Condensation transitions in a model for a directed network with weighted links

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An exactly solvable model for the rewiring dynamics of weighted, directed networks is introduced. Simulations indicate that the model exhibits two types of condensation: (i) a phase in which, for each node, a finite fraction of its total out-strength condenses onto a single link; (ii) a phase in which a finite fraction of the total weight in the system is directed into a single node. A virtue of the model is that its dynamics can be mapped onto those of a zero-range process with many species of interacting particles—an exactly solvable model of particles hopping between the sites of a lattice. This mapping, which is described in detail, guides the analysis of the steady state of the network model and leads to theoretical predictions for the conditions under which the different types of condensation may be observed. A further advantage of the mapping is that, by exploiting what is known about exactly solvable generalizations of the zero-range process, one can infer a number of generalizations of the network model and dynamics which remain exactly solvable.

I. INTRODUCTION

Networks, and in particular weighted networks, have a long history in the social, natural, and engineering sciences. The many and varied examples of networks range from systems such as transportation networks to ecological, biochemical, and social networks [1,2]. Basically, a network is a graph containing nodes connected by links (or edges)—the network is said to be "weighted" when weights are assigned to the links. The interest in networks within the physics community was initially with regard to the statistical properties of the connectivity structure of unweighted networks (i.e., networks where links are restricted to have weight one or zero only, indicating a connection or no connection, respectively); studies focused, for example, on the degree distribution, i.e., the distribution of the number of links connected to a node, and the clustering coefficient which probes how trios of nodes are correlated. Subsequently simple models for growing networks exhibiting interesting statistical properties were proposed [3].

Recently, weighted networks have also become of interest to this community. These networks may be defined through their adjacency matrix w_{ij}, which gives the weight of the link from node i to node j. The links may be directed or undirected corresponding to an asymmetric or symmetric adjacency matrix. Data are available for many real weighted networks, of either directed or undirected kind, leading to studies of the statistical properties of scientific collaboration networks (SCNs) [4,5] and the worldwide airport network (WAN) [6,7]. Typical quantities used to describe the topology of general weighted networks are the distribution of in-strength and out-strength, which are defined as the total weight going into or out of a node due to all the connected links; weighted clustering coefficients; generalizations of the idea of minimal spanning trees to weighted networks [8,9]. An interesting aspect of weighted networks is how the weights of the links are correlated to the topology of the network: the weights may be determined solely by the global topology, they may be independent, or they may be correlated in some more complicated way. For example, in trans-portation networks, where the weight represents the flow through a link, the weights are determined solely by the topology; in the SCN it appears that the degree of a node and weights of its links are uncorrelated; in the WAN, correlations between the node degree and the weights of its links lead the strength to grow faster than the degree.

Attention has recently focused on constructing simple models of "growing" weighted networks, with the aim being to investigate the resulting degree and weight distributions and the relation between the two. Initial work had the weight of links determined by the degree of the node they were attached to [9–12]. To loosen this coupling between weight and degree, a model with dynamical evolution of weights during growth was introduced in [13–15]. Moreover, models of growing networks in which the dynamics depend on the weights of the links rather than the degree of the nodes were proposed in [16]. For a review of recent work on weighted networks see [7].

An alternative class of evolving network models, which is the focus of this work, is that of "rewiring" or "equilibrium" networks [2,17,18]. In these models, usually considered for unweighted networks, the number of nodes is fixed and the dynamics involves the rewiring of links between nodes, although the effect of creating and destroying links has been examined recently [19]. For rewiring dynamics, one is interested in the steady-state properties of an ensemble of networks. Under certain conditions on the rewiring rules [20] one can obtain a condensed phase where one node (the condensate) attracts a finite fraction of the available links. Thus there is a single extensively connected node while the other nodes exhibit a power-law background in the degree distribution. Hence the network is scale-free if one discounts the condensate. The transition is reminiscent of the "gelation" transition in growing networks from the scale-free phase to a phase with a dominant "hub" [21–23].

These rewiring networks may be related to interacting particle systems such as the zero-range process [24] for which condensation transitions have been widely studied—for a recent review see [20]. The zero-range process is defined such that particles hop between the sites of a lattice

with a rate that depends on the number of particles at the site of departure. The idea behind the mapping is to identify the nodes of the network with the sites of the lattice model and the links of the network become the particles—the rewiring of links corresponds to particles hopping from site to site. At the simplest level, this mapping is approximate in that the number of particles at a site represents only the degree of the corresponding node, but does not determine the other nodes to which a node is attached. However, the steady states of the two systems have the same form.

The aim of the present work is to introduce a model for the rewiring dynamics of a directed, weighted network. By virtue of an exact mapping between the network model and a set of coupled interacting particle systems, we are able to analyze exactly conditions on the rewiring rates under which the network will exist in some kind of condensed phase. Specifically, we define the network model in Sec. II, the key features of which are that (1) the network is directed; (2) the out-strength of each node is conserved under the dynamics but the in-strength evolves; and (3) the dynamics are governed by the weights of links and the in-strength of the nodes. In addition, the weights are integer variables, although this constraint may be relaxed (as we discuss in Sec. V). Thus we define a weighted network model with a fixed number of nodes where strong nodes and links with large weight may tend to attract more weight.

In Sec. II A, we show how this model enjoys a mapping to an interacting particle system known as a multispecies zero-range process [26,27]. The idea is that, since the out-strength of each node is conserved, the dynamics at each node is basically the exchange of weight between the links coming out of that node. Thus each node may be related to an interacting particle system in which the exchange of particles between sites represents the exchange of weight between links. However, since the dynamics at each node also depends on the in-strength, these interacting particle systems are coupled. This mapping of the weighted network to a set of coupled interacting particle systems contrasts with the previous mappings of an unweighted network to a single interacting particle system discussed in [2,17,18,20].

The results of simulations, presented in Sec. III, indicate two distinct types of condensation within this model: the first is when, for any given node, a finite fraction of the out-strength condenses onto one weight out of that node; the second is when a finite fraction of the total weight in the system is directed onto one particular node. The first scenario gives a realization of a transition in the "disparity," the idea of disparity, discussed in the context of internet traffic [28] and simple growing weighted network models [29], being that one weight from a node is dominant over the others from that node. The second scenario is related to the usual condensation transition occurring in unweighted rewiring networks, wherein a single hub acquires a finite fraction of the total number of links in the system, as observed in [2,17,18,20]. An additional feature of our model is that there is a condensation of weight onto each condensed link.

We exploit the mapping to the interacting particle system in Sec. IV, in order to solve and analyze steady-state properties of the network model exactly. In particular, we derive conditions on the rewiring rates which lead to the two types
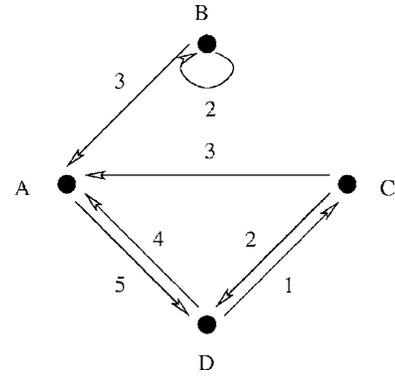

FIG. 1. A picture of a weighted directed network with $L=4$ nodes, labeled A, B, C, and D. The direction and weight of each link are shown. The corresponding adjacency matrix is also shown.

of condensation observed in simulations. The mapping also enables one to identify a number of possible generalizations of the network model and its rewiring dynamics, which we discuss in Sec. V. Finally, we conclude in Sec. VI.

