## Chapter 1

# Mobility Models for Systems Evaluation A Survey

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## 1.1 Introduction

Mobility models are used to simulate and evaluate the performance of mobile wireless systems and the algorithms and protocols at the basis of them. The definition of realistic mobility models is one of the most critical and, at the same time, difficult aspects of the simulation of applications and systems designed for mobile environments. There are essentially two possible types of mobility patterns that can be used to evaluate mobile network protocols and algorithms by means of simulations: traces and synthetic models [15]. Traces are obtained by means of measurements of deployed systems and usually consist of logs of connectivity or location information, whereas synthetic models are mathematical models, such as sets of equations, which try to capture the movement of the devices.

Currently, there are very few and very recent public data repository of traces capturing movement of people. Examples are GPS traces and Bluetooth connectivity traces (i.e., traces containing the Bluetooth identifiers of the devices that have been in radio range of a device). For instance, researchers at the Intel Research Laboratory and the University of Cambridge distributed Bluetooth devices to people, in order to collect data about human movements and study the characteristics of the colocation patterns among people. These experiments were firstly conducted among students and researchers in Cambridge [17] and then among the participants of INFOCOM 2005 [37]. Examples of similar projects are the Wireless Topology Discovery project at UCSD [57] and the campus-wide WiFi traffic measurements that have been carried out at Dartmouth College [31]. At this institution, a project with the aim of creating a repository of publicly available traces for the mobile networking community has also been started [46].

In general, synthetic models have been largely preferred [15]. The reasons of this choice are many. First of all, as mentioned, the publicly available traces are limited. Telecommunication companies usually collect and analyze large sets of data but these are kept secret since they may represent a source of competitive advantage, for example, for investments and marketing choices. Secondly, these traces are related to very specific scenarios (such as campus environments) and it is currently difficult to generalize their validity. However, it is important to note that these data show surprising common statistical characteristics, such as the same distribution of the duration of the contacts and inter-contacts intervals[1]. Thirdly, the available traces do not allow for sensitivity analysis of the performance of algorithms, since the values of the parameters that characterize the simulation scenarios, such as the distribution of the speed or the density of the hosts, cannot be varied. Finally, in some cases, it may be important to have a mathematical model underlying the movement of the hosts in simulations, in order to formally analyze its impact on the design of protocols and systems.

For these reasons, many mobility models for the generation of synthetic traces have been presented [15]. The most widely used of such models are based on random individual movements; the simplest, the Random Walk mobility model (equivalent to Brownian motion), is used to represent pure random movements of the entities of a system [23]. Another widely adopted random model is the Random Way-Point mobility model [41], in which pauses are introduced between changes in direction or speed. More recently, a large number of more sophisticated random mobility models for ad hoc network research have been presented [50, 39, 55].

However, all synthetic models are suspect because it is quite difficult to assess to what extent they map reality. It is not hard to see, even only with empirical observations, that the random mobility models generate behavior that is most unhuman-like. This analysis is confirmed by the examination of the available real traces [46]. As we will discuss later in this chapter, mobility models based on random mechanisms generate traces that show properties (such as distributions of the duration of the contacts between the mobile nodes and the inter-contacts time between two subsequent connections) that are different from those observed in real scenarios[2].

[1] We define *contact duration* as the time interval during which two devices are in radio range. We define *inter-contacts time* as the time interval between two contacts. These indicators are particularly important in ad hoc networking and, in particular, in delay tolerant mobile ad hoc networks [59, 29], since inter-contacts times define the frequency and the probability of being in contact with the recipient of a message or a potential message carrier in a given time period.

[2] However, as we will discuss in Section 1.4, Karagiannis et alii in [43] demonstrate that the inter-contacts time distributions generated by means of classic random mobility models such as the Random Way-Point model show properties that can also be observed in real traces such as power-law behavior in a certain range of values and an exponential tail after a characteristic time. Power-law distributions are characterized by the following form:

$$P(x) = x^{-k}$$

with $k \geq 0$. A power-law distribution is also called scale-free since it remains unchanged to within a multiplicative factor under a re-scaling of the independent variable $x$ [66].

An alternative approach to the problem of modeling human mobility is designing *synthetic* models starting from *real* traces. The challenge is to capture and model the key statistical properties of the traces in order to be able to reproduce and, possibly, to generalize them providing sets of realistic input data for simulators. The first examples of this kind of models are [35, 88], in which the authors considered, respectively, the movement traces collected from a campus scenario and direct empirical observations of pedestrians in downtown Osaka as a basis of the design of their models. Many refined models have been presented in the last years such as [38, 53, 101, 45]. A key research area is the analysis and mathematical characterization of the available traces. The goal is to derive the fundamental properties of human mobility and connectivity. In fact, connectivity models derived from the analysis of the traces have also been proposed [14, 103]. Finally, another promising approach is the application of social network theory results to the design of mobility models, since mobile devices are carried by humans and, therefore, the resulting mobility and connectivity patterns are strongly influenced by human relationships [61].

This paper is organized as follows: in Section 1.2 we outline the most significant examples of synthetic mobility models, whereas in Section 1.3 we present the recent research efforts in exploiting traces to build realistic mobility models. Then, in Section 1.4 we discuss some key results in human mobility modeling from an analytical point view. In Section 1.5 we present an overview of the concepts at the basis of the design of mobility models based on social networks. The design of connectivity models is discussed in Section 1.6. Section 1.7 provides a brief overview of the available tools for protocol simulations and mobile systems testing. Finally, a roadmap for future research in the field of mobility modeling is outlined in Section 1.8.

## 1.2 Purely Synthetic Models

We firstly consider the class of purely random synthetic mobility models. We outline the main characteristics of these models and the most recent relevant results about the analytical characterization of such models. In [15] Camp, Boleng and Davids provide an excellent survey of the most relevant and popular random synthetic mobility models used in ad hoc network research.

### *1.2.1 Random Walk Mobility Model*

The simplest mobility model is the Random Walk mobility model [23, 62], also called Brownian motion; it is a widely used model to represent purely random movements of the entities of a system in various disciplines from physics to meteorology. However, it cannot be considered as a suitable model to simulate wireless environments, since human movements do not present the continuous changes of direction that characterize this mobility model.

### *1.2.2 Random Way-Point Mobility Model*

Another example of random mobility model is the Random Way-Point mobility model [41]. This can be considered as an extension of the Random Walk mobility model, with the addition of pauses between changes in direction or speed. However, also in this case, the realism of the model in terms of geographical movement is far from being realistic. First of all, the initial placement of the nodes in the network does not mirror any real-world situation[3]. The model also suffers from the fact that the nodes concentrate in the middle of the area if we consider a bounded area. A possible solution is to assume spherical or toroidal surfaces, but clearly these geometrical abstractions are utterly unrealistic. An additional problem is related to the stationarity of the model (i.e., the variance of the characteristics of the model over time). This model suffers from the fact that the transient (i.e., non-stationary) regime may last for a very long time. One method for avoiding such a bias is to remove the initial part of the simulations in order to avoid the transient regime. However, this does not guarantee that the simulation has reached a stationary regime, since the time that is necessary to reach a stationary regime may be longer than the duration of the simulation itself. Finally, it has also been shown that the model also exhibits speed decay over time [99]. A partial solution to this problem have been proposed in [100].

In [50, 51], the authors present a generalization of the Random Walk and Random Way-Point mobility models that they call Random Trip model. The authors introduce a technique to sample the initial simulation state from the stationary regime (a methodology that is usually called *perfect simulation*) based on Palm Calculus [49] in order to solve the problem of reaching time-stationarity. Perfect simulation for the Random Way-Point model was originally proposed by Navidi and Camp in [63].

The analytical properties of the Random Way-Point model have been analyzed in several works from different perspectives such as the stationary distribution of nodes [9, 10], the node spatial distribution [75] and the evolution of the distribution of the nodes by means of partial differential equations [26].

[3] As discussed in the introduction, this position has been disputed in [43]. We will present more details about this current discussion in the community in Section 1.4.

### *1.2.3 Other Synthetic Single Node Mobility Models*

Starting from the Random Walk and Random Way-Point models, many variations have been proposed. The common characteristic of this class of models is that the movements of the nodes are independent from each other and that the movements are based on random distributions. Notable examples include the Random Direction mobility model [62], the Gauss-Markov mobility model [54] and the Smooth Random mobility model [8]. The choice of these mobility models is usually driven by the need of using a model that is easily mathematically tractable.

