Scale-free networks from self-organization

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We show how scale-free degree distributions can emerge naturally from growing networks by using random walks for selecting vertices for attachment. This result holds for several variants of the walk algorithm and for a wide range of parameters. The growth mechanism is based on using local graph information only, so this is a process of self-organization. The standard mean-field equations are an excellent approximation for network growth using these rules. We discuss the effects of finite size on the degree distribution, and compare analytical results to simulated networks. Finally, we generalize the random walk algorithm to produce weighted networks with power-law distributions of both weight and degree.

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I. INTRODUCTION

Many networks seen in the real world have a degree distribution which is a power law for large degrees [1–5], at least to some approximation. This means that there are many more vertices with large degrees, "hubs" of a network, than one would find with the traditional Erdős and Rényi random graphs with their short-tailed Poisson degree distribution [6]. Such long-tailed distributions have been of considerable interest for some time in a wide range of fields, see Ref. [7] for a brief overview.

On the theoretical side, scale-free graphs are generated in several models. Most are characterized by a probability, Π, for choosing a particular existing vertex in an existing graph to which a new edge is to be added. In particular, if a finite fraction of new edges are attached with probability proportional to the degree k of the existing vertices, $\Pi(k) \propto k$, at least for large degree vertices, then the graph will be scale free [1–3,5,7]. Such attachment of edges with probability proportional to the degree of target vertices is often termed preferential attachment.[1] This is a feature of the model by Simon [8] and of the more recent Barabási and Albert model [9].

However, a key result is that if the $\Pi(k) \propto k^{\alpha}$, then for *any* $\alpha \neq 1$ we do not get a simple power law degree distribution for a large degree in the large graph limit [10]. So, if scale-free laws are often found in nature, where does the precisely linear preferential attachment with $\alpha = 1$ come from? Further, it is crucial to know what the total number of edges is in a network to provide the normalization for the linear preferential attachment probability. This is simple for numerical models and theoretical analysis. However, it is a piece of *global* information not usually available at nodes in real systems. The authors of web pages do not know, nor do they care, how big the web is, for instance.

It is evident that the processes shaping networks in the real world are usually *local*, i.e., they rely mostly on structural properties of the networks in the neighborhood of a vertex. Hence realistic models of network evolution should likewise be based on local rules [11–14]. Here, our focus is on random walks on networks [15,16]. A random walk on a graph tends to arrive at a vertex with a probability proportional to the number of ways of arriving at that vertex, i.e., the degree of that vertex. A random walk can be viewed as natural way for preferential attachment to appear using only the local properties of a graph. For instance, consider the graph of vertices representing film actors, joined if they have appeared in the same film [3,5]. One can imagine a new actor has one or two initial contacts with established actors. They may not know of any suitable jobs for the newcomer, but they pass the word on to their contacts. These in turn might pass the word on to their contacts, until by chance a suitable job is found. A new edge is formed to an existing node chosen by a walk along existing links in the network and this is equivalent to choosing a vertex proportional its degree. Indeed, in anthropology it has long been noted that providing access to a wider pool of resources than is locally available is often an important role of many kinship networks.

The random walk algorithm illustrates how the network structure can be driven naturally to a scale-free form as result of purely local microscopic processes. It is the very structure of the graph itself which guides the search, and thus it is not too surprising that the asymptotic limit has a common feature, a scale-free distribution. Although the algorithm itself is an idealization, we argue that the scale-free nature of many real world networks is a consequence of network evolution driven by this type of mechanism. For this argument to hold, the details of the random walk mechanism should not change the outcome, i.e., the form of the resulting distributions

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[1]Such a "rich get richer" algorithm echoes the well known Pareto 80:20 law of economics. It does not matter if the graph is growing, or if it is just being rewired with fixed numbers of edges and vertices, or anything in between. If preferential attachment dominates for edge attachment to large degree vertices, a scale-free graph will emerge for large graphs.

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should be robust to variations in the algorithm.

The purpose of this paper is to extend the work of Saramäki and Kaski [15] and to demonstrate the robustness of the walk algorithm. First, we will discuss the mean-field equations for the network evolution, the length scales present in finite-sized networks, and the form of the degree distribution for finite-size networks based on preferential attachment growth. Then, we will present the generalized random walk algorithm, and compare results from numerical simulations to theoretical ones. Finally, we will generalize the algorithm of Ref. [15] to the case of weighted graphs, yielding asymptotically scale-free distributions of both degree and weight.

II. MEAN FIELD EQUATIONS

The mean field equations are a good approximation for the behavior of degree distributions in many different algorithms. These will serve to fix our notation, but solutions to these approximate equations also match practical models and we will be referring to them later.

Consider a sequence of graphs $\{G(t)\}$, consisting of $N(t)$ vertices and $E(t)$ edges. Here t is a *timelike* integer parameter, where in going from t to $t+1$ we add a vertex a fraction ϵ of the time, while each time adding on average a total of m edges.[2] The total number of vertices $N(t)$ and the total number of edges $E(t)$ grow on average as

$$N(t) = \sum_k n(k,t) = N_0 + \epsilon t, \tag{1}$$

$$E(t) = \frac{1}{2}\sum_k kn(k,t) = E_0 + mt, \tag{2}$$

where the degree of each vertex is k and the number of vertices of degree k at time t is $n(k,t)$, the degree distribution. The probability degree distribution is just $p(k,t) = n(k,t)/N(t)$. The average degree K tends to a constant with

$$\lim_{t\to\infty} K(t) = \lim_{t\to\infty} \frac{2E(t)}{N(t)} = \frac{2m}{\epsilon}. \tag{3}$$

The new edges added have one end attached to any new vertex if it is created, then the remaining ends are attached to vertices of the existing graph chosen with the attachment probability Π. In the mean field approach, we assume that the average value for the degree distribution at any one time can be described by what happens to the graph on average. This also means that all the parameters ϵ, m could represent an average value for each time step, and the equations are still an approximation to such a growth. The evolution of the degree distribution is given in such a mean field approximation by

$$n(k,t+1) - n(k,t) = r[-n(k,t)\Pi(k,t) + n(k-1,t)\Pi(k-1,t)] + \epsilon\delta_{k,m}. \tag{4}$$

$$r := [(1-\epsilon)2m + \epsilon m]. \tag{5}$$

For the sake of simplicity, we will take the simple and often studied form for the attachment probability Π,

$$\Pi = p_v \frac{1}{N} + (1-p_v)\frac{k}{2E}. \tag{6}$$

This represents a combination of random and preferential attachment, such that existing vertices are chosen at random[3] p_v of the time (first term), while preferential attachment is used $(1-p_v)$ of the time (second term). Note that both terms require *global* information on the network through their normalizations.

The network evolution is therefore governed by four parameters, r, m, ϵ, and p_v. However, for almost all numerical runs we will work with $\epsilon=1$, $p_v=0$ which corresponds to pure preferential attachment in the mean field case.

With the attachment probability Π of the simple form (6), the mean field equation can be solved exactly in the long time, large N limit. It is also straightforward to show that for a wider class of attachment probabilities[4] Π the solutions tend towards a power law form for a large degree. In particular for the form (6) one finds [10,17–22]

$$\lim_{k\to\infty}\lim_{t\to\infty} p(k,t) \propto k^{-\gamma}, \tag{7}$$

$$\gamma = 1 + \frac{1}{p_v\left(1-\frac{\epsilon}{2}\right)}. \tag{8}$$

Since we study growing networks, $0<\epsilon\leqslant 1$, and since now $0<p_v\leqslant 1$, we have that $2<\gamma<\infty$. The lower limit of the power, $\gamma=2$, can be linked to the requirement that the average degree is finite, that is, the first moment of the probability degree distribution $K=[\int dk\, kp(k)]/[\int dk\, p(k)]$ is finite. As $p_v\to 0$ we get attachment to vertices chosen randomly, and the distribution turns into an exponential,

$$\lim_{k\to\infty}\lim_{t\to\infty} p(k,t) \propto \exp\left\{\frac{\epsilon}{r}k\right\}. \tag{9}$$

Although the attachment is random, this is not a standard Erdős-Renyí random graph.

Note that Eq. (8) is a long time, large N solution. However, all numerical models and all data sets are of finite size. This introduces some natural scales and one would expect these to lead to deviations from a simple power law in practical examples. At low degree, the minimum number of edges added to a new vertex (here m) sets such a scale. However, most power laws refer to the large degree behavior. There, for a real system, the continuous part of the spec-

[2]Note that for a realistic model t is probably a monotonic function of the real physical time since one might expect large graphs to grow faster in real time than small ones. However, all we require for our analysis is that the number of edges added per new vertex is constant and this in turn provides a definition of our t parameter in terms of the growth of any real world network.

[3]If we do not specify, then random means we draw randomly from a uniform distribution.