II. MODEL

We study a model of a dynamically evolving, directed network of L nodes with weighted links. Since the weights are integers we will denote the weight associated with the link from node k into node l by an integer $n_{kl} \geq 0$ (instead of the usual w_{kl}). When $n_{kl}=0$, this represents no link from k to l. We depict such a network with $L=4$ nodes in Fig. 1.

The dynamics of the network are such that one unit of the weight associated with the link pointing from node k into node l is rewired to point into another randomly selected node l' with a rate $u_k(\underline{n}_l)$, where $\underline{n}_l \equiv n_{1l}, \ldots, n_{Ll}$. In general, this rate is a function of the weights associated with all of the links pointing into node l, and it depends on the source node k—for the example in Fig. 1, the rate at which the one unit of weight for the link connecting node C to node A is rewired to another node is $u_C(n_{AA}, n_{BA}, n_{CA}, n_{DA})$. After the rewiring, $n_{CA}=2$ and any of n_{CB}, n_{CC} or n_{CD} have increased by 1. These dynamics conserve the *out-strength* $M_k=\Sigma_{l=1}^{L} n_{kl}$ which is the total weight of all links pointing out of node k; the total weight of all links pointing into node l, i.e., the *in-strength* $X_l=\Sigma_{k=1}^{L} n_{kl}$ is not conserved. For simplicity we will take $M_k=M$ for all k. Later, in Sec. V, we will consider several generalizations of the model and dynamics. In particular we consider rewiring dynamics, which depend on the node to which a link is being rewired. This allows one to make a connection with a form of preferential attachment in which links are preferentially rewired to nodes with large in-strengths [13]. We proceed with the dynamics defined above in order to make a clear connection to well-studied interacting particle systems. We stress that either alternative for the dynamics yields the same behavior and transitions.

A. Mapping to a system of interacting particles

To make the connection with interacting particle systems, we use the adjacency matrix A to encode the network: the
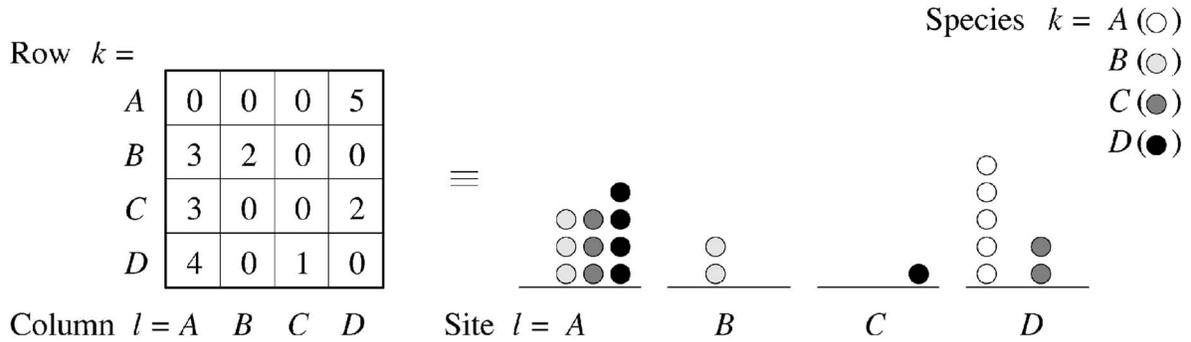
FIG. 2. A picture of the interacting particle systems which represent the network depicted in Fig. 1. On the left-hand side is the two-dimensional lattice model with the occupation numbers n_{kl} entered in row k and column l of the lattice. On the right-hand side is the corresponding multispecies ZRP (here there are four species)—note that there is no ordering among the particles at a particular site.

value of element (k,l) of the matrix is n_{kl}; the weight of the link pointing out of node k into node l, as shown for example in Fig. 1. Note that here, because the network is directed, $A \neq A^T$. The idea is to represent the adjacency matrix by a lattice, where site (k,l) of the lattice represents element (k,l) of the adjacency matrix. The value of the element (k,l), n_{kl}, is then understood as the number of particles at site (k,l) of the lattice. The lattice is therefore two dimensional, since it represents the elements of a matrix, even though the network model may typically be defined in a fully connected geometry (i.e. a link pointing into one node is rewired to point into any other randomly selected node).

The network dynamics then causes the elements of the adjacency matrix to change. Thus the corresponding particle configurations of the lattice model also evolve according to dynamical rules, rules which have their origin in the dynamics of the network model. For the network dynamics described above the corresponding interacting particle system is a generalization of the much studied zero-range process [20], for which the steady state is exactly solvable.

B. Model as a zero-range process with L species of particles

The interacting particle system is defined on a square lattice (since the adjacency matrix is a square matrix) with $L \times L$ sites. On this lattice n_{kl} labels the number of particles at the site located at row $k=1,\ldots,L$, column $l=1,\ldots,L$. There are M particles in each row, a total of LM in the system. Under the network dynamics described in Sec. II, both M and L are conserved. Rewiring single units of the weight of a link connecting node k to node l corresponds, in the interacting particle system, to a particle in row k and column l hopping to another randomly selected site *within the same row* with a rate $u_k(\underline{n}_l)$, given by Eq. (1).

We remark that these are the dynamics of a zero-range process (ZRP) with L species of particles, labeled $k=1,\ldots,L$. Each site $l=1,\ldots,L$ of a one-dimensional lattice contains n_{kl} particles of species k. A particle of species k then hops with a rate $u_k(\underline{n}_l)$ to any other site on the lattice, i.e., a rate which depends upon the number of particles of each species at the departure site l. Thus we identify rows of the two-dimensional lattice with different particle species (so the total number of particles of each species is conserved) and

the columns of the two-dimensional lattice are identified with sites of a one-dimensional lattice, as illustrated in Fig. 2. This mapping is useful because much is known about the exact steady states of zero-range processes and many of its generalizations. In Secs. III and IV we will specialize to a rate of the form

$$u_k(\underline{n}_l) = u^s(n_{kl})u^c\left(\sum_{k=1}^{L} n_{kl}\right), \tag{1}$$

which depends on the weight of the link being rewired, through the function $u^s(n_{kl})$, and the total in-strength of node l, through the function $u^c(\Sigma_{k=1}^{L}n_{kl})$. This model can be solved exactly in the steady state: the analysis which follows exploits this knowledge and one expects that many variations of the network model will also be exactly solvable; those that are can be inferred from the corresponding zero-range process.