Other random mobility models were designed with the goal of reproducing movements in a urban space. The movements of the nodes are constrained by the topology of streets and their associated maximum speed. Examples of this class of models are the City section [15], the Freeway and the Manhattan models [4]. These models are particularly useful for applications of ad hoc mobile networking technologies to vehicular settings.

### *1.2.4 Synthetic Group Mobility Models*

These models and similar existing ones are used to represent the movements of single mobile nodes, however, in some situations the behavior of mobile hosts that move together, such as platoons of soldiers, group of students or colleagues and so on need to be modeled. For these reasons, group mobility models have been devised such as the Reference Group mobility model [34], the Reference Velocity Group mobility model [95] and the Structured Group mobility model [12]. These models are based on a set of equations that link the movements of a node to the positions of a subset of the other nodes of the network. These models are useful to reproduce scenarios characterized by the presence of clusters of people, however, the generated movements do not map those observed in the real worlds since the groups move randomly in the simulation space. The membership mechanisms are also usually hardwired and single nodes cannot join other groups during the simulation time. Recently, Piorkowski et alii propose a synthetic model called Heterogeneous Random Walk [74] that is able to reproduce the presence of clusters that are observed in real-world traces. The goal of this model is to have a mathematically tractable model to study and explain the emergence of clustered networks.

### *1.2.5 Modeling Obstacles*

Another key issue is the modeling of obstacles (such as buildings and walls) in simulation scenarios. This problem is highly intertwined with the definition of realistic radio propagation models [80]. This is an open research area and very few solutions have been proposed. The most remarkable solution is probably [39], where the authors present a technique for the creation of more realistic mobility models that include the presence of obstacles. The specification of obstacles is based on the use of Voronoi graphs in order to derive the possible pathways in the simulation space. The approach proposed by the authors is general and can be applied to other mobility models.

## 1.3 Trace-based Mobility Models

In recent years, many researchers have tried to refine existing models in order to make them more realistic by exploiting the available mobility traces [46]. The key underlying idea of these models is the exploitation of available measurements such as connectivity logs to generate synthetic traces that are characterized by the same statistical properties of the real ones.

Various pioneering measurement studies have been conducted both in infrastructure-based and infrastructure-less environments since the first wireless networks have been deployed. Extensive measurements about the usage of the early deployed Wireless Local Area Networks (WLANs) have been conducted, for instance, in [87], in [5], and in [6]. A detailed analysis of the usage of the WLAN of the Dartmouth College campus is presented in [31].

The first examples of mobility models are based on traces of WLAN campus usage. In [88] a mobility model based on real data from the campus WLAN at ETH in Zurich is presented. The authors use a simulation area divided into squares and derive the probability of transitions between adjacent squares from the data of the access points. Also in this case, the session duration data follow a power-law distribution. This approach can be considered as a refined version of the Weighted Way-Point mobility model [11, 35]. The authors of this model represent the probability of user movements between different areas of the USC campus by means of a Markov model. The model is extracted from data collected from user surveys (i.e, the users were asked to keep a diary of their movements for one month).

The Model T and it evolution, the Model T++, proposed in [38] and [53] generate traces also mirroring the spatial registration patterns of user movements inside a campus WLAN (i.e., the connections to the access points spread in the campus area). The authors define the concept of popularity gradient between different access points and its influence on users' movements. This model is evaluated using traces from Dartmouth College. In [101] another model extracted from real traces based on the study of probability of transitions between different locations is presented. The evaluation of the model is essentially based on the matching of the geographical movements and density of users, rather than on the analysis of the patterns of connectivity among them.

A mobility model based on the extraction of user mobility characteristics from the wireless network traces of the Dartmouth College WLAN is presented in [45]. The authors define popular regions in the campus and characterize the transitions among these areas by means of a Markovian model. Another key finding of the authors is the fact that pause time and speed follow log-normal distributions. These models only represent the transitions between five and sixth locations respectively. The data present characteristics, similar to [45], that evidently differ from those generated by means of classic synthetic random mobility models. In [76] Resta and Santi present a model of user movement between access points driven by the quality of service perceived by the users themselves. This approach is very generic and it is composed of different models that allow for the simulation of user mobility, network traffic, underlying wireless technology and quality of service.

Another interesting model representing the movement inside downtown Osaka is discussed in [55]: the authors reproduce the movements of pedestrians by analyzing the characteristics of the crowd in subsequent instants of time and maps of the city using an empirical methodology, without relying on any wireless measurements.

With respect to mobility models for vehicular networks, a large amount of traces mapping the movements of vehicles in cities and in highways are collected by the traffic authorities but they are not publicly available also for security reasons. Starting from these traces and from empirical observations, several models have been recently presented. Examples include the model proposed by Saha and Johnson [79] extracted from the TIGER traces [90], GrooveSim [56] and STRAW [19].

Finally, a model for the generation of the inter-contacts time duration between buses derived from the log traces of the DieselNet is presented in [103]. We note that this is not a mobility model, but a connectivity model, i.e., it is used to represent topological and not geographical information over time. We will discuss these models in detail in Section 1.6.

## 1.4 Characterization and Analytical Models of Human Connectivity

A number of pioneering works [87, 5, 6, 31] have been focussed on traces in order to gain insight about human mobility patterns. A key study in this area is the work on connectivity patterns presented by Chaintreau et alii in [18] which illustrates the fundamental insight that contacts duration and inter-contacts time between individuals can be represented by means of power-law distributions and that these patterns may be used to develop more efficient opportunistic protocols.

The work confirms the results of other studies conducted at Dartmouth [31], UCSD [57] and University of Toronto [86]. At the same time, it is interesting to note that these observed connectivity patterns are at odds with those that can be extracted from random mobility models that show an exponential decay of inter-contacts time intervals [83]. In a previous work [37], similar connectivity patterns have also been observed among the participants of INFOCOM'05.

Recently, Karagiannis, Le Boudec and Vojnovic in [43] offered a novel perspective to the problem of the approximation of these distributions. The authors consider 6 sets of traces and derive several analytical results that can be summarized as follows. First of all, the authors verify the power-law decay of inter-contacts time CCDF between mobile devices. Secondly, they demonstrate that beyond a characteristic time of about 12 hours the CCDF exhibits exponential decay. This is the major novel contribution, especially with respect to the findings presented in [18]. Thirdly, they present an analytical framework demonstrating that mobility models such as the Random Way-Point model should not be abandoned since they are able to represent power-law decay of inter-contact time with an exponential tail after this characteristic time. Finally, they show that the return time of mobile nodes to the same location can be modeled by means of a function composed of a scale-free distribution for a certain range between 0 and a characteristic time with an exponential tail.

Connectivity patterns have been studied by the authors of the aforementioned Model T [38] and Model T++ [53]. The main result of these studies is that user registration patterns exhibit a distinct hierarchy, and that WLAN access points (APs) can be clustered based on registration patterns. Cluster size distributions, intra-cluster transition probabilities and trace lengths are highly skewed and can be modeled by a heavy-tailed Weibull distribution with a good degree of approximation. The fraction of popular APs in a cluster, as a function of cluster size, can be modeled by exponential distributions.

The spatio-temporal correlation in the user registration patterns has also been investigated in [52]. The mobility patterns are modeled using a semi-Markov process by means of the transition probability matrix. The authors estimate the long-term wireless network usage among different access points. By comparing the steady-state distributions of semi-Markov models based on trace data collected at different time scales, they characterize the degree of correlation in time and location. The analysis is founded on the logs from Dartmouth College [47]. An analysis of the periodic properties of the movements between access points using Fourier transforms is presented in [44].

Rhee et alii proposed a possible modelization of human movement by means of Lévy flights [77] but the analysis show that this approximation is valid only considering a coarse-grained geographical scale. Recently, Gonzalez et alii [28] present the analysis of the movements of 100.000 mobile phone users by analyzing their registration patterns. According to this study human trajectories show a high degree of temporal and spatial regularity; each user usually move between a few highly frequented locations. They also disprove the theory that a pure Lévy flights model can be used to represent human trajectories, since random jumps typical of this model are not observed in their traces.

We would also like to mention briefly the considerable amount of work done by mathematical biologists in modeling animal movements [89]. One of the most interesting studies is that about animal foraging behavior. It was believed that the movement of animals for foraging can be modeled by means of Lévy flights; many different species have been studied including albatrosses [93], deer [94] and grey seals [2]. Lévy flights are random walks characterized by step lengths extracted from probability distributions with heavy tails: the result is that sequences of short steps are followed by rare long steps. However, in a study published on Nature in 2007 [22], by reanalyzing the data about albatrosses, the authors conclude that the movement can be modeled with gamma distributions with an exponential decay and not by means of a Lévy flights model.