[4]Basically $\lim_{k\to\infty}\Pi \propto k$ is all that is required.

trum ends around $k_{\rm cont}$, which can be defined through

$$p(k_{\rm cont}) = \frac{1}{N}. \tag{10}$$

That is, for $k \gtrsim k_{\rm cont}$ there will be some degree values in any one example with no vertices of that degree. Likewise, for $k \lesssim k_{\rm cont}$, we expect all $n(k) > 0$. If we have a power law distribution, $k_{\rm cont}$ should scale as $k_{\rm cont} \propto N^{1/\gamma}$. Another large scale exists for long-tailed distributions, such as a power law, where there are vertices with degree $k \gg k_{\rm cont}$. For instance, the vertex of largest degree is the rank one vertex, and its degree is likely to be k_1, where

$$\sum_{k=k_1}^{\infty} p(k) = \frac{1}{N}. \tag{11}$$

This scales as $k_1 \propto N^{1/(\gamma-1)}$ for a power law distribution.

An approximate analytic finite time or size solution to the mean field equation (4) for the case of pure preferential attachment with number of edges equal to the number of vertices (here $m=1$, $p_v=0$, $\epsilon=1$) was given by Krapivsky and Redner [13] (see also Refs. [23–25]). The form is

$$p(k,t) = p_\infty(k) F_s(k,t), \tag{12}$$

$$p_\infty(k) = \frac{2m(m+1)}{k(k+1)(k+2)}. \tag{13}$$

Asymptotically the finite size scaling function F_s is a function of $x = k/(2t^{1/2})$ and it differs from one only for $x \gtrsim 1$. With $\gamma=3$ for this case, we have that $N \sim t \sim (k_1)^2$ so $F_s \neq 1$ only for $k \gtrsim k_1$. It also follows that it is sensitive to initial conditions since the vertices of biggest degree are the oldest. For the initial conditions $n(k=m,t=1) = 2n(k \neq m, t=1) = 0$ and generalizing the arbitrary m but keeping pure preferential attachment ($p_v=0, \epsilon=1$), we use the approach of Ref. [13] to find that

$$F_s(k,t) \approx \mathrm{erfc}(x) + \frac{e^{-x^2}}{\sqrt{\pi}}\left(2x + \sum_{n=3}^{m+2} \frac{8}{n!}[1 + (1 + m)\delta_{m+1,n}] x^n H_{n-3}(x)\right) \tag{14}$$

and it is made up of the complementary error function erfc and Hermite polynomials H_n.

The analytic form of the finite size function F_s (14) is a good approximation to that found from a direct numerical solution of the mean field equations as Fig. 1 shows.

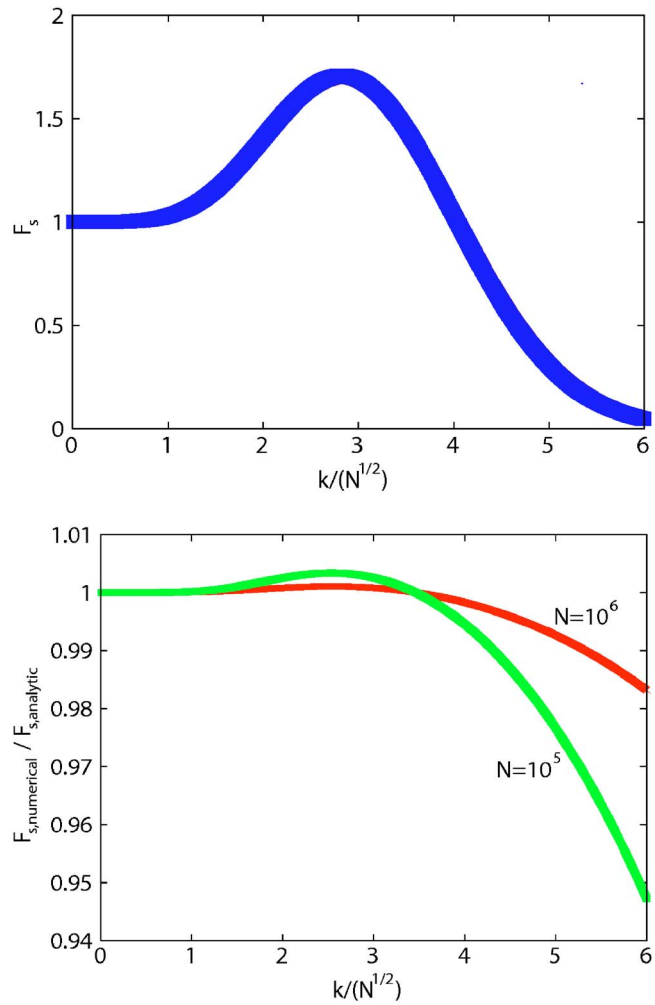

FIG. 1. (Color online) At the top there are three curves for the scaling function F_s derived from the mean field equations: the analytic approximation $F_{\rm s,analytical}$ valid for arbitrary N, and numerical solutions $F_{\rm s,numerical}$ for $N=10^5$ and $N=10^6$. In these networks, at each time step 1 vertex is added ($\epsilon=1$) with two edges attached ($m=2$) using pure preferential attachment ($p_v=0$). Since we cannot distinguish the three cases on the lower plot we show the numerical data divided by the analytic solution on the right hand plot.

III. GENERALIZED WALK ALGORITHM

The mean field equations (4) can be implemented in a straightforward manner, by choosing vertices in the existing graph at random using the probability $\Pi(k)$ implemented explicitly in an algorithm. This is done in most cases. As discussed in the Introduction, the walk algorithm provides a natural mechanism for such a probability to emerge naturally from an intrinsic property of the graph. The basic walk algorithm we will consider is merely a generalization of the original Saramäki and Kaski [15] algorithm:[5]

(i) Start with any graph[6] $G(t=0)$ and start the time counter at $t=0$.

(ii) With probability ϵ choose to add a new vertex v_0. The remaining time, let v_0 be a random vertex in the graph chosen with probability Π. Now start adding new edges, counting from $i=1$.

(iii) To start the random walk we choose a vertex v_i in the existing graph, $G(t)$. We will consider several different ways to do this.

[5]Preliminary studies of such models were also made independently by one of us, T.S.E., in collaboration with Klauke [16].

[6]In fact, the way the algorithm is phrased we require that no vertex has zero degree but with a small adjustment even this limitation could be dropped.

(iv) Now make one step in a random walk on the graph by choosing one of the neighbors of v_i at random.[7] Move to this neighbor and now set v_i to be this vertex.

(v) Repeat the previous step l times.

(vi) Repeat from step three m times, increasing i each time $i=1,2,\ldots,m$.

(vii) Now create $G(t+1)$ by adding vertex v_0 and the edges $\{(v_0,v_i)|i=1,2,\ldots,m\}$ to the graph $G(t)$. At this point one might also choose to reject some potential edges and maintain some characteristic of the graph.

(viii) Increase t by 1 and repeat from the second step.

There are several variations within the general algorithm which we will study. We will indicate our choices by the binary bits of a parameter v.

(a) The walks can be started from a vertex chosen randomly $[(v\&1)=1]$, as done in Ref. [15], or by taking a random end of a random edge $[(v\&1)=0]$.

(b) One could start a new walk for every new edge $[(v\&2)=1]$. Alternatively, as in Ref. [15], we could start a new walk at each time step, the $i=1$ edge, but then we take the end of the previous walk v_{i-1} to start the walk for the ith edge $[(v\&2)=0]$.

(c) The length of the random walks can be fixed to be l as in Ref. [15] $[(v\&4)=0]$. This might not be realistic in many cases so we have also looked at the case where a further step on the walk is made with probability $p_l=l/(1+l)$ so that the average walk length was $l[(v\&4)=1]$.

(d) The number of edges could be fixed to be m at each time step as in Ref. [15] $[(v\&8)=0]$. This could be varied in a similar manner to the walk length, with one edge always added (to ensure a connected graph) but subsequently another edge is added with probability $p_e=(m-1)/m$ so on average m will be added $[(v\&8)=1]$.

Intuitively, the initial point of the random walk should be immaterial for "long" walks. In Ref. [15] it was indicated that for their algorithm [essentially the $(v\&1)=1$ choice here] long was just one step.[8] Presumably, this indicates that there is already little correlation between the connectivity of nearest neighbor vertices, and it is this correlation length, rather than mean shortest separation or diameter length scales, which is important. This is also an assumption behind the mean field approximation, so we should expect that the mean field equations are a good approximation to graphs produced from random walk algorithms. This will be confirmed below.

For the stochastic choices in options (c) and (d), the Markov process used here produces a large peak at small values. Thus for the walks of random length in case (c), a fraction $(1-p_l)$ vertices are attached to the vertex at the start of the walk. If this initial vertex is chosen randomly $[(v\&1)=1$ in option (a)], and given that one step is often sufficient to produce reasonable scale-free behavior, then we are actually reproducing the mixed preferential attachment and random attachment algorithms mentioned above with $p_v \sim (1-p_l) = 1/(1+l)$. This is yet another way that a walk algorithm might produce various powers γ as Eq. (8) indicates. Many other distributions could be tried for stochastic choices so the Markov process used here is merely exemplary.

