of the p from 0 to 1.0 we see a randomly rewired graph almost all the nodes connected differently

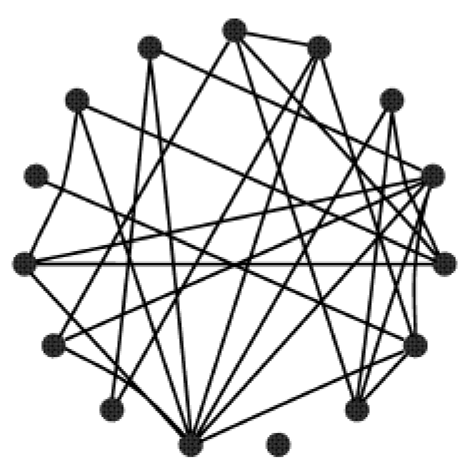


Fig. 15 Small world network with probability of rewiring p=1.0.

3.2.1 Value of Small World Networks

Several small world networks with different number of nodes are generated using different binomial distribution for random number generation and with variable probability values for the rewiring. In every network for every node we count the number of other nodes to which it is connected and the total value of the network is estimated. We considered several repetitions of the generations and the average case value is considered.

No. of Nodes	Calculated Value	Metcalfe's	Odlyzko
100	747	10000	200
90	689	8100	176
80	634	6400	152
70	518	4900	129
60	490	3600	107
50	345	2500	86
40	256	1600	64

Table. 2. Comparison between the calculated value, n^2 and *n log n* values of small world networks with different sizes with *p*=0.18

The graph showing the different value curves as observed for a small world network with a probability of rewiring *p* as 0.18 and 0.32 in Figures 16 and 17.

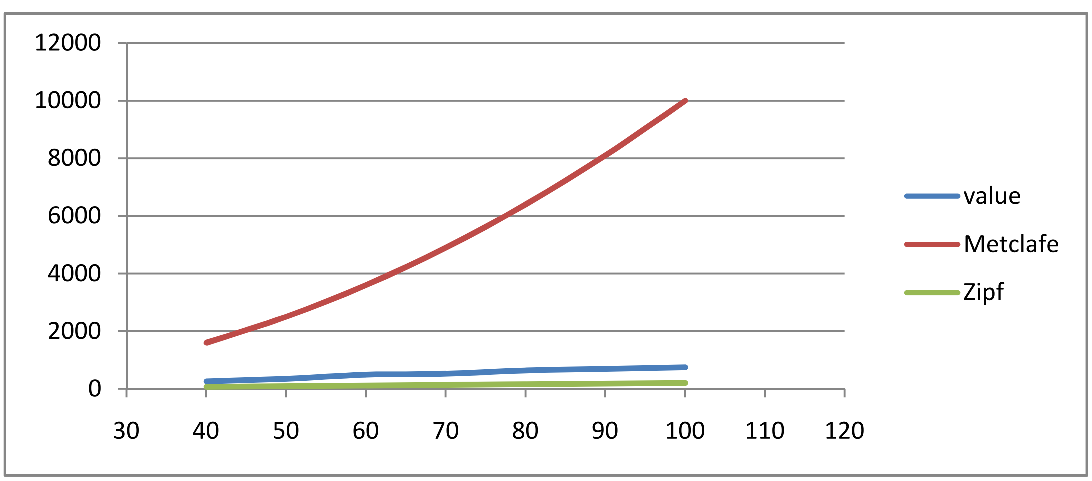


Fig. 16 Graph comparing the Values of small world network with a *p*=0.18

No. of Nodes	Calculated value	Metcalfe	Zipf
100	1296	10000	200
90	1221	8100	176
80	1025	6400	152
70	830	4900	129
60	730	3600	107
50	522	2500	85
40	384	1600	64

Table. 3. Comparison between the calculated Value, n^2 and *n log n* values of small world networks with different sizes with probability of rewiring *p*=0.32