## 1.5 Social Network based Mobility Models

In this section we discuss a recent development of mobility modeling [61], i.e., the introduction of social networking concepts as a basis of the representation of people movements. These models are usually trace based, i.e., they are generally founded or evaluated by means of real traces. The modeling of these relationships and their implications to human mobility is of paramount importance to test protocols and systems that exploit the underlying social structure, such as socially-aware delay tolerant forwarding protocols [21, 20].

Social network mobility models are based on a simple observation. In mobile networks, devices are usually carried by humans, so the movement of such devices is necessarily based on human decisions and social behavior. A key characteristic is the presence of clusters that are usually dependent on the relationships among the members of the social group. In order to capture this type of behavior, mobility models dependent on the structure of the relationships among people carrying the devices have been defined. However, existing group mobility models fail to capture this social dimension [15][4].

[4] These mobility models can also be used to test other types of networks. Within the emerging field of sensor networks, mobile hosts are not necessarily carried directly by humans. However, sensor networks are usually embedded in artifacts and vehicles (such as cars, planes or clothing) or are spread across a geographical area (such as environmental sensors). In the former case, the movements of the sensors embedded in cars or in airplanes, for instance, are not random but are dependent on the movements of the carriers; in the latter, movement is not generally a major issue.

### 1.5.1 Social Network Models

In recent years, social networks have been investigated in considerable detail, both in sociology [97] and in other areas, most notably mathematics and physics [1]. Various types of networks (such as the Internet, the World Wide Web and biological networks) have been studied by researchers especially in the statistical physics community. Theoretical models have been developed to reproduce the properties of these networks, such as the so-called small worlds model proposed in [98] or various scale-free models [65, 92]. Excellent reviews of the recent advances in complex and social networks analysis can be found in [1] and [65].

As discussed in [68], social networks appear to be fundamentally different from other types of networked systems. In particular, even if social networks present typical small-worlds behavior in terms of the average distance between pairs of individuals (the so-called *average path length*), they show a greater level of clustering. In [68] the authors observe that the level of clustering seen in many non-social systems is no greater than in those generated using pure random models. Instead in social networks, clustering appears to be far greater than in networks based on stochastic models. The authors suggest that this is strictly related to the fact that humans usually organize themselves into *communities*. Examples of social networks used for these studies are rather diverse and include, for instance, networks of coauthorships of scientists [64] and the actors in films with Kevin Bacon [98].

### 1.5.2 The Community Based Mobility Model

In [60] the authors propose the Community based mobility model, founded on social network theory[5]. A key input of the mobility model is the social network that links the individuals carrying the mobile devices in order to generate realistic synthetic network structures [98]. The model allows collections of hosts to be grouped together in a way that is based on social relationships among the individuals. This grouping is only then mapped to a topographical space, with topography biased by the strength of social ties. The movements of the hosts are also driven by the social relationships among them. The model also allows for the definition of different types of relationships during a certain period of time (i.e., a day or a week). For instance, it might be important to be able to describe that in the morning and in the afternoon of weekdays, relationships at the workplace are more important than friendships and family one, whereas the opposite is true during the evenings and weekends.

The model is evaluated by means of real mobility traces provided by the Intel Research Laboratory [82]; the authors show that the model provides

[5] This model can be considered an evolution of the basic model initially proposed in [58].

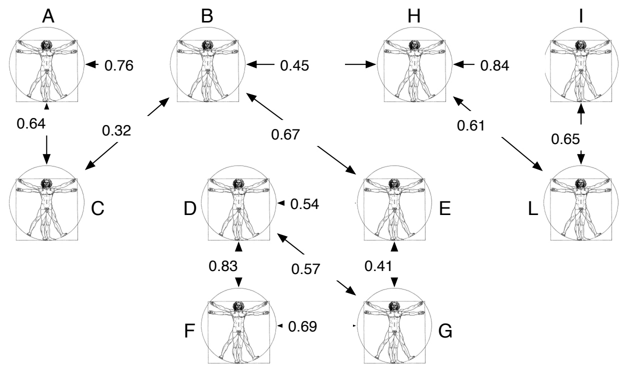


**Fig. 1.1** Example of social network.

a good approximation of real movements in terms of some fundamental parameters, such as the distribution of the contacts duration and inter-contacts time. In particular, the data show that an approximate power law holds over a large range of values for the inter-contacts time. Instead, contacts duration distribution follows a power law for a more limited range of values. These statistical characteristics are also very similar to those observed by the researchers at the University of California at San Diego and Dartmouth College [17].

We now describe in more details the key aspects of the Community based mobility model, starting from the representation of the social graph. One of the classic ways of representing social networks is using *weighted graphs*. An example of social network is represented in Figure 1.1. Each node represents one person. The weights associated to each edge of the network are used to model the strength of the interactions between individuals [81]. It is our explicit assumption that these weights, which are expressed as a measure of the strength of social ties, can also be read as a measure of the likelihood of geographic colocation. We model the degree of social interaction between two people using a value in the range $[0, 1]$. 0 indicates no interaction; 1 indicates a strong social interaction. Different social networks can be valid for different parts of a day or of a week.

As a consequence, the network in Figure 1.1 can be represented by the $10 \times 10$ symmetric matrix $\mathbf{M}$ showed in Figure 1.2, where the names of nodes correspond to both rows and columns and are ordered alphabetically. We refer to the matrix representing the social relationships as *Interaction Matrix*.

The generic element $m_{i,j}$ represents the interaction between two individuals $i$ and $j$. We refer to the elements of the matrix as the *interaction indicators*. The diagonal elements represent the relationships that an individual has with himself and are set, conventionally, to 1. In Figure 1.1, we have represented only the links associated to a weight equal to or higher than 0.25. A key issue of this model is the definition of this Interaction Matrix. This

$$\mathbf{M} = \begin{bmatrix} 1 & 0.76 & 0.64 & 0.11 & 0.05 & 0 & 0 & 0.12 & 0.15 & 0 \\ 0.76 & 1 & 0.32 & 0 & 0.67 & 0.13 & 0.23 & 0.43 & 0 & 0.05 \\ 0.64 & 0.32 & 1 & 0.13 & 0.24 & 0 & 0 & 0.15 & 0 & 0 \\ 0.11 & 0 & 0.13 & 1 & 0.54 & 0.83 & 0.57 & 0 & 0 & 0 \\ 0.05 & 0.67 & 0.24 & 0.54 & 1 & 0.2 & 0.41 & 0.2 & 0.23 & 0 \\ 0 & 0.13 & 0 & 0.83 & 0.2 & 1 & 0.69 & 0.15 & 0 & 0 \\ 0 & 0.23 & 0 & 0.57 & 0.41 & 0.69 & 1 & 0.18 & 0 & 0.12 \\ 0.12 & 0.43 & 0.15 & 0 & 0.2 & 0.15 & 0.18 & 1 & 0.84 & 0.61 \\ 0.15 & 0 & 0 & 0 & 0.23 & 0 & 0 & 0.84 & 1 & 0.65 \\ 0 & 0.05 & 0 & 0 & 0 & 0 & 0.12 & 0.61 & 0.65 & 1 \end{bmatrix}$$

**Fig. 1.2** Example of an Interaction Matrix representing a simple social network.

$$\mathbf{C} = \begin{bmatrix} 1&1&1&0&0&0&0&0&0&0 \\ 1&1&1&0&1&0&0&1&0&0 \\ 1&1&1&0&0&0&0&0&0&0 \\ 0&0&0&1&1&1&1&0&0&0 \\ 0&1&0&1&1&0&1&0&0&0 \\ 0&0&0&1&0&1&1&0&0&0 \\ 0&0&0&1&1&1&1&0&0&0 \\ 0&1&0&0&0&0&0&1&1&1 \\ 0&0&0&0&0&0&0&1&1&1 \\ 0&0&0&0&0&0&0&1&1&1 \end{bmatrix}$$

**Fig. 1.3** Example of a Connectivity Matrix representing a simple social network.

is clearly a simplified model of human relationships. The definition of these weights is an open research area also in sociology [97].

The Interaction Matrix is also used to generate a *Connectivity Matrix*. From matrix **M** we generate a binary matrix **C** where a 1 is placed as an entry $c_{ij}$ if and only if $m_{i,j}$ is greater than a specific threshold $t$ (i.e., 0.25). The Connectivity Matrix extracted by the Interaction Matrix in Figure 1.2 is showed in Figure 1.3. The idea behind this is that we have an *interaction threshold* above which we say that two people are interacting as they have a strong relationship.

