An Improved BA Model for Router-level Internet Macroscopic Topology

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Abstract—**Router-level Internet macroscopic topology modeling is studied in this paper. The frequency-degree power exponent and the degree-rank power exponent of the macroscopic topology, according to corresponding power law analyses, are 2.1406 and [0.29981, 0.84639], respectively. After the scale-free property of Internet macroscopic topology is proved, the traditional Barabasi-Albert (BA) model is proposed and improved to match up the corresponding power exponents of the Internet topology by the optimization of Genetic Algorithm. Finally, generation algorithm for the improved BA model is given.**

Index Terms—**BA model, genetic algorithm, Internet topology modeling, power-law distribution.**

I. Introduction

Generally speaking, the degree distribution of a target network (topology) is said to agree with principle of power-law distribution, if the network is of uneven topology structure and most of its nodes have small degree, whereas a rather few nodes have very large degree. General terminologies such as Max degree, Min degree or Average degree, however, could not appropriately character topology properties of such network, and power-law distribution might be introduced as an alternative[1][2].

Internet is an example of such network and power-law approaches have already become one of the most powerful analytical tools in Internet topology research related area[1][2][4]. In 1999, for the first time, Faloutsos made use of a notion of frequency-degree power-law to character the topology of both AS-level and router-level Internet, thereafter, definitions of degree-rank power-law, eigenvalue-rank power-law and so on were brought forward[1]. In 2003, Siganos found in his research[3] that frequency-degree power-law distribution was quite similar to and better than the probability density function (PDF) with degree (*d*) as independent variable and frequency (*f*) as dependent variable. Then, Complementary Cumulative Distribution Function(degree), short for CCDF(d)-degree, power-law distribution was found[3]. So, power-law approaches would be mainly used in studies of Internet topology modeling in this paper.

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A. Mathematical description of power-law distribution

Power-law distribution is mathematically denoted by $y = cx^{-r}$, where *x*, *y* are random variables, and *c*, *r* are constants greater than 0. Perform logarithm on it, we then get $\ln y = c' \ln x$. There is a linear relationship between $\ln y$ and $\ln x$, i.e., a straight line should exist in a dual-logarithmic coordinates. And this linear relationship, or the straight line in dual-logarithm graph, would be regarded as a primary judgment identifying whether power-law distribution is suited or not.

Three important power-law distributions mostly used in Internet topology researches are listed in table I[3][4], and their parameters are in table II.

TABLE I
THE BASIC EQUATIONS OF POWER-LAW DISTRIBUTIONS

Power-law distributions	Mathematical models
frequency-degree	$p_v \propto d_v^R$
degree-rank	$d_v \propto r_v^R$
CCDF(d)-degree	$D_d \propto d^D$

TABLE II
DEFINITIONS OF THE PARAMETERS AND SYMBOLS

Variable	Definition
G	Undirected graph
N	Number of the nodes in a graph
E	Number of the links in a graph
d_v	Degree of node *v*
d	Average degree of a graph, $\bar{d} = 2E / N$
p_v	Frequency of node whose degree is *v*
D_d	CCDF(complementary cumulative distribution function)
r_v	Order of node *v*
λ	eigenvalues of $N*N$ Matrix A: $X{:}X \in R^N \backslash \{0\}$ and $AX=\lambda X$
ACC	Absolute value of the correlation coefficient, the closer the ACC is to 1, the more accurate the fitting model is

B. The measured samples of the router-level Internet

1) Measuring methods

Dynamic methods based on the active probing are the main approaches to measure the router-level Internet topology[16].

The dynamic methods, at present, are mainly divided into three categories[19]: (1) single-monitor-measuring by recording the source routers in the route path, such as the Internet Mapping Project (IMP) in Bell Lab.[20], and the Mercator[21] projects; (2) active measuring based on the Public Traceroute Server (PTrS), such as the ISP topology measuring project by Boston University[22]. (3) multi-monitor-measuring or measuring-from-multiple-vantage-points by self-developed software engines, such as the CAIDA[1] projects[17][18], and Active Measuring Project by Harbin Institute of Technology[19].

