Mobility Models, Traces and Impact of Mobility on Opportunistic Routing Algorithms: A Survey

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***Abstract*—Mobile Opportunistic Network (MON) is characterized by intermittent connectivity where communication largely depends on the mobility pattern of the participating nodes. In MON, a node can take the custody of a packet for a long time and carry it until a new forwarding path has been established, unlike mobile adhoc network (MANET), where a node must drop the packet otherwise. Therefore, routing in MON depends on the repeated make-and-break of communication links, which again depends on the mobility of the nodes as they encounter and drift away from each other. MONs can simply be formed by humans carrying hand-held devices (like Personal Digital Assistant [PDAs] or cell phones) or on-board devices installed in vehicles. Therefore, with mobility playing a major role in the performance of MON, researchers have repeatedly tried to understand the nature of mobility with respect to humans, vehicles, and wild animals. To study the nature of mobility, researchers have collected mobility traces, proposed mobility models, and analyzed the performance of MON with respect to various mobility parameters. This article provides a detailed survey of different mobility models which have been proposed to date and how mobility largely determines the performance of opportunistic routing. We divide the article into four major sections. First, we provide a detailed survey of all the synthetic mobility models which have been developed to date. Second, we study the various mobility traces which have been collected and analyzed. Third, we study how mobility parameters affect the performance of MON. Finally, we highlight on some of the research areas and open challenges which yet remain unsolved.**

***Index Terms*—Mobile opportunistic network, mobility models, mobility traces, performance.**

I. Introduction

DUE to recent availability of large number of small hand-held devices with network interfaces, a keen interest on infrastructure-less communication has led to the development of Mobile Adhoc Networks (MANET). MANETs consist of autonomous devices where each device can act as a source, a destination, as well as an intermediate router. Hence, in such networks packets are transmitted in a hop-by-hop basis with the co-operation of other network nodes (also known as relay nodes). It is however worth mentioning that in such network a contemporaneous path must be established before packets can be forwarded along a definite route. Packets with unreachable destination are always dropped.

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It has however been observed that such a dedicated path from source to destination may not always be available and that packets may otherwise be transferred by making use of brief, sporadic contacts between mobile nodes. Loss of communication between any two nodes may occur due to number of physical and environmental factors; for example, nodes may periodically sleep to preserve their energy, mobile nodes having short communication range (like Bluetooth, Wi-Fi) may drift outside each other's range or even physical obstructions like buildings and trees may disrupt a constant communication. Thus, the concept of Mobile Opportunistic Network (MON) was spawned from a more generic MANET, where mobile nodes instead of discarding packets, store and carry them until a communication link is established. In opportunistic network, frequent and long lasting disconnection between mobile nodes are considered a part of normal operation of the network and such networks are resistant to long delays created due to large communication gaps. In a MON, messages are forwarded as bundles [1] (group of messages) whenever there is a transfer opportunity and bundles are delivered in a hop-by-hop basis. When a source node is in contact with an intermediate node, a message is replicated and copied to this node that carries it until a new contact opportunity is made. This process is repeated as messages are relayed hop-by-hop to destination. Therefore, message transfer and performance of opportunistic network is largely dependent on the nature of node mobility and encounter events between devices (users) as they congregate and disperse. Hence, a methodical study of mobility models is required which can aid in designing routing protocols for such networks.

Performance modelling is an important and integral part of any research which helps in gaining insight to the system under study. Since mobility plays an important role in opportunistic network and determines its performance to a large extent, modeling device contacts has been a coveted area of research in this field of networking. As a result large part of research has been directed towards a) studying and proposing new mobility models and, b) analyzing mobility (especially humans) using real-life mobility traces and, c) studying performance of MON under various mobility models. This article intends to provide a detailed survey on the state-of-art researches on mobility models, collection and analysis of mobility traces, and impact of mobility on the opportunistic routing algorithms. We divide the entire document into four major sections. First, we provide a detailed and exhaustive survey on the synthetic mobility models which have been proposed from its inception to its current date. In this section, we also provide detailed information on all the proposed synthetic mobility models which have been developed to date to imitate real life movement patterns of humans, animals, and vehicles. We conclude this section by providing a brief survey of how artificial mobility traces can be generated and used in simulators. Second, we describe how researchers in this field have collected movement/mobility traces with the help of different wireless devices to study, analyze, and characterize the inter-device contact pattern. In this section we also provide a detailed survey on the nature of distribution curves obtained by analyzing the traces and conclusions derived by a systematic study of such curves. Third, we present detailed information on how mobility affects performance of opportunistic forwarding algorithms. We study how the nature of mobility impacts various routing metrics like delay, throughput, transmission overhead, and packet loss. Finally, we discuss some open challenges which yet remain unsolved and are open to the researchers in this field of networking. It is worth mentioning that study of mobility models come with a concrete mathematical background. Therefore for the sake of completeness, we have supplemented the theory with some mathematical formulas (where deemed necessary) which would otherwise render the subject matter incomplete.

II. Preliminaries

With the advancement of microprocessor and fabrication technology, computers and computing devices started growing smaller and researchers started developing methods for communication between non-fixed devices. The invention of digital wireless communication revolutionized the world of inter-device communication, especially among mobile devices. This led to the birth of new area in the field of computer network known as the Mobile Adhoc Network (MANET) where researchers started developing protocols for delivering packets inside a highly dynamic network with constantly changing topological characteristics. Concurrently with (but separate from) the MANET activities, DARPA had funded NASA, MITRE and others to develop a proposal for the Interplanetary Internet (IPN). Internet pioneer Vint Cerf and others developed the initial IPN architecture [2], relating to the necessity of networking technologies that can cope with the significant delays and packet corruption of deep-space communications. In 2002, Kevin Fall [1], used the same concept to design terrestrial networks and coined the term delay tolerant network, since in such networks the nodes are resistant to long delays caused due to intermittent connectivity. In such network, nodes experience brief contact duration followed by long isolation. Due to frequent changes in link status, it is also known as the intermittently connected network or disruption tolerant network. Researchers of DTN research group (DTNRG) initially developed architectures and RFC 4838 and RFC 5050 were published in 2007 to define a common abstraction to software running on disrupted networks. Commonly known as the Bundle Protocol (RFC 5050), this protocol defines a series of contiguous data blocks as a bundle, where each bundle contains enough semantic information to allow the application to make progress where an individual block may not. Bundles are routed in store-carry-forward manner between participating nodes over IP and non-IP based transport layer protocols. Since bundles are transferred opportunistically that is, when two nodes are within the communication range of each other, this network also came to be known as mobile opportunistic network.[1] Since then a number of bundle layer routing protocols have been developed and is still an active research area in this field. A number of applications like DAKNET [4], ZebraNet [5], SNC [6], Telemedicine [7], and others have been developed based on opportunistic data transfer. Applications and routing protocols in VANET have also been developed for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication [8], [9].

However time and again, researchers have proved that routing efficiency heavily relies on the nature of node movement and the same protocol can perform differently for different types of node movement. Hence, a part of research has been dedicated towards studying mobility traces and proposing new mobility models which is able to emulate real life movement characteristics of humans and vehicles. There are number of parameters governing the nature of mobility viz., inter-contact time, contact time, remaining inter-contact time, return time, and flight length. By studying the distribution of these parameters researchers try to develop models which have the same nature of movement as observed in real life mobility traces. A number of mobility models have also been proposed inspired by sociology and social network, based on the argument that human mobility largely depends on its social community and nature of social structure. Apart from routing, there are other areas in MON like contention control, buffer management, congestion control, QoS, security, and application development in which researchers are actively involved, and which are otherwise well understood in traditional computer networks.

A. *Mobility: A Curse or a Boon?*

In a traditional communication network, mobility can significantly affect the performance of the network. In such networks a continuous path must be established form source to destination before packets can be routed. In MANET several algorithms have been proposed for establishing optimal paths although repeated update of such paths can increase overhead and delay. Gupta and Kumar [10] proposed a model for studying the capacity of fixed adhoc networks, where nodes are randomly located but are immobile. Each source node can choose a random destination in the network with which it can communicate and every node in the network can act both as a source and a destination as well as relay node. They showed that as the number of nodes per unit area n increase, the throughput per node decrease approximately in the order of $\sqrt{n}$.

However, it has been observed that capacity (throughput per node) of such networks can actually increase due to node mobility where mobility is an inherent characteristic of the network and changes in topology occur over time-scale of packet delivery [11]. It has also been shown that node speed has no effect on the scaling properties of per-node throughput although it can significantly impact the average delay in such networks.

[1] Some researchers distinguish between DTN and MON depending on the periodicity of encounter events. In DTNs encounter events are periodic and hence predictable like IPN [2] and data mules [3]. However, in MON encounter events are random and not easily predictable like vehicular and human social networks.

And the intriguing fact is that delay is inversely proportional to the average node speed. Thus, a lower node speed can cause higher delay. Therefore, without any constraint on the delay, mobility can be exploited to increase network capacity. Hence by using relays and opportunistic contacts (due to large amount of mobile nodes in the network), we can actually overcome the capacity bounds of static networks. Mobility can also be helpful for a number of other scenarios. For example, it has been shown that mobility can improve the coverage of sensor networks [12] and also help with security issues in adhoc networks [13]. And above all mobility can overcome the lower bound of $\Omega(\sqrt{n})$ of network capacity and also reduce network congestion [11]. However, with a tighter delay constraint the maximum achievable throughput will decrease.