The Interaction Matrix (and, consequently, the Connectivity Matrix) can be derived by available data (for example, from a sociological investigation) or using mathematical models that are able to reproduce characteristics of real social networks. The default implementation of the model uses the so-called Caveman model [98] for the generation of synthetic social networks with realistic characteristics (i.e, high clustering and low average path length). However, this is a customizable aspect and, if there are insights on the type of scenarios to be tested, a user-defined matrix can be used as input.

The simulation scenario is established by mapping groups of hosts to certain areas in the geographical space. After the definition of the social graph described above, groups, i.e., the highly connected set of nodes in the graph, need to be isolated. The authors use the algorithm proposed in [67] to detect the presence of community structures in social networks represented by matrices, like the Connectivity Matrix that we have defined in the previous section. This algorithm is based on the calculation of the so-called *betweenness* of edges. This provides a measure of the centrality of nodes.

In order to illustrate this process, let us now consider the social network in Figure 1.1. Three communities (that can be represented by sets of hosts) are detected by running the algorithm: $C_1 = \{A, B, C\}$, $C_2 = \{D, E, F, G\}$ and $C_3 = \{H, I, L\}$. Now that the communities are identified given the matrix, they need to be associated with locations.

After the communities are identified, each of them is randomly associated to a specific location (i.e., a square) on a grid[6]. We use the symbol $S_{p,q}$ to indicate a square in position $p, q$. The number of rows and columns are inputs of the mobility model.

Going back to the example, in Figure 1.4 we show how the communities we have identified can be placed on a 3x4 grid (the dimension of the grid is configurable by the user and influences the density of the nodes in each square). The three communities $C_1$, $C_2$, $C_3$ are placed respectively in the grid in the squares $S_{a,2}$, $S_{c,2}$ and $S_{b,4}$. Each node of a certain community is placed in randomly selected positions inside the assigned square.

As described in the previous section, a host is initially positioned in a certain square in the grid. Then, in order to drive movement, a goal is assigned to the host. More formally, we say that a host $i$ is associated to a square $S_{p,q}$ if its goal is inside $S_{p,q}$. Note that host $i$ is not necessarily always positioned inside the square $S_{p,q}$, despite this association (see below).

The goal is simply a point on the grid which acts as *final destination* of movement like in the Random Way-Point model, with the exception that the selection of the goal is not as random. When the model is initially established, the goal of each host is randomly chosen inside the square associated to its community (i.e, the first goals of all the hosts of the community $C_1$ will be chosen inside the square $S_{a,2}$).

When a goal is reached, the new goal is chosen according to the following mechanism. A certain number of hosts (zero or more) are associated to each square $S_{p,q}$ at time $t$. Each square (i.e., place) exerts a certain *social attractivity* to a certain host. The social attractivity of a square is a measure of its importance in terms of the social relationships for the host taken into consideration. The social importance is calculated by evaluating the strength of the relationships with the hosts that are moving towards that particular square (i.e., with the hosts that have a current goal inside that particular square). More formally, given $C_{S_{p,q}}$ (i.e., the set of the hosts associated to square $S_{p,q}$), we define *social attractivity* of that square towards the host $i$ $SA_{p,q_i}$, as follows:

[6] A non random association to the particular areas of the simulation area can be devised, for example by deciding pre-defined *areas of interest* corresponding for instance to real geographical space. However, this aspect is orthogonal to the mechanisms at the basis of this model.

$$SA_{p,q_i} = \frac{\sum\limits_{j \in C_{S_{p,q}}} m_{i,j}}{w} \tag{1.1}$$

where $w$ is the cardinality of $C_{S_{p,q}}$ (i.e., the number of hosts associated to the square $S_{p,q}$). In other words, the social attractivity of a square in position $(p, q)$ towards a host $i$ is defined as the sum of the interaction indicators that represent the relationships between $i$ and the other hosts that belong to that particular square, normalized by the total number of hosts associated to that square. If $w = 0$ (i.e., the square is empty), the value of $SA_{p,q_i}$ is set to 0.

The mobility model allows for two alternative mechanisms for the selection of the next goal that are described, a *deterministic* one based on the selection of the square that exerts the highest attractivity and a *probabilistic* one based on probability of selection of a goal in a certain square proportional to their attractivities. Using the first one, the goals are chosen only inside the squares associated to the community, whereas with the second, the hosts may also randomly select their goals in other squares of the simulation area, with a certain non zero probability. In other words, the second mechanism allows for the selection of the destinations not only based on social relationships adding more realism to the model. According to this mechanism, the new goal is randomly chosen inside the square characterized by the highest social attractivity; it may be again inside the same square or in a different one. New goals are chosen inside the same area when the input social network is composed by loosely connected communities (in this case, hosts associated with different communities have, in average, weak relationships between each others). On the other hand, a host may be attracted to a different square, when it has strong relationships with both communities. From a graph theory point of view, this means that the host is located between two (or more) clusters of nodes in the social network[7].

An alternative mechanism is based on a selection of the next goal proportional to the attractivity of each square. In other words, we assign a probability $P(s = S_{p,q_i})$ of selecting the square $S_{p,q_i}$ as follows:

$$P(s = S_{p,q_i}) = \frac{SA_{p,q_i} + d}{\sum_{j=1}^{p \times q}(SA_{p,q_j} + d)} \tag{1.2}$$

where $d$ is a random value greater than 1 in order to ensure that the probability of selecting a goal in a square is always non zero[8].

The parameter $d$ can be used to increase the randomness of the model in the process of selection of the new goal. This may be exploited to increase

[7] This is usually the case of hosts characterized by a relatively high betweenness that, by definition, means that they are located *between* two (or more) communities.

[8] The role of $d$ is similar to the *damping factor* used in the calculation of the Google PageRank [13]. In fact, the transitions between squares can also be similarly represented using a Markov Chain model with $P(s = S_{p,q_i})$ as probability of transitions between states (squares).

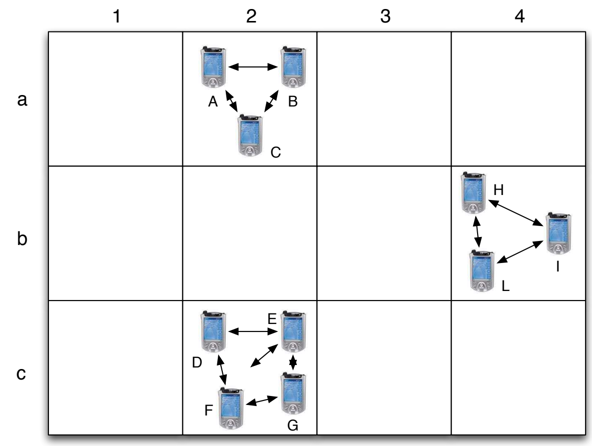


**Fig. 1.4** Example of initial simulation configuration.

the realism of the generated scenario, since in real situations, humans also move to areas without people or for reasons not related to their social sphere.

### *1.5.3 Other Social Network based Mobility Models*

Another notable example of mobility model founded on the social relationships between the individuals carrying the mobile devices is presented in [32]. This work is based on assumptions similar to [60], but it is considerably more limited in scope. Hosts are statically assigned to a particular group during the initial configuration process, whereas [60] accounts for movement between groups. Moreover, the authors claim that mobile ad hoc networks are scale-free, but the typical properties of scale-free networks are not considered in the design of the model presented by the authors. The scale-free distribution of mobile ad hoc networks is still not proven in general, since very limited measurements are available and it is worth noting that the scale-free properties are strictly dependent on the movements of hosts and, therefore, they are dependent on the actual application scenarios [27]. The idea of using communities to represent group movements in an infrastructured WiFi network has also been exploited in [85] and in its time-variant extension presented in [36]. More specifically, this model preserves two fundamental characteristics, the skewed location visiting preferences and the periodical re-appearance of nodes in the same location. Recently, Ekman et alii propose a model based on the daily activities of the users (and group of users) and their movements between place of interests in a city map [24].

## 1.6 From Mobility to Connectivity Models

Another class of models for mobile networking research is that of connectivity models, that focusses on the evolution of the emergent connectivity graph that is changing over time as nodes move. Topological properties are fundamental for analyzing, for example, the performance of protocols and systems where (intermittent) connectivity plays an essential role such as protocols for delay tolerant networks or solutions for bandwidth provision in WLANs. This is a very open area and very few models have been proposed. Most of them are based on the analysis of the available connectivity traces, i.e. from logs of Bluetooth contacts or WLANs registration patterns.