In the upper three methods, the PTrS (method No.2) is quite limited due to the following reasons[19]. Firstly, PTrS are quite unevenly distributed in Internet and not all ISP render services of PTrS. Reference [19] showed that only one of nine ISPs providing PTrS, so PTrS method is not reliable for measuring Internet. Secondly, it's rather hard to control these PTrS from the ISPs due to security considerations, which directly make measuring Internet topology impossible.

The first method is similar to the third one (e.g., CAIDA), they are all based on traceroute or the traceroute-like programs[17][18], but the first method is inferior since it's totally upon single-monitor-measuring tools. CAIDA, however, could implement multi-monitor-measuring tools and consequently yield better measuring results[17][18]. The Active Measuring Project by Harbin Institute of Technology (HIT) also used multi-monitor-measuring tools, but it had fewer monitors in its project than CAIDA has, what's more, the HIT project mainly focused on the China part Internet topology[2][19], inferior to the world-wide Internet from CAIDA. So CAIDA was selected for this paper.

2) Problems of the measuring results

The measuring results from CAIDA monitors are complete but in coarse granularity. There are two main problems in it: IP Alias problem and the sampling bias problem due to single-monitor-measuring[6][19].

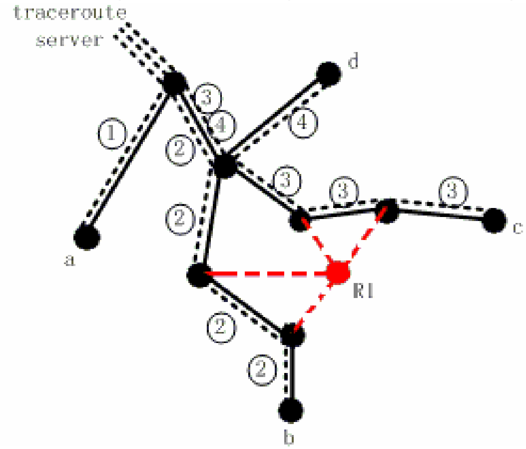
3) Problems of IP Alias

[Def 1] IP Alias[23][24]: Different ports with different IP addresses for one Internet router are mistaken for different routers during the active measuring programs. And this problem is known as IP Alias.

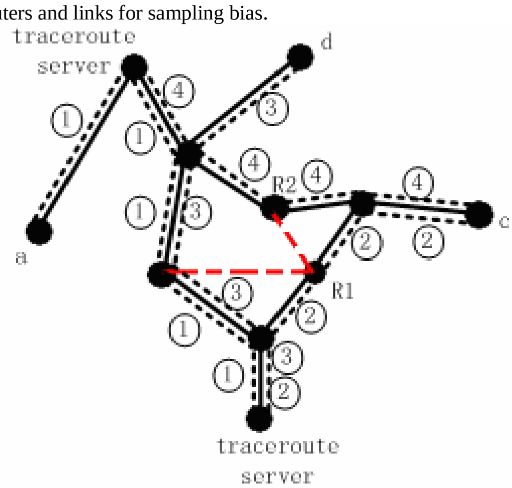
IP Alias Resolution[25] is a way to distinguish the IP addresses and solve the problem of IP Alias. However, the researches on IP Alias Resolution is still in progress, and only a few methods or tools are provided at present and they still could not solve the whole problem of IP Alias, only to some extent[23][24]. Among these tools, three of them are comparatively practicable, and they are iffinder tool[26] from CAIDA, Mercator[27] and Rocketfuel tool[28] from Boston University. Rocketfuel tools implemented the distinguishing of the aliased IP addresses by some complicated algorithm such as recognizing the TTL segment of the ip datagram. And some researches found Rocketfuel tool could find Alias IP addresses three times more than the other present tools[28]. So it was selected as IP Alias Resolution tool in this paper.

4) Problems of Sampling Bias

Some recent researches[6][19] found that the measuring results were usually different from real network topology and tended to show stronger power-law (frequency-degree power-law) relations when only one monitor or just a few monitors was used during the active measuring. For instance, one measuring monitor prardigm is illustrated in Fig.1(a).