If the length of the walk is zero then we get some special behavior. If we choose the vertices v_i at random, we are then generating a graph with an exponential distribution for $n(k)$ [Eq. (9)]. On the other hand, choosing to connect to vertices in the existing graph by choosing the random end of a random edge is guaranteed to generate a scale-free graph as noted in Ref. [23]. Thus we expect that with this start for the random walks, all graphs are scale-free whatever the walk length.

Finally, we note that one might often wish to limit the graphs generated to be simple, with no multiple edges between vertex pairs and no edges with the same vertex at both ends. We have done numerical simulations both with and without this limitation, and found that for $N=10^6$ and other typical values used here, the difference is negligible with a very small fraction of edges rejected.[9]

IV. RESULTS FOR UNWEIGHTED GRAPHS

A. Degree distributions

First, we will note how robust the walk algorithm is at producing scale-free networks. Figure 2 shows the degree distributions for an exemplary walk algorithm which started all random walks from a random end of a randomly chosen edge. This is equivalent to pure preferential attachment if no walk is made ($l=0$). Longer walks or other variations in the algorithm do not alter this result.

More revealing are algorithms which start their walks from a randomly chosen vertex as seen in Fig. 3. As expected from the mean field approximation, starting from a random vertex but doing no walk ($l=0$) produces an exponential distribution seen by the very short-tailed distribution in all cases for the $l=0$ lines of Fig. 3. This is also illustrated in the semilog plot of Fig. 4. On the other hand, any walk of $l \geqslant 1$ produces a distribution with a power-law-like tail that is much longer than the exponential distributions (9) of the zero step walks. The $(v=1)$ variant of the algorithm, where a new walk is started only for every new vertex, with l, m, and ϵ fixed, produces very consistent degree distributions for $l \geqslant 1$ (Fig. 3, top left panel). This is essentially the algorithm used by Saramäki and Kaski [15]. When l is small, other variations of the walk have an effect on the slope of the degree distribution. In particular, the variants using a Markov

[7] One can vary this aspect. By using a biased walk, say choosing neighbors preferentially based on color of vertices or weights of edges, or based on other vertex properties such as the degree or clustering of the target, one might get interesting variations.

[8] The general network with redirection model in Refs. [13,22] is similar to our single step walks with a stochastic element $(v\&4)=1$, and there good power laws were also noted.

[9] In one run with an implementation of an algorithm exactly as stated, so allowing multiple edges and edges connected to one vertex only, with $N=10^6$ vertices and $E=2\times10^6$ edges, using a walk of fixed length of seven steps and starting a new walk from a random vertex for every new edge added, and $\epsilon=1$, there were just 76 double edges produced, with no triples or higher. In Ref. [15] the graph generated was simple.

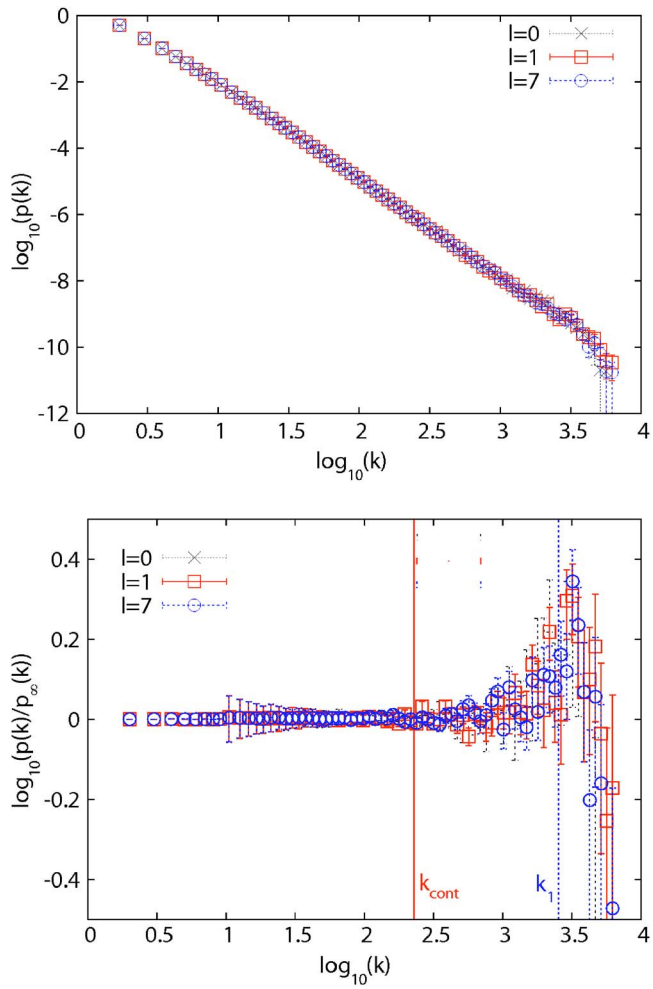

FIG. 2. (Color online) Degree distributions $p(k)$ for networks of size $N=10^6$, generated using random walks started from a random end of a randomly chosen edge. The top panel displays the raw degree distribution, and the bottom the degree distribution normalized by equivalent mean field $t\to\infty$ solution $p_\infty(k)$, with finite size correction F_s visible for $k>k_{\text{cont}}$. All variations with these types of algorithm ($v\&1=0$) show the same behavior. Here, one vertex ($\epsilon=1$) with two edges ($m=2$) are added per time step. The results are shown for average walk lengths of $l=0$ (crosses), 1 (squares), and 7 (circles) steps, with data averaged over 100 runs. In this example, a new walk is started for every new edge added ($v=2$ algorithm).

process for a single step walk (e.g., $l=1$, $v=15$) fit a power law in their tails which is closer to $\gamma=5$ (Fig. 3, bottom panel). This value corresponds to the earlier discussion, where a probability $(1-p_l)$ of making a zero step walk from a random vertex start [in option (c)] can be taken as a first approximation to be equivalent to the probability p_v for random vertex attachment in the mean field equations (6). Our one step Markov walk results (cases $l=1$ and $v=5$, 7, 15 in Fig. 3) support this and will be considered again with Fig. 8 below. Likewise the variation with the length of walk l is also shown in Fig. 10 below and different algorithms for the same long seven step walks, Fig. 9 will be discussed in more detail below.

In the case of $l=1$, starting a new walk from a randomly chosen vertex for each of the m new links ($v=3$) (Fig. 3, top right panel) appears to result in a much smaller power than $\gamma=3$, unlike in the ($v=1$) case where the vertices are selected using one continuous walk. This is possibly because in the $v=3$ algorithm all vertices chosen are only one step away from a randomly chosen vertex, while in the $v=1$ case [15], one vertex is one step and the other two steps, on average 1.5 steps, from a randomly chosen vertex. This suggests that there are weak correlations between properties of neighboring vertices, but not between next to nearest neighbors. Thus the effective longer range of a $v=1$ one step walk over a $v=3$ one step walk accounts for the differences between these two variants.

Certainly, the longer the walk, the more the distributions become identical, whatever the details of the algorithm for our large $N=10^6$ networks, with tails approaching a power law with powers around $\gamma=3$.

Varying the average degree $2m$ but holding the number of edges fixed shows nothing of note except when $m=1$, i.e., where we generate a tree graph with no loops, as one can see in Fig. 5.

B. Finite-size effects

The degree distributions discussed above are not simple power laws. This is to be expected since the solutions to the mean field equations do not predict this as Eq. (12) shows. Also the mean field equation is itself an approximation, but it should be closest to models with genuine preferential attachment. Figure 6 displays the degree distribution for networks generated with algorithms where the random walks start from an end of a randomly chosen edge [$(v\&1)=0$], compared against the numerical mean field solutions. The data fits the finite N mean field solutions well, with the deviation from mean field comparable to the apparent statistical variation and systematic effects from the logarithmic binning. However, it is clear that the data have large fluctuations and so are poor for large degrees, $k>k_{\text{cont}}$.

Given that the mean field solutions (12) are an excellent representation of genuine preferential attachment models, it is interesting to see if this is useful for the results of all random walk models. However, before we look at more data we need to consider the sizes of the scales in our finite sized examples to understand deviations from a pure power law. For large scales, $k\gtrsim k_1$, modifications to a pure power law result from a finite size correction similar to the F_s (14) found for pure preferential attachment models. However, this correction is not of practical importance by as definition there are essentially no data for $k\gtrsim k_1$. The data are best for $k\lesssim k_{\text{cont}}$ of Eq. (10). In practice this scale is not large, for a million vertex graphs (few data sets have bigger graphs) k_{cont} is only[10] of order 100. Thus most data sets, and certainly our

[10]For the mean field model solution (13) with $m=2$ the large scales are $k_{\text{cont}}=105$ and $k_1=796$ ($N=10^5$), $k_{\text{cont}}=227$, $k_1=2520$, and ($N=10^6$). In fact the degree with local power γ_{eff} (15) closest to the theoretical value is found just above k_{cont} at $k_{\max}=149$ for $N=10^5$ while for $N=10^6$ this is at $k_{\max}=388$.