B. Motivation

The idea of 'Small World' was established with the groundbreaking experiment conducted by Stanley Milgram [14] on social networks, where they conjectured that each person in the world was connected to any other person by at most six-degrees of separation. The same idea was again re-established (by studying time evolving graphs) for mobile opportunistic network where it was shown, that a destination node could be reached by a small number of relays [15] (small diameter of opportunistic network). Such experiments revealed that human mobility models are not random but are driven by socializing behavior of the humans. Hence, such a methodical study of human mobility can provide us with insights which may be used to disseminate messages "opportunistically". These ideas led to a growing interest amongst the researchers to collect and study mobility traces and find patterns and common traits in the movement of all individuals. Even renowned physicists such as A. Einstein [16] showed deep interest in studying mobility (studied Brownian motion), although his interest rested completely on studying mobility of microscopic particles. Studying mobility and proposing new mobility models became a subject of its own since it has grown to be a primary factor in deciding the performance of next generation adhoc networks. Since, data forwarding in opportunistic network is highly dependent on the path availability and mobility of the nodes, researchers all over the globe started collecting vehicular and human mobility traces to understand the factors affecting the nature of such mobility. There have been some early works [116], [117], [131] which have made a brief survey of mobility models and their impact on adhoc routing. However, the area of research on mobility models is ever expanding and several advancements have been made in the recent years, especially with respect to human mobility models. Moreover, researchers have gained insight on the effect of mobility on opportunistic routing and a thorough and comparative study in this field is lacking. These factors motivated us to create a collective and a comprehensive guide on the study of mobility models, mobility traces and the impact of mobility on performance of opportunistic networks.

C. Scope of the Article

Over the years mobile adhoc networks have experienced a paradigm shift as researchers look for more efficient but highly dynamic network. Mobile adhoc networks have gone truly "mobile" with constantly changing topology and with longer communication gap. Delay Tolerant Network (DTN), Mobile Opportunistic Network (MON), or Intermittently Connected Network (ICN); named whatever may be, such networks are finding its way deeper into the realms of network communication as more and more applications are being developed based on this new idea. From NASA's deep space communication to vehicular application to disaster management; this new area of research has been constantly evolving since the last decade. With the evolvement of new technologies like VLSI and nanotechnology, devices have shrunk in size, become 'faster' and hold more application than before. Devices such as mobiles/cell phones, laptops, palmtops, PDAs have become an integral part of daily human life. Individuals carry such devices to their work places, and social gatherings and opportunistic network can be spontaneously formed using such devices. And the basic science governing the performance of such networks is the physical motion of the devices participating in the network.

From the early part of 1990, physicists, biologists and other groups of researchers have been studying human and animal movement patterns. Their study revealed that such motions are largely influenced by several factors such as habitat, foraging, food location, and tendency to form groups, communities or herds. Humans are social animals and therefore their mobility is largely influenced by social aspects and the community to which they belong. Even animals tend to stay or move in groups and herds. However, human mobility is more complex than animals and is still under research. And to study movement patterns of humans and animals, researchers collected statistical data by simple observation or used communication devices to collect mobility traces. By studying mobility traces they were able to understand the very nature such mobility. It revealed that human and animal motion is not random at all but have a definite and repetitive pattern.

Inspired by the long legacy of research in this interesting field, which forms the very core of opportunistic routing, we try to congregate bits of work into a well-arranged survey. The main aim of this survey is to perform a general study on the mobility models and the traces that have been collected to study the nature of mobility observed in nature. One of the main aims of mobility models is to help in studying the network performance (against a routing protocol) in any type mobile networks. And one such mobile network is mobile opportunistic network. As a result the performance of a given routing protocol in opportunistic network largely depends on the nature of mobility. The study on the affect of mobility in opportunistic network is incomplete unless we have a thorough background on mobility models. Hence, we first perform a thorough study on mobility models and the traces which have been collected to study the nature of mobility observed in real life. Then we study its effect on mobile opportunistic network. This tutorial will serve as a basic guideline for all those who aspire in this field of research. It is worth noting that the study of mobility models and mobility traces is highly interdisciplinary while the performance study is restricted to those who are (broadly) interested in network communication. Over the years, mobility models have been proposed to simulate

TABLE I
COMPARISION: SYNTHETIC MOBILITY MODELS AND MOBILITY TRACES

Characteristics	Synthetic Mobility Models	Mobility Traces
Scalable	Yes	No
Similarity with real life movement pattern	Low	High
Time overhead	Small	Large
Complexity	High	Low
Deployment cost	Low	High
Computation overhead	Large	Low

human, animal and vehicular mobility; and hence have been studied by researchers from all fields, including researchers from mobile adhoc networks. The reader must be aware that mobility models are not restricted to any specific (mobile) network; it is only one of the many characteristics of such networks. It is also to be noted that we do not describe models and their implementation, results or derivations in details. Since the article is intended to be prepared as a survey or tutorial, we highlight only the main results and provide a high level overview of the theories. Hence, we recommend that study of any particular section should be supplemented with the study of original research paper to have deeper insight to the work. The readers will find detailed glossary of references at the end and citations at appropriate places.

III. Mobility Models

To validate new protocols and applications for ad-hoc networks, it is important to use a mobility model that will emulate a real life scenario. During the course of time, modeling mobility have grown to be a subject of its own where researchers study and propose new mobility models which is able to imitate real life mobility. Apart from using a synthetic mobility model, researchers have also collected and used mobility traces to validate new opportunistic routing protocols. However, collecting traces is a tedious task, since deploying devices on a large scale is very much limited and costly. Although mobile phones and PDAs have been commonly used in collecting connectivity traces and are a good choice in terms of memory and battery power, they are expensive to deploy on a larger scale. It has been observed most of the times that traces are limited to a university campus or a small conference area. Moreover, there is a large time overhead (6 months–1 year), since traces should be collected over a long time period so as to avoid any biased data from appearing in the data set. For the above limitations synthetic mobility models have gained importance among the researchers. Such models can be applied to an arbitrary number of nodes and over a large scale. Table I shows the pros and cons of synthetic mobility models and real-life mobility traces.

A. *Taxonomy of Mobility Models*

Several synthetic mobility models have been proposed to date and so as to provide a methodical study of these models, we provide a hierarchical classification of these mobility models. Synthetic models are those which are formed out of concrete mathematical models (and formulas) along with physical laws of motion. We divide the entire class of synthetic mobility models into four subclasses viz., the entity mobility models, the correlated or group based mobility models, the human or sociality based mobility models and, the vehicular mobility models. In simple terms, entity mobility models are those in which the mobility of the nodes is independent of each other. Correlated or group based mobility models are those where movement of a node is dependent on mobility of other nodes. However, it is actually a combination of both of these types that we get to observe in real life. For example, an individual sometimes move as single entities like pedestrians and sometimes move in groups with correlated motion patterns. Vehicular movement can also be cited as an example of correlated mobility model (although we prefer to mention it as a separate class of mobility model) since the movement of a vehicle is highly governed by the motion of other vehicles; for example, the speed of a vehicle moving in queue (such a highway) generally cannot exceed the speed of vehicles ahead of it. Human or sociality based mobility models are those which are governed by human nature and their tendency to socialize. Mobility of an individual may be governed by other human when they socialize and tend to move in groups; for example, group of rescue workers or soldiers. And lastly, vehicular mobility models are those which are governed by nature of vehicular movement on road or highway observed in daily life. Vehicular movement is affected by several factors such as traffic signals, movement of vehicles ahead, lane speed limit, accidents, and so on. Apart from synthetic mobility models, we have the class of real life mobility observed in humans, vehicles, and animals. Some authors [17] prefer to classify the real-life mobility into the following types; pedestrians, vehicles, aerial, dynamic medium, robot and outer space motion. Fig. 1 shows the proposed taxonomy of mobility models.

The entity mobility models can be further subdivided into random mobility models, models with temporal dependency, models with spatial dependency, and models with geographic restriction. Next section provides a detailed overview of all the well-known synthetic mobility models proposed to date.

B. *Entity Mobility Models*

1) Random Mobility Models: In random mobility model nodes move freely and without restriction. All the mobility attributes like speed, direction, and waypoints (destination) are selected randomly and independent of previous selection. Hence, these mobility models are generally termed memoryless, since speed (or direction) at time instant t is independent of speed (or direction) at previous time instant $t - \Delta t$.

Random waypoint mobility model (RWP) [18]: The random waypoint mobility model was first proposed by Johnson and Maltz [18] and soon it became a benchmark for evaluating MANET routing protocols and applications because of its simplicity. In random waypoint a node randomly chooses a new destination (x, y) (within a given playfield area) and a speed that is uniformly distributed between $[minspeed, maxspeed]$. The node then moves towards the chosen destination at the selected speed. Upon arrival at the destination, the MN pauses