Although the model we consider can be thought of as a ZRP with L species of particles, we will proceed with the terminology of the rows and columns of a two-dimensional lattice, since this retains closer contact with the adjacency matrix of the original network model.

III. SIMULATIONS

In this section we present results from simulations of the model that show the two types of condensation: *site condensation*, where a finite fraction of the particles in each row condenses onto a single randomly located site of the row; and *column condensation*, where a finite fraction of all the particles in the system condenses into a single column. In the network context this corresponds to a finite fraction of the weight from each node being contained in a single link from that node; and a finite fraction of the weight pointing from all nodes to a single node, respectively. We also present simulations that exhibit characteristics of both types of condensation, which are interesting from a network perspective.

The model is simulated using a simple Monte Carlo algorithm. At each time step the following update procedure is followed.

(1) A site of the lattice (k,l) is chosen at random.
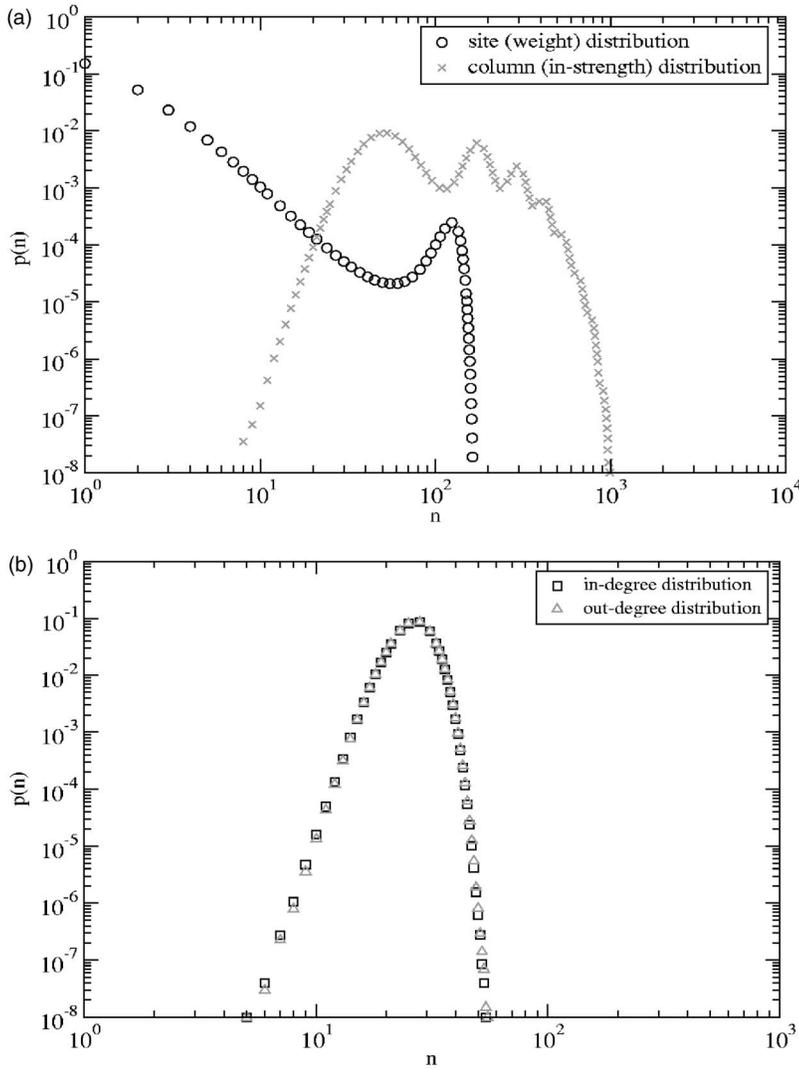(2) If the site is occupied then a particle will be removed

FIG. 3. Distributions from simulation of the model with the hop rate chosen to display site condensation. (a) Site and column occupation distributions, corresponding to the distributions of weight among links and in-strength among nodes in the network context, respectively. (b) In- and out-degree distributions.

from this site with probability $u(\underline{n}_l)\delta t$, where u is the hop rate (1) and δt is the time interval, chosen such that the probability of a hop occurring is always less than or equal to 1.

(3) If a particle was removed, then a second site (k,m) (within the same row) is chosen at random and a particle is added to this site.

All simulations were run on lattices of size 100×100, i.e., on networks with 100 nodes, and for $\mathcal{O}(10^7)$ Monte Carlo sweeps. The first half of each run was used to relax to the steady state and the second half to measure probability distributions. Distributions were measured for the number of particles at a site (link weight); the number of particles in a column (node in-strength); and the number of occupied sites in a column and row (in- and out-degree, respectively). Typical configurations of the lattice were also output.

In order to compare with theory (see Sec. IV), the following hop rates were chosen to show the two condensation types. Recall that we consider a hop rate for particles from site (k,l) of the form (1). For site condensation we make the choice

$$u^s(n) = (1 + b^s/n) \quad \text{and} \quad u^c(n) = 1, \tag{2}$$

with $b^s = 4$ and for $n > 0$. For column condensation we make the choice

$$u^c(n) = \begin{cases} 1 + b^c & \text{for} \quad n \le L, \\ 1 + b^c L/n & \text{for} \quad n > L, \end{cases} \quad \text{and} \quad u^s(n) = 1, \tag{3}$$

with $b^c = 1.05$.

A. Site condensation

The simulations for the site condensation case were run with 175 particles in each row starting from a random initial configuration. The site condensation can be seen clearly from the site distribution [black circles, Fig. 3(a)]. The peak at around $n = 150$ represents the site condensates, it has an area of order $1/L$ and there are L^2 sites indicating that L sites have occupations of around 150 particles. As the number of particles in each row is fixed at 175, there can be at most one such site in a row and an occupation of this size represents an appreciable fraction of the total number of particles available to a site, hence implying a condensation in the thermodynamic limit. Thus we have a single condensed site in each row. Note also that the site distribution has an apparently power-law background before the condensate peak. This is reminiscent of the behavior of a single-species ZRP [20];
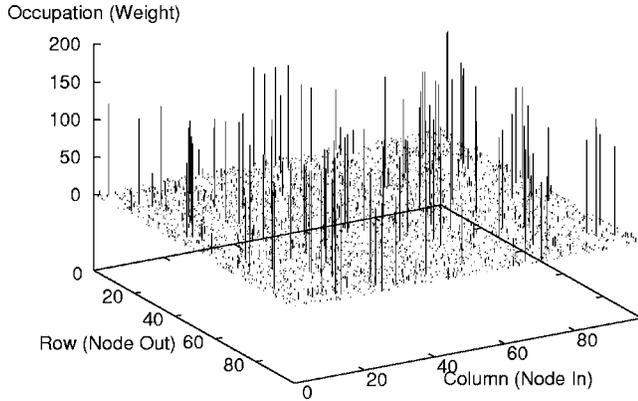
FIG. 4. Typical configuration of the system; output from simulation of the model with the hop rate chosen to display site condensation.

indeed as the column attraction has effectively been switched off, the system is a collection of single-species ZRPs. The column distribution [gray crosses, Fig. 3(a)] shows that, in the absence of any coupling between the rows, the condensed sites are randomly distributed among the columns—as one would expect. The first peak in the distribution at around $n=50$ shows that some columns do not contain any condensed sites, just those from the power-law background. The second, third, etc. peaks correspond to columns with one, two, etc. condensed sites in them, plus a background from the rest of the sites. This is exactly what one would expect if the condensed sites were randomly distributed in the columns and a random sampling of the site distribution to create a column distribution agrees closely with the simulation. The typical configuration (Fig. 4) bears this out, condensates can be seen on individual sites, but no column ordering can be discerned. Although not shown here, systems with weak column attraction showed similar behavior, i.e., as though no column attraction was present.