In [14] the authors propose the Connectivity Trace Generator (CTG). This work differs from previous approaches in that probability distributions describing the patterns of colocation of mobile users (in terms of contact duration and inter-contacts time) are exploited for the first time as *direct inputs* of a synthetic traces generation tool. More specifically, the input parameters of this component are the relevant parameters of the connectivity model, namely: number of nodes, the contacts duration (i.e., the time interval in which two devices are in radio range) and inter-contact time (i.e., the time interval between two contacts), and node degree (i.e., number of neighbors) distributions.

All these distributions can be extracted by measurements of connectivity on real traces. The key steps of the proposed simulation framework are depicted in Figure 1.5. The input of the CTG is a set of real traces. These are processed by a trace analyzer to generate the parameters describing user connectivity required by the tool. These are essentially the coefficients of the curves used to approximate the distributions of the inter-contacts times, contacts durations and link degrees characterizing the social graph of the contacts among the users. This is a graph of the potential contacts between pair of nodes, i.e., an edge between two nodes exists if there is a probability different from zero that these two nodes will meet in a specified time interval equal to the simulation duration. This graph is also built from the traces. Additionally, a range of variations for the parameters is provided in input.

The process of generation is based on the selection of the desired number of hosts and on the construction of a connectivity graph of all the potential contacts of each host. In other words, we map each host to a node of the graph and we link a pair of nodes with an edge if the two hosts can potentially get in contact. The connectivity graph is then used to unfold a number of connection links between users for each time instant. In other words, we use the connectivity graph as a basis for a *time-varying graph of instant connectivity* for each instant $t$. In these time-varying graphs (one for each time instant), each link is either active if the two hosts are colocated, or is not present if the two are not.

Each link is activated and de-activated according to the distributions of the contacts duration and inter-contacts time. Let us consider an example. Each

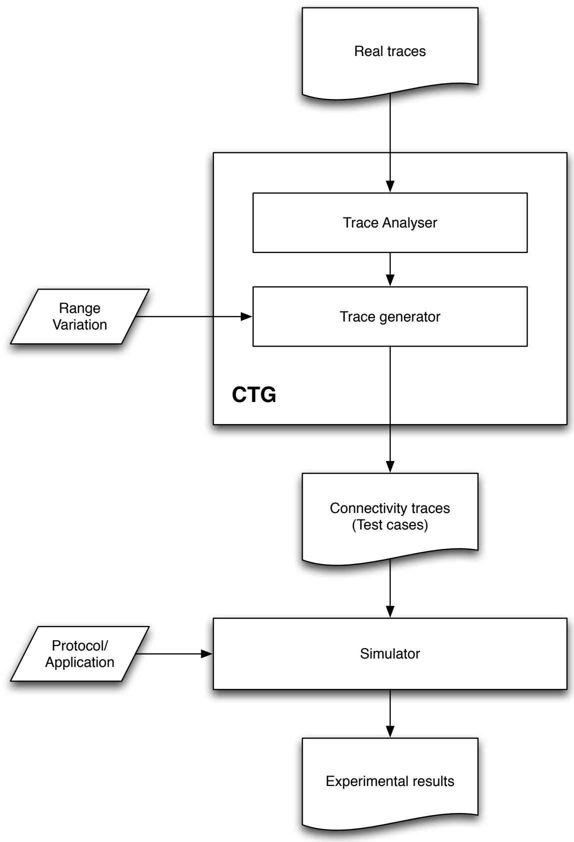


**Fig. 1.5** Connectivity Trace Generator.

pair at the beginning is initially disconnected. Let us consider the connectivity pattern between two hosts $A$ and $B$. At the beginning, the model generates an initial disconnection time (an “inter-contacts time”) sampled from the inter-contacts time distribution. Let us assume that this is equal to 15 seconds. Then after 15 seconds, the model has to generate a colocation time from the distribution of the contacts duration. Let us assume that this is equal to 30 seconds. An edge between $A$ and $B$ is activated for 30 seconds to represent the colocation of the hosts $A$ and $B$ between the instants $15s$ and $45s$. In other words, the edge will be present in the graph for the next 30 seconds and then removed. Then the model generates another value, this time from the distribution of the inter-contacts time, for example 4 minutes. After 4 minutes, the link between $A$ and $B$ is re-activated for a duration time that is again generated from the distribution of the contacts duration interval and so on.

This process is completely automated and implemented by the trace generator component that produces traces containing the events of connections and disconnections for each pair of nodes of the simulation scenario and the time of each event. These traces can be used as test cases for the testing of opportunistic mobile systems [25].

As a concrete case study, the authors used the log session traces of the campus WLAN of Dartmouth College [47], to obtain empirical distributions for residence time, colocation and degree distribution of the nodes. These traces were used in conjunction with an original model developed by the authors that aims at representing the properties of the *colocation* of two users as a function of the probability for a user of being in a specific place for a given period of time. Two hosts were considered colocated if they were registered to the same access point.

As we said, the design of connectivity models is still an open research area; to the best of our knowledge, the other existing proposal is the position paper by Nykvist and Phanse [72]. With respect to vehicular networks modeling, the only existing example of connectivity models is that of the buses of the DieselNet project [103] discussed in Section 1.3. Another recent work analyzing the connectivity properties of a bus transportation system is [33].

## 1.7 Testing Tools and Mobility Modeling

The first step of any performance evaluation exercise based on simulations is the choice of the simulator tool. Various network simulators are available for the evaluation of protocols and systems of mobile networks; the most popular are ns-2 [70] with the so-called Monarch extension [42] (and the upcoming new version ns-3 [71]), Glomosim [102] and Opnet [73]. Another class of tools for simulation of generic complex systems (not only computer systems, but also economic, biological, industrial, etc.) are the so-called *discrete-event simulators*. These tools only provide primitives for the concurrent execution of multiple entities and communication among them usually by means of message passing based paradigms. OMNeT++ [91] and Parsec [3] are examples of this class of simulators.

These tools generally receive in input traces with different formats usually in the form of a series of triplets that specify when the change of direction has to take place, the next goal (that defines the direction of the host) and the node speed. Unfortunately, there is no standard format for this kind of these traces. More in general, no standards have been defined also for measurement traces both of movements represented by means of geographical positions or connectivity traces (such as those collected by means of Bluetooth or ZigBee radio devices).

The results of simulations performed by means of different simulators may show significant differences; this fact may be explained by the various modeling techniques and assumptions and by the different levels of details offered by these simulators. In [16] the authors show and discuss the divergent results obtained by using OPNET Modeler, ns-2 and Glomosim. Other problems can be related to the methodology followed by the researchers and, unfortunately, this has caused a decreasing confidence in simulation results to evaluate the performance of protocols and systems: this is motivated by the apparent issues in terms of scientific standards of some of the existing published papers [48]. With respect to mobility modeling, the use of unrealistic mobility models or the absence of a meaningful number of runs to achieve a sufficient statistical validity of the results has contributed to this lack of confidence. It is interesting to note that there is a clear problem of achieving statistical validity when a limited set of traces is used to evaluate an algorithm or a protocol. More specifically, in presence of a limited set of nodes and/or of a limited duration of the traces, there is a critical issue of generality. For this reason we believe that tools like the CTG that allows the researchers to vary the parameters describing the mobility patterns distributions in order to explore their impact are needed.

There is also a growing interest in approaches for testing mobile systems and applications (see for instance [84]). Most of these approaches, however, concentrate on testing aspects related to context awareness (see, for example, [96]). Mobility and connectivity can be considered as context elements; however, these tools do not provide specific support for modeling these essential aspects of this class of systems.

The CTG presented in Section 1.6 provides automatic generation of connectivity test cases in order to evaluate the performance of communication protocols and applications in opportunistic mobile systems. The approach allows flexible performance testing of new protocols and applications. Indeed, when a system is being prototyped, usage patterns logs could be collected through a small scale trial. The connectivity traces could then be analyzed and, using the methodology proposed by the authors of the CTG, a simulation on a larger scale could be carried, using larger synthetic traces by a higher number of hosts or different colocation or inter-contacts time distributions.

A tool for the generation of traces for vehicular networking simulations is presented in [7]. The model allows for the generation of traces that reproduce steady-state random trips on real road topology from the Swiss Geographic Information System (GIS).

However, there are no comprehensive solutions for the verification of mobile systems; for example the CTG lacks a metric for coverage criteria of the generated test cases. An investigation along these lines for a similar problem has been presented in [78]: the authors of the CTG leave the issue of evaluating coverage conditions open for future work.

