Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM) Model for Mobile Social Networks (MSN)

Zunnun Narmawala(✉)

Institute of Technology, Nirma University, Ahmedabad, India
zunnun80@gmail.com

Abstract. Peer-to-peer opportunistic communication between mobile devices carried by humans without using any infrastructure is largely unexploited. The encounter pattern of the devices depends on human mobility pattern which is governed by human social behaviour. Individuals belong to multiple communities. These social ties significantly affect humans' movement pattern. Traditional mobility models, such as Random Way Point (RWP) and Brownian Motion (BM), model device mobility as random. However, researchers have shown that human mobility is rarely random and such models do not provide a reliable analysis of network protocol performance. Various characteristics of human mobility are derived in the literature from mobility traces and social network theory. None of the mobility models in the literature incorporate all of them. In this paper, Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM) model is proposed incorporating all of these characteristics.

Keywords: Mobility model · Overlapping community structure
Opportunistic networks · Mobile Social Networks · ONE simulator

1 Introduction

In recent times, the growth of mobile devices (especially smartphones) is phenomenal. These devices support Bluetooth and Wifi connectivity. As these devices are carried by humans, their encounter patterns depend on human mobility patterns. Thus, knowledge of human movement behaviour and social structure can be exploited for efficient peer-to-peer communication [1,3] between these devices. As a result, this network paradigm is called as Mobile Social Network (MSN).

To analyze the performance of protocols which aim to exploit human movement behaviour through simulation, it is essential to design realistic mobility models which can mimic human mobility patterns as closely as possible. A number of experimental projects have been undertaken to collect encounter information of devices carried by humans [4,12]. These traces can be used in the

Z. Patel and S. Gupta (Eds.): ICFITT 2017, LNICST 220, pp. 137–146, 2018.
https://doi.org/10.1007/978-3-319-73712-6_14

simulation to evaluate and analyze the performance of different protocols. While this approach generates realistic mobility patterns, its usefulness is limited as the performance of a protocol can be evaluated only for limited values of network parameters for which traces are available. Nonetheless, from analysis of these traces, various statistical properties of human mobility are derived [4,7,12,27]. Well-known and widely used mobility models such as Random Way Point (RWP) [14], Brownian Motion (BM) [8] etc. do not exhibit these properties. Further, movement of nodes is not independent. Nodes move as per the underlying overlapping community structure of humans who carry them. These mobility characteristics have a significant impact on the performance of forwarding strategy.

Community Aware Heterogeneous Human Mobility (CAHM) model [21] incorporates all these trace-based and social characteristics of human mobility. But, CAHM does not incorporate one important property of human mobility, i.e. locations that share many common users visiting them frequently tend to be located close to each other. In this paper, CAHM is improved by incorporating this property and this improved CAHM is called as Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM).

In the following Sect. 2, literature survey of existing mobility models for Mobile Social Networks (MSN) is presented. The proposed Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM) model is described in Sect. 3. Simulation results are discussed in Sect. 4. Finally, Sect. 5 concludes the paper.

2 Literature Survey

To study characteristics of human mobility, many experimental studies at various universities (UCSD [18], Dartmouth [10], MIT [4], and University of Illinois [28]) and conferences (Infocom 2005 [12], Infocom 2006 [3], and SIGCOMM [24]) have been undertaken. In these experiments, humans participating in the experiment carry devices equipped with Wifi/Bluetooth and/or GPS sensor. These devices log encounter, location, and time information for a period of time.

From the analysis of these traces, various statistical properties of human mobility are derived which are as follows.

- T.1 Aggregate inter-contact time follows power-law distribution with exponential cutoff [3,12].
- T.2 Pause time follows truncated power-law distribution [27].
- T.3 Humans visit nearby locations more frequently compared to far-away locations [7].
- T.4 Humans have location preferences and they periodically re-appear at these locations [7].
- T.5 Speed at which humans move increases with distance to be traveled [27].

2.1 Real-Trace Based Models

Real-trace based models try to capture features of individual's independent movement observed from mobility traces. Working Day Mobility (WDM) model [5] and Time Variant Community (TVC) model [11] incorporate properties T.1 and T.4. Small World In Motion (SWIM) model [19] incorporates all properties T.1 to T.5. Self-similar Least Action Walk (SLAW) model [17] incorporates properties T.1, T.2, and T.3.