The degree distributions for the site condensation case [Fig. 3(b)] appear to be binomial in nature: a binomial distribution constructed from the measured probability of a site having zero occupation matches very closely the data shown. Thus in the network context, for the site condensation we have connectivity similar to that of a random graph (which also has a binomial connectivity distribution). In addition to this we have a condensed link weight from each site with a power-law background, and an in-strength which is a random sum of link weights.

B. Column condensation

The simulations for the column condensation case were run with 1000 particles in each row. The initial condition was taken with all particles on the same site. The column condensation can be seen clearly from the column distribution (gray crosses, Fig. 5(a)]. The peak at around $n=85\,000$ corresponds to the condensate; it has an area of order $1/L$ and there are L columns, indicating that a single column has an occupation of around 85 000, an appreciable fraction of the total number of particles in the system $L \times M = 100 \times 1000$.

The other, lower peak at around $n=100$ represents the columns that do not contain a condensate. The site distribution [black circles, Fig. 5(b)] also shows condensation onto sites in the peak at around $n=850$. If the column interaction were to be switched off leaving L uncoupled single-species ZRPs, it is known that the chosen $u^s(n)(=$const$)$ would not give condensation in this fully connected homogeneous system; see, for example, [20]. Thus in this case it is the column interaction that has induced a site condensation. Note that both the column and site distributions have apparent power-law pieces, with equal or close exponents. The theory presented in Sec. IV allows one to construct the critical column distribution at the transition point—shown as the dotted line in Fig. 5(a). This fits the noncondensate background part of the measured column distribution very well. The typical configuration of the system, Fig. 6, shows the column condensate comprises site condensates all in the same column.

The out-degree distribution for the column condensation case [gray triangles, Fig. 5(b)] is similar to the site condensation case, being distributed according to a binomial distribution. However, the in-degree distribution [Fig. 5(b), black squares] is significantly different; in particular, it has a broader tail and also a single site that is connected to all others, as shown by the lone data point at degree L with probability $1/L$ ($L=100$ in this case). Thus in the network context the out-connectivity resembles that of a random graph, but the in-degree distribution displays a broader tail and there is a single node to which all others point—the node corresponding to the condensed column. Furthermore, all links pointing to this node hold a finite fraction of the weight available and the node holds a finite fraction of the total in-strength available to it. Broadly tailed degree distributions are often observed in real networks, weighted and unweighted alike. While the tail observed in these simulations is not as broad as many observed, it is at least broader than that of the equivalent random graph. Also apart from the condensed pieces the in-strength and weight distributions display power-law tails, again something that has been observed in many real networks. Thus, as with equilibrium networks [2,18], certain distributions may take a power-law form at a critical point.

As mentioned at the beginning of this subsection, we employed a fully condensed initial condition. The reason is that, for a random initial configuration, the dynamics slows down as the system reaches a state in which several columns contain a large number of particles; the single column condensate is attained only on prohibitively long time scales.

C. Further behavior

In the preceding sections the somewhat extreme cases of the absence of site or column attraction in the presence of the other (u^s or u^c set equal to 1) were considered. This was to allow for a direct comparison with theory. Cases where some forms of nontrivial attraction are present in both u^s and u^c are difficult to compare directly with theory. However, such systems do display interesting behavior and so in this section we present some numerical data from simulations of such a system.
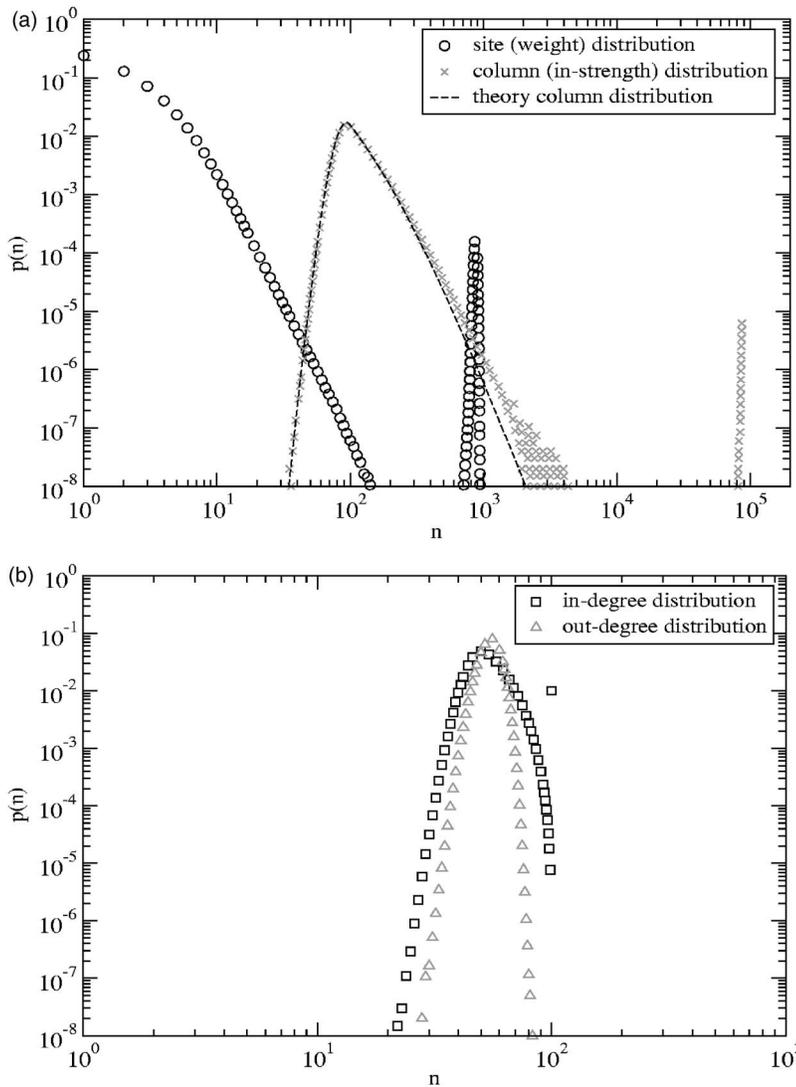
FIG. 5. Distributions from simulation of the model with the hop rate chosen to display column condensation. (a) Site and column occupation distributions, corresponding to the distribution of weight among links and in-strength among nodes in the network context respectively. (b) In- and out-degree distributions.