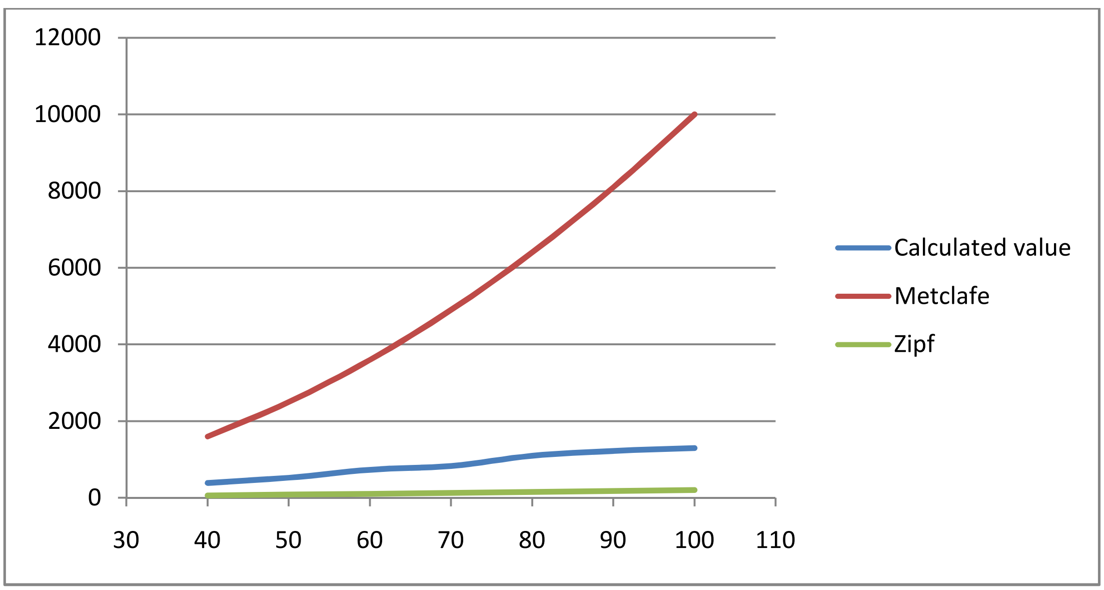


Fig. 17 Graph comparing the values of small world network with a *p*=0.32

We observe that in Table 2 and Table 3 that the calculated value is 4 and 6 times that of *n log n* respectively. Table 4 presents these results.

Probability	No. of Time higher
0.56	10
0.32	6
0.18	4
0.06	3
0.03	2.8

Table 4. Showing the relation between calculated and *n log n* value for a different probability

We plotted a graph for the above table and established a relation between probability and number of times the calculated value is more than that of *n log n* as and where the functional relationship is given by the following quadratic relationship

$$Y=12.045x^2 + 6.59x+2.5533$$

The regression value for this quadratic function is quite close to 1.