2.2 Social-Aware Models

Following are the main characteristics derived from the social network theory which affect human mobility.

- S.1 Humans form communities based on their social relationships [22].
- S.2 Humans belong to multiple communities and so, communities overlap [23].
- S.3 Different individuals have different local popularity within a community and different global popularity in the social network [13].
- S.4 Community size, the number of communities in which a node is a member and overlap size approximately follow power-law distribution where overlap size is defined as the number of individuals which are common in two communities [23].
- S.5 Locations that share many common users visiting them frequently tend to be located close to each other [15].

Community-based Mobility Model (CMM) [20], Home-cell CMM (HCMM) [2], and N-body [31] models incorporate only S.1 of social network theory based properties. CMM and HCMM also incorporate some of the properties derived from mobility traces. But, these models do not incorporate properties S.2, S.3, S.4, and S.5 which are very important properties and have a significant impact on the performance of routing protocols. Social, sPatial, and Temporal mobility framework (SPoT) [15] is flexible and controllable mobility framework. But, it generates only contact traces and proposal in the paper for generating movement traces is preliminary. Further, it takes a social graph as an input instead of generating community structure synthetically. So, it lacks the flexibility of generating a large number of different social graphs for simulation. A detailed review of human mobility in opportunistic networks is available in [26].

Community Aware Heterogeneous Human Mobility (CAHM) model incorporates properties S.1 to S.4 derived from social network theory to generate community structure synthetically. CAHM is able to generate any number of overlapping community structures on its own based on input parameters. It does not take real life social network as an input, as requiring real life social network as an input restricts possible scenarios for which performance evaluation can be done. Further, it also does not use Social Network Models (SNM) such as Caveman model [29] to generate community structure, as these models are quite simplistic and do not take into account all social network theory based properties. It also incorporates all trace-based properties. However, it does not incorporate property S.5. So, Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM) model is proposed in this paper to incorporate property S.5. The summary of the comparison of different mobility models for MSN is presented in Table 1.

Table 1. Comparison of mobility models for MSN

Mobility model	T.1	T.2	T.3	T.4	T.5	S.1	S.2	S.3	S.4	S.5
SLAW [17]	✓	✓	✓							
WDM [5]	✓	✓	✓	✓						
TVC [11]	✓	✓	✓	✓						
SWIM [19]	✓	✓	✓	✓	✓					
N-body [31]	✓					✓				
CMM [20]	✓			✓		✓				
HCMM [2]	✓		✓	✓		✓				
HHW [30]	✓			✓		✓	✓	✓	✓	
CAHM [21]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
P-CAHM (Proposed)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

As P-CAHM is based on CAHM, an overview of CAHM model is given in the following sub-section.

2.3 Overview of Community Aware Heterogeneous Human Mobility (CAHM) Model

In overlapping community structure, each individual n in the social network may belong to number of communities denoted as membership number Λ_n. Further, any two communities x and y may share $S^{ov}_{x,y}$ individuals, defined as overlap size between two communities. Let us denote size of community x as S^{com}_x and probability distribution functions of membership number, overlap size and community size as P(Λ), P(S^{ov}) and P$(S^{'com})$ respectively. Here, $S^{'com} = S^{com} - k$ to keep minimum community size equal to k where k is clique size. A k-clique is complete sub-graph of size k and k-clique community is union of all k-cliques that can be reached from one another through series of adjacent k-cliques where two k-cliques are adjacent if they share $k-1$ nodes [23]. Based on the analysis of a variety of social networks, Palla et al. [23] conclude that P(Λ), P(S^{ov}) and P$(S^{'com})$ approximately follow power-law distribution P$(x) \sim x^{-\tau}$, with exponents $\tau = \Upsilon_\Lambda$, $\tau = \Upsilon_{Osize}$ and $\tau = \Upsilon_{Csize}$, respectively. Further, they report that values of Υ_Λ and Υ_{Osize} are not less than 2, and the value of Υ_{Csize} is between 1 and 1.6. These statistical properties are used to synthetically construct k-clique overlapping community structure.