Simulations were run on a system with 175 particles in each row and the hop rate given by $u^c(n) = 1 + b^c/L$ for $n \leq L$, $u^c(n) = 1 + b^c/n$ for $n > L$ and $u^s(n) = 1 + b^s/n$, with $b^c = 16$ and $b^s = 2.5$. If u^c were set equal to 1, then no conden-

FIG. 6. Typical configuration of the system output from simulation of the model with the hop rate chosen to display column condensation.

sation would occur at this particle number [20]. If u^s were set equal to 1, then no condensation would take place at any finite particle number (see Sec. IV). Results from simulations show that this system, with both site and column attraction present in forms that separately show no condensation behavior, does show something that could be interpreted as a condensationlike phenomenon. The following results were obtained from a random initial configuration.
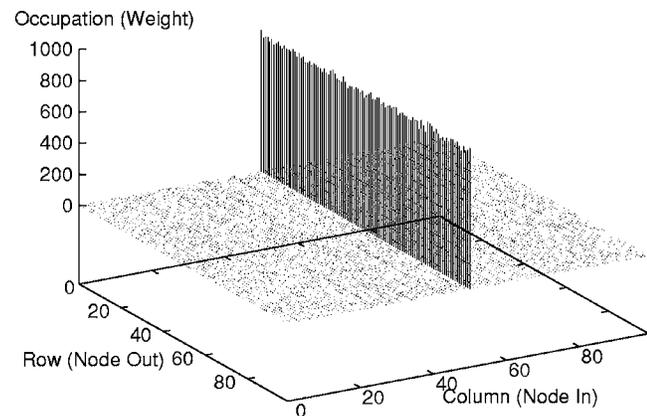
In Fig. 7(a), it can be seen that the site occupation distribution (black circles) has a decaying part and a peak at around $n = 150$ and is generally reminiscent of a condensed system. The column distribution [Fig. 7(a), gray crosses] also shows a large n peak, at around $n = 3500$, although it is much broader than one usually associated with a clear condensation. The typical configuration data in Fig. 8 indicate that the high n bump of the column distribution represents more than one highly occupied column, each composed of many site condensates. Without a direct comparison with theory available, it is difficult to interpret this broad peak: it could be a finite-size effect that will not be seen in larger systems, but on the other hand it could be a true condensation that is being adversely affected by the finite size of the system. In
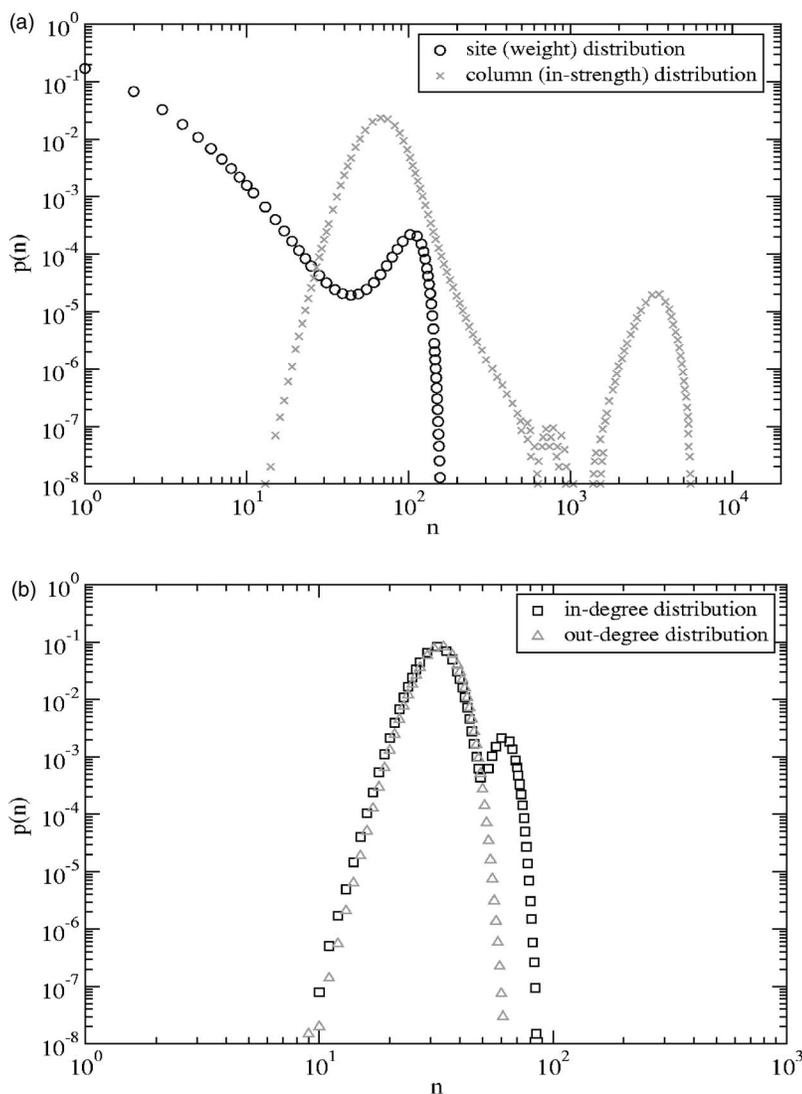
FIG. 7. Distributions from simulation of the model with the hop rate chosen such that without the site or column attraction elements no condensation would be present. (a) Site and column occupation distributions, corresponding to the distributions of weight among links and in-strength among nodes in the network context, respectively. (b) In- and out-degree distributions.

either case it is interesting from a network point of view as real-world networks are often of finite size.

The degree distributions of this system are also interesting. They both have a binomial form for low degree, but the in-degree distribution departs from this at high degree—it has a small secondary peak implying that several sites are highly connected, but a completely connected site to which all others point, as arises in the column condensation case, is absent. Thus in the network context we have a network with connectivity much like that of a random graph, except for the existence of several well-connected hub nodes which would not be present in the random case. These hub nodes also have many high weight links pointing to them, giving them a large in-strength.

For an initial configuration with all particles located on a single site, we obtain distributions of the same form as above and configurations typically contain more than one highly occupied column.

IV. THEORY

In this section we present the exact steady state of the model and exploit this solution in order to understand theo-
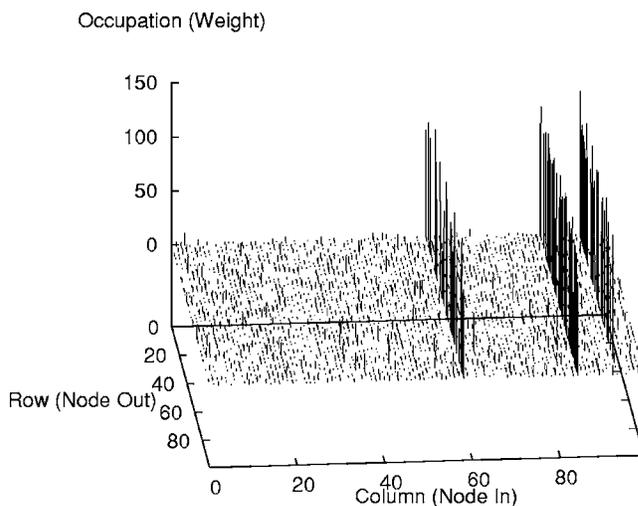

FIG. 8. Typical configuration of the system output from simulation of the model with the hop rate chosen such that without the site or column attraction elements no condensation would be present.

retically the condensation transitions observed in simulations.