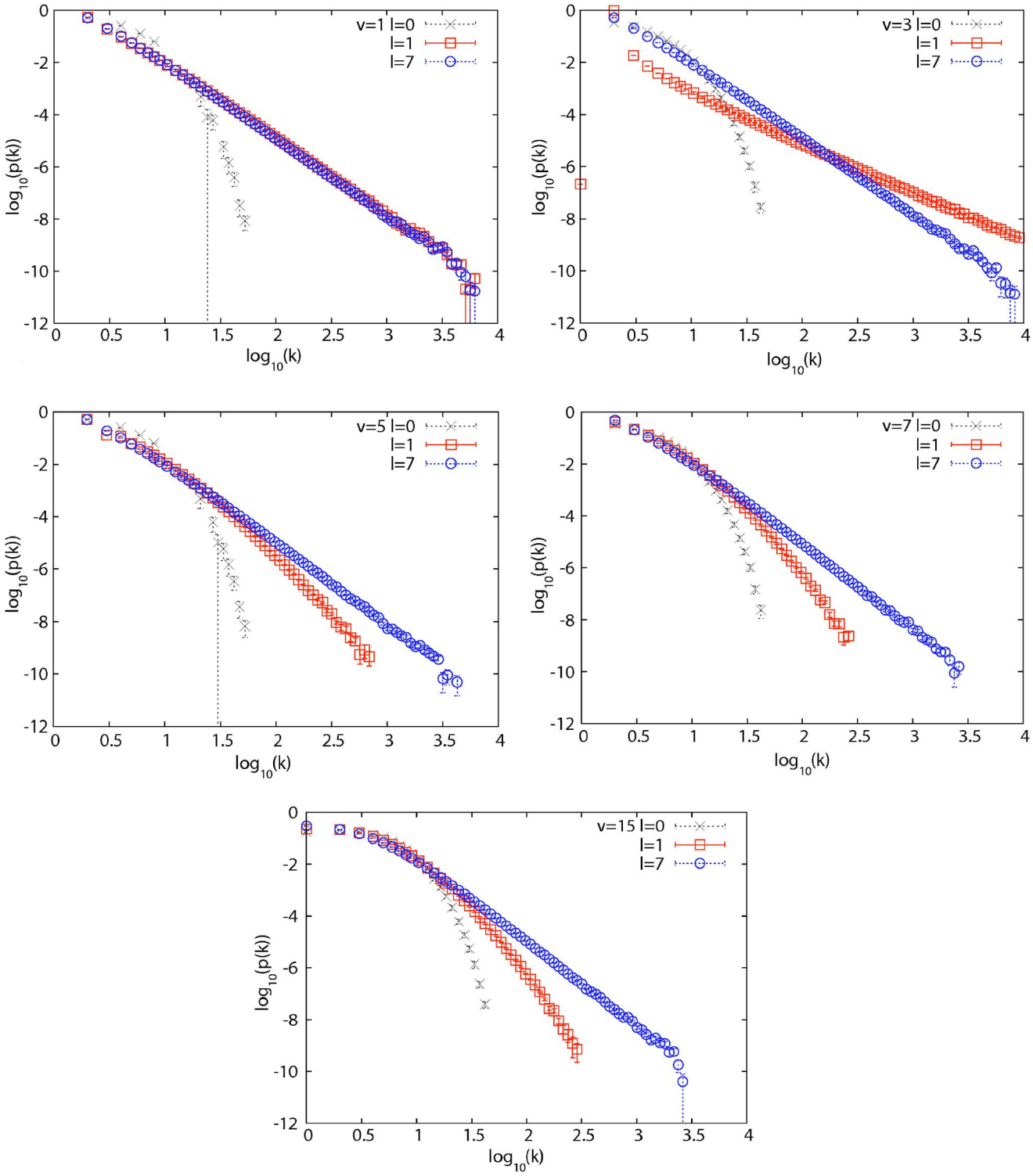

FIG. 3. (Color online) Log-log plots of degree distributions $p(k)$ for $N=10^6$ degree networks generated by random walks started from a randomly chosen vertex $[(v\&1)=1]$, with one vertex ($\epsilon=1$) and two edges ($m=2$) added at each time step. In each graph, the results are shown for average walk lengths l of 0 (crosses), 1 (squares), and 7 (circles) steps, with data averaged over 100 runs. In the top row, the walk length is fixed to be length $l[(v\&4)=0]$, whereas in the middle row the length is varied by using a Markov process $[(v\&4)=1]$. In the left column all m new edges are attached to vertices chosen in one continuous walk $[(v\&2)=0]$, whereas in the right column a new walk is started for each edge added $[(v\&2)=1]$. The algorithm used for the bottom figure has variable numbers of edges and variable walk length ($v=15$). Multiple edges are allowed here.

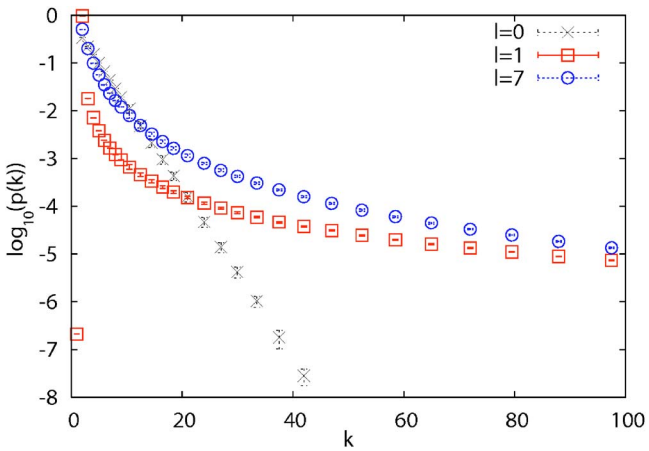

FIG. 4. (Color online) Semilog plots of degree distributions $p(k)$ for $N=10^6$ degree networks, generated using walks of fixed length started from a randomly chosen vertex for each new edge $[(v\&1)=3]$, with one vertex ($\epsilon=1$) and two edges ($m=2$) added at each time step. The walks are of fixed lengths l of 0 steps (crosses) with a clear exponential distribution, and of fixed lengths 1 (squares) and 7 (circles) steps. Data are averages over 100 runs. Multiple edges are allowed here.

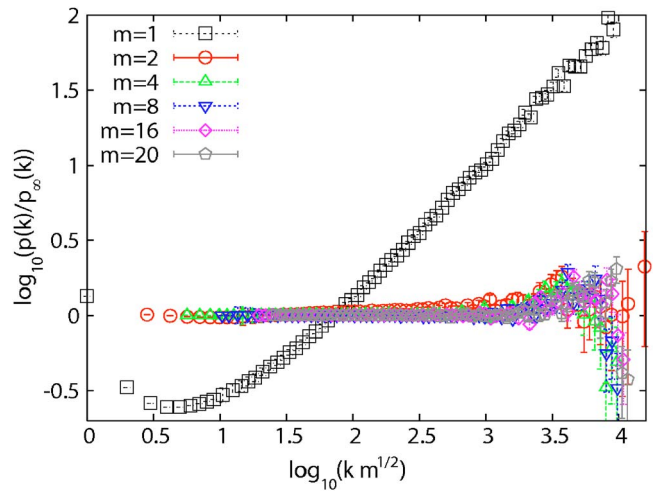

FIG. 5. (Color online) The degree distributions normalized against the appropriate large network solution $p_\infty(k)$ for fixed number of edges $E=2\times10^6$, with one vertex ($\epsilon=1$) added at each time step ($\epsilon=1$) but with the average degree ($2m$) varied. Plotted against $\log_{10}(km^{1/2})$ to take account of large scale finite size effects since here the number of vertices is $N\propto 1/m$. For random walks starting from a random vertex for every new edge, of fixed length $l=7$ and averaged over 100 runs. Note that the tree graphs formed when $m=1$ (squares) are the only ones showing a strong deviation from the expected cubic power law, but they still show good power law behavior with a power of $\gamma\approx 2.0$.

model runs, are actually mesoscopic systems. It also means that there are significant deviations from a power law because of the *small scale* effects. For instance, the mean field large time solution (13) shows deviations from the inverse cubic large degree behavior for degree scales $k\sim O(1)$. These small scale deviations are finite N effects in the sense that k_{cont} is finite only for finite N and is in practice close to 1.

We can illustrate the problem by studying the mean field solutions, fitting a power law to neighboring points and estimating the power γ through

$$\gamma_{\text{eff}}(k) = -\frac{\ln[p(k+1)/p(k)]}{\ln[(k+1)/k]}. \tag{15}$$

In fact for pure preferential attachment models this effective measure of the power law coefficient γ is always below the large N value for any useful degree k since using Eq. (13) we have

$$\gamma_{\text{eff}}(k) = 3\left[1-\frac{1}{k}+O\left(\frac{1}{k^2}\right)\right] \quad (1\ll k\ll k_1). \tag{16}$$

For $N=10^6$ (larger than most data sets) $k_{\text{cont}}\sim 100$ is the largest degree with useful data so we would expect the local power to be at least of order 1% below the large N value associated with the formation mechanism for the graph. So even in this perfect pure preferential attachment model, simple power law fits to reasonable data sets are going to underestimate the power which in turn would lead to a misunderstanding of the underlying formation mechanism, e.g., though formulas such as Eq. (8). In practice, results are likely to be worse than this.