P-CAHM model is composed of four components: (1) Establishing overlapping community structure, (2) Generating heterogeneous local degree, (3) Mapping communities into geographical zones, and (4) Driving individual motion. These components are explained in following four sub-sections.

Establishing *k*-clique Overlapping Community Structure. A day (or a week or any time duration) is divided into periods, and overlapping community structures are different in each of these periods but is same in the same period of different days. Let us define nodes with membership number larger than 2, equal to 2 and equal to 1 as M-3 nodes, M-2 nodes, and M-1 nodes respectively. Community structure for each period is constructed as follows:

1. Generate nodes' membership numbers such that they follow $\mathrm{P}(\Lambda)$ with exponent Υ_Λ. Then, establish initial empty communities whose sizes S^{com} follow $\mathrm{P}(S^{'com})$ with exponent Υ_{Csize} such that $\sum_i \Lambda_i = \sum_j S_j{}^{\mathrm{com}}$.
2. Use all M-3 nodes to establish initial overlaps between pairs of communities.
3. Modify initial overlaps by allocating all M-2 nodes to communities such that overlaps' sizes follow $\mathrm{P}(S^{ov})$ with exponent Υ_{Osize}.
4. Allocate all M-1 nodes to unsaturated communities.

Generating Heterogeneous Local Degree. Local degree of a node within a community is defined as the number of neighbours of the node in the community. A node's local popularity depends on its local degree. Let $Local_i^n$ denote local degree of node n in its community i where $Local_i^n \geq k-1$ as per the definition of k-clique community. These values are generated such that they follow a power-law distribution with exponent Υ_{Local}.

Mapping Communities into Geographical Zones. To simulate n mobile nodes in a two-dimensional square plane, the model divides the plane into a grid of non-overlapping square cells. For each period, a community x with size S_x is associated with a zone composed of C_x adjacent cells. The location of a zone within the simulation plane is chosen randomly such that zones of different communities do not overlap. Each node n is randomly associated with $Local_i^n$ cells within the zone of its community i. Let μ_x be the average local degree and N_x be the number of nodes in community x. Let m be the community density index denoting denseness of a community. Then,

$$C_x = m \times \mu_x \times N_x \tag{1}$$

Driving Individual Motion. Initially, each node randomly selects one of its associated cells and then it is located at a random position inside that cell. To move, a node chooses an associated cell as next goal based on the distance it will have to travel with truncated power-law distribution $\mathrm{P}(D)$ with exponent Υ_D between the minimum distance and the maximum distance a node can travel.

As found in [27], speed increases with the increase in flight length because individuals use transportation to travel long distances instead of walking. They have also derived following relation between flight time (t) and flight length (l) from different mobility traces.

$$t = p \times l^{1-\eta}, 0 \leq \eta \leq 1 \tag{2}$$

From mobility traces, Rhee et al. [27] have proposed $p = 30.55$ and $\eta = 0.89$ when $l < 500\,\mathrm{m}$, and $p = 0.76$ and $\eta = 0.28$ when $l \geq 500\,\mathrm{m}$. CAHM uses this model to calculate speed at which a node should travel to next goal.

The overlapping community structure, corresponding associated zones and cells change at the start of the new period. When the period changes, after reaching its current goal, the node selects next goal inside one of its newly associated cells of the new period.

3 Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM) Model

In CAHM, the location of a zone associated with a community is selected randomly. But, locations of communities are not random. As shown in [15], locations that share many common users visiting them frequently tend to be located close to each other. So, CAHM is modified such that distances between communities are proportional to the number of common members of communities.

To decide the location of zones associated with communities, consider the network of communities as a graph where communities are nodes and two communities are connected by an edge if they have some common member nodes. Initially, zones are placed randomly in the simulation plane such that two zones do not overlap. Our goal is to place these zones such that distance between them is proportional to the number of common member nodes in corresponding communities.

Consider this as the n-body problem of physics. Two zones attract and repel each other with the force proportional to the number of common member nodes of the corresponding two communities. The pseudo-code is presented in the Algorithm 1. The algorithm is based on the one presented in [6] to draw a graph such that all vertices are placed at equal distance from each other. We need to place communities at distances which are proportional to the number of common member nodes of communities and instead of a point on the plane, a community requires an area on the plane.