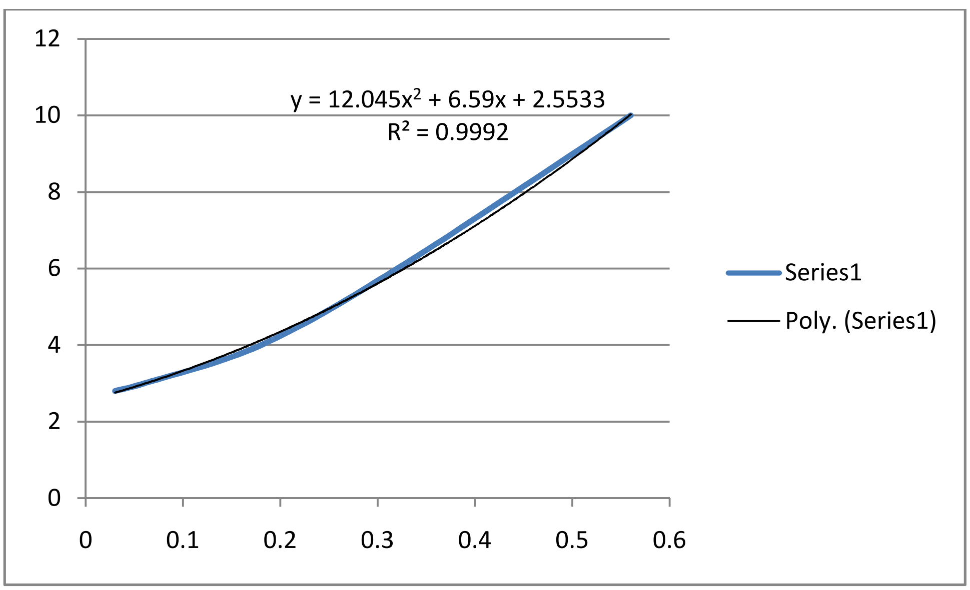


Fig. 18 Graph showing the relation between probability and the no. of times calculated value is more than *n log n*

3.3 Scale Free Networks

A scale free network is network whose degree distribution follows a power law. We have simulated Barabasi and Albert (B-A) [10, 11] model of scale free networks. We generated a network of small size, and then used that network as a seed to build a greater sized network, continuing this process until the actual desired network size is reached. The initial seed used need not have scale free properties, while the later seeds may happen to have these properties.

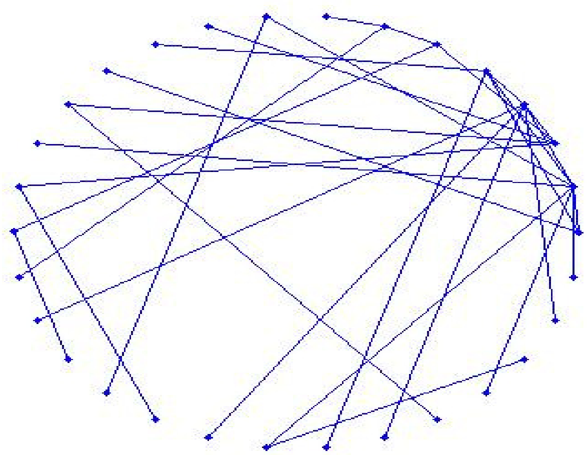


Fig. 19 B-A Scale Free graph with 30 nodes

We can draw a best fit line to the frequency of degrees distribution of the nodes. Degree is the number of links that connect to and fro a single node. For scale free networks, the frequency of degrees distribution forms a power- law curve, with a exponent usually between -2 and -3.