The discussion above highlights the problems in interpreting any power fitted to finite N data. With these warnings in mind let us now turn to more general random walk models and look at the power law behavior, focusing more on the comparison between the various random walk algorithms. We will also compare against the appropriate numerical mean field equation solutions, for which we have a complete understanding of the finite size effects.

First it is interesting to note that, while even short walks have long-tailed distributions that are well approximated by a power law (for $N=10^6$ at least), the different algorithms do make a difference to the power. The best fit to the finite N mean field value is that using a walk of fixed length, fixed numbers of edges and vertices added each time and a new walk started only with every new vertex added ($v=1$) which is essentially the original Saramäki-Kaski algorithm, as Fig. 7 shows. This has a power which is always below the large N prediction of 3 but it is close to the mean field solution.

As was noted earlier, when a Markov process is used to choose walks of random length [option (c)] this simulates a mixed preferential attachment and random attachment algorithm. For such cases with an average walk of length $l=1$ half the edges are connected to a random vertex so we would expect a power of 5. Interestingly this is never quite reached so a network of a million vertices is still not large enough though the data are clearly tending towards this expected value, and it is certainly bigger than the $\gamma=3$ power found when a fixed walk is used. Figure 8 shows this.

On the other hand, other variations of the walk algorithm, even for long walks, $l=7$, while equally well approximated by power laws, have powers which can be consistently 10% or 20% higher than the finite N mean field solution as Fig. 9 shows. This effect mitigates the finite N reduction in the effective power as compared to the large N mean field pre-

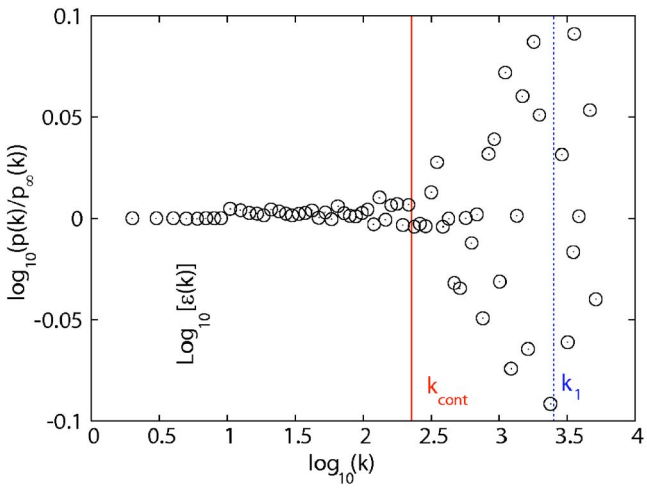

FIG. 6. (Color online) Degree distribution $p(k)$ from random walk algorithm ($N=10^6$, $\epsilon=1$, $v=2$, $l=0$, $m=2$, averaged over 100 runs) normalized by the numerical solutions to the mean field equations $p_{\mathrm{mf,num}}(k)$. The vertical lines indicate the characteristic scales k_{cont} (left) and k_1 (right) and the results show close agreement below these scales.

diction (here 3.0). It is clear from this that while changes in the random walk algorithm and parameters do not alter the shape of the distribution from one that is roughly approximated by a power law, it does produce differences in the measured powers.

As noted, the large N corrections occur at high degrees $k \sim k_1$ where the data are poor anyway; for all practical purposes we may as well compare against the long time mean field solution $p_\infty(k)$ of Eq. (13). This is done in Fig. 9 for varying v and in Fig. 10 for varying l. Again the evidence for power law behavior is clear from even the shortest walks, but only the longer ones come close to the exact mean field form expected for graphs of this type. Walks which contain some zero length walks ($v=7$ and $v=15$) show larger deviation reflecting the way they mimic mixed preferential and random attachment.

Overall we see that the appearance of a long tail and scale-free behavior is a robust result of all nontrivial walk algorithms. This is presumably because the relevant scale is a correlation distance for the degree of vertices ξ steps apart, and it appears that $\xi \lesssim 1$. However, the power of the distribution varies considerably and is sensitive to the details of the algorithm.

C. Global length scales

The diameter and average shortest path length were not studied in Ref. [15]. We note that in our random walk algorithm they show the expected behavior of scaling as $\ln(N)$ as Fig. 11 shows. The average shortest distances between points and the diameters (a lower bound at least) are shown for different total numbers of vertices N, with the average degree held fixed ($m=2$) and a walk length of seven ($l=7$) for an exemplary algorithm. Both clearly scale with $\ln(N)$. Other variations of the walk algorithm show similar behavior though the diameters and shortest distance measures do depend on the particular random walk algorithm used.

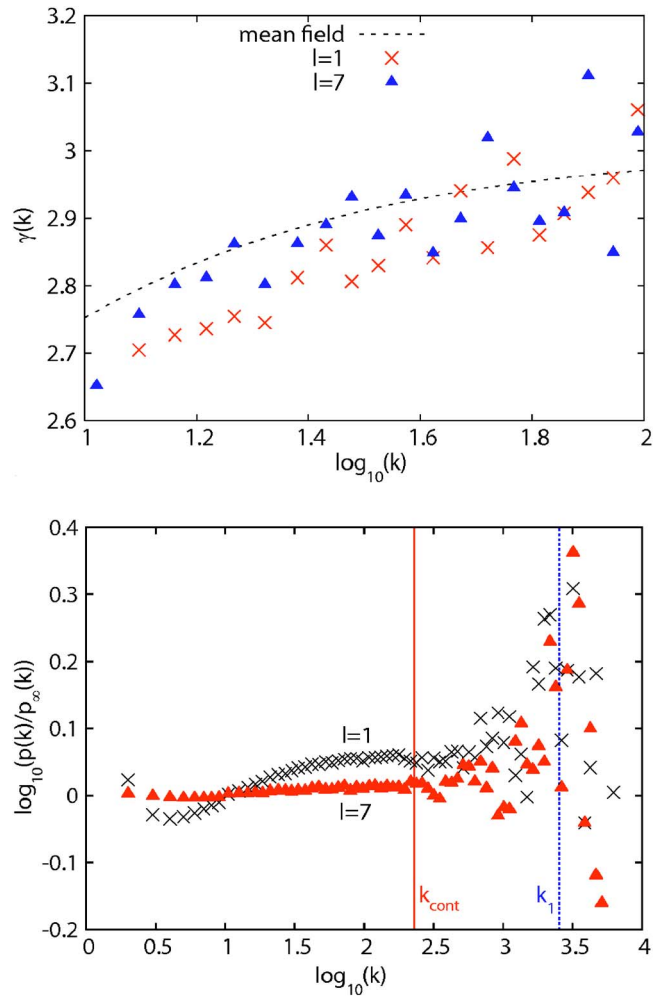

FIG. 7. (Color online) Comparison of one and seven step walks ($l=1$ crosses, $l=7$ triangles) for the Saramäki-Kaski style algorithm $N=10^6$, $\epsilon=1$, $m=2$, $v=1$. The effective power $\gamma(k)$ at the top compared against numerical mean field solution shows reasonable agreement even for short walks. On the bottom data is normalized by the large N mean field solution for graph of similar characteristics.

Figure 12 shows how average shortest distances and the diameters vary for different fixed numbers of vertices $N=10^6$, fixed average degree $K=4$ but varying length for the random walk. Just as in the case of the clustering coefficient [15] there is an interesting pattern for odd and even walk lengths when the walks are of fixed length (here the $v=3$ runs). This is an artifact of the discrete nature of the algorithm because there is a good chance on short walks that one returns to the original vertex when the length of the walk is even. It is not seen in the smoother algorithm of the $v=15$ runs where the number of edges added and the number of steps taken is varied but the averages are kept the same. As the walk lengthens we are tending to a fixed value suggesting that the simplest algorithms generate some correlations for short walks.