A. Steady state

First, we give the steady state, the proof of which is given in Appendix A. The steady-state probabilities $P(\{\underline{n}_l\})$, for finding the system in a configuration $\{\underline{n}_l\}$, are given by the simple form

$$P(\{\underline{n}_l\}) = Z_{L,M}^{-1} \prod_{l=1}^{L} f(\underline{n}_l), \qquad (4)$$

i.e., a product over columns. Here, the functions $f(\underline{n}_l)$ depend on a single column (i.e., the in-links of node l), and for the rates (1), they are given by

$$f(\underline{n}_l) = f^c(X_l) \prod_{k=1}^{L} f^s(n_{kl}), \qquad (5)$$

where we are using $X_l = \Sigma_{k=1}^{L} n_{kl}$ to represent the total number of particles in a column (the node in-strength), and where

$$f^a(x) = \prod_{i=1}^{x} u^a(i)^{-1} \qquad (6)$$

for $a = s, c$, where $f^a(0) = 1$. The normalization $Z_{L,M}$ in Eq. (4) is given by

$$Z_{L,M} = \sum_{\{n_{kl}\}} \prod_{l=1}^{L} \left(f^c(X_l) \prod_{k=1}^{L} f^s(n_{kl}) \right) \prod_{k=1}^{L} \delta \left(\sum_{l=1}^{L} n_{kl} - M \right). \qquad (7)$$

The δ function in this normalization enforces particle conservation within each row (which is the conservation of node out-strength in the network): it is this δ function that induces correlations between different columns in the steady state.

B. Condensation theory

Now, we exploit the exact steady state in order to understand theoretically the condensation transitions observed in simulations. Ideally, one would wish to demonstrate condensation in the site and column distributions of particles, $p^s(n)$ and $p^c(n)$. The expressions for these distributions involve the normalization $Z_{L,M}$ given by Eq. (7), which can be thought of as a canonical partition function since M is fixed. However, as we now outline, it turns out to be simplest to work within the grand canonical ensemble in which the particle number is allowed to fluctuate.

1. Grand canonical ensemble

We introduce the grand canonical partition function in the usual way, by defining fugacities $\{z_k\}$ so that we can replace the canonical partition function (7) by

$$\mathcal{Z}_L = \sum_{\{n_{kl}=0\}}^{\infty} \prod_{k=1}^{L} z_k^{\sum_l n_{kl}} \prod_{l=1}^{L} \left(f^c(X_l) \prod_{k=1}^{L} f^s(n_{kl}) \right), \qquad (8)$$

where the fugacities are chosen to ensure that, on average, each row contains the proper number of particles M_k:

$$z_k \frac{\partial \ln \mathcal{Z}_L}{\partial z_k} = \overline{\sum_l n_{kl}} = M_k. \qquad (9)$$

Here, the overbar indicates an average taken in the grand canonical ensemble. Since we are interested in the case where $M_k = M$ for all values of k, the left hand side (LHS) of this equation must be independent of k therefore $z_k = z$ for all values of k; in this case, the fugacity z is chosen to determine the *total* number of particles in the system. After a little rearrangement, Eq. (8) can be written

$$\mathcal{Z}_L = \prod_{l=1}^{L} \left[\left(\prod_{k=1}^{L} \sum_{n_{kl}} \right) f^c(X_l) \prod_{k=1}^{L} f^s(n_{kl}) z^{n_{kl}} \right] \qquad (10)$$

$$= \left[\sum_{\{n_k\}} f^c(X) \prod_{k=1}^{L} f^s(n_k) z^{n_k} \right]^L, \qquad (11)$$

where in going from the first to the second line we use the fact that the l subscript on the n_{kl} plays no role—each column makes the same contribution to $\mathcal{Z}_L$—and the quantity in square brackets can simply be raised to the power of L. Now, $X = \Sigma_k n_k$. By taking derivatives of $\mathcal{Z}_L$ with respect to z, one finds that the fugacity must be chosen to satisfy

$$M = z \frac{\partial \ln F(z)}{\partial z}, \qquad (12)$$

where we have defined the function

$$F(z) = \sum_{\{n_k\}} f^c(X) \prod_{k=1}^{L} f^s(n_k) z^{n_k}. \qquad (13)$$

Equation (12) is the key result of this section. Condensation typically arises when one is unable to satisfy (12) above some critical density; under these circumstances, the grand canonical ensemble is no longer valid and the change of the partition function from the grand canonical form below the critical density to some other form above it signals the phase transition. We now discuss conditions under which (12) can be satisfied in order to illustrate how one can theoretically understand and predict the condensed phases observed in simulations.

2. Condensation

It is straightforward to show that the function $F(z)$ is a smoothly increasing function of its argument z. Let us assume that we have chosen hop rates such that the sums that determine $F(z)$ have a radius of convergence α. The convergence properties of $F(z)$ and its derivative determine whether or not the system undergoes condensation. These convergence properties are determined by the form of the function $f(\underline{n})$ which in turn provides the conditions on the rewiring rates under which the system condenses. We now present two very simple examples to illustrate the two types of condensation.

First, we consider conditions to observe site condensation. We take $f^c(x) = 1$, which is the case when $u^c(x) = 1$ for all x; hence

$$F(z) = \left[\sum_{n=0}^{\infty} f^s(n) z^n \right]^L. \qquad (14)$$

Hence, from Eq. (12), the fugacity is determined by

$$\rho = \frac{\sum_{n=0}^{\infty} n f^s(n) z^n}{\sum_{n=0}^{\infty} f^s(n) z^n}, \qquad (15)$$

where $\rho = M/L$ is the density of particles in each row. When both the numerator and denominator approach finite values as z approaches the radius of convergence α there exists a finite critical density ρ_c above which Eq. (12) cannot be satisfied. This signals condensation: for $\rho > \rho_c$, each row contains $(\rho - \rho_c)L$ "excess" particles which condense in a single, randomly located site within each row. In order that ρ_c is finite, one requires that $f^s(n)$ decays asymptotically like $f^s(n) \sim \alpha^{-n} n^{-b}$ for large n where $b > 2$. This in turn implies that the hop rates $u^s(n)$ must decay asymptotically as

$$u^s(n) \sim \alpha(1 + b/n), \qquad (16)$$

again, where $b > 2$, if one is to observe site condensation in each row at finite density. In the network model, this implies that the rate of rewiring a node must decay more slowly than $2/n$, where n is the weight of the link pointing out of the node being rewired. These considerations guide the choice of hop rates (2) discussed in Sec. III A.