## 1.8 Summary and Outlook

In this survey, we have presented a description of the state of the art in mobility modeling, considering different classes of synthetic and trace-based models. We have also discussed the analytical models that have been developed to understand human movements. Finally, we have presented the concepts at the basis of the design of mobility models based on social networks. We now present a summary of the open research challenges in this area, outlining a research agenda for the mobile networking and systems community in this area. The research challenges can be summarized as follows:

**Specificity of Available Models** The available traces describe very specific situations like campuses or conference environments and, for this reason, it is difficult to generalize the results obtained using the traces directly or the mobility models derived from the analysis of these traces. With high probability, different types of mobility patterns characterize specific application scenarios, both in terms of contacts distribution and scale of movements in the geographical space. The main research challenge resides in the identification of the common features of human mobility and the characterization of the specificity of a set of deployment scenarios. This problem will be tackled more and more effectively with the increasing availability of mobility traces extracted from heterogeneous environments.

**Mobility Models vs Connectivity Models** In this survey, we have introduced and discussed the concept of connectivity models. This kind of models are not *alternative* but *complementary* to the existing models. In fact, mobility models (i.e., containing information about the locations of the nodes) are necessary for testing several classes of protocols and applications such as geocasting protocols [40] or location-aware applications [30]. An open problem is how to integrate the use of connectivity and mobility models in an effective way to characterize human mobility. Connectivity models can be derived by mobility models but the former represent a much more powerful tool for the statistical characterization of colocation patterns. These models are very useful for designing and evaluating protocols and systems where these aspects are fundamental such as in the case of performance evaluation of delay tolerant protocols or wireless peer-to-peer systems (for example to evaluate the available transmission bandwidth among a set of hosts). As for mobility models, further investigations are needed to characterize common properties of human connectivity and distinct features of specific application environments. Another open issue is the characterization of the interaction between human movement and the surrounding environment: more specifically, the influence of the geographical features of the simulation spaces such as the presence of obstacles (e.g., buildings, hills, green areas) on human connectivity and mobility patterns has not been studied yet.

**Benchmarks for Protocol and System Evaluation** Unfortunately, the choice of values for parameters of simulations for mobile (in particular, ad hoc) networks research is extremely variable. In fact, the ad hoc and delay tolerant research communities lack of consistent scenarios to validate and to benchmark the different solutions. As cited previously, in [48] Kurkoswski, Camp and Colagrosso reported an analysis of the performance evaluation of papers published at MobiHoc from 2000 to 2005, showing evident flaws of a large number of works from a scientific point of view in terms of simulation methodology. The community should define a common set of mobility traces that should be used to verify the performance of protocols. A possible idea is to define a series of sets of traces for different classes of application scenarios such as dense networks, urban environments and sparse networks, for instance for the evaluation of delay tolerant networking protocols or Bluetooth based systems. This can be seen as a medium term goal, given also the limited amount of available traces. However, following the introduction of more powerful and, at the same time, affordable devices such as phones equipped with GPS units and Bluetooth, we believe that the amount of available information will increase hugely in the next few years.

**Tools** There is a very limited number of available tools, in particular open source and free, for academic and industrial testing of mobile applications. With respect to mobility modeling, there is a concrete need of network emulators that are able to simulate connectivity based on an underlying mobility model (or directly on traces). An interesting example of this kind of systems is [69]. Another very useful class of systems for performance evaluation studies are emulators based on virtualization techniques on a single machine for testing multiple instances of mobile applications by means of virtual communication interfaces (such as Bluetooth or ZigBee) and infrastructure-based (such as based on access points or GPRS), also providing radio propagation models.

**Standardization of the Trace Formats** Unfortunately, the available traces (see, for example, those stored in the CRAWDAD repository [46]) do not follow a common standard and scripts are needed to convert them to the various formats in order to be processed by the different simulators. The mobile networking and systems community should allow for common standards in order to promote an easy data exchange among researchers for cross-comparisons, also for the establishment of benchmarks for the community, as it happens in other fields of computer science.

# References


1. R. Albert and A.-L. Barabasi. Statistical mechanics of complex networks. *Review of Modern Physics*, 74:47–97, 2002.
2. D. Austin, W. D. Bowen, and J. I. McMillan. Intraspecific variation in movement patterns: modeling individual behaviour in a large marine predator. *Oikos*, 105(1):15–30, 2004.
3. R. Bagrodia, R. Meyer, R. Takai, Y. Chen, X. Zeng, J. Martin, B. Park, and H. Song. A parallel simulation environment for complex systems. *IEEE Computer*, pages 77–85, October 1998.
4. F. Bai, N. Sadagopan, and A. Helmy. IMPORTANT: A framework to systematically analyze the Impact of Mobility on Performance of RouTing protocols for Adhoc NeTworks. In *INFOCOM'03*, 2003.
5. A. Balachandran, G. M. Voelker, P. Bahl, and P. V. Rangan. Characterizing user behavior and network performance in a public wireless LAN. In *Proceedings of SIGMETRICS'02*, pages 195–205, New York, NY, USA, 2002. ACM Press.
6. M. Balazinska and P. Castro. Characterizing Mobility and Network Usage in a Corporate Wireless Local-Area Network. In *1st International Conference on Mobile Systems, Applications, and Services (MobiSys'03)*, San Francisco, CA, May 2003.
7. R. Baumann, F. Legendre, and P. Sommer. Generic Mobility Simulation Framework (GMSF). In *Proceedings of First ACM SIGMOBILE International Workshop on Mobility Models for Networking Research (MobilityModels'08)*, Hong Kong S. A. R., China, May 2008.
8. C. Bettstetter. Smooth is better than sharp: a random mobility model for simulation of wireless networks. In *Proceedings of MSWIM'01*, pages 19–27, New York, NY, USA, 2001. ACM.
9. C. Bettstetter, H. Hartenstein, and X. Pérez-Costa. Stochastic properties of the random waypoint mobility model. *Wireless Networks (Special Issue on Modeling and Analysis of Mobile Networks)*, 10(5):555–567, 2004.
10. C. Bettstetter, G. Resta, and P. Santi. The Node Distribution of the Random Waypoint Mobility Model for Wireless Ad Hoc Networks. *IEEE Transactions on Mobile Computing*, 2(3):257–269, 2003.
11. D. Bhattacharjee, A. Rao, C. Shah, M. Shah, and A. Helmy. Empirical modeling of campus-wide pedestrian mobility observations on the USC campus. In *Proceedings of Vehicular Technology Conference, 2004 (VTC2004-Fall). 2004 IEEE 60th*, volume 4, pages 2887–2891, 2004.
12. K. Blakely and B. Lowekamp. A structured group mobility model for the simulation of mobile ad hoc networks. In *Proceedings of MobiWac'04*, pages 111–118, New York, NY, USA, 2004. ACM.