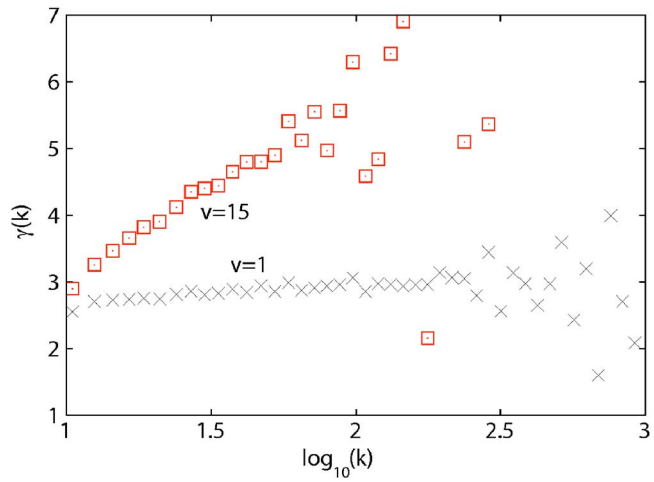

FIG. 8. (Color online) Variation of the effective power $\gamma(k)$ for different variants of the random walk algorithm but for walks of average length of one step. All with $N=10^6$, $\epsilon=1$, $m=2$, and $l=1$. The $v=1$ case (crosses) always uses one step random walks and is close to the large N value of $\gamma=3$. The Markov process walk though is expected to be similar to a mixed random or preferential attachment algorithm with $1/2=p_l\approx p_v$ so we expect $\gamma=5$ in the large N limit. Indeed the $v=15$ (squares) example could be tending towards this value and certainly has a much higher power.

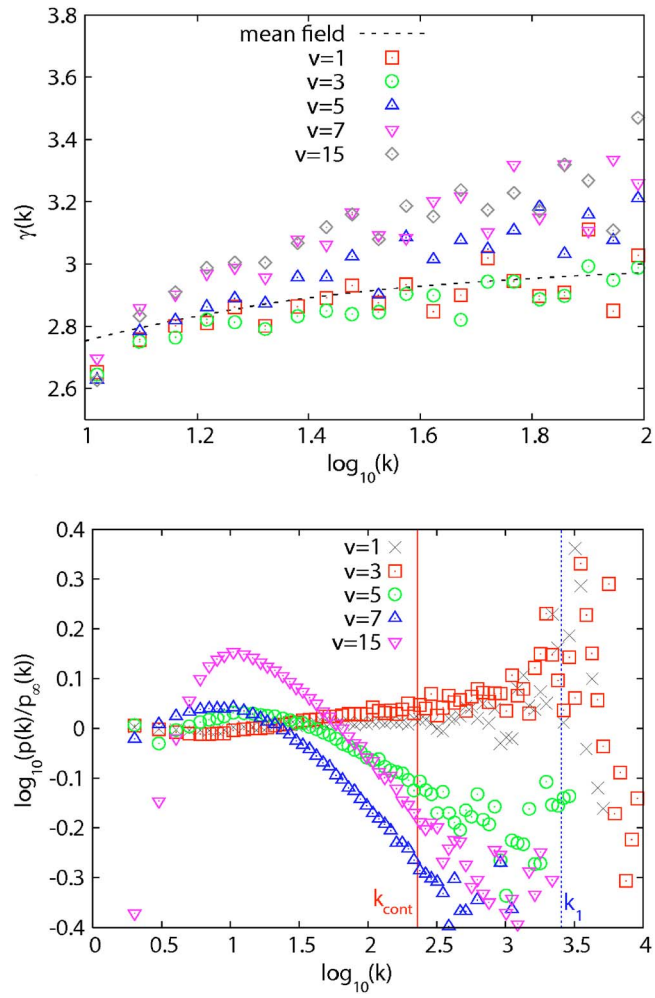

FIG. 9. (Color online) Variation of the power law behavior for long walks with different variants of the random walk algorithm. All with $N=10^6$, $\epsilon=1$, $m=2$, and $l=7$. First the effective power with the straight line for the corresponding numerical mean field solution. Second the deviation from the large N mean field solution.

V. WEIGHTED GRAPHS

Many graphs are not simple graphs but their vertices and edges often carry other information. This is readily taken into account by considering the edges to be *weighted* [26–30], so that every edge is characterized by its weight w. Then, a natural generalization of vertex degree is the vertex *strength* s [27], defined as the sum of weights of edges connected to the vertex. The weights provide an additional degree of freedom, and their dynamics can be coupled to network evolution. Recently, Barrat *et al.* [28] (BBV) proposed an algorithm where networks are grown based on a strength-driven preferential attachment rule. In the BBV model, new nodes joining the network are connected to vertices chosen with a probability proportional to their strength with links initially having unity weight. Then, an amount of δ^* of extra weight is divided among the old edges of each parent vertex in proportion to their weights: $w_{ij}\to w_{ij}+\delta^* w_{ij}/s_i$. This leads to asymptotic power law distributions of both the vertex degrees and the vertex strengths, with an exponent $\gamma=(4\delta^*+3)/(2\delta^*+1)$, i.e., the power law gets broader with increasing δ^*. Also the distribution of weights follows an asymptotic power law, $P(w)\sim w^{-\alpha}$, where $\alpha=2+1/\delta^*$.

In the following, we will show that the walk algorithm can readily be generalized to the weighted case, providing a natural model for evolving weighted networks. We will focus just on the weight aspect of the problem and work in this section with a basic random walk algorithm, so that we always use walks of fixed lengths and at every time step add one vertex ($\epsilon=1$) and add a fixed number of edges m, each attached at one end to the new vertex.

The algorithm we use is as follows. The network dynamics is divided into two aspects: (i) network growth and (ii) modification of the existing weights, which both take place successively during each time step t. Both cases are based on random walks, where we modify the random walking rule so that the next step in the walk is always chosen so that the probability of following a link is directly proportional to its weight, i.e., if the walker is located at vertex v_i, it next moves to vertex v_j with the probability $w_{ij}/\Sigma_k w_{ik}$, where the sum is over all neighbors of v_i.

With the exception of the above modification, the network growth phase proceeds as detailed earlier, so that the m vertices are chosen using random walks of length l. If we assume that there is no correlation between the strength of neighboring vertices, this reduces to the simple case of

$$\Pi = s/S(t), \tag{17}$$

that is, we will have pure preferential attachment in terms of strength rather than degree. When the parent vertices have been selected, an initial weight of w_0 is assigned to the new

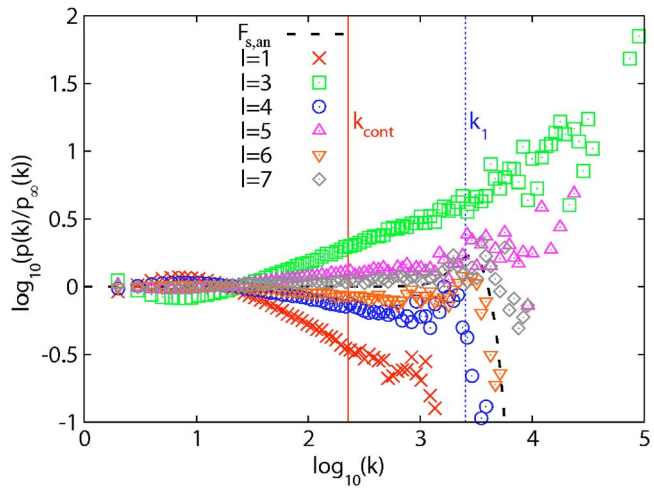

FIG. 10. (Color online) Data are for random walk algorithms starting a new walk from a new random vertex for every edge added, making a fixed length walk ($v=3$), creating graphs of average degree 4 ($m=2$) and $N=10^6$ vertices. The length of the walk is varied from $l=1$ to $l=7$. Data are the average of 100 runs. Note that again there is clear evidence of good power law behavior even for the short walks. However, there is significant deviation from the form of the mean field solution for short walks, which decreases for longer walks. Also note evidence of some finite size features, F_s, for large degrees $k\sim 1000$. The mean field solution for the equivalent graph is the continuous line in the center. The mean field calculated values for k_{cont} (left) and k_1 (right) are indicated by the vertical lines.

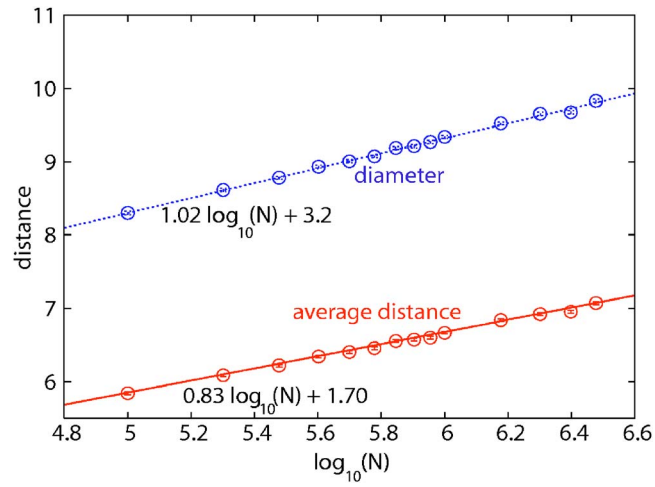

FIG. 11. (Color online) Average shortest distances and diameters for different total numbers of vertices N, with the average degree held fixed ($m=2$). The error bars on data points are drawn but are comparable with the size of the symbol. The data are for 100 runs for a $v=3$ algorithm where a new random walk starting for every edge added ($m=2$ per new vertex) and of fixed length $l=7$. The straight lines are a best fit to the data.

edges. Then, we modify the existing weights by performing a second type of walk so that

(i) to start the random walk we choose a vertex v_j in the existing graph $G(t)$, choosing at random from a uniform distribution;

(ii) now make one step in a random walk on the graph by choosing one of the neighbors of v_j at random using the above biasing rule—the edge we follow has its weight increased by δ;

(iii) repeat the previous step l_d times.