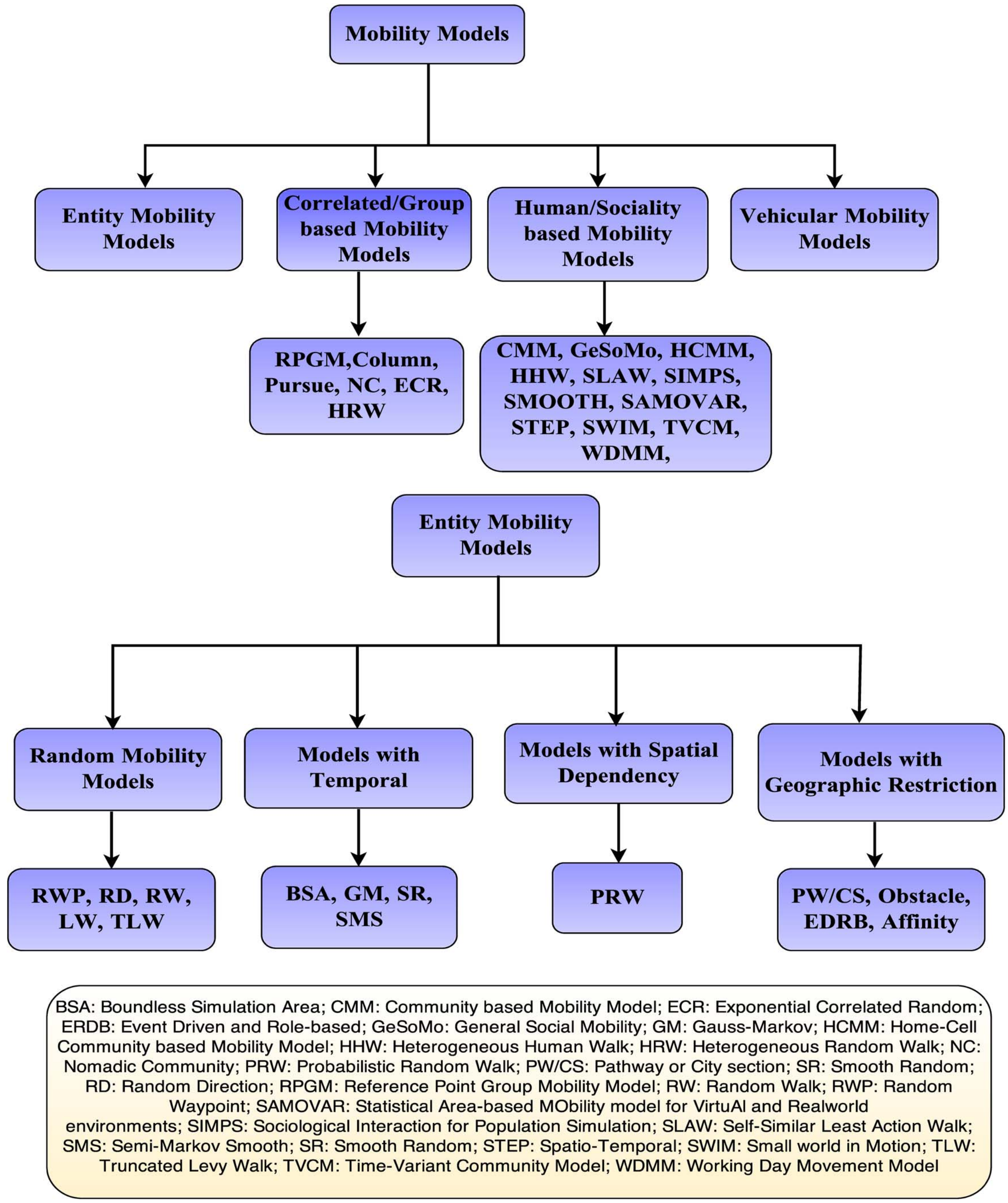

Fig. 1. Taxonomy of mobility models.

for a specified time period after which it again selects a random destination and speed and continues likewise. Such a node movement as above is known as the epoch based mobility; that is during a given period called epoch, a node moves towards a given destination with same speed. At the start of simulation the nodes are randomly distributed over a given area. It has been noticed that there is a high variability in average neighbor percentage which largely affects the performance results of a simulation [19]. Hence, researchers have proposed to discard first 1000 seconds of simulation (also known as the warm-up period) to nullify the initialization problem. Since its inception researchers have studied the stochastic properties of random waypoint and derived the closed form of a number of mobility parameters like probability density function (p.d.f) of transition length, expected transition length, variance of transition length, spatial node distribution, and transition time. For readers interested in the derivation of the above parameters they should refer [20], [21].

However, researchers have found several flaws with random waypoint mobility. Bettstetter [22] and Blough *et al.* [23] respectively observed that the spatial node distribution of Random Waypoint model is transformed from uniform distribution to non-uniform distribution after the simulation starts. As the simulation time elapses, the unbalanced spatial node distribution becomes even worse. Finally, it reaches a steady state. In this state, the node density is maximum at the center region, whereas the node density is almost zero around the boundary of simulation area. This phenomenon is called non-uniform spatial distribution. Another similar pathology of Random Waypoint model, called density wave phenomenon (i.e., the average number of neighbors for a particular node periodically fluctuates along with time), was observed by Royer, Melliar-Smith and Moser [19]. Random waypoint also suffers from speed decay problem. Yoon *et al.* [24] showed that average node speed consistently decrease over time and therefore should not be used for simulation.

Random direction mobility model (RD) [19]: To overcome the non-uniform spatial distribution of nodes and solve the density wave problem, Royer, Melliar-Smith and Moser [19] proposed the random direction mobility model. Instead of selecting a random destination within the simulation field, in the Random Direction model the node randomly and uniformly chooses a direction between $[0, 2\pi]$ and a velocity between $[minspeed, maxspeed]$ by which to move along until it reaches the boundary. After the node reaches the boundary of the simulation field and stops with a pause time T, it then randomly and uniformly chooses another direction between $[0, \pi]$ to travel. This way, the nodes are uniformly distributed within the simulation field. A slight modification to the Random Direction Mobility Model is the Modified Random Direction Mobility Model also proposed by Royer *et al.* [19]. In this modified version, MNs continue to choose random directions but they are no longer forced to travel to the simulation boundary before stopping to change direction. Instead, an MN chooses a random direction and selects a destination anywhere along that direction of travel. The MN then pauses at this destination before choosing a new random direction. Other simplified versions of Random direction mobility is available in literature [25].

Lévy walk model (LW) [26]: In Lévy Walk model, the mobile node chooses a step-length L and a direction of movement θ drawn uniformly from $[0, 2\pi]$ and travels the distance with a constant velocity. At the next epoch, it repeats the process independent of the past. When the first or the second moment of the step-length L becomes infinite, the model is called a Lévy walk [26]. For a Lévy walk model, the p.d.f of step-length is given by

$$f_L(l) \sim l^{-\mu},\ 1 < \mu < 3$$

Under a Lévy walk mobility model, a mobile node occasionally moves along a very long straight line with non-negligible probability, interspersed with successive short steps with random orientation. A variation of Lévy walk called the Truncated Lévy walk has been proposed in [26] in which the flight length and pause time follow truncated power laws (Section IV-C).

Random walk mobility model (RW) [27]: The Random Walk model was originally proposed as Brownian motion (or Brownian mobility model) to emulate the unpredictable movement of microscopic particles suspended in a fluid. Because some mobile nodes are believed to move in an unexpected way, Random Walk mobility model is proposed to mimic their movement behavior [16]. The Random Walk model has similarities with the Random Waypoint model because the node movement has strong randomness in both models. The Random Walk Mobility Model was first described mathematically by A. Einstein in 1926 [16]. In this mobility model, a MN moves from its current location to a new location by randomly choosing a direction and speed in which to travel. The new speed and direction are both chosen from pre-defined ranges, $[minspeed, maxspeed]$ and $[0, 2\pi]$ respectively. Each movement in the Random Walk Mobility Model occurs in either a constant time interval t or a constant distance travelled d, at the end of which a new direction and speed are calculated. In this model, if a MN reaches the simulation boundary, it is "bounced" off the simulation border with an angle determined by the incoming direction (known as the border effect [22]). Although simple, Random Walk Mobility Model creates unrealistic movement patterns. Random Walk mobility is a memoryless mobility process because it retains no knowledge concerning its past locations and speed values [13]. The current speed and direction of an MN is independent of its past speed and direction. However, this is not the case in most of the real life scenario since the current velocity of a mobile node may depend on its previous velocity. Thus the velocities of single node at different time slots are not "correlated". To overcome this limitations four mobility models with temporal dependency were proposed viz., a) Gauss-Markov mobility model, b) Smooth Random mobility model, c) Semi-Markov Smooth mobility model and, d) Boundless Simulation Area mobility model.

2) Models With Temporal Dependency: When node movement has temporal dependency, it means that mobility is governed by physical laws of motion and its current movement is dependent on its movement history. For example, a node's current velocity may depend upon the previous velocity. Again, in most cases nodes move along a given path; for example vehicles move along roads and movements of pedestrians are may be blocked by buildings.

Gauss-Markov mobility model (GM) [28]: The Gauss-Markov Mobility Model was first introduced by Liang and Haas [28] and was originally proposed for the simulation of a PCS (Personal Communication System). In this model, the velocity of mobile node is assumed to be correlated over time and modeled as a Gauss-Markov stochastic process. Initially each MN is assigned a current speed and direction. At fixed intervals of time, t, movement occurs by updating the speed and direction of each MN. Specifically, the value of speed and direction at the t^{th} instance is calculated based upon the value of speed and direction at the $(t-1)^{th}$ instance and a random variable using the following equations:

$$\overline{V_t} = \overline{\alpha}.\overline{V}_{t-1} + (1-\overline{\alpha}).\overline{\upsilon} + \overline{\sigma}.\sqrt{1-\overline{\alpha}^2}.\overline{W}_{t-1} \qquad (1)$$

where $\overline{V_t} = [\nu_t^x, \nu_t^y]^T$ and $\overline{V}_{t-1} = [\nu_{t-1}^x, \nu_{t-1}^y]^T$ in (1) are the velocity vectors at time t and $t-1$ respectively. $\overline{W}_{t-1} = [w_{t-1}^x, w_{t-1}^y]^T$ is the uncorrelated random Gaussian process with mean 0 and variance σ^2, and $\overline{\alpha} = [\alpha^x, \alpha^y]^T$, $\overline{\upsilon} = [\upsilon^x, \upsilon^y]^T$ and $\overline{\sigma} = [\sigma^x, \sigma^y]^T$ are the vectors that represent the memory level, asymptotic mean and asymptotic standard deviation, respectively.

A node in a Gauss-Markov model is forced to remain away from the boundary of the simulation area by changing/flipping its direction by 180 degree whenever it reaches near the boundary. The memory level $\overline{\alpha}$ plays an important role in determining the level of temporal dependency in node movement where $0 \leq \overline{\alpha} \leq 1$. As $\overline{\alpha}$ tends to 1, its current velocity becomes more dependent on the previous velocity.

Smooth random mobility model (SR) [29]: Due to unrealistic nature of node movement in random waypoint, Bettstetter [29] proposes incremental and smooth change in node velocity instead of sharp turn and sudden acceleration and deceleration. It has been observed that nodes in real life move at certain preferred speeds $V^1_{pref}, V^2_{pref}, \ldots, V^n_{pref}$, rather than at speeds purely uniformly distributed between $[0, V_{max}]$. Therefore, in smooth random mobility model, the probability distribution of node velocity is as follows: the speed within the set of preferred speed values has a high probability, while uniform a distribution is assumed on the remaining part of entire interval $[0, V_{max}]$. In Smooth Random Mobility Model, the frequency of speed change is assumed to be a Poisson process. The speed of mobile node is changed incrementally from the current speed $v(t)$ to the targeted new speed $v'(t)$ by an acceleration speed or a deceleration speed of $a(t)$. The probability distribution function of acceleration or deceleration $a(t)$ is uniformly distributed among $[0, a_{max}]$ and $[a_{min}, 0]$ respectively.