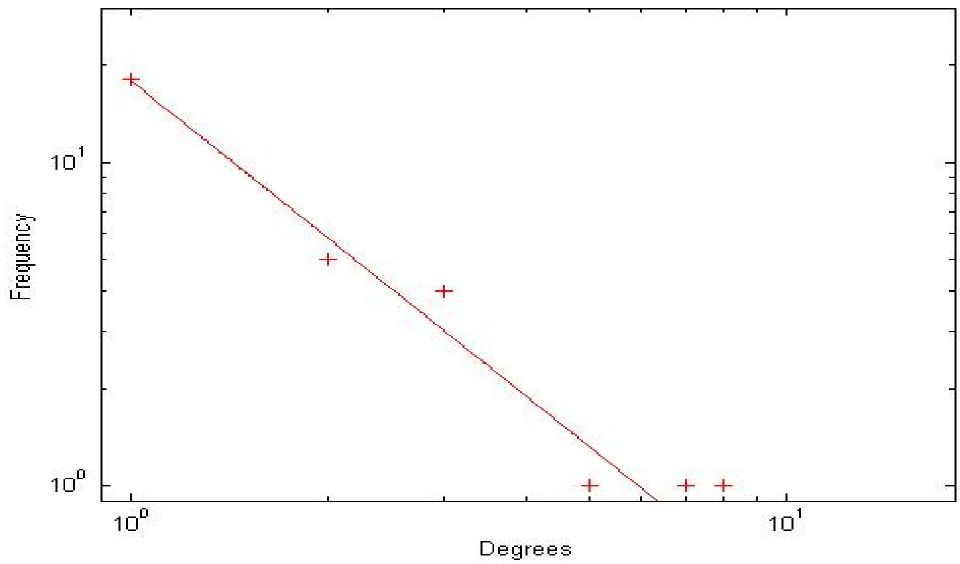


Fig. 20 Power-law curve for the small world network in Fig.18.

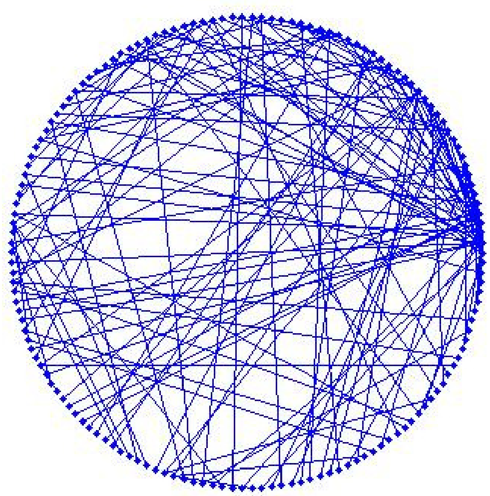


Fig. 21 B-A small world network with 150 nodes

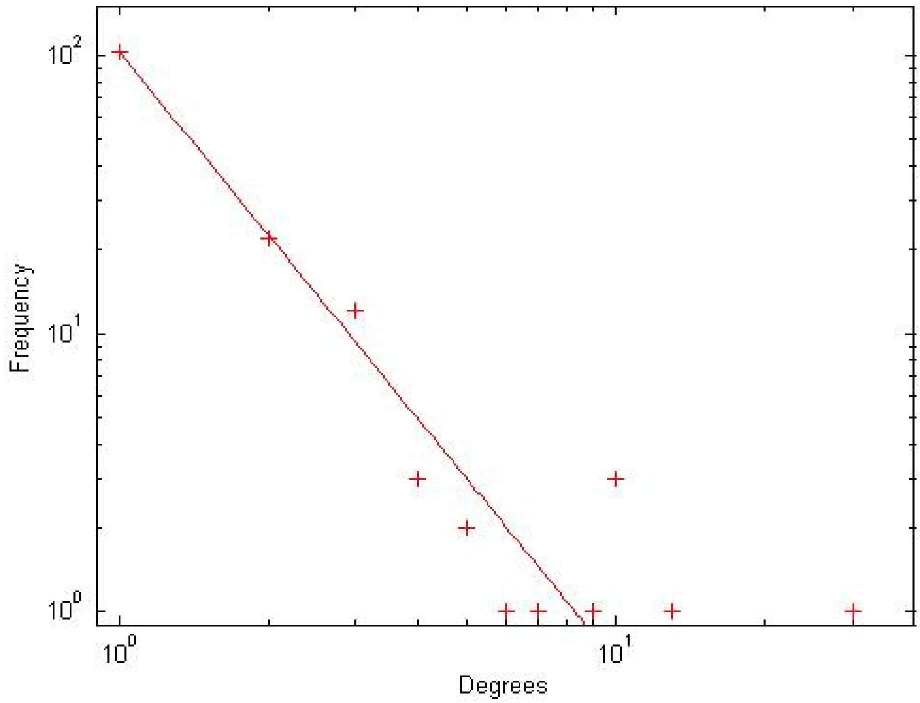


Fig. 22 Graph showing the power law distribution for the small world network in Fig.20

3.3.1 Value of Scale Free Networks

Several of these scale free networks are generated and the average case for the value calculation is taken into account. These scale free networks follow the Power law and therefore the values associated with them correspond to *n log n.*