(a) Measuring a target network with four nodes (a, b, c and d) from one monitor with traceroute-like tools. The measure covers four path indicated by (1)(2)(3)(4). The dotted links and R1 are the missing routers and links for sampling bias.



(b) Measuring the three leaf nodes (a, c and d) from two traceroute monitors. The covered path are indicated by (1)(2)(3)(4). The dotted links are the missing routers and links.

Fig. 1. Illustrations of measuring a network from different monitors.

From Fig.1(a), Router R1 and four links (the dotted links) are missed out. And difference between the measuring results from the real network is known as sampling bias[6]. Sampling bias is directly associated with the number of measuring monitors[6][19]. To prove this, let's go on with experiments illustrated in Fig.1(b), which has two monitors.

From Fig.1(b), Router R1 and two links missed in Fig.1(a) were successfully found. But there are still two dotted links missed due to sampling bias. Though it's still hard to find

1 CAIDA, the Cooperative Association for Internet Data Analysis, is a worldwide research center on Internet-related research fields. CAIDA has more than thirty monitor nodes which are distributed throughout the whole world, measuring and monitoring the variations of Internet. Three of them are located in

perfect approaches solving the sampling bias problems at present[6][19], we still found an easy and effective way from the last two figures. To solve, in some extent, the problem of sampling bias, it is helpful to use more monitors in measuring target network. And this is also the way we used in this paper.

5) The router-level Internet measuring samples after IP Alias Resolution and Sampling Bias handling

The rough measuring results in this paper are the Internet topology data measured at 30th, Jan. 2006 from twenty-one CAIDA monitors. And after the IP Alias resolution, we get twenty-one set of measuring samples. With these samples, we first gather them together to form a complete testing sample in order to reduce the impact of sampling bias to an extreme extent. As we know, this copy of sample is the ever best one in this paper in solving the problem of IP Alias and sampling bias, so, undoubtedly, this copy of sample would be our key sample in experiments of the paper.

However, we still made several other incomplete testing samples for comparison reason and to analyze how much sampling bias would effect on the samples, and they are sample(1) comprising data from only one monitor (arin monitor), and sample(2) from two monitors (arin, b-root), till sample(20) from as many as twenty monitors. We eventually had twenty-one set of measuring samples including the key testing sample for studies in this paper.

II. Power-law Analysis

A. Frequency-degree power-law

Calculate the frequency and degree from one-monitor sample, two-monitor sample, five-monitor sample and twenty-one-monitor sample (the key sample) and the power-law curve fitting results were showed in table III.

TABLE III
Power Exponent of the Frequency-Degree Power-law Analysis

Number of monitors	ACC	*|R|*
1	0.9675	**2.8279**
2	0.9560	**2.7834**
5	0.9601	**2.5495**
21	0.9824	**2.1406**

From table III, we observe that the curve fitting results (the straight line) are close to the sample, and all four ACCs (Absolute value of the correlation coefficient) are greater than 0.95, meaning that the curve fitting results are acceptable.

Besides, we find a phenomenon from table III that the power exponent |R| is getting smaller with increasing monitors. Considering the fact that a greater |R| means a stronger power-law relationship, we find that the power-law relationship of Internet topology is getting weaker with increasing monitors. Since the sampling bias might tend to produce extra power-law relations, the reason of the above phenomenon is easy to figure out. And what was found here on the router-level Internet in Fig.2 is quite similar to the research in [5].

When it comes to the twenty-one-monitor samples, i.e., the key sample of the paper, the power-law property might be least influenced by the sampling bias. Under such conditions, obvious power-law relations still exists, meaning that the there is definite power-law relationship in Internet topology.

Then, frequency-degree power exponent of the router-level Internet topology is found 2.1406, quite close to the power-exponent 2.2 of AS-level Internet topology in [6]–[8]. As we know, AS-level Internet topology is a coarse granularity of router-level Internet topology, the two research outcomes are expected to be similar to each other. And the analogs, in return, help to testify the accuracy of the frequency-degree power-law research results in this paper.