Thus, the speed may be controlled to increase or decrease continuously and incrementally. If $a(t)$ is a small value, then the speed is changed slowly and the degree of temporal correlation is expected to be strong. Otherwise, the speed can be changed quickly and the temporal correlation is small. However, unlike speed, direction is assumed to be purely uniformly distributed in the interval $[0, 2\pi]$. Once a movement direction is chosen, the node moves in a straight line until the direction changes. The direction difference $\Delta\delta(t)$ between the new direction and old direction is distributed in the interval $[-\pi, \pi]$ and this change may be a large value. However, to make this direction change smooth, $\Delta\delta(t)$ is divided into several incremental small direction changes $\Delta\varphi(t)$. Hence, this change can be achieved in $\frac{\Delta\delta(t)}{\Delta\varphi(t)}$ time slots. For each time slot in the period of direction change, the mobile node only changes its movement direction by $\Delta\varphi(t)$ degree as follows:

$$\delta(t + \Delta t) = \delta(t) + \Delta\varphi(t)$$

Thus, in smooth random mobility model both speed and movement direction is partly decided by their previous values thus capturing some degree of temporal dependency. The degree of temporal dependency is affected by its acceleration $a(t)$ and the maximum allowed direction change per time slot $\Delta\varphi(t)$.

Semi-Markov smooth mobility model (SMS) [30]: Zhao *et al.* [30] found several flaws with GM and SR mobility models. A MN following SR movement may have new speed change during the speed transition and does not stop unless the target speed is specified as zero, which is not flexible for movement control. In the GM model, mobile nodes cannot travel along a straight line as long as the temporal correlation (memory) parameter is not equal to 1, and they do not stop during the simulation, which is quiet contrary to the real life mobility.

The Semi-Markov Smooth (SMS) mobility model consists of four consecutive phases viz., Speed Up or accelerating phase, Middle Smooth phase, Slow Down or deceleration phase, and Pause phase based on the physical laws of motion. Each phase lasts for certain but unequal time intervals which are arbitrarily selected at the beginning of each phase. Each phase is again quantized into k equi-distant time steps (Δt), where $k \epsilon \mathbb{Z}$. For example, if the speed up phase has α quantas, then this phase lasts for $[t_0, t_\alpha] = [t_0, t_0 + \alpha\Delta t]$. The three parameters, that is, target speed v_α, target direction ϕ_α and number of quantas or times steps α are selected from the range $[v_{min}, v_{max}]$, $[0, 2\pi]$ and, $[\alpha_{min}, \alpha_{max}]$ respectively at the beginning of each phase. The direction during the step up phase does not change. In the smooth phase, the speed and direction may change depending on the memory variable ζ which ranges over [0, 1]. Thus, by adjusting the parameter ζ, we can easily control the degree of temporal correlation of velocity between two consecutive steps. In slow down phase the node eventually decelerates from the final speed in v_β (in smooth phase) to 0, without changing the direction, using some definite number of time-steps γ selected from the range $[\gamma_{min}, \gamma_{max}]$. The authors show that SMS has uniform node distribution and can also be extended to group mobility models and adapted to geographic constraints.

Boundless simulation area mobility model (BSA) [31]: In Boundless Simulation Area Mobility Model, a relationship exists between the previous direction of travel and velocity of an MN with its current direction of travel and velocity. A velocity vector $\overline{v} = (v, \theta)$ is used to describe an MN's velocity v and its direction θ; the MN's position is represented as (x, y). Both the velocity vector and position vector are updated at every Δt time steps according to the following formulae:

$$\begin{aligned}
v(t + \Delta t) &= min\left[max\left(v(t) + \Delta v, 0\right), V_{max}\right];\\
\theta(t + \Delta t) &= \theta(t) + \Delta\theta;\\
x(t + \Delta t) &= x(t) + v(t) \times \cos\theta(t);\\
y(t + \Delta t) &= y(t) + v(t) \times \sin\theta(t); \qquad (2)
\end{aligned}$$

where V_{max} in (2) is the maximum velocity defined in the simulation, Δv is the change in velocity which is uniformly distributed between $[-A_{max} \times \Delta t, A_{max} \times \Delta t]$, A_{max} is the maximum acceleration of a given MN, $\Delta\theta$ is the change in direction which is uniformly distributed between $[-\alpha \times \Delta t, \alpha \times \Delta t]$, and α is the maximum angular change in the direction an MN is travelling. In the Boundless Simulation Area Mobility Model, MNs that reach one side of the simulation area continue travelling and reappear on the opposite side of the simulation area. This technique creates a torus-shaped simulation area allowing MNs to travel unobstructed.

Apart from the above mobility models, we have the Continuous Time Markovian Model [60] and the Discreet Time Markovian Model where nodes move between "hubs" and meet only when any two nodes are within the same hub. Community based mobility model (Section III-C [2]) and other human mobility models are a generalization of the above two models with strong node inter-dependence.

3) Models With Spatial Dependency: Movements of nodes are not always random or have temporal dependency. It has been observed on many occasions that the destination of a node may be dependent on its current location. Such node movements are said to have spatial dependency as the location of a node at next time instant is probabilistically related to its location at the present time instant.

Probabilistic random walk mobility model (PRW) [32]: A probabilistic random walk mobility model uses a probability matrix to determine the position of a particular MN at the next time instant, which is represented by three different states for position x and three different states for position y. State 0 represents the current position (x, y) of a MN, state 1 represents the MN's previous position and state 2 represents the MN's next position if the MN continues to move in the same direction. The probability matrix is:

$$\begin{bmatrix} P(0,0) & P(0,1) & P(0,2) \\ P(1,0) & P(1,1) & P(1,2) \\ P(2,0) & P(2,1) & P(2,2) \end{bmatrix}$$

where each entry $P(a, b)$ represents the probability that MN will go from state a to b. The values within this matrix are used for updating both the x and y position of a MN and each node moves randomly with a preset average speed.

This implementation produces probabilistic rather than purely random movements, which may yield more realistic behaviors. For example, as people complete their daily tasks they tend to continue moving in a semi-constant forward direction. However, choosing appropriate values of $P(a, b)$ may prove difficult, if not impossible, for individual simulations unless traces are available for a given movement scenario.

4) Models With Geographic Restriction: Sometimes node movement may be restricted to a bounded area; for example movement in a conference area or in an academic institution and campus. Such mobility models are said to have geographic restriction. For example, movement of an individual may be guided by pathways and obstructed by buildings. It may also depend on the specific role of an individual.

Pathway or city section mobility model (PW/CS) [33]: In real life nodes do not move randomly, but along predefined path on a map; that is mobility of nodes have a geographic constraints. The map is predefined in the simulation field. Tian *et al.* [34] utilize a random graph to model the map of city. This graph can be either randomly generated or carefully defined based on certain map of a real city. The vertices of the graph may represent the buildings of the city, junctions or turns and the edges model the streets and freeways between two any junctions. Initially, the nodes are placed randomly on the edges of the graph. Then for each node a destination is randomly chosen and the node moves towards this destination through the shortest path along the edges. Upon arrival, the node pauses for a certain time T_{pause} and again chooses a new destination for the next movement. This procedure is repeated until the end of simulation.

To incorporate a more realistic approach, streets may have speed limits and MNs may accelerate and decelerate while moving. There are some other variations of pathway mobility model like freeway and Manhattan mobility model [35]. However, since the destination of each motion phase is randomly chosen, a certain level of randomness still exists for this model. So, in this graph based mobility model, the nodes are travelling in a pseudo-random fashion on the pathways.

Obstacle mobility model [36]: Another geographic constraint playing an important role in mobility modeling includes the obstacles in the simulation field. To avoid the obstacles on the way, the mobile node is required to change its trajectory. Therefore, obstacles do affect the movement behavior of mobile nodes. Moreover, the obstacles also impact the way radio propagates. For example, for the indoor environment, typically, the radio system could not propagate the signal through obstacles without severe attenuation. For the outdoor environment, the radio is also subject to the radio shadowing effect. When integrating obstacles into mobility model, both its effect on node mobility and on radio propagation should be considered. Jardosh *et al.* [36] also propose and implement an obstacle based scenario where they randomly place some obstacles in the simulation field. These obstacles are utilized to both restrict node movement as well as wireless transmissions. The obstacles are placed within a network area to model the location of buildings within an environment, for example, a college campus. In addition to the inclusion of obstacles, they construct movement paths using the Voronoi diagram [37] of obstacle vertices. Nodes are then randomly distributed across the paths, and use shortest path route computations to destinations at randomly chosen obstacles. Moreover, in this model nodes are allowed to enter and leave the building. Also when nodes transmit, the obstacles obstruct the propagation of the transmission in an area defined as the obstruction cone of the node.

Event-driven and role-based mobility model (EDRB) [38]: Event-driven and role-based mobility model is based on the human movement caused due to environmental or local events and role that an individual may have at any given time. Nelson *et al.* [38] simulate such mobility in a disaster recovery scenario. They argue that different classes of individuals are attracted (or repelled) towards (or away from) a given event depending on their roles. For example, civilians may flee from a disaster prone area while rescue workers and army personnel may be attracted towards the event to maintain law and order. The authors used gravitational model to realize this attraction/repulsion nature of individuals. Additionally, each event has an event horizon defined as the maximum distance upto which an event affects objects. Each entity in the disaster scenario is represented by a triplet as (role, event, action). For example, (Civilian, In event Horizon, Flee) or (Police, In Event Horizon, Approach).

By simulating the scenario they observed a clustering effect around the disaster prone area. Thus the total area is divided into three primary areas: 1) Areas inside event horizon, 2) Areas at or near event horizon, and 3) Areas outside event horizon. They show that average node density in the disaster mobility model increases in response to events. This is due to the gathering of nodes around the event horizon, forcing them into smaller regions. This however makes the network highly partitioned compared to random waypoint or random walk indicating a more fragile network.