In the algorithm, there are four steps in each iteration: calculate the effect of attractive forces on each community, then calculate the effect of repulsive forces, limit the total displacement by the 'temperature', and translate new positions of communities such that they are within simulation area. In using the 'temperature', the idea is to limit maximum displacement of a community to some maximum value, and this maximum value decreases over time. So, as the layout becomes better, the amount of adjustment becomes finer.

4 Simulation Results

P-CAHM model is implemented in ONE simulator [16]. It is a de facto simulator for Delay Tolerant Network (DTN) research. P-CAHM is simulated with the following scenario. There are 500 nodes in a simulation plane of $40\,\text{km} \times 40\,\text{km}$, divided into a grid of cells with size $252\,\text{m} \times 252\,\text{m}$ each. The transmission range of each node is $40\,\text{m}$. The speed follows Eq. 2 and pause time is generated using power-law distribution with exponent 2 between 0 and $1000\,\text{s}$. 4-clique communities are generated, i.e. $k = 4$. Power-law exponents are set with $\Upsilon_\Lambda = 3$,

Algorithm 1. Algorithm to place communities based on number of common member nodes

$simulation\_area = maxX * maxY$
$G = (V, E)$ {Initial positions of communities V are random}
{k is the desired distance between mid-points of two communities and x is the current distance}
function $f_a(k, x) =$ begin return x^2/k end
function $f_r(k, x) =$ begin return k^2/x end
for $i = 1$ to *iterations* **do**
  {Calculate repulsive forces}
  for v in V **do**
    {Each vertex has two vectors: .pos and .disp where .pos represents mid-point of a community}
    $v.disp = 0$
    for u in V **do**
      if $u \neq v$ **then**
        {Δ is the short hand for the difference vector between the positions of the two vertices}
        $\Delta = v.pos - u.pos$
        {r_v is the radius of community v, $tieStrength(u, v)$ represents number of common
        member nodes of u and v scaled between 0 and 1}
        $k = r_v + r_u + (1 - tieStrength(u, v))/(1 - avgTieStrength) * \sqrt{(maxX * maxY - totalCommunityArea)/|V|}$
        $v.disp = v.disp + (\Delta/|\Delta|) * f_r(k, |\Delta|)$
      end if
    end for
  end for
  {Calculate attractive forces}
  for e in E **do**
    {Each edge is an ordered pair of vertices $.v$ and $.u$}
    $\Delta = e.v.pos - e.u.pos$
    $k = r_v + r_u + (1 - tieStrength(u, v))/(1 - avgTieStrength) * \sqrt{(maxX * maxY - totalCommunityArea)/|V|}$
    $e.v.disp = e.v.disp - (\Delta/|\Delta)|) * f_a(k, |\Delta|)$
    $e.u.disp = e.u.disp + (\Delta/|\Delta)|) * f_a(k, |\Delta|)$
  end for
  {Limit the maximum displacement to the temperature t}
  for v in V **do**
    $v.pos = v.pos + (v.disp/|v.disp|) * min(v.disp, t)$
  end for
  for v in V **do**
    {Prevent from being displaced outside frame}
    $v.pos.x = translate(v.pos.x, min(.pos.x), max(.pos.x), r_v, maxX - r_v)$
    $v.pos.y = translate(v.pos.y, min(.pos.y), max(.pos.y), r_v, maxY - r_v)$
  end for
  {Reduce the temperature t as layout approaches better configuration}
  $t = cool(t)$
end for

$\Upsilon_{Osize} = 2$, $\Upsilon_{Csize} = 1.2$, $\Upsilon_{Local} = 2.4$, and flight length exponent $\Upsilon_D = 2$. All these values are in the range recommended for these exponents in the literature from mobility traces [22,23,27]. With a random seed, the model generates 14 communities with sizes 8, 121, 70, 6, 227, 7, 51, 91, 22, 3, 157, 3, 3, and 12. Because of space constraint, figures are not included. We run the simulation for 72,000 s.

To verify that in P-CAHM also, similar to CAHM, aggregate inter-contact time distribution is power-law with exponential cutoff, the simulation is done for two days. Simulation result shows that Complementary Cumulative Distribution Function (CCDF) of aggregate inter-contact times of P-CAHM follows power-law distribution with exponential cutoff which matches with the CCDF of aggregate inter-contact times of mobility traces [21].