Now, we consider conditions to observe column condensation. To deal with the sum over particle configurations in $F(z)$, it turns out to be convenient to sum over the variable X and introduce a δ function to ensure that X represents the number of particles in a column. Thus $F(z)$ may be written in the form

$$F(z) = \sum_{\{n_k\}} \sum_{X=0}^{\infty} f^c(X) \delta \left(\sum_{k=1}^{L} n_k - X \right) \prod_{k=1}^{L} f^s(n_k) z^{n_k}, \qquad (17)$$

where the k subscripts refer to the rows within a single column. To proceed, we take $f^s(n) = 1$, which is the case when $u^s(n) = 1$ for all n. With this choice, the sum over $\{n_k\}$ is straightforward to perform—the δ-function constraint supplies a combinatorial factor associated with the number of ways of adding L integers to get X—and one finds

$$F(z) = \sum_{X} \binom{L-1+X}{L-1} f^c(X) z^X. \qquad (18)$$

In this case, the RHS of Eq. (12) represents the average number of particles in a column, $\bar{X}$. The asymptotics of $f^c(X)$ determine the convergence properties of $F(z)$ [Eq. (18)]. In order to deduce the required asymptotics, we expand the binomial factor for $X \gg L$, using the approximation

$$\binom{L-1+X}{L-1} \approx \frac{X^{L-1}}{(L-1)!}, \qquad (19)$$

for large X. To observe column condensation, the RHS of Eq. (12) must converge to a value $X_c = O(L)$ as $z \to \alpha$. This is the case when $f^c(X)$ decays asymptotically like $f^s(n) \sim \alpha^{-X} X^{-\lambda}$ with $\lambda > 1 + L$. When these conditions are satisfied, the system condenses above a critical density $\rho_c = X_c/L$ in such a way that every site in a single, randomly located column typically contains $(X - X_c)$ particles. A hop rate that yields $f^c(X)$ with the required asymptotics is

$$u^c(X) \sim \alpha(1 + cL/X), \qquad (20)$$

where $c > 1$, which motivates the choice of hop rates (3) discussed in Sec. III B.

Thus these two simple examples, $f^c(x) = 1$ and $f^s(n) = 1$, illustrate site and column condensation, respectively. We would like to stress that in both site and column condensation, while only the asymptotics determine whether or not the system condenses, the actual value of the critical density depends on the details of the form of the rewiring rates for all values of their arguments, not just the asymptotics.

We now indicate how one can use the grand canonical ensemble to predict the background particle distribution in the condensed phase. We consider the case $f^s(n) = 1$, for which $p^c(X)$, the probability that a column contains exactly X particles, is given by

$$p^c(X) = \frac{\binom{L-1+X}{L-1} f^c(X) z^X}{F(z)}. \qquad (21)$$

This equation holds throughout the low density phase. In the condensed phase, the grand canonical ensemble breaks down; however, Eq. (21) with $z = \alpha$ correctly reproduces the form of the background distribution of column occupation numbers. For the rates (3), Eq. (21) cannot be written in a convenient form at $z = 1$; however, it can easily be evaluated numerically for a given value of b^c. The result of such a computation, with $b^c = 1.05$, is compared with simulation in Fig. 5(a).

V. GENERALIZATIONS

In this section we consider some generalizations of the network model which, in the steady state, are still given by a factorized form. The aim is to illustrate that the class of network models with factorized steady states extends to a wide variety of rewiring dynamics and so, by making the connection between network dynamics and interacting particle systems, we are rewarded with a versatile approach to the analysis of network properties.

A. General dependence of the rewiring rates on departure and destination nodes

We begin by considering three generalizations of the rewiring rates.

(1) General dependence of the rewiring rates on the

weights of links rather than the specialized form (1).

(2) Rewiring rates that depend on both the weights of the links pointing into the node from which the link is being removed, and the weights of the links pointing into the node into which the link is being rewired—this allows one to consider preferential attachment.

(3) Heterogeneity in the rewiring dynamics such that one can consider rates that differ depending on the source, departure, and destination nodes of the link.

With these generalizations, one unit of the weight associated with the link pointing from node k into node l is rewired to point into another randomly selected node l' with a rate $u_{kl}(\underline{n}_l)t_{kl'}(\underline{n}_{l'})$. The heterogeneity described in the above point 3 enters through the k, l, and l' superscripts on u and t. The corresponding interacting particle system has been discussed in the literature in the context of "urn" models (discussed in [30]) and "misanthrope" processes (discussed in [20]) in a fully connected geometry, in which particle hop rates depend on the numbers of particles at both the site of departure and the destination site, but now defined with L species of particles.

In the steady state, this model can still be expressed in the factorized form

$$P(\{\underline{n}_l\}) = Z_{L,M}^{-1}\prod_{l=1}^{L} f_l(\underline{n}_l) \qquad (22)$$

[though note that $f_l(\underline{n}_l)$ now carries a subscript l] provided the hop rates satisfy the constraint

$$\frac{u_{kl}(\underline{n}_l;n_{k'l}-1)t_{kl}(\underline{n}_l;n_{kl}-1)}{u_{kl}(\underline{n}_l)t_{kl}(\underline{n}_l;n_{kl}-1,n_{k'l}-1)} = \frac{u_{k'l}(\underline{n}_l;n_{kl}-1)t_{k'l}(\underline{n}_l;n_{k'l}-1)}{u_{k'l}(\underline{n}_l)t_{k'l}(\underline{n}_l;n_{kl}-1,n_{k'l}-1)} \qquad (23)$$

for all pairs of rows k and k'. We have introduced the notation $\underline{n}_l;n_{kl}-1$ which represents the configuration $\underline{n}_l$ but with the term n_{kl} replaced by $n_{kl}-1$. When the hop rates satisfy this constraint, the functions $f_l(\underline{n}_l)$ can be written

$$f_l(\underline{n}_l) = \prod_{k=1}^{L} \left(\prod_{i=1}^{n_{kl}} \frac{t_{kl}(0,\dots,0,i-1,n_{k+1l},\dots,n_{Ll})}{u_{kl}(0,\dots,0,i,n_{k+1l},\dots,n_{Ll})}\right), \qquad (24)$$

having chosen $f(0,\dots,0)=1$. This can be written in a number of different forms due to (23)—the symmetry in $f_l(\underline{n}_l)$ is obscured within this constraint. A proof of this steady state is presented in Appendix B.