Affinity based mobility model [39]: This is another form of mobility model with geographic restriction. It has been observed (in real life) that MNs within a given playfield tend to remain confined to a given area or has more affinity towards a certain region over other. The spatial distribution of nodes is not equal or uniform over a given area. The nodes depending on their nature, may spend more time and visit more frequently a given region (known as hot spots) compared to other regions. For example, students within a campus tend to remain near classes or canteens than other places such as staff/faculty rooms. In this, the entire area is divided into number of regions, such as classrooms, canteens, playground, library, etc and each region denoted by their max-min co-ordinates (x_{min}, y_{min}) and (x_{max}, y_{max}). To keep the model simple, the nodes within a given region move randomly following random waypoint or random walk mobility model. Each node in the network has a certain degree of "biasness" (d) towards one or more regions, where $0 \leq d \leq 1$. $d \geq 0.5$ suggests a positive bias and $d < 0.5$ suggests negative bias. For example, if the degree of biasness or affinity towards a certain region is denoted by:

$$x_{min} \leq x \leq x_{max},\ y_{min} \leq y \leq y_{max}\ for\ d = 0.8$$

the chance of finding the node within the biased area is 80% and in other area is 20%. However, affinity towards a given region may vary from one region to another. Even this causes a certain degree of clustering (within the biased area) and causes the network to be partitioned. Moreover, there is still some degree of randomness within a given area.

There are several other simplified models which capture such geographic restriction. For example, we have the Home-Markovian Evolving Graph (Home-MEG) [101] model which is a simple pair-wise contact model based on the observation that pairs of nodes in the network tend to meet in very few, selected locations (home locations). We also have the graph based mobility models which uses randomly generated graphs for node movement.

C. Correlated/Group Based Mobility Models

Group based mobility models are those in which nodes tend to move in groups and behave in a co-operative manner. The waypoint of a node is largely affected by the other members that belong to the group. They tend to form clusters and rarely deviate from a reference point within the group. The group based mobility model includes six models viz., a) Reference Point Group mobility model, b) Column mobility model, c) Pursue mobility model, d) Nomadic Community mobility model, e) Exponential Correlated Random mobility model, and f) Heterogeneous Random Walk.

Reference point group mobility model (RPGM) [40]: In reference point group mobility model the entire node population is divided into number of groups, with each group having a leader. The leader can be a logical center or a pre-defined leader node. The motion of the group center completely characterizes the movement of its corresponding group of MNs, including their direction and speed. Individual MNs randomly move about their own pre-defined reference points, whose movements depend on the group movement. Both the movement of the logical center for each group, and the random motion of each individual MN within the group are implemented via the Random Waypoint Mobility Model. For each node, mobility is assigned with a reference point that follows the group movement. Upon this predefined reference point, each mobile node could be randomly placed in the neighborhood. Formally, the motion vector of group member i at time t, $\vec{V}_i^t$, can be described as:

$$\vec{V}_i^t = \vec{V}_{group}^t + R\vec{M}_i^t \tag{3}$$

where in $\vec{V}_{group}^t$ in (3) is the group motion vector and $R\vec{M}_i^t$ is a random vector deviated by group member i from its own reference point. The vector $R\vec{M}_i^t$ is independent identically distributed (i.i.d) random process whose length is uniformly distributed in the interval $[0, r_{max}]$ (where r_{max} is maximum allowed distance deviation) and whose direction is uniformly distributed in the interval $[0, 2\pi]$.

The RPGM was first proposed in [40] and then used in [41].With appropriate selection of predefined paths for group leader and other parameters, the RPGM model is able to emulate a variety of mobility behaviors. Some different applications of RPGM were also proposed:

- **In-place mobility model**: the entire field is divided into several adjacent regions. Each region is exclusively occupied by a single group. One such example is battlefield communication.
- **Overlap mobility model**: different groups with different tasks travel on the same field in an overlapping manner. Disaster relief is a good example of this model.
- **Convention mobility model**: this scenario is to emulate the mobility behavior in the conference. The area is also divided into several regions while some groups are allowed to travel between regions.

Several variations of RPGM such as Reference Velocity Group Mobility Model (RVG) [42] and Structured Group Mobility Model (SG) [43] were further developed to meet the demands of real life mobility characteristics.

Column mobility model [44]: The Column Mobility Model represents a set of mobile nodes (e.g., row of soldiers marching together) that move in a certain fixed direction. This mobility model can be used in searching and scanning activity, such as destroying mines by military robots. The nodes move relative to a reference point on a reference grid, which should be initially defined. The MNs are allowed to move randomly around this reference point (authors proposed random walk mobility model) which is updated periodically after a certain time instant. The new reference point is defined as:

$$new\_reference\_point = old\_reference\_point + advance\_vector$$

where $old\_reference\_point$ is the MN's previous reference point and $advance\_vector$ is a pre-defined offset to move the reference grid at time t. The predefined offset that moves the reference grid is calculated via a random distance and a random angle (between 0 and π since movement is in a forward direction only). If a node tends to move beyond the boundary, its direction is flipped by 180 degree.

Pursue mobility model [44]: The Pursue Mobility Model emulates scenarios where several nodes attempt to capture single mobile node ahead or MNs tracking a particular target. For example, this model could represent police officers attempting to catch an escaped criminal. The node being pursued can move freely according to any mobility model (such random walk or random waypoint) and other nodes move using a single update equation:

$$new\_position = old\_position + acceleration \times (target - old\_position) + random\_vector$$

where $acceleration \times (target - old\_position)$ is information on the movement of the MN being pursued and $random\_vector$ is a random offset for each MN and can be used to control the degree of randomness.

Nomadic community mobility model (NC) [44]: The Nomadic Community Mobility Model is to represent the mobility scenarios where a group of nodes move together. This model could be applied in mobile communication in a conference or military application. Within each community or group of MNs, individuals maintain their own "personal spaces" where they move in random ways. A class of students touring an art museum is a good example of such mobility model where individual students may roam around the given reference point. The whole group of mobile nodes moves randomly from one location to another based on changes in reference point. Unlike column mobility where each node has its own reference point, this model has only a single reference point for the whole group. Moreover, the movement in nomadic community mobility model is sporadic while it is more or less constant in column mobility model.

Exponential correlated random mobility model (ECR) [45]: This is one of the first group mobility models to be proposed. In this model, a motion function is used to create MN movements. Given a position $\vec{b}(t)$ (MN or group) at time t, $\vec{b}(t+1)$ is used to define the next position of MN or group at time $t+1$. Therefore,

$$\vec{b}(t+1) = \vec{b}(t)e^{-\frac{1}{\tau}} + \left(\sigma\sqrt{1-\left(e^{-\frac{1}{\tau}}\right)^2}\right) r \tag{4}$$

where τ in (4) adjusts the rate of change from the MN's previous location to its new location (i.e., small τ leads to large change) and r is a random Gaussian variable with variance σ. However, it is not possible to create a given motion pattern by selecting appropriate values for (τ, σ) in the exponential correlated random mobility model.

Heterogeneous random walk (HRW) [46]: This mobility model was proposed for the simulation of clustered networks. In this model the simulation area is divided into two sections, C and $\overline{C}$. C is the union of M circles which have uniformly distributed centers and radius R, and $\overline{C}$ represents the remaining part of the simulation area. Each node performs Random Walk within a given circle but having heterogeneous speeds.

D. Human or Sociality Based Mobility Models

Human or sociality based mobility models finds its application in Pocket Switched Networks (PSN) [47]. Humans are social animals; hence their movement is largely governed by the type of community to which they belong. Moreover, people tend to remain confined to their own social group and rarely move outside it. Hence, numerous mobility models have been developed, especially with respect to human movement, inspired by the idea of social network. For example, people spend their day in office, evening in pub/bars and return home at night.

Community based mobility model [48]: In mobile ad-hoc networks, the movement of mobile devices carried by humans is based on human decision and socialization behavior. Humans by nature tend to socialize and form communities. They move in groups and in between groups. This mobility model (inspired by social networks) captures the social nature of humans and is heavily dependent on the structure of relationships among the people carrying devices. To model social relationship, the authors used an *Interaction matrix*. Each element $m_{i,j}$ of the matrix represent the strength of interaction between any two individuals i and j. From the interaction matrix, a connectivity matrix (C) is obtained where a $c_{i,j} = 1$ if and only if $m_{i,j}$ is greater than a certain threshold (say 0.25) or else a $c_{i,j} = 0$. From the connectivity matrix they detect the community structures in social network by means of algorithms proposed by Newman and Girvan [49]. Each community is initially placed within a specific location or a square inside a grid.

The position of a given node changes after a time-interval t and the next destination of a node depends on the position of other nodes with which it has a strong social connectivity. For example, if B is connected to A, then B will influence the choice of A's destination proportional to the weight of their social relationship. Thus any given node may be found in a different community at different time instant. This is consistent with real life human activity, since a person may be found at different locations at different times of a day. Example, from morning till afternoon a person is most likely to found in his office, in the evening he is among his friend (in pub/bar) and at night he is (at home) among his family members. However, it may so happen that node communities may change over a (long) period of time and a node may no longer belong to a community. Such characteristics is not captured by this model.

Time-variant community model (TVCM) [50]: By analyzing a large amount of Dartmouth WLAN traces, the authors observed two important mobility characteristics which have not been captured in earlier mobility models. The authors identified skewed location visiting preferences and periodical re-appearance at the same location as two prominent trends existing in multiple traces. Skewed location visiting preferences address how one spends its time at different location. From the traces authors observed that a node on average spends 65% of its online time at a given AP and more than 95% of online time at as few as 5 APs. Periodical re-appearance at the same location captures the time period after which a node tends to visit the same location again.

In TVCM, communities are assigned to each node and nodes visit its own community more often than other areas. Different nodes are assigned different communities and hence do not behave identical to one another. To implement periodic re-appearance at the same location, time structure is divided into time periods. Each time period is again divided into two parts viz., normal movement period (NMP) T_m, and concentration movement period (CMP) T_c. A high probability can be assigned for a node to visit its own community during CMP, so that it re-appears at its community after a period of $T_m + T_c$. Such structure in time not only creates periodicity, but also naturally captures the omnipresent time-dependent behavior in our daily lives, e.g., people go to offices during working hour, restaurants for lunch during noon time, and home after work with higher probability [51].