No. of nodes	Calculated value	Odlyzko n log n
30	60	44.31
40	80	64.082
50	100	84.94
60	120	106.689
70	140	129.156
80	160	152.247
90	180	175.88
100	200	200

Table 5. Showing the Values Scale Free networks with different nodes

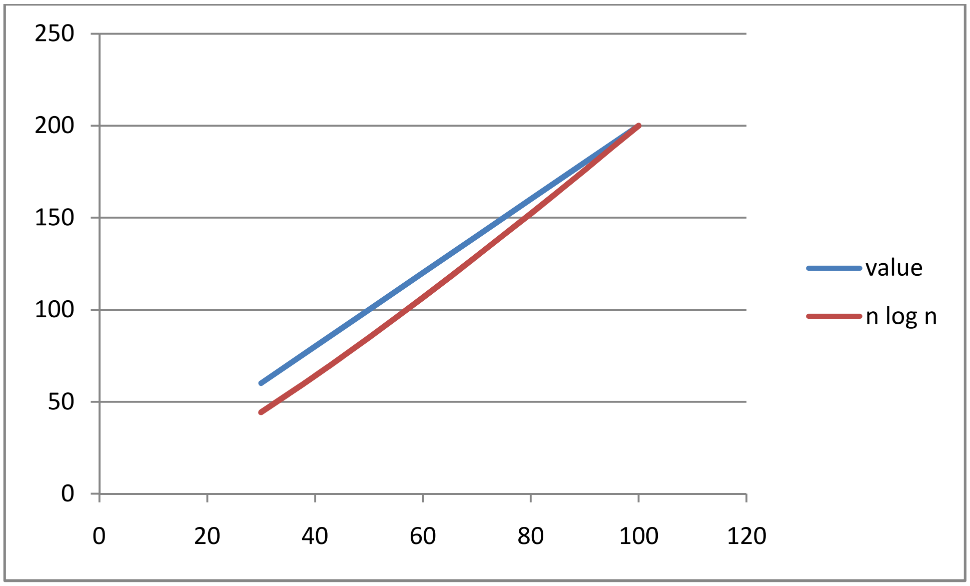


Fig. 23 Graph comparing the value of scale free network and *n log n*

This is also seen in Figure 23. We conclude that the property of being scale free captures the underlying foundation of the Zipf's law.

CHAPTER IV

CONCLUSION

The main contribution of the thesis is the demonstration that the Zipf's law, originally proposed on heuristic grounds, is valid for scale free and small world networks. We have shown empirically that the expression of value for a Watts- Strogatz small world network of *n* nodes is

$$f(p)\, n \log n$$

$$f(p) = 12.054p^2+6.59p+2.5533$$

where *p* is the probability of rewiring. We have computed the value of $f(p)$ for various *p* and found that the quadratic function provides an excellent fit. We believe that this is the first study broadly validating the heuristic claim of Odlyzko *et al* on the value of social networks.

Although no specific relationship between size and value can be fixed for random networks, our simulation shows that this value lies between Zipf's law and Metcalfe's law.

As future study one would like to determine if non-Watts-Strogatz small world networks also follow the Zipf's law.

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Findings and Conclusions:

Different laws have been proposed for the value of a social network. According to Metcalfe's law, the value of a network is proportional to n^2 where n is number of users of the network, whereas Odlyzko *et al* propose on heuristic grounds that the value is proportional to $n \log n$, which is the Zipf's law. In this thesis we have examined scale free, small world and random social networks to determine their value. We have found that the Zipf's law describes the value for scale free and small world networks although for small world networks the proportionality constant is a function of the probability of rewiring. We have estimated the function associated with different values of rewiring to be described well by a quadratic equation. We have also shown experimentally that the value of random networks lies between Zipf's law and Metcalfe's law.

ADVISER'S APPROVAL: Subhash C Kak