B. Degree-rank power-law

The degree-rank power-law relationship between the degree and its rank is showed in table IV, and that of the twenty-one-monitor sample is illustrated in Fig.2.

TABLE IV
Power Exponent of the Degree-Rank Power-law Analysis

Monitor size	ACC	*|R|*	**Num_{ld}/Num_{sld}**
1	0.9734	**0.6550**	**3.3921**
2	0.9727	**0.7128**	**4.2578**
5	0.9830	**0.7762**	**6.7064**
21	0.9941	**0.8464**	**17.4633**

Note: Num_{ld} is the number of nodes with the least degree, and Num_{sld} is the number of nodes with the second least degree in the Internet topology graph.

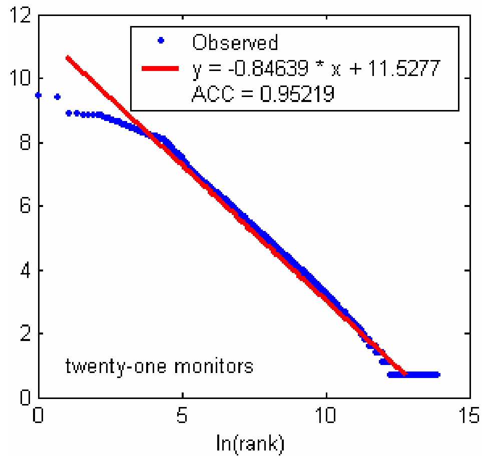


Fig. 2. The illustration of degree-rank power law analysis of the twenty-one-monitor sample.

Obvious power-law relationship is found in Fig. 3. And From table IV, ACCs are greater than 0.97 meaning the fitting result is good. |R| is increasing with increasing monitors. To better explain this phenomenon, we make reference to the research results of [2] that the power-exponent |R| would increase or decrease exactly with increasing or decreasing Num_{ld}/Num_{sld}[2] in degree-rank power-law analysis. What was found in table IV is quite the same, proving that the results of the degree-rank analysis in this paper are so far correct.

After further studies on Fig.3, we find that there are bad curving fitting parts when ln(rank) is less than around 3 in all sub-graphs, especially in sub-graph 4. Since sub-graph 4 is out of the key sample of the paper, we would perform further studies on the bad parts, which is illustrated in Fig.4.

The cross position of two straight lines in Fig.4 is around 3.6 on axis x. Besides the power-law relationship where ln(rank) is greater than 3.6 as we discussed above, the straight line where ln(rank) is less than 3.6, also proves a power-law property since the fitting ACC is greater than 0.95. Thus, there are two phases of degree-rank power-law relations found in Internet topology graph, and power exponents of the two parts are 0.29981 and 0.84639, respectively.

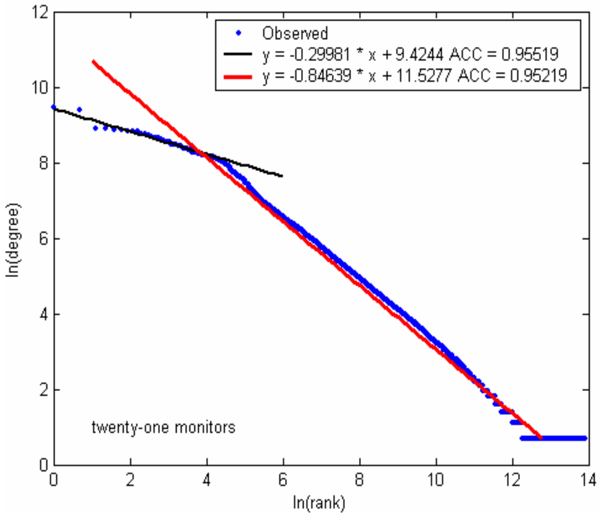


Fig. 4. Two phase degree-rank power-law relationship analysis

The founding power exponents could be used to quantitatively depict the power-law properties of Internet topology and would be used in Internet topology modeling later.

C. CCDF(d)-degree power-law

There are several mathematical models to calculate CCDF, and table V includes the CCDF(d)-degree power-law fitting results. To judge which one is best fitting the CCDF(d)-degree power-law of the Internet topology, a notation of SSSR(standard square sum of residual) is also listed in table V.