13. S. Brin and L. Page. The anatomy of a large-scale hypertextual web search engine. In *Proceedings of the 7th International Conference on World Wide Web*, pages 107–117, April 1998.
14. R. Calegari, M. Musolesi, F. Raimondi, and C. Mascolo. CTG: A Connectivity Trace Generator for Testing the Performance of Opportunistic Mobile Systems. In *Proceedings of the European Software Engineering Conference and the International ACM SIGSOFT Symposium on the Foundations of Software Engineering (ESEC/FSE07)*, Dubrovnik, Croatia, September 2007. ACM Press.
15. T. Camp, J. Boleng, and V. Davies. A survey of mobility models for ad hoc network research. *Wireless Communication and Mobile Computing Special Issue on Mobile Ad Hoc Networking: Research, Trends and Applications*, 2(5):483–502, 2002.
16. D. Cavin, Y. Sasson, and A. Schiper. On the Accuracy of MANET Simulators. In *Proceedings of the Workshop on Principles of Mobile Computing (POMC'02)*, pages 38–43, October 2002.
17. A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott. Pocket Switched Networks: Real-world mobility and its consequences for opportunistic forwarding. Technical Report UCAM-CL-TR-617, University of Cambridge, Computer Laboratory, February 2005.
18. A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott. Impact of human mobility on opportunistic forwarding algorithms. *IEEE Transactions on Mobile Computing*, 6(6):606–620, 2007.
19. D. R. Choffnes and F. E. Bustamante. An integrated mobility and traffic model for vehicular wireless networks. In *Proceedings of VANET'05*, pages 69–78, New York, NY, USA, 2005. ACM.
20. P. Costa, C. Mascolo, M. Musolesi, and G. P. Picco. Socially-aware routing for publish-subscribe in delay-tolerant mobile ad hoc networks. *IEEE Journal on Selected Areas in Communications*, 26(5):748–760, June 2008.
21. E. M. Daly and M. Haahr. Social network analysis for routing in disconnected delay-tolerant MANETs. In *Proceedings of MobiHoc'07*, pages 32–40, New York, NY, USA, 2007. ACM.
22. A. M. Edwards, R. A. Phillips, N. W. Watkins, M. P. Freeman, E. J. Murphy, V. Afanasyev, S. V. Buldyrev, M. G. E. da Luz, E. P. Raposo, H. E. Stanley, and G. M. Viswanathan. Revisiting Lévy flight search patterns of wandering albatrosses, bumblebees and deer. *Nature*, (449):1044–1048, October 2005.
23. A. Einstein. *Investigations on the Theory of the Brownian Movement*. Dover Publications, 1956.
24. F. Ekman, A. Keränen, J. Karvo, and J. Ott. Working Day Movement Model. In *Proceedings of First ACM SIGMOBILE International Workshop on Mobility Models for Networking Research (MobilityModels'08)*, Hong Kong S. A. R., China, May 2008.
25. K. Fall. A delay-tolerant network architecture for challenged internets. In *Proceedings of SIGCOMM'03*, August 2003.
26. M. Garetto and E. Leonardi. Analysis of random mobility models with PDE's. In *Proceedings of MobiHoc'06*, pages 73–84, New York, NY, USA, 2006. ACM.
27. I. Glauche, W. Krause, R. Sollacher, and M. Greiner. Continuum percolation of wireless ad hoc communication networks. *Physica A*, 325:577–600, 2003.
28. M. C. Gonzalez, C. A. Hidalgo, and A.-L. Barabasi. Understanding individual human mobility patterns. *Nature*, 453(7196):779–782, 2008.
29. K. Harras, K. Almeroth, and E. Belding-Royer. Delay Tolerant Mobile Networks (DTMNs): Controlled Flooding Schemes in Sparse Mobile Networks. In *IFIP Networking 2005*, pages 1180–1192, May 2005.
30. M. Hazas, J. Scott, and J. Krumm. Location-aware computing comes of age. *Computer*, 37(2):95–97, February 2004.
31. T. Henderson, D. Kotz, and I. Abyzov. The changing usage of a mature campus-wide wireless network. In *Proceedings of MobiCom'04*, pages 187–201, New York, NY, USA, 2004. ACM Press.

32. K. Hermann. Modeling the sociological aspect of mobility in ad hoc networks. In *Proceedings of MSWiM'03*, pages 128–129, San Diego, California, USA, September 2003.
33. I. W. H. Ho, K. K. Leung, J. W. Polak, and R. Mangharam. Node connectivity in vehicular ad hoc networks with structured mobility. In *Proceedings of the 32nd IEEE Conference on Local Computer Networks (LCN'07)*, pages 635–642, Washington, DC, USA, 2007. IEEE Computer Society.
34. X. Hong, M. Gerla, G. Pei, and C.-C. Chiang. A group mobility model for ad hoc networks. In *Proceedings of the 2nd International Workshop on Modeling Analysis and Simulation of Wireless and Mobile Systems (MSWiM'99)*, pages 53–60, 1999.
35. W. Hsu, K. Merchant, H. Shu, C. Hsu, and A. Helmy. Weighted Waypoint Mobility Model and its Impact on Ad Hoc Networks. *ACM Mobile Computer Communications Review (MC2R)*, pages 59–63, January 2005.
36. W. Hsu, T. Spyropoulos, K. Psounis, and A. Helmy. Modeling time-variant user mobility in wireless mobile networks. *Proceedings of INFOCOM'07*, pages 758–766, May 2007.
37. P. Hui, A. Chaintreau, J. Scott, R. Gass, J. Crowcroft, and C. Diot. Pockets Switched Networks and Human Mobility in Conference Environments. In *Proceedings of ACM SIGCOMM'05 Workshops*, pages 244–251, August 2005.
38. R. Jain, D. Lelescu, and M. Balakrishnan. Model T: an empirical model for user registration patterns in a campus wireless LAN. In *Proceedings of MobiCom'05*, pages 170–184, New York, NY, USA, 2005. ACM.
39. A. Jardosh, E. M. Belding-Royer, K. C. Almeroth, and S. Suri. Real world Environment Models for Mobile Ad hoc Networks. *IEEE Journal on Special Areas in Communications - Special Issue on Wireless Ad hoc Networks*, 23(3), March 2005.
40. X. Jiang and T. Camp. A review of geocasting protocols for a mobile ad hoc network. In *Proceedings of the Grace Hopper Celebration (GHC 2002)*, 2002.
41. D. B. Johnson and D. A. Maltz. Dynamic Source Routing in ad hoc wireless network. In T. Imielinski and H. Korth, editors, *Mobile Computing*, chapter 5, pages 153–181. Kluwer Academics Publisher, 1996.
42. D. B. Johnson and D. A. Maltz. Protocols for adaptive wireless and mobile networking. *IEEE Personal Communications*, 3(1):34–42, February 1996.
43. T. Karagiannis, J.-Y. L. Boudec, and M. Vojnović. Power law and exponential decay of inter contact times between mobile devices. In *Proceedings of MobiCom'07*, pages 183–194, New York, NY, USA, 2007. ACM.
44. M. Kim and D. Kotz. Periodic properties of user mobility and access-point popularity. *Journal of Personal and Ubiquitous Computing*, 11(6), August 2007.
45. M. Kim, D. Kotz, and S. Kim. Extracting a mobility model from real user traces. In *Proceedings of IEEE INFOCOM'06*, April 2006 2006.
46. D. Kotz and T. Henderson. CRAWDAD: A Community Resource for Archiving Wireless Data at Dartmouth. *IEEE Pervasive Computing*, 4(4):12–14, October-December 2005.
47. D. Kotz, T. Henderson, and I. Abyzov. CRAWDAD trace dartmouth/campus/movement/01_04 (v. 2005-03-08). Downloaded from http://crawdad.cs.dartmouth.edu/, March 2005.
48. S. Kurkowski, T. Camp, and M. Colagrosso. MANET Simulation Studies: the Incredibles. *SIGMOBILE Mobile Computing and Communications Review*, 9(4):50–61, 2005.
49. J.-Y. Le Boudec. Understanding the simulation of mobility models with Palm calculus. *Performance Evaluation*, 64(2):126–147, 2007.
50. J.-Y. Le Boudec and M. Vojnovic. Perfect simulation and stationarity of a class of mobility models. In *Proceedings of IEEE INFOCOM'05*, pages 72–79, March 2005.
51. J.-Y. Le Boudec and M. Vojnovic. The random trip model: stability, stationary regime, and perfect simulation. *IEEE/ACM Transactions on Networking*, 14(6):1153–1166, 2006.

52. J.-K. Lee and J. C. Hou. Modeling steady-state and transient behaviors of user mobility: formulation, analysis, and application. In *Proceeding of MobiHoc'06*, pages 85–96, New York, NY, USA, 2006. ACM.
53. D. Lelescu, U. C. Kozat, R. Jain, and M. Balakrishnan. Model T++:: an empirical joint space-time registration model. In *Proceedings of MobiHoc'06*, pages 61–72, New York, NY, USA, 2006. ACM Press.
54. B. Liang and Z. J. Haas. Predictive distance-based mobility management for multidimensional pcs networks. *IEEE/ACM Transactions on Networking*, 11(5):718–732, 2003.
55. K. Maeda, K. Sato, K. Konishi, A. Yamasaki, A. Uchiyama, H. Yamaguchi, K. Yasumotoy, and T. Higashino. Getting urban pedestrian flow from simple observation: Realistic mobility generation in wireless network simulation. In *Proceedings of MSWiM'05*, pages 151–158, September 2005.
56. R. Mangharam, D. S. Weller, D. D. Stancil, R. Rajkumar, and J. S. Parikh. GrooveSim: a topography-accurate simulator for geographic routing in vehicular networks. In *Proceedings of VANET'05*, pages 59–68, New York, NY, USA, 2005. ACM Press.
57. M. McNett and G. M. Voelker. Access and Mobility of Wireless PDA User. *Mobile Computing Communications Review*, 9(2):40–55, April 2005.
58. M. Musolesi, S. Hailes, and C. Mascolo. An ad hoc mobility model founded on social network theory. In *Proceedings of the 7th ACM international symposium on Modeling, analysis and simulation of wireless and mobile systems*. ACM Press, October 2004.
59. M. Musolesi, S. Hailes, and C. Mascolo. Adaptive routing for intermittently connected mobile ad hoc networks. In *Proceedings of WoWMoM'05. Taormina, Italy*. IEEE press, June 2005.
60. M. Musolesi and C. Mascolo. A community based mobility model for ad hoc network research. In *Proceedings of the 2nd ACM/SIGMOBILE International Workshop on Multi-hop Ad Hoc Networks: from theory to reality (REALMAN'06)*. ACM Press, May 2006.
61. M. Musolesi and C. Mascolo. Designing mobility models based on social network theory. *ACM SIGMOBILE Mobile Computing and Communication Review*, 11(3), July 2007.
62. P. Nain, D. Towsley, B. Liu, and Z. Liu. Properties of random direction models. In *Proceedings of INFOCOM'05*, March 2005.
63. W. Navidi and T. Camp. Stationary distributions for the random waypoint mobility model. *IEEE Transactions on Mobile Computing*, 3(1):99–108, 2004.
64. M. E. J. Newman. The Structure of Scientific Collaboration Networks. In *Proceedings of the National Academy of Science*, volume 98, pages 404–409, 2001.
65. M. E. J. Newman. The structure and function of complex networks. *SIAM Review*, 19(1):1–42, 2003.
66. M. E. J. Newman. Power laws, Pareto distributions and Zipf's law. *Contemporary Physics*, 46:323, 2005.
67. M. E. J. Newman and M. Girvan. Finding and evaluating community structure in networks. *Physical Review E*, 69, February 2004.
68. M. E. J. Newman and J. Park. Why Social Networks are Different from Other Types of Networks. *Physical Review E*, 68, 2003.
69. E. Nordstrom, P. Gunningberg, and H. Lundgren. A testbed and methodology for experimental evaluation of wireless mobile ad hoc networks. In *Proceedings of the First International Conference on Testbeds and Research Infrastructures for the DEvelopment of NeTworks and COMmunities (TRIDENTCOM'05)*, pages 100–109, Washington, DC, USA, 2005. IEEE Computer Society.
70. The ns-2 Project. http://www.isi.edu/nsnam/ns/, 2008.
71. The ns-3 Project. http://www.nsnam.org/, 2008.