Working day movement model (WDMM) [52]: The working day movement model (WDMM) is intended to capture the daily life movement pattern of humans from morning till night. People tend to move from one place to another depending on the time of the day and spend certain amount of time at a given location. WDMM is a combination of 4 different sub-models viz, home activity sub-model, office activity sub-model, evening activity sub-model, and transport sub-model. These sub-models are repeated everyday which represent the periodic and repetitive movement pattern of humans. Each node is assigned a home location and a wake-up time, which determines when a node should start from home. At wake time nodes leave their homes, and use different modes of transport like buses and cars to travel to work.

Home activity sub-model is used for evening and night while office activity is used for day time. The nodes can move inside office and is assigned a desk. It stays in its desk for a certain amount of time (drawn from pareto distribution) and then randomly select a new co-ordinate inside office where it again waits for certain amount of time. The movement between desk and randomly selected co-ordinate repeats until the work day is over. For node movement from home to office and back, transport sub-model is used. The evening activity sub-model is used when nodes move in groups to some selected area like clubs or pubs where they spend certain amount of time. After a certain amount of time, they split and use transport model to travel back to their home. The transport sub-model again consists of walking, car and bus sub-models. All the nodes move on a map which defines the space and the routes over which nodes can move.

However, this model still lacks some details like speed limits, traffic queues and changes in mobility due to various factors like traffic jam, obstacles, etc. Moreover, human mobility is not same everyday and may vary from day to day. A slight variation of WDM was proposed as Interest based Model [53] where the entire area was partitioned into number of activity areas each having certain degree of attraction.

Sociological orbit aware location approximation and routing (SOLAR) [111]: SOLAR takes its concept from repeated visit by an individual to a closed set of locations. It has been observed that the humans routinely spend certain amount of their daily lives at specific locations which authors call as *hubs*. Hence, the *mobility profile* of an individual is a repetition of inter-hub movement that is, the movement is mostly orbital or periodic. SOLAR takes advantage of the "macro-mobility" information obtained from the sociological movement pattern of mobile DTN users [111].

In SOLAR the entire playfield is divided into number of hubs. Each node randomly selects a hub-list which is the set of hubs a node can visit. Each node stays or moves inside the hub based on the *hub-stay time* and then moves over to the next hub. At any point of time a fresh list of hubs can be selected by any node. Intra-hub movement can be random waypoint or random walk and inter-hub movement is linear. This model can represent the heterogeneously limited walkabout areas [111] for different people, that is different people mostly move about their own confined area.

Sociological interaction for population simulation (SIMPS) [54]: Sociological Interaction for Population Simulation (SIMPS) aims at modeling human crowds with pedestrian movement. The authors try to find out the causes of human mobility and the driving force behind the nature of human mobility. SIMPS is a translation of "sociostation" in the domain of human motion: each individual tries to regulate her socialization to her own sociability (intrinsicality) by the effect of her actions (interactivity). In SIMPS each individual is associated with sociability level and a context-aware indicator. To meet the desired sociability level, individuals alternately tend to socialize (meet with other individuals) or isolate (move away from individuals). Hence, individuals constantly try to stay at an equilibrium level of sociability. The context-awareness indicates the individual's perception of current socialization i.e., number of individuals in current surrounding, presence of undesired individuals, etc. Thus the effect of socialize and isolate behavior respectively raise or lower one's perceived surrounding. To model the above behavioral pattern, SIMPS is divided into two parts; social motion influence and motion execution unit. The social motion influence updates an individual's current behavior to either socialize or isolate. The motion execution unit is responsible for translating the behavior adopted by an individual into motion.

Small world in motion (SWIM) [55]: SWIM or Small World in Motion mobility model is based on two simple facts of human mobility; 1) people tend to frequently visit some popular locations which are near to their home and rarely visit places which are far away and less popular, and 2) people spend most of their time at these popular places and less time at places which are less popular.

In SWIM, each node is assigned a home location. The entire area is divided into number of destination points and each destination is assigned a weight proportional to the popularity of the destination and inversely proportional to the distance of the destination from the home location. Once a node selects a new destination it starts moving towards it with constant speed. Every time a node visits a destination its popularity is updated depending on number of nodes that are present at the same time. After a node reaches a destination it stays there for some time and then chooses a new destination. The authors show that

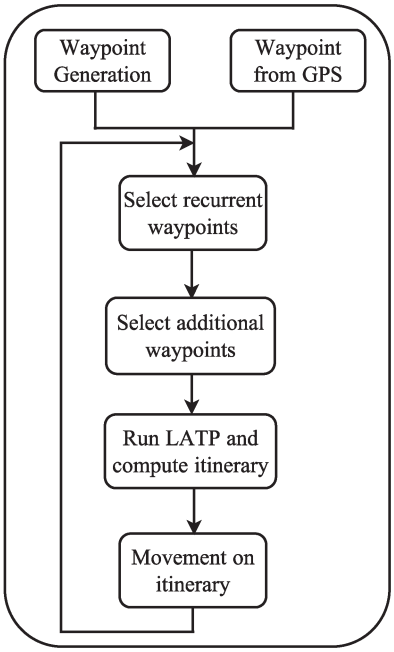

Fig. 2. Diagramatic representation of SLAW.

SWIM is able to exhibit a power law and exponential decay dichotomy (Section IV-B) and that it can accurately predict the performance of forwarding protocols.

Self-similar least action walk (SLAW) [56]: The Self-Similar Least Action Walk (SLAW) is developed to incorporate five important features of human mobility:

- Heavy-tail flight and pause-time distribution
- Heterogeneously bounded mobility areas of individuals
- Truncated power-law inter-contact times
- Self-similar dispersal of destinations
- Least-action trip planning (LATP)

Self-similar dispersal of waypoints implies that people are always attracted to popular places and their visiting destinations are heavily clustered. That is the more popular places are heavily clustered while the less popular places are far from each other. This is also known as the fractal distribution of waypoints. Moreover, places with high popularity are rare and places with less popularity are plenty. Slaw takes two parameters; a Hurst parameter value and a weight on distance in performing LATP. The Hurst value decides the degree of self-similarity for waypoint (destination) dispersion. The weight factor of LATP determines the likelihood of visiting a nearby destination from any of the multiple destinations. Fig. 2 shows the diagrammatic representation of SLAW.

Home-cell community based mobility model (HCMM) [57]: The authors identified three important phenomenon of human mobility. First, larger the social network, higher is the mobility and vice-versa. This implies that nodes will move frequently and will visit more locations if they have many "friends" scattered all over the network. Second, users tend to visit just a few locations, where they spend most of their time. That is, node densities are unevenly distributed and there occurs concentration points like malls, universities, offices, etc. Third, users prefer short paths over long paths. That is there are occasional short flight distances and very rare long flight distances. Thus, HCMM is developed to incorporate all these movement properties. Besides this HCMM joins social and location attractions i.e., it integrates social nature of mobility with its spatial dimension. Therefore, HCMM is a simple extension of CMM which adds spatial attraction and incorporates power-law distribution of the jumps. As in CMM, nodes are organized into social communities, and each community is initially assigned to one of the cells of the grid. Differently from CMM, HCMM, as the name suggests, uses the concept of home cell. Each user is assumed to belong to a main social community (at any given point in time). The user's home cell is defined as the cell within which the members of the user's main social community preferentially move. As in CMM, in HCMM when a node is located in its home cell, it selects its cell or another cell according to the social attraction exerted on it. Unlike in CMM, in HCMM the social attraction (SA_{C_i}) exerted by a generic cell C_i is computed as the sum of the weights of the social links between node x and all nodes that have C_i as their home cell, irrespective of their current location:

$$SA_{C_i} = \frac{\sum_{y \epsilon C_i} W_{xy}}{|C_i|}$$

Heterogeneous human walk (HHW) [58]: The main aim of Heterogeneous Human Walk (HHW) mobility model is to generate realistic mobility patterns, especially heterogeneous human popularity based on the observation of social networks. It also tries to capture the spatio-temporal regularity of human mobility. The heterogeneous popularity can be global or local. A node has a local popularity within its community and a global popularity across the whole network. Since a node can belong to multiple communities, it can have multiple local popularities.

The HHW model is composed of three components viz., establishment of overlapping community structure and heterogeneous local degree, mapping communities into geographical zones and driving individual motion. To make the model simple HHW directly constructs synthetic overlapping communities by using three parameters viz., community size, overlap size, and membership number. The membership number denotes the number of different communities to which a node belongs; overlap size denotes the number of individuals that are common to any two communities and community size denotes the number of members present in the community. The node movement is modeled similar to community based mobility model (CMM).

General social mobility model (GeSoMo) [59]: GeSoMo (General Social Mobility Model) is a social mobility model that generates a number of existing models by separating the social mobility model (SMM) from social network model (SNM). Social network model can be used to generate social network which can be fed to GeSoMo that creates mobility pattern or traces. The traces can be used for simulating a network of mobile nodes. The model consists of certain points (or locations) called *anchors* where social interaction occurs between the nodes. Anchors exert time-varying *attractions* on nodes which causes a node to move from one anchor to other creating spatial and temporal regularities. Nodes are also *attracted* or *repulsed* based on the strength of their social relationship. At the beginning, each node is assigned a home location or anchor point.

Thus, GeSoMo is able to generate mobility traces which have the spatio-temporal characteristics observable in real life mobility traces. The authors by comparing the model with real-life mobility traces show GeSoMo produces realistic mobility characteristics.

SMOOTH [107]: SMOOTH mobility model was proposed by Munjal *et al.* [107] to incorporate two important characteristics of human mobility viz., truncated power-law distribution of flight length and pause times. The entire simulation area is divided into number of *Landmarks* which represent each cluster or communities. Each mobile node is initially and placed inside a randomly selected cluster. To simulate motion, each mobile node chooses to explore a new location with the probability proportional to the number of distinct locations visited so far. For the new location first the flight length is generated using a power-law distribution. If a node chooses to visit one of the locations it has visited before, the location is selected with probability proportional to the total number of times the node has visited the location so far. Node velocity is proportional to the flight length and pause time follows truncated power-law distribution.