TABLE V
FOUR CCDFS AND THEIR FITTING RESULTS

Function name	CCDF	No. of monitors	SSSR$_1$
Power law	$F'(x) = -\frac{C}{\alpha+1}x^{\alpha+1}$	1	**12455.6927**
		2	**24215.0629**
		5	**114594.8493**
		21	**485010.9747**
Power law(2)	$F'(x) = -\frac{C}{\alpha+1}x^{\alpha+1} + Dx$	1	**219431.0825**
		2	**303397.4291**
		5	**503785.6687**
		21	**1160172.4009**
Weibull(2-parameter)	$F'(x) = e^{-(x/b)^C}$	1	**11594.8785**
		2	**20133.3965**
		5	**59191.7273**
		21	**221809.1604**

First, SSSR of the CCDF of power-law(2) is greater than the other two CCDFs, so power-law(2) is the worst in three. For the other two CCDFs, SSSR of power-law in all four sub-graphs is greater than that of Weibull(2-parameter), thus Weibull(2-parameter) is better than power-law in fitting the Internet topology samples. So, we made conclusions that the CCDF(d)-degree power-law distribution might not be the best way to quantitatively character the Internet topology compared with Weibull(2-parameter) distribution. And this research result is completely identical to the studies in [9]–[11].

III. INTERNET TOPOLOGY MODELING

A. BA Model

Now we began to construct an Internet topology model according to the power-law analyses results. The power exponent of frequency-degree power-law is |R|=2.1406. To find a way to construct a model that could generate a network with such frequency-degree power exponent is what we need do first.

Some researches[4][14] indicated that, the network having frequency-degree power-law properties is a kind of scale-free network, and the traditional model - Barabasi-Albert (BA) model[29] is viewed as one of the best choices to generate such scale-free networks. With this, we might use BA model as a base to form the Internet topology model.

A short description of BA algorithm is: generate m_0(m_0>1) nodes, and link them randomly; repeat the following step: for network G(t-1) at present, add one new node with n links to G(t-1) and form a new network G(t). The n links should be connected between the new added node and any selected current node in the network if the selected node i's $\Pi_i = k_i / \sum_j k_j$ is greater than a given threshold, where i, j are nodes existed in G(t-1) and k_i, k_j are degree value of corresponding nodes.

Network generated by the upper algorithm conforms to a frequency-degree power-law distribution of $p(k) \sim k^{-\alpha}$, where the power exponent α is irrelevant to m_0 and n.

Researches [4], [14] showed that the power exponent of the network generated by BA model is usually 3, which is different from 2.1406 in this paper. So improvement of BA model is necessary.

B. Improvement of BA Model

1) Improvement approaches

Researches on how to modulate the power exponent generated by BA model are still scarce at present. Reference [15] gives an algorithm using limit calculation and is too complicated to fit for the improvement requirement in this paper. Reference [7] gave an easier way: according to the probability model of linking nodes:

$$\Pi_i = k_i / \sum_j k_j \quad (1)$$

where k_i, k_j are degree value of node i and j. If it's changed to:

$$\Pi_i = k_i^{1+\varepsilon} / \sum_j k_j^{1+\varepsilon} \quad (2)$$

Then the power exponent of BA model would be around 2.2 when parameter ε is set in interval [0.1, 0.3][7]. Since value 2.2 is close to value 2.1406 in this paper, this method seemed to be effective for our requirement and would be adopted in this paper. And now we began to find the appropriate ε.