To check the efficacy of our algorithm for the placement of communities proportional to the distances between them, Spearman's rank correlation coefficient (ρ) [25] is used. First of all, for initial random placement of communities, distances between communities are calculated and ordered list of initial distances is generated. ρ for this ordered list and the ordered list of tie strengths between communities comes out to be 0.19. Here, tie strengths between communities are number of common member nodes of communities scaled between 0 and 1. It shows that initially there is very weak correlation between distances and tie strengths. After the completion of the algorithm, the ρ comes out to be 0.52 which denotes a strong correlation between distances and tie strengths.

To check the effect of proximity property on the network performance in the given network scenario, 1/12 messages per second are generated in the network with the message size of 8 kB. In the steady state, with P-CAHM model, average message delivery delay and delivery ratio are 18000 s and 55% respectively. With CAHM model, they are 19029 s and 51%. In P-CAHM, as common member nodes need to travel less distances between communities, delivery delays of the messages they carry get reduced as compared to CAHM. As a consequence, less number of messages time out. So, the delivery ratio also improves.

5 Conclusion

To analyze the performance of routing protocols aiming to exploit human movement behaviour through simulation, it is essential to design realistic mobility models which can mimic human mobility patterns as closely as possible. Various characteristics of human mobility are derived from mobility traces and from social network theory in the literature. No existing mobility model, except CAHM, generates community structure synthetically incorporating all these characteristics and without using Social Network Models such as Caveman model. In this paper, Proximity and Community Aware Heterogeneous Human Mobility (P-CAHM) model is proposed with the following modification in CAHM: Instead of placing communities at random locations in the simulation plane, they are placed such that distances between them are proportional to the number of common member nodes of the communities. Simulation result demonstrates that P-CAHM successfully establishes a strong correlation between distances among communities and number of common member nodes of communities. Also, CCDF of inter-contact times in P-CAHM follows power-law distribution as desired. Further, CAHM model under-reports network performance as compared to P-CAHM. The ONE simulator along with the P-CAHM mobility model can be downloaded from https://sites.google.com/a/nirmauni.ac.in/zunnun/.

References

1. Boldrini, C., Conti, M., Passarella, A.: Impact of social mobility on routing protocols for opportunistic networks. In: IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks, WoWMoM 2007, pp. 1–6. IEEE (2007)
2. Boldrini, C., Passarella, A.: HCMM: modelling spatial and temporal properties of human mobility driven by users social relationships. Comput. Commun. **33**(9), 1056–1074 (2010)
3. Chaintreau, A., Hui, P., Crowcroft, J., Diot, C., Gass, R., Scott, J.: Impact of human mobility on opportunistic forwarding algorithms. IEEE Trans. Mob. Comput. **6**(6), 606–620 (2007)
4. Eagle, N., Pentland, A.: Reality mining: sensing complex social systems. Pers. Ubiquit. Comput. **10**(4), 255–268 (2006)
5. Ekman, F., Keränen, A., Karvo, J., Ott, J.: Working day movement model. In: Proceedings of the 1st ACM SIGMOBILE Workshop on Mobility Models, pp. 33–40. ACM (2008)
6. Fruchterman, T.M., Reingold, E.M.: Graph drawing by force-directed placement. Softw. Pract. Exp. **21**(11), 1129–1164 (1991)
7. Gonzalez, M.C., Hidalgo, C.A., Barabasi, A.L.: Understanding individual human mobility patterns. Nature **453**(7196), 779–782 (2008)
8. Groenevelt, R., Altman, E., Nain, P.: Relaying in mobile ad hoc networks: the Brownian motion mobility model. Wireless Netw. **12**(5), 561–571 (2006)
9. Han, B., Hui, P., Kumar, V., Marathe, M.V., Pei, G., Srinivasan, A.: Cellular traffic offloading through opportunistic communications: a case study. In: Proceedings of the 5th ACM Workshop on Challenged Networks, pp. 31–38. ACM (2010)
10. Henderson, T., Kotz, D., Abyzov, I.: The changing usage of a mature campus-wide wireless network. Comput. Netw. **52**(14), 2690–2712 (2008)
11. Hsu, W.J., Spyropoulos, T., Psounis, K., Helmy, A.: Modeling spatial and temporal dependencies of user mobility in wireless mobile networks. IEEE/ACM Trans. Netw. **17**(5), 1564–1577 (2009)
12. Hui, P., Chaintreau, A., Scott, J., Gass, R., Crowcroft, J., Diot, C.: Pocket switched networks and human mobility in conference environments. In: Proceedings of the 2005 ACM SIGCOMM Workshop on Delay-Tolerant Networking, pp. 244–251. ACM (2005)
13. Hui, P., Crowcroft, J., Yoneki, E.: Bubble rap: social-based forwarding in delay-tolerant networks. IEEE Trans. Mob. Comput. **10**(11), 1576–1589 (2011)
14. Hyytiä, E., Koskinen, H., Lassila, P., Penttinen, A., Roszik, J., Virtamo, J.: Random waypoint model in wireless networks. In: Networks and Algorithms: Complexity in Physics and Computer Science, Helsinki (2005)