The strength distribution in the mean field approximation follows a similar equation as for the degree, namely

$$n(s,t+1)-n(s,t)=r_s[-n(s,t)\Pi(s,t)+n(s-\delta,t)\Pi(s-\delta,t)]+\epsilon\delta_{s,w_0}, \tag{18}$$

$$r_s := [2l_d+(w_0/\delta)]. \tag{19}$$

The total strength $S(t)$ is given by

$$S(t)=\sum sn(s,t)=S(0)+2(l_d\delta+w_0) \tag{20}$$

while now $N(t)=N(0)+t$. The analysis of the strength distribution is then exactly as before, and for large graphs we find that the asymptotic form for the distribution is a power law,

$$\lim_{s\to\infty}\lim_{t\to\infty} n(s,t)=s^{-\gamma_s}, \tag{21}$$

$$\gamma_s=\frac{3m+4l_d\delta}{m+2l_d\delta}. \tag{22}$$

Note the relation to the BBV model's exponent for the strength distribution [28], $\gamma_{BBV}=(4\delta^*+3)/(2\delta^*+1)$. The total increase of weight in the modification phase equals $\Delta=m\delta^*$ in the BBV model, and $\Delta=l_d\delta$ in our weighted walker model. Both exponents can be rewritten using this quantity as $\gamma=(3m+4\Delta)/(m+2\Delta)$.

Now, we may expect that for individual vertices $k\propto s$, because in the network growth phase the probability that a random walk arrives at a given vertex is proportional to its strength. Substituting this as an ansatz we find that the degree distribution also follows a power law with $\gamma_k=\gamma_s$. Note that the same exponents also emerge from analysis based on continuum mean field rate equations in the same manner as done in Ref. [28].

It is also possible to apply the mean field approach to the weights on each edge. In the limit of $N\to\infty, t\to\infty$ we again find a power law for the distribution of weights of

$$p(w)\propto w^{-\alpha}, \tag{23}$$

with the exponent $\alpha=2+m/(l_d\delta)$. This also reproduces the form found in Ref. [28].

We can conclude that the main characteristic distributions of networks grown with the weighted walker model are equivalent to the ones of the BBV model. However, the models are not identical. We have deliberately chosen to start the weight modification walks from randomly selected vertices, instead of ones connected to newly joined vertices. This illustrates that the distributions are of a general nature and a result of strength-driven attachment in combination with preferential increase of weights—strong weights get stronger, a feature that is implicitly present in the BBV model in

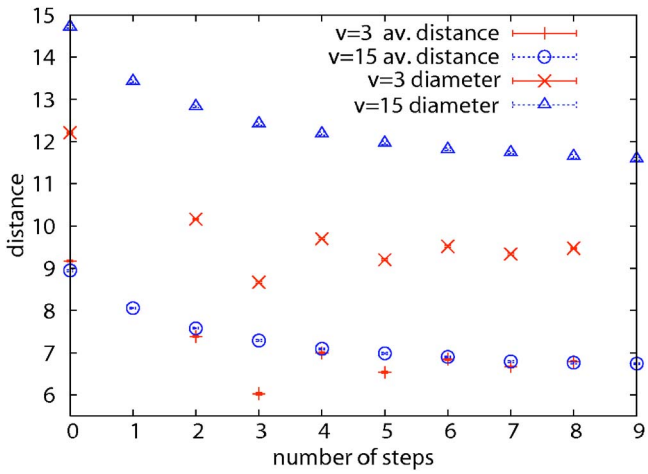

FIG. 12. (Color online) Average shortest distances and diameters for varying lengths of random walk, fixed vertex, and edge numbers ($N=10^6, \epsilon=1, m=2$) with walks starting from a random vertex. The data shown are for two types of algorithm. Crosses are for fixed walk length starting a new walk for every edge ($v=3$ algorithm). The circles and triangles have a variable number of edges added per vertex and a new walk of variable length is used for every new edge but averages are kept as before ($v=15$ algorithm). Note the dependence on the odd or even nature of the $v=3$ case and the clear trend to fixed values as the walk length gets longer. Error bars are shown but are smaller than the sizes of the symbols.

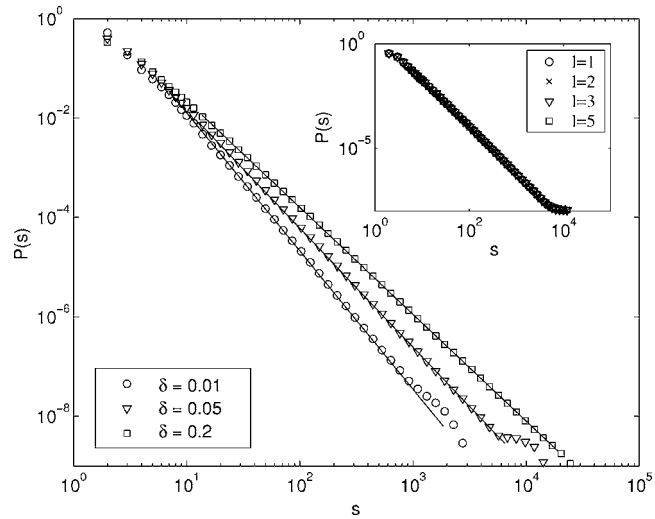

FIG. 13. Distribution of vertex strength $p(s)$, averaged over 1000 realizations of $N=2\times10^5$, $m=2$ networks grown using the weighted walk algorithm with $l=15$, $l_d=30$, and $\delta=0.01$ (○), $\delta=0.05$ (▽), and $\delta=0.2$ (□). The solid lines indicate slopes for respective asymptotic power laws calculated using Eq. (18). Inset: $p(s)$ averaged over 2500 realizations of $N=5\times10^4$ networks, with $\delta=0.1$, for various walk lengths $l=1, 2, 3, 5$. The power-law behavior is visible even for the shortest walks.

the form of dividing the weight increase proportionally among edges. Furthermore, as shown for unweighted networks elsewhere in this paper and in Ref. [15], we expect other characteristics such as the degree of clustering and the network diameter to depend on the random walk lengths. Especially, with short growth-phase random walk lengths l, the networks are expected to show high degrees of clustering, a feature found in several real-world networks. We choose to leave further investigations of these issues for future work.

Numerical results

Figure 13 illustrates the probability distribution for strength $p(s)$ calculated from simulating the random walker network growth process, together with the mean field prediction of Eq. (18). The networks were grown to size $N=2\times10^5$, with $l=15$, $l_d=30$, $m=4$, and δ as illustrated. The results are averages over 1000 realizations. They fit the mean field power laws of the form (22) as Fig. 13 shows.

As noted, we expect in this algorithm that the degree distribution in this weighted random walk algorithm will show the same form as the strengths and this is seen in Fig. 14. Finally, Fig. 15 illustrates the power law distribution of weights. Also in this case the slopes match the mean field approximation of Eq. (23).

VI. CONCLUSIONS

Random walks on graphs provide a variety of different types of networks, as seen in the variations in distance scales.[11] However, apart from some special cases in the limit of zero length (no) walks, they are invariably characterized by having a degree distribution with a very long tail, and a power law will often be a sufficiently good description of this tail.

We have stressed that most networks in numerical studies or in studies of real systems are mesoscopic systems. That is, even for systems of the order of a million vertices, finite size effects are noticeable. For instance, a simple power law fit to data from a theoretical model should give a power that is anywhere from 0.1% to 10% below that expected for the infinite sized graph due to the effects of small degree deviations from simple power laws. Further, our numerical studies are idealized with 100 or 1000 examples used so we expect real noisy single data sets will be harder to interpret. Note also that such differences from an exact power law are hard to detect by eye on log-log plots of distributions, even in our idealized situations. Thus while power laws reported in the literature may be an "acceptable" description of a data set in many circumstances, it may be difficult to distinguish between different underlying processes or even between different types of degree distribution [7].

However, given that proviso, we believe that the random walk algorithm does provide one of the few realistic explanations as to why so many different systems have degree distributions which are consistent with power laws. Further, we suggest that many of these real-world networks are in fact genuine scale-free networks and would have pure power laws in the infinite time, infinite graph limit. We have studied a wide set of variations on the basic random walk algorithm of Saramäki and Kaski [15], including an extension to more

[11] Also for clustering coefficients as seen in Ref. [15].