2) Optimize parameter ε by Genetic Algorithm

Genetic Algorithm (GA)[30][31] is used in this paper to try to find and optimize parameter ε in interval (0, 0.6] (enlarged to make sure ε could be finally found). GA algorithm repeats the operations such as cross, mutation and so on till network model with ε found by GA could produce power exponent of 2.1406.

i) Gene code: We define a gene code ***x*** as a vector comprising primary parameters to be optimized.

$$x = (\varepsilon) \tag{3}$$

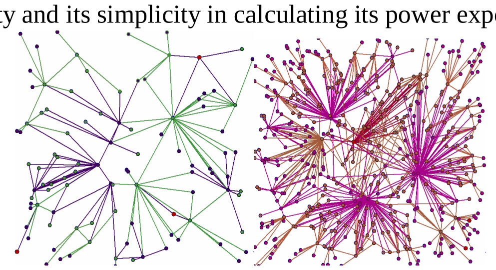
ii) Random initialization of gene group: Randomly initialize a gene group having *N* genes, *N* is set to 100 here.

iii) Evaluation function: Optimization of ε is to minimize the difference between the found power exponents and 2.1406. So the evaluation function should be:

$$f(x) = |P_\varepsilon(n) - 2.1406| \tag{4}$$

where $P_\varepsilon(n)$ is the power exponent of the generated network with parameter ε, and *n* is the size of the network. *n* is an important parameter because it's closely related to the calculation efficiency of the target network's power exponent. It's easy to know that the greater *n* is, the longer time is needed to calculate the power exponent. So a good choice of *n* would produce better and quicker outcome.

Two scale-free networks with 100 and 500 nodes respectively are illustrated in Fig.5. From the figure, there is a sign of scale-free property in Fig.5(a), and a much better property in Fig.5(b). So the average, 300, is taken in this paper, to ensure that the 300-node network generated by improved BA model could show both clear scale-free property and its simplicity in calculating its power exponent.



(a) 100 nodes (b) 500 nodes

Fig. 5. Two scale-free networks.

iv) Selection: Genes were sorted in descending order by scores in the gene group, and the first *m***N* genes, *m* is a random number (0<*m*<1), were selected for the next round of calculation by GA. We duplicate the best *m***N* genes and remove the last (worst) *m***N* genes in the sorted group, so that group size remains *N*.

v) Crossover: Crossover operation is:

$$\begin{aligned} \varepsilon_i' &= \varepsilon_i(1-\alpha) + \beta\varepsilon_j \\ \varepsilon_j' &= \varepsilon_j(1-\alpha) + \beta\varepsilon_i \end{aligned} \tag{5}$$

where α, β are random numbers, and $0 < \alpha < 1, 0 < \beta < 1$.

vi) Mutation: Mutation operation is:

$$\begin{aligned} \varepsilon_i &= \varepsilon_i(1+\alpha) \ \ if \ \ \gamma \geq 0.5 \\ \varepsilon_i &= \varepsilon_i(1-\alpha) \ \ if \ \ \gamma < 0.5 \end{aligned} \tag{6}$$

where α, γ are random numbers, and $0 < \alpha < 1, 0 < \gamma < 1$.

Unlike crossover operations, not all genes were selected to perform mutation. We set up a threshold of 0.3 in the algorithm, which means only 30% genes would mutate.

vii) Termination conditions: Basically there are two termination conditions in GA. The first condition is when evaluation function outcome of the best gene in the group is less than a threshold *s*, *s* is set to be 0.01 in the algorithm. The other condition is an iteration of 1000 runs. This is to guarantee ending GA in an appropriated way.

According to GA experiments, parameter ε was finally optimized to be 0.1886 in this paper.

C. Construct Internet topology model based on the improved BA model

Studies on AS-level Internet topology in [32] indicated that nodes in a network would not definitely conform to only one power exponent, especially the CCDF(d)-degree power-law and degree-rank power-law distribution. Likewise, the outcome of degree-rank power-law analysis is divided into two parts with two different power exponents in this paper, and they are 0.29981 and 0.84639.

So, the improved BA (IBA) model should be modulated again to conform to this property. This improvement could be implemented as a periodical modulation operation in the generation algorithm of the IBA model, and the algorithm is listed in table VI.