Statistical Area-based MObility model for VirtuAl and Real-world environments (SAMOVAR) proposed by Shen *et al.* [108] is another human based mobility model which follow the same concept (as SMOOTH) but has been derived or recreated from real world traces.

Spatio-temporal mobility model (STEP) [60]: Most human mobility models consider only the spatial properties of human mobility while ignoring the temporal features. Human contact patterns reveal that individuals meet not only because they are at the same place but because they are at the *same place* (spatial property) at the *same time* (temporal property). STEP uniquely models *lifecycles*[2] of hotspots as their temporal variations of populations located in those hotspots and uses the lifecycle as a factor of time-varying attraction to a hotspot. (e.g., a restaurant supposed to gather people at lunch or dinner time may have higher value of lifecycle at such moments compared to the rest of a day so as to attract more people to come to the place at those moments).

In STEP the waypoint map is divided into rectangular grids each representing a hotspot. The change in population density over time (known as the periodicity) is approximated by Fourier Transform. Each LCF may contain one or more *primary period* when the population density crosses certain threshold. The average population of a hotspot h is made proportional to W^h and number of primary periods inversely proportional to W^h where W is the set of all waypoints and W^h represents the number of waypoints in h. The individual mobility is modeled as a sequence of trips to randomly selected hotspots. Each hotspots contain a number of waypoints and the order of visits to these waypoints is determined as a function of distances to the waypoints and the LCFs of the hotspots. STEP is shown to have better statistical realism than the existing models in terms of flight and ICT distributions as well as temporal distance distribution.

[2]A life cycle function (LCF) of a hotspot is the function representing the changes of population over time.

Table II shows the comparative study of Entity, Group based and Sociality based mobility models. Fig. 3 depicts a comparison based on some qualitative aspects of mobility models. The qualitative features which have been included are: a) Realistic, Scope: whether a given mobility model is realistic and is able to imitate observed mobility close enough to be used for network performance evaluation. Moreover some models are restricted to specific scopes and cannot be used as generic mobility model. b) Scalable: whether the mobility model is able to incorporate an increasing number of nodes *easily* without affecting the observed properties of the model, c) Mathematical representation and analysis: some mobility models or its parameters can be represented by a closed equation; for example the flight length of Lévy walk model can be represented by $f_L(l) \sim l^{-\mu}, 1 < \mu < 3$, d) Use of social graph: some models like CMM and HCMM use social graphs to control the node movements, e) Use of geographic map: some models use geographic map over which nodes can move, f) Can be simulated: some models cannot be easily simulated simply due to complexity of the model or due computational overhead. Some models are too heavy such that they do not observe the scalability property. If a model satisfies a given property we denote it by Y (yes) or else N (no). Some properties of a given mobility model are subjected to dispute and are debatable. We denote such properties as A (ambiguous).

E. Vehicular Mobility Models

Vehicular Communication has become an integral part of intelligent transport system (ITS) and is the key factor in maintaining the road safety. Vehicular communication consists of two basic components viz., vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I). V2V and V2I communication has been used in information dissemination, travel time prediction and congestion management. Categorized under VANET, a number of application and routing protocols has been developed for V2V and V2I communication, whose evaluation strictly depends on modeling vehicular mobility. Vehicular mobility model emulate vehicle movement along road/highway, changes in speed, movement in queues and stops at traffic signals. Moreover, vehicle movement follow shortest path algorithm from a given source to a destination. To model the movement of vehicles, vehicular mobility model has been developed. Early works such as [61], classfied vehicular mobility into either microscopic or macroscopic. However, according to [79], the authors classified vehicular mobility model into a) Synthetic models, b) Survey based models, c) Trace-based models, and d) Traffic Simulator-based models. Fig. 4 shows the taxonomy of vehicular mobility models proposed in [79].

1) Synthetic Models: These are mathematical models developed considering the physical motion characteristics of vehicles. Fiore [63] classified this type into 5 sub-categories;

TABLE II
A COMPARISON OF MOBILITY MODELS

	Mobility Models	Speed	Direction/Destination	Acceleration/ Deceleration	Pause Time	Flight Length	Return Time/Visiting Frequency
Entity Mobility Models	RWP[18]	UD	NA	NA	C/UD	NA	NA
	RD[19]	UD	UD	NA	C//UD	NA	NA
	TLW[26]	C	UD	NA	TPL	TPL	NA
	RW[27]	UD	UD	NA	C/UD	C	NA
	GM[28]	HB+ML	UD	NA	C/UD	NA	NA
	SR[29]	UD over preferred set of velocities	UD	UD	C/UD	NA	NA
	SMS[30]	UD	UD	UD	NA	NA	NA
	BSA[31]	HB	HB	UD	C/UD	NA	NA
	PRW[32]	UD	PD	NA	C	NA	NA
	PW/CS[33]	C/UD	UD on set of waypoints	NA	C/UD	NA	NA
	Obstacle[36]	C/UD	UD on set of waypoints	NA	C/UD	NA	NA
	EDRB[38]	R	C	R	NA	NA	NA
	Affinity[39]	C	PD	NA	C/UD	NA	NA
Correlated Mobility Models	RPGM[40]	Based on Reference point	Based on Reference point	NA	C/UD	NA	NA
	Column[44]	C	Based on Reference point	NA	NA	NA	NA
	Pursue[44]	C	C/HB	C	NA	NA	NA
	NC[44]	NA	Around Reference point	NA	NA	NA	NA
	ECR[45]	C/UD	HB	NA	C/UD	NA	NA
	HRW[46]	C/UD	C	NA	C/UD	NA	NA
Human Mobility Models	CMM[48]	NA	PD	NA	C	NA	P
	TVCM[50]	NA	PD	NA	C	NA	P
	WDMM[52]	C/UD	C	C/UD	C	NA	P
	SIMPS[54]	C/UD	C	NA	C	NA	P
	SWIM[55]	NA	UD on set of locations	NA	C/UD	NA	P
	SLAW[56]	NA	PD on set of destinations	NA	TPL	TPL	P
	SMOOTH[107]	NA	PD on set of destinations	NA	TPL	TPL	P
	SAMOVAR[108]	NA	PD on set of destinations	NA	TPL	TPL	P
	HCMM[57]	NA	PD on set of communities	NA	NA	PD	P
	HHW[58]	C/UD	PD on set of communities	NA	C/UD	NA	P
	GeSoMo[59]	NA	PD on set of destinations	NA	C	NA	P
	STEP[60]	NA	PD on set of hotspots	NA	C/UD	NA	P

C: Constant, HB: History Based, ML: Memory Level, NA: Not Applicable, P: Periodic,
PD: Probabilistically Distributed, R: Random, TPL: Truncated Power-law, UD: Uniformly Distributed

stochastic models, traffic stream models, car following model, queue model and behavioral model.

- Stochastic model: In this model the vehicles move in a purely random motion.
- Traffic Stream Model / Fluid Traffic Model: In this, vehicular movement is similar to the motion of fluid through a pipeline or a channel. The speed of the vehicle is adjusted given the local density of the traffic.
- Car-following Model: In this model the movement of a car depends on the motion of a car ahead of it. A number of models have been developed based on car following model such as Krauss model [64], Nagel and Schreckenberg Model [65], Wiedeman Psycho-Physical model [66], General motors model [67], Gipps model [68], and intelligent driver model (IDM) [69]. There are other models such as lane changing models [62] and intersection models.
- Queue Model: In this the vehicles move as FIFO queue.
- Behavioral Model: In this model, each movement of the car is determined by social influences.

2) Survey-Based Models: Survey based mobility models are developed by collecting extensive statistical data and then incorporating such statistics into a generic mobility model. UDel mobility model [70] typically falls into this category. Vehicular statistics can be collected from a central traffic repository which records periodic lane based traffic data such as vehicle

Mobility Model	Realistic, Scope	Scalable	Can be mathematically represented or analysed	Uses social graph	Uses geographic map	Can be simulated
RWP	N	Y	Y	N	N	Y
RD	N	Y	Y	N	N	Y
TLW	A	A	Y	N	N	N
RW	N	Y	Y	N	N	Y
GM	N	Y	Y	N	N	Y
SR	N	Y	Y	N	N	Y
SMS	N	Y	Y	N	N	Y
BSA	N	Y	Y	N	N	Y
PRW	N	Y	A	N	N	Y
PW/CS	N, City	Y	N	N	N	Y
Obstacle	A, City	Y	N	N	A	Y
EDRB	N, Disaster Scenario	Y	N	N	A	Y
Affinity	N	Y	Y	N	N	Y
RPGM	N	Y	A	N	N	Y
Column	N	Y	Y	N	N	Y
Pursue	N	Y	Y	N	N	Y
NC	N, Nomadic Movement	Y	N	N	N	Y
ECR	N	Y	Y	N	Y	Y
HRW	N, Clustered Network	Y	A	N	N	Y
CMM	Y	Y	N	Y	N	Y
TVCM	Y	Y	Y	N	Y	Y
WDMM	Y	Y	N	N	Y	Y
SIMPS	Y	Y	A	Y	N	A
SWIM	Y	Y	Y	N	Y	Y
SLAW	Y	N	A	N	Y	Y
SMOOTH	N	Y	N	N	Y	Y
SAMOVAR	N	N	N	N	Y	Y
HCMM	Y	Y	A	Y	Y	Y
HHW	A	Y	A	Y	N	Y
GeSeMo	A	Y	A	Y	Y	Y
STEP	A	Y	N	N	Y	Y

Y— Yes, N — No, A— Ambiguous

Fig. 3. Qualitative features of mobility models.

density, average lane speed, signal times, etc. Agenda-based mobility model [71], combines both the social activities and the geographic movements. The movement of each node is based on individual agenda, which includes all kind of activities on a specific day.