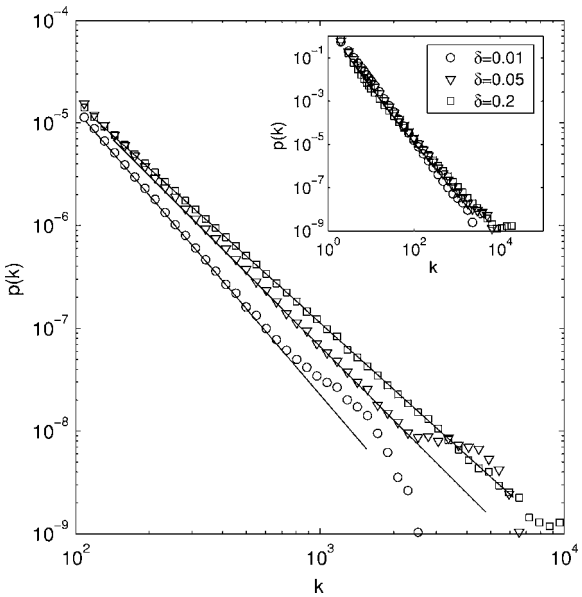

FIG. 14. Degree distribution $p(k)$ for the same networks as in Fig. 13. The solid lines indicate slopes for mean-field power laws. The inset shows the distribution over the whole k range.

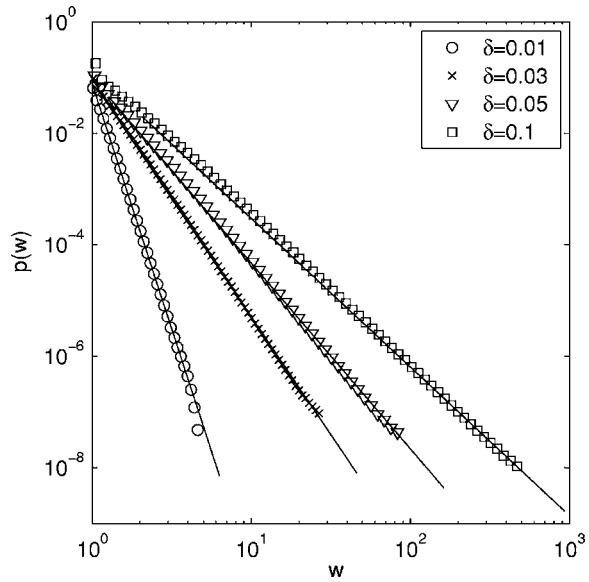

FIG. 15. Weight distribution $p(w)$ for $N=2\times10^5$ networks, averaged over 10^3 realizations, with $m=2$, $l=15$, $l_d=30$, and δ as shown in the legend. The solid lines indicate slopes for mean field power laws of Eq. (23).

realistic weighted graphs. In almost all cases we have found that power laws emerge naturally. Various powers for the power law are possible depending on the algorithm and on its parameters but a power-law-like distribution is an extremely robust result of the generic random walk algorithm. The random walk algorithm exploits the structure of the graph[12] yet it requires no global information to operate. This is in sharp contrast with most numerical and algebraic analyses, for example, Refs. [8,9,28], where preferential attachment is assumed and implicit global information is used in the normalization. Thus in this sense we see the random walk algorithm as a process of self-organization, the very structure of the graph inevitably leads microscopic local processes to a scale-free form.

While this may be useful way to understand why so many scale-free networks are seen in the real world, the walk algorithm could be useful in practical problems. Due to its robustness and purely local nature, the random walk algorithm could be used to engineer new networks which self-organize to a scale-free form. For instance, this might be of use for distributed computing and peer-to-peer network problems.

[12]Indeed, as far as the degree distribution goes, a simple preferential attachment model need have no graph present at all. For instance, Simon [8] makes no reference to a graph though one can invent one if one wishes for his examples. Conversely, while the web provides a natural example of a network, one can easily count the links on a web page and hence obtain the outgoing degree distribution without any reference to an underlying graph structure. The preferential attachment model of Barabási and Albert [9], who refer to the graph, is no different to that of Simon [8], who has no graphs, as far as the degree distribution goes.

ACKNOWLEDGMENTS

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APPENDIX: MEAN FIELD FINITE SIZE CALCULATIONS

The mean field equation for the degree distribution for a network grown with mixed random and preferential attachment was given in Eq. (4). In the long time, large graph limit for pure preferential attachment (corresponding to our parameters $p_v=0$, $\epsilon=1$) the solution is $p(k,t)=p_\infty(k)F_s(k,t)$ [Eq. (12)] where the finite size corrections to the infinite time distribution p_∞ are contained in the function F_s. A solution for the case where the average degree of the network tends to 2 ($m=2$ here) was given by Krapivsky and Redner [13] (see also Refs. [23–25]). We have followed the approach of Ref. [13] and generalized this to arbitrary m. We define a generating functional

$$F=\sum_{t=1}^{\infty}\sum_{k=m}^{\infty} w^{t-1}z^k n(k,t). \tag{A1}$$

Switching to variables x and y where

$$x=-\frac{1}{4}\ln(1-w)+\frac{1}{2}\ln\left(\frac{z}{1-z}\right), \tag{A2}$$

$$y = -\frac{1}{4}\ln(1-w) - \frac{1}{2}\ln\left(\frac{z}{1-z}\right),$$

the mean field equation (4) becomes

$$\frac{1}{2}\frac{\partial F}{\partial x} - F = \frac{z^m}{(1-w)^2} \tag{A3}$$

which has the solution

$$F = 2e^{2x}e^{4y}\int^x dx' \frac{e^{(2+m)x'}}{(e^{x'}+e^y)^m}. \tag{A4}$$

Now one must impose some initial conditions to provide the boundary conditions needed to find the explicit solution. The first vertices tend to be the largest degree vertices in the long run and so the shape of scaling function F_s is sensitive to this choice. We choose

$$n(k=m,t=1)=2, \quad n(k\neq m,t=1)=0 \tag{A5}$$

which gives

$$F(x,y) = 2e^{2x}e^{4y}\int_{-y}^x dx' \frac{e^{(2+m)x'}}{(e^{x'}+e^y)^m} + F_b(y), \tag{A6}$$

$$F_b(x,y) = \frac{2e^{2x}e^{2y}}{(1+e^{2y})^m}. \tag{A7}$$

The integral can be performed in terms of a variable $q=e^{x'}+e^y$.

Now starting from Eq. (A1) we see that by substituting in the form (12) we can show that

$$\frac{\partial^3}{\partial z^3}(z^2F) = \sum_{t=1}^{\infty}\sum_{k=m}^{\infty} w^{t-1}z^{k-m-1}(N_0+t)2m(m+1)F_s(k,t), \tag{A8}$$

where $N_0=1$ is the number of vertices at $t=0$. Working in terms of variables $\epsilon=e^{-2x}e^{-2y}=(1-w)$ and $\eta=e^ye^{-x}=(1-z)/z$ we are interested in the limit where $w,z\to 1$ or equivalently $\epsilon,\eta\to 0$ such that $\eta/\epsilon^{1/2}=s$ is constant. In this limit we find that the left-hand side of Eq. (A8) can be written as

$$\frac{\partial^3}{\partial z^3}(z^2F) = \frac{1}{\epsilon^{5/2}}J_m(s), \tag{A9}$$

$$J_m(s) = 2m(m+1)\left[\sum_{n=1}^{m=2}\frac{1}{(1+s)^n} + \frac{m+2}{(1+s)^{m+3}}\right] \tag{A10}$$

for $m=1$, 2, 3, 4 and we conjecture the same for higher m. The $m=1$ value coincides with that in Ref. [13].

Now we look at the right-hand side of Eq. (A8) and assume that the scaling function is of the form $F_s=F_s(k/t^{1/2})$. We are interested in the large degree and time effects so we can approximate the sums by integrals from zero to infinity over the variables $\xi=k\epsilon^{1/2}$ (for the k sum) and $\tau=t\epsilon$ (for the t sum). In the same way we can approximate $w^t\approx e^{-\tau}$ and $z^k\approx e^{-s\xi}$ and interpret these integrals as Laplace transforms. In particular the right-hand side of Eq. (A8) is the Laplace transform over ξ (or k) of a function Φ where

$$\Phi(\xi) = 2m(m+1)\int_0^\infty d\tau\, \tau e^{-\tau}F_s(\xi/\tau^{1/2}). \tag{A11}$$

Thus Eq. (A8) can now be expressed as the inverse Laplace transform,

$$\Phi(\xi) = \frac{1}{2\pi i}\int_{c-i\infty}^{c+i\infty} e^{\xi s}J_m(s) \tag{A12}$$

$$= 2m(m+1)e^{-\xi}\left[\sum_{n=0}^{m+1}\frac{\xi^n}{n!} + \frac{\xi^{m+2}}{(m+1)!}\right]. \tag{A13}$$

Comparing this with Eq. (A11) we have

$$\Phi(\xi) = 2m(m+1)\xi^4\int_0^\infty d\zeta e^{-\xi^2\zeta}[\zeta F_s(\zeta^{-1/2})], \tag{A14}$$

where $\zeta=\tau/\eta^2$. By treating this as the Laplace transform in ζ of a function $G(\zeta)=\zeta F_s(\zeta^{-1/2})$ with respect to a variable $p=\xi^2$ we just have to use inverse standard Laplace transforms to produce the answer (14).

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