1. Preferential attachment

To illustrate how one might exploit this steady state, we consider a network model with preferential attachment rewiring dynamics. Thus we choose $u_{kl}(\underline{n}_l)=1$ for all k and l, and

$$t_{kl'}(\underline{n}_{l'}) = t^s(n_{kl'})t^c\left(\sum_{k=1}^{L} n_{kl'}\right), \qquad (25)$$

which defines the rate at which a link pointing from node k into node l is rewired to point into node l'. This rate therefore is a function of the weight of the link pointing from source node k into the destination node l' before the rewiring

event, and a function of the total in-strength of the destination node. It satisfies the constraint (23) and one finds that the functions $f(\underline{n}_l)$ are given by Eq. (5), where

$$f^a(x) = \prod_{i=1}^{x} t^a(i-1) \qquad (26)$$

for $a=s$, c, where $f^a(0)=1$. In order that this model will exhibit the behavior observed in simulations, one can follow the analysis of Sec. IV B 2 to deduce that if the hop rates decay asymptotically like

$$t^s(n) \sim 1 - b/n \qquad (27)$$

with $b>2$, then one observes site condensation above some finite critical system density, and if

$$t^c(X) \sim 1 - \lambda/X \qquad (28)$$

for $X \gg L$ with $\lambda > L+1$, then one observes row condensation above some finite critical system density.

B. Further generalizations

There are a number of further ways one can choose to redefine the model and still obtain a factorized steady state. One way is to consider geometries other than the fully connected one, such as rewiring dynamics in which the weight being rewired from node l is always rewired to a "neighboring" node $l+1$. All the models considered so far also have factorized steady states in this geometry although there may exist extra constraints in certain cases. Generalizations to more complicated geometries are also possible, and have been discussed in the context of the ZRP in [24].

We can also relax the property of integer weights and consider the case where the weights are continuous variables and an arbitrary amount of the weight is allowed to be rewired. The approach is similar to the way one generalizes the zero-range process to continuous masses [31].

It is straightforward to allow each node to have a different total out-strength, but more complicated generalizations whereby these out-strengths are not conserved may also be possible. Nonconservation in the context of the ZRP has been discussed in [19,20]. Another straightforward modification of the model is to prohibit links that point into the same node they point out of, i.e., restrict consideration to $n_{kk}=0$. A further possibility is to allow negative weights, as well as positive, which corresponds to a generalization of the so-called bricklayers' model [32]—positive and negative weights have been considered in a rewiring social network in [25].

A point about the factorized steady states we would like to emphasize is that one is free to choose any form for $f(\underline{n}_l)$ and then infer the rewiring rates from a recursion such as Eq. (B3).

VI. CONCLUSION

In summary we have introduced a dynamical model of a weighted, directed network wherein the out-strength of each node is conserved but the in-strength is not. The rewiring

dynamics of this model can be mapped onto a multispecies zero-range process for which the steady state is exactly solvable.

Through numerical simulations and theoretical analysis we have identified two condensation transitions in the steady state. In the network context they correspond to a disparity transition where for each node a single link contains a finite fraction of the out-strength, and the more familiar condensation transition where the in-strength of a single node captures a finite fraction of the out-strengths for all nodes in the system. These transitions demonstrate some of the varied behavior that is possible in weighted directed networks.

Within the multispecies ZRP picture these transitions correspond to, in the first case, condensation of all species at independent sites or, in the second case, a collective condensation of all species onto the same site. From our knowledge of the multispecies ZRP we are able to identify a number of generalizations of the model and dynamics which preserve the exactly solvable steady state. For example these correspond in the network context to continuous weights, preferential attachment dynamics, and node fitness. It would be interesting to explore further the different possible behaviors afforded by these and other generalizations.

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APPENDIX A: PROOF OF STEADY STATE (4)–(6)

The steady state (4)–(6) can be demonstrated by noting that, since the network model is defined in a fully connected geometry (i.e., a link can be rewired from a node to any other node in the network), the steady-state probabilities must satisfy detailed balance with respect to the rewiring dynamics. (In Sec. V we comment on how one generalizes to other geometries.) The detailed balance condition implies that

$$u^s(n_{kl}+1)u^c(X_l+1)P(\{\underline{n}_l\};n_{kl}+1,n_{km}-1)$$
$$= u^s(n_{km})u^c(X_m)P(\{\underline{n}_l\}), \qquad \text{(A1)}$$

where we have introduced the notation $\{\underline{n}_l\}$; $n_{kl}+1$, $n_{km}-1$ to represent a particle configuration with n_{kl} replaced by $n_{kl}+1$ and n_{km} replaced by $n_{km}-1$. In this balance equation, the LHS represents a particle hop from site kl to site km and the

RHS represents the reverse process. We now regard a solution of the form (4) and (5) as an ansatz, substitution of which into the balance equation (A1) yields

$$u^s(n_{kl}+1)\frac{f^s(n_{kl}+1)}{f^s(n_{kl})}u^c(X_l+1)\frac{f^c(X_l+1)}{f^c(X_l)}$$
$$= u^s(n_{km})\frac{f^s(n_{km})}{f^s(n_{km}-1)}u^c(X_m)\frac{f^c(X_m)}{f^c(X_m-1)}, \qquad \text{(A2)}$$

after canceling common factors and rearranging slightly. This is satisfied for

$$u^a(x+1)f^a(x+1) = f^a(x) \qquad \text{(A3)}$$

for $a=s$, c, which is iterated to give Eq. (6). This proves the steady state (4)–(6).

APPENDIX B: PROOF OF STEADY STATE (22)–(24)

The steady state (22)–(24) can be demonstrated by asking that the steady-state probabilities satisfy detailed balance with respect to the rewiring dynamics; hence

$$u_{kl}(\underline{n}_l;n_{kl}+1)t_{kl'}(\underline{n}_{l'};n_{kl'}-1)P(\{\underline{n}_l\};n_{kl}+1,n_{kl'}-1)$$
$$= u_{kl'}(\underline{n}_{l'})t_{kl}(\underline{n}_l)P(\{\underline{n}_l\}) \qquad \text{(B1)}$$

for each $k=1,\ldots,L$ and all pairs $l \neq l'$. Inserting the steady state (22), canceling common factors, and rearranging yields

$$\frac{u_{kl}(\underline{n}_l;n_{kl}+1)}{t_{kl}(\underline{n}_l)}\frac{f_l(\underline{n}_l;n_{kl}+1)}{f_l(\underline{n}_l)} = \frac{u_{kl'}(\underline{n}_{l'})}{t_{kl'}(\underline{n}_{l'};n_{kl'}-1)}$$
$$\times \frac{f_{l'}(\underline{n}_{l'})}{f_{l'}(\underline{n}_{l'};n_{kl'}-1)}, \quad \text{(B2)}$$

again, for each $k=1,\ldots,L$. Both sides of this equation must be equal to a constant which we choose, without loss of generality, to be equal to 1, whereby we obtain the recursion

$$f_l(\underline{n}_l) = \frac{t_{kl}(\underline{n}_l;n_{kl}-1)}{u_{kl}(\underline{n}_l)}f_l(\underline{n}_l;n_{kl}-1), \qquad \text{(B3)}$$

which can be iterated to obtain Eq. (24). This recursion also implies the constraint on the choice of the hop rates: one can obtain two expressions for $f_l(\underline{n}_l)$ in terms of $f_l(\underline{n}_l;n_{kl}-1,n_{k'l}-1)$; one comes by applying the recursion (B3) first to k, then to k'; the other comes by applying the recursion to k' before k. Performing these operations yields the constraint (23).

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