15. Karamshuk, D., Boldrini, C., Conti, M., Passarella, A.: SPoT: representing the social, spatial, and temporal dimensions of human mobility with a unifying framework. Pervasive Mob. Comput. **11**, 19–40 (2014)
16. Keränen, A., Ott, J., Kärkkäinen, T.: The one simulator for DTN protocol evaluation. In: Proceedings of the 2nd International Conference on Simulation Tools and Techniques, p. 55. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering) (2009)
17. Lee, K., Hong, S., Kim, S.J., Rhee, I., Chong, S.: SLAW: a new mobility model for human walks. In: INFOCOM 2009, pp. 855–863. IEEE (2009)
18. McNett, M., Voelker, G.M.: Access and mobility of wireless PDA users. ACM SIGMOBILE Mob. Comput. Commun. Rev. **9**(2), 40–55 (2005)
19. Mei, A., Stefa, J.: SWIM: a simple model to generate small mobile worlds. In: INFOCOM 2009, pp. 2106–2113. IEEE (2009)
20. Musolesi, M., Mascolo, C.: Designing mobility models based on social network theory. ACM SIGMOBILE Mob. Comput. Commun. Rev. **11**(3), 59–70 (2007)
21. Narmawala, Z., Srivastava, S.: Community aware heterogeneous human mobility (CAHM): model and analysis. Pervasive Mob. Comput. **21**, 119–132 (2015)
22. Newman, M.E.: The structure and function of complex networks. SIAM Rev. **45**(2), 167–256 (2003)
23. Palla, G., Derényi, I., Farkas, I., Vicsek, T.: Uncovering the overlapping community structure of complex networks in nature and society. Nature **435**(7043), 814–818 (2005)
24. Pietilänen, A.K., Diot, C.: Dissemination in opportunistic social networks: the role of temporal communities. In: Proceedings of the Thirteenth ACM International Symposium on Mobile Ad Hoc Networking and Computing, pp. 165–174. ACM (2012)
25. Pirie, W.: Spearman rank correlation coefficient. In: Encyclopedia of Statistical Sciences (1988)
26. Pirozmand, P., Wu, G., Jedari, B., Xia, F.: Human mobility in opportunistic networks: characteristics, models and prediction methods. J. Netw. Comput. Appl. **42**, 45–58 (2014)
27. Rhee, I., Shin, M., Hong, S., Lee, K., Kim, S.J., Chong, S.: On the levy-walk nature of human mobility. IEEE/ACM Trans. Networking (TON) **19**(3), 630–643 (2011)
28. Vu, L., Do, Q., Nahrstedt, K.: Jyotish: constructive approach for context predictions of people movement from joint Wifi/Bluetooth trace. Pervasive Mob. Comput. **7**(6), 690–704 (2011)
29. Watts, D.J.: Small Worlds: The Dynamics of Networks Between Order and Randomness. Princeton University Press, Princeton (1999)
30. Yang, S., Yang, X., Zhang, C., Spyrou, E.: Using social network theory for modeling human mobility. IEEE Network **24**(5), 6–13 (2010)
31. Zhao, C., Sichitiu, M.L., Rhee, I.: N-body: a social mobility model with support for larger populations. Ad Hoc Netw. **25**, 185–196 (2015)