72. J. Nykvist and K. Phanse. Modeling connectivity in mobile ad-hoc network environments. In *Proceedings of the 6th Scandinavian Workshop on Wireless Ad-hoc Networks (ADHOC'06)*, 2006.
73. OPNET Technologies Inc. Opnet modeler, 2004.
74. M. Piorkowski, N. Sarafijanovic-Djukic, and M. Grossglauser. On Clustering Phenomenon in Partitioned Mobile Networks. In *Proceedings of First ACM SIGMOBILE International Workshop on Mobility Models for Networking Research (MobilityModels'08)*, Hong Kong S. A. R., China, May 2008.
75. G. Resta and P. Santi. An analysis of the node spatial distribution of the random waypoint mobility model for ad hoc networks. In *Proceedings of POMC'02*, pages 44–50, New York, NY, USA, 2002. ACM.
76. G. Resta and P. Santi. The QoS-RWP mobility and user behavior model for public area wireless networks. In *Proceedings of the 9th ACM international symposium on Modeling analysis and simulation of wireless and mobile systems (MSWiM'06)*, pages 375–384, New York, NY, USA, October 2006. ACM Press.
77. I. Rhee, M. Shin, S. Hong, K. Lee, and S. Chong. On the Lévy-walk Nature of Human Mobility. In *Proceedings of INFOCOM'08*, Arizona, USA, 2008.
78. M. J. Rutherford, A. Carzaniga, and A. L. Wolf. Simulation-based test adequacy criteria for distributed systems. In *Proceedings of the 14th ACM SIGSOFT international symposium on Foundations of software engineering (FSE-14)*, pages 231–241, New York, NY, USA, 2006. ACM Press.
79. A. K. Saha and D. B. Johnson. Modeling mobility for vehicular ad-hoc networks. In *Proceedings of VANET'04*, pages 91–92, New York, NY, USA, 2004. ACM.
80. T. K. Sarkar, M. C. Wicks, M. Salazar-Palma, and R. J. Bonneau. A survey of various propagation models for mobile communication. *Smart Antennas*, pages 239–307, 2004.
81. J. Scott. *Social Networks Analysis: A Handbook*. Sage Publications, London, United Kingdom, second edition, 2000.
82. J. Scott, R. Gass, J. Crowcroft, P. Hui, C. Diot, and A. Chaintreau. CRAWDAD data set cambridge/haggle (v. 2006-01-31). Downloaded from http://crawdad.cs.dartmouth.edu/cambridge/haggle, Jan. 2006.
83. G. Sharma and R. R. Mazumdar. Scaling laws for capacity and delay in wireless ad hoc networks with random mobility. In *IEEE International Conference on Communications (ICC'04)*, pages 3869– 3873, June 2004.
84. T. Sohn, W. G. Griswold, J. Scott, A. LaMarca, Y. Chawathe, I. E. Smith, and M. Y. Chen. Experiences with Place Lab: an open source toolkit for location-aware computing. In *Proceedings of ICSE'06*, pages 462–471. ACM Press, 2006.
85. T. Spyropoulos, K. Psounis, and C. S. Raghavendra. Performance analysis of mobility-assisted routing. In *Proceedings of MobiHoc'06*, pages 49–60, New York, NY, USA, 2006. ACM.
86. J. Su, A. Chin, A. Popivanova, A. Goel, and E. de Lara. User mobility for opportunistic ad-hoc networking. In *Proceedings of the Sixth IEEE Workshop on Mobile Computing Systems and Applications (WMCSA'04)*, pages 41–50, Washington, DC, USA, 2004. IEEE Computer Society.
87. D. Tang and M. Baker. Analysis of a local-area wireless network. In *Proceedings of MobiCom'00*, pages 1–10, New York, NY, USA, 2000. ACM Press.
88. C. Tuduce and T. Gross. A Mobility Model Based on WLAN Traces and its Validation. In *Proceedings of INFOCOM'05*, pages 19–24, March 2005.
89. P. Turchin. *Measuring and Modeling Population Redistribution in Animals and Plants*. Sinauer Associates, 1998.
90. U.S. Census Bureau. Tiger, tiger/line and tiger-related products. Available at http://www.census.gov/geo/www/tiger/.
91. A. Varga. The OMNeT++ discrete event simulation system. In *Proceedings of the European Simulation Multiconference (ESM'01)*, Prague, June 2001.

92. A. Vasquez, R. Pastor-Satorras, and A. Vespignani. Large-scale topological and dynamical properties of the Internet. *Physical Review E*, 67, 2003.
93. G. M. Viswanathan, V. Afanasyev, S. V. Buldyrev, E. J. Murphy, P. A. Prince, and H. E. Stanley. Lévy flight search patterns of wandering albatrosses. *Nature*, (381):413–415, May 1996.
94. G. M. Viswanathan, S. V. Buldyrev, S. Havlin, M. G. E. da Luz, E. P. Raposo, and H. E. Stanley. Optimizing the success of random searches. *Nature*, 401(6756):911–914, 1999.
95. K. Wang and B. Li. Group mobility and partition prediction in wireless ad-hoc networks. *Proceedings of ICC'02*, 2:1017–1021, 2002.
96. Z. Wang, S. Elbaum, and D. Rosenblum. Automated generation of context-aware tests. In *Proceedings of ICSE'07*. ACM Press, 2007.
97. S. Wasserman, K. Faust, and D. Iacobucci. *Social Network Analysis : Methods and Applications (Structural Analysis in the Social Sciences)*. Cambridge University Press, November 1994.
98. D. J. Watts. *Small Worlds The Dynamics of Networks between Order and Randomness*. Princeton Studies on Complexity. Princeton University Press, 1999.
99. J. Yoon, M. Liu, and B. Noble. Random waypoint considered harmful. In *Proceedings of INFOCOM'03*, 2003.
100. J. Yoon, M. Liu, and B. Noble. Sound mobility models. In *Proceedings of MobiCom'03*, pages 205–216, New York, NY, USA, 2003. ACM.
101. J. Yoon, B. D. Noble, M. Liu, and M. Kim. Building realistic mobility models from coarse-grained traces. In *Proceedings of MobiSys'06*, pages 177–190, New York, NY, USA, 2006. ACM Press.
102. X. Zeng, R. Bagrodia, and M. Gerla. GloMoSim: a library for parallel simulation of large-scale wireless networks. In *Proceedings of the 12th Workshop on Parallel and distributed simulation (PADS'98)*, pages 154–161, Washington, DC, USA, 1998. IEEE Computer Society.
103. X. Zhang, J. Kurose, B. N. Levine, D. Towsley, and H. Zhang. Study of a bus-based disruption-tolerant network: mobility modeling and impact on routing. In *Proceedings of MobiCom'07*, pages 195–206, New York, NY, USA, 2007. ACM.