TABLE VI
THE IBA MODEL GENERATION ALGORITHM

contents
(1) Input number *N*. *N* is the number of the nodes in the to-be-generated network; /* *N* should be input by users */
(2) Loop steps (3)(4) and (5) until a *N*-node network is generated;
(3) /* Growth by the frequency-degree power-law properties */ Add a new node to the current network, and it would be linked to the randomly selected *m* nodes in the present network according to the linking probability function (shown in Equation (2) with parameter ε optimized as 0.1886), and *m* is less than or equal to the total number of the nodes in the network. If the outcome out of the linking probability function is greater than a threshold t0=0.6, then a link between node *i* and the new added node will be added to the network. Or else, the link would not be added to the network. /* Threshold t0=0.6 is set by the program, and it helps avoid constructing a network with too many or too few links */
(4) Define a threshold t1=10%, if the increment percentage of the new added nodes is greater than t1, then go to step (5) for degree-rank power-law modulation operation; or else go back to step (2).
(5) /* Degree-rank power-law modulation */ Sort the nodes of the present network in descending order, for each node lying in a range where ln(rank) is less than 3.6, calculate its degree by the degree-rank power-law distribution with the power-exponent of |R|=0.29981. If node *i*'s calculated degree is less than its present degree, then add links by rules of step (3). Loop the operation till the degree equals to the calculated degree. If node *i*'s calculated degree is greater than its present degree, delete links. Randomly select node *j*, if the linking probability between *i* and *j* out of equation (2) is greater than t0=0.6 and there is a link between node *i* and *j*, then delete it. Loop the operation till node *i*'s degree equals to the calculated degree.

D. Evaluations

1) Power-law evaluations

The way to evaluate the IBA model in this paper is to test the power-exponent of the generated networks by the model, and the experiments results are shown in Fig. 6.

The power-exponents of two randomly generated networks are 2.2609 and 1.8753, with SSSE of 85.547 and 251.6474, indicating that the results are acceptable. Though different from 2.1406, the two power-exponent are rather close, from which a conclusion could be gained that the IBA model is acceptable despite minute errors.

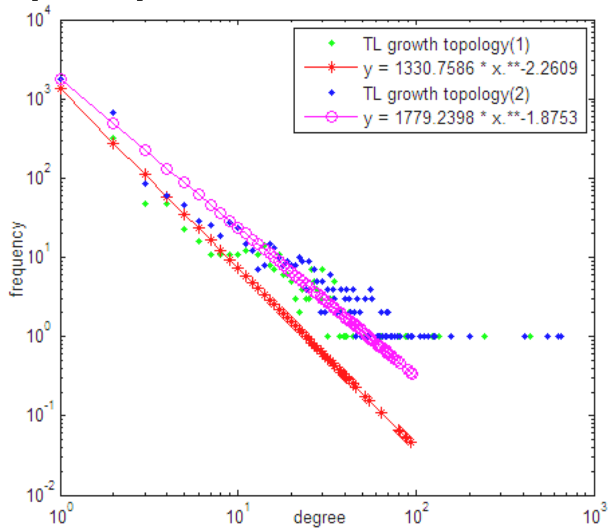


Fig. 6. Two networks generated by IBA model with power-exponent of 2.2609 and 1.8753, respectively.

2) Qualitative evaluations

Firstly, peer models such as a static model: Inet[32] model, a dynamic model: GLP[33] model are mainly designed and implemented for AS-level Internet topology. And the model in this paper, different from these models, is designed on the basis of Internet router-level topology. Thus, it's clear to say that the current studied model could generate a topology closer to real Internet.

Besides, the model in this paper encompasses both merits form static model and dynamic model, and thus is superior to the sole static models or sole dynamic models.

IV. Conclusions

With CAIDA samples, research approaches of the frequency-degree power-law, degree-rank power-law were performed, and obvious power-law properties were found in Internet macroscopic topology. The frequency-degree power exponent is found 2.1406, and the degree-rank power exponents are found to have two values, 0.29981 and 0.84639. Finally, we improved the traditional BA model (IBA model) and optimized it by Genetic Algorithm according to the gained power-exponents. Experiments proved the efficiencies of the IBA model in modeling Internet macroscopic topology.

The network generated by the IBA model, however, only comprises nodes with degree greater than or equal to two. As is known, Internet topology has a large amount of nodes whose degree is one, e.g., the leaf nodes in a network. And modeling Internet with these nodes would be our next work.

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