3) Trace-Based Models: Trace based mobility models depend on collecting motion traces by means of various devices like GPS, iMote or Wi-Fi and then extracting mobility patterns from these traces. Hot-spots and points of interest are two important parameters which can be extracted from vehicular traces. Also different lanes may have different vehicle density at different times of the day and may be represented by different colors over a map. There are number of vehicular traces which have been collected by different organizations. However, the most difficult part in this approach is to extrapolate patterns not observed directly by the traces. Moreover, results obtained can be analyzed only after a long time (may be 6 months or a year).

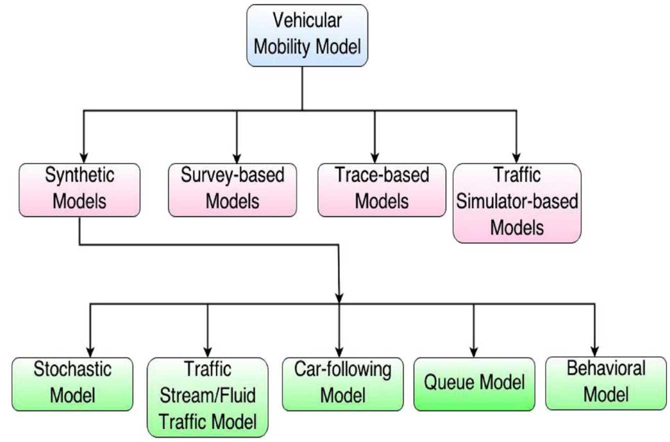

Fig. 4. Taxonomy of vehicular mobility models.

4) Traffic Simulator-Based Models: Simulators can also be used to generate vehicular mobility traces considering a number of vehicle mobility factors. Simulators like PARAMICS [72], CORSIM [73], VISSIM [74], TRANSIM [75] and SUMO [76] can be used to model urban microscopic traffic. Initially vehicular mobility was simulated as random motion similar to random waypoint or random walk. Later simulators were developed where vehicles could move over a graph thus restraining the movement of vehicles and providing a more realistic approach. The MONARCH project developed a tool that could extract real road maps from TIGER [77] database. To give a more realistic nature, obstacles were added to the road maps depicting buildings and residential areas. Attraction points were added to depict the hot-spots and heterogeneous distribution of vehicle density. STRAW [78] implements complex intersection management using traffic signs and signals. Sommer *et al.* in [130] showed how more realistic mobility models can lead to vastly different results, how bidirectionally coupled network and road traffic simulation can open up new possibilities in Vehicular Ad Hoc Network research. Interested readers may refer [79] for a more detailed survey of vehicular mobility models.

F. Artificial Mobility Traces

The inherent limitations of real-life mobility traces and synthetic mobility models are a major hindrance to a *perfect* evaluation of adhoc network protocols. Instead of directly implementing the node mobility, artificial mobility traces can be generated and used in the simulators. Artificial mobility traces can be generated using indigenous softwares in formats conforming to respective (network) simulators. One of the well-known softwares for generating artificial mobility trace is Bonn Motion [118]. Bonn Motion is a Java based software which can be used to create and analyze mobility scenarios. Traces of several well-known mobility models like Random Walk, SLAW, Disaster Area and others can be generated through this software.

An important aspect of artificial mobility traces is, that these traces can be generated using specific learning algorithms from real-life mobility traces. One of the important contributions towards this direction was made by Geyik *et al.* [119] where they used Probabilistic Context Free Grammars (PCFG) for generating artificial mobility traces. PCFG is a generalization of a context free grammar in which each production rule is augmented with a probability with which this production is applied during sentence generation. A PCFG can be inferred from real-life mobility traces and then this can be used to generate mobility trace of arbitrary length mimicking the actual mobility pattern of mobile nodes. In another paper [120] Markov models were used to predict and generate mobility traces. In this, the transition between the areas were modeled by their probabilities. The authors also show that a 2-level Markov model performs better than 3 or 4-level predictor. In [121], Maeda *et al.* generate walking behavior of humans in urban areas from given densities of pedestrains observed at several points. Using linear programming technique, the authors reproduce Urban Pedetrain Flow (UPF) scenario which is seens to be consistent with the observed densities in real life. Giurlanda *et al.* [129] generated synthetic traces using Human Mobility Simulator (HUMsim) that generates daily trajectories reflecting the habits of a person. HUMsim generates semantic trajectories which are sequences of semantic waypoints, that is, locations labelled with semantic tags. Semantic trajectories are generated according to a behavioral model of a person, which describes his daily behavior in terms of visited semantic waypoints. There were several other attempts for generating artificial mobility traces from real-life trace ranging from methods based on connectivity graph [122], action profiles [123] and studying group behavior [124].

Use of artificial mobility traces greatly reduces computational overhead of the simulators and leads to faster output. On one hand it can overcome the scalability bound of the real-life traces and on the other it can reduce the complexity on the part of the programmer. Moreover, real-life traces (most of the times) do not comply to the input formats required by the specific simulators. The available traces (for example, those stored in the CRAWDAD repository [125]) do not follow a common standard. Hence, they need to be analysed and converted to the correct formats conforming to the simulators.

IV. Mobility Traces

Although mobility models are easy to design and use in simulations, most of the time they fail to reflect the nature of mobility observed in real life. Several mobility models have been designed and developed to date and each of them try to focus on one or few parameters of mobility. As a result, collecting traces has gained much attention along pass decade since they are able to reflect the true nature of human and vehicular mobility. Besides that, researchers have also focused on modeling contacts, since mobility greatly influences the information dissemination and MANET routing protocols. Researchers have constantly sought to understand the mobility

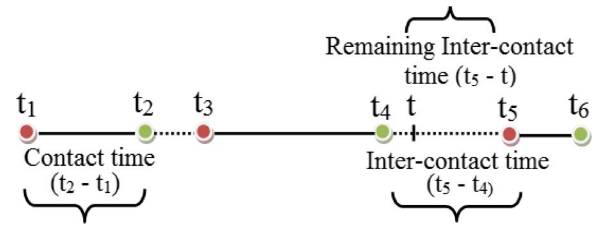

Fig. 5. Diagramatic representation of CT, ICT, and RICT.

behavior of the human, vehicles and wild animals. Collecting traces reveals a great deal about the opportunistic contact and helps in validating new protocols and applications. A number of mobility parameters have been identified since its inception which determines the nature of mobility of an individual or a population. Fig. 5 shows the diagrammatic representation of some important mobility parameters. We shall now discuss the general aspects of mobility which impact the performance of a mobile network.

- Contact Time (CT): Contact time (also known as the contact duration) is time interval during which two mobile nodes are within each other's communication range and can exchange messages. Contact times determine the amount of information or data that could be transferred during a single contact opportunity.
- Inter-Contact Time (ICT): It is defined as the time elapsed between two successive contact periods for a given pair of devices. The inter-contact time values and its distribution over a long a time period are important, since it determines the likelihood that a device will be encountered again within a given time period. Inter-contact time characterizes the frequency with which data can be transferred between any two network nodes. However, the inter-contact time distribution is largely influenced by the experiment's duration and its granularity (i.e., the time elapsed between two successive scan for the same device). Inter-contact times that last more than the duration of the experiment cannot be observed, and inter-contact times close to the duration are less likely to be observed. Likewise, we cannot observe the inter-contact time that last less than the granularity of measurement (which ranges from two to five minutes for different experiments).
- Remaining Inter-Contact Time (RICT): For any pair of devices, the remaining inter-contact time at any instant t is the time it takes after t until they meet again.
- Inter-any-contact Time: For a given device, it is the time elapsed between two successive contacts with any other device. This metric largely depends on the density of the network (number of nodes per unit area), as it characterizes the time that devices spend without meeting any other device.
- Return Time: Return time refers to time gap or interval between two consecutive visits to the same location. Repeated appearances at the same location have been widely studied and the frequency of revisit is direct measurement of the location popularity. Popularity of a location also

known as the *hot-spot* is denoted by the frequency of revisits and the number of nodes making such revisits.

- Flight Length/Jump Size: Flight length is defined as the distance traveled by a node between two waypoints without a pause time. Most mobility models consider an epoch based motion; that is, between two waypoints a node moves without change in velocity. Moreover, nodes move in a straight line between two waypoints rather than a curvilinear fashion or without a change in direction.
- Mean Square displacement (MSD): MSD measures the displacement of a node at time t from a given location at time t_0. This denotes how far a node spreads out over a given location over a period of time. MSD is defined as $M(t) = E[\|Z_t - Z_0\|^2]$ that is, the second moment of the displacement $\|Z_t - Z_0\|$ between position Z_0 at time t_0 and current position Z_t at time t and $\sqrt{M(t)}$ gives the amount of displacement of the mobile node after time t. Here $Z_t \epsilon \mathbb{R}^2$ denotes the position vector of mobile node at time t. MSD helps in characterizing the "diffusive" behavior of the mobile nodes, that is, the rate at which the mobile node spreads out.
- Radius of Gyration (RoG): Radius of gyration denotes how far and how frequently a user moves and is the characteristic of the range of the area travelled by a user upto an observation time t. In other words, the radius of gyration is the radius of the representative movement area of a user, in which the more frequent travel points are given more weight to calculate the area. This idea of radius of gyration is the same as the radius of gyration of an object but the objects parts are represented by the travel points and their masses are represented by the frequency of passing the points. Thus the radius of gyration is the standard deviation of a users positions to the users center of mass (that can be the average location over all users positions) [112].

Apart from these there are other parameters such as prevalence [110] or dwell time, activity range [110], persistence [111] and visiting time.

- Prevalence: Fraction of time a user spends at a given location. Prevalence depends on the popularity of the location.
- Activity Range: Also known as the mobility range. It is the total area covered by a user for visiting all the locations.
- Persistence: Amount of time a user stays connected to an access point (AP).
- Visiting time: Number of times a user visits a given location within a given time period.

This section is intended to provide the audience an in-depth knowledge of mobility traces, trace collection methods, pros and cons of collecting traces and using traces for simulations. This section is divided into two sub-parts: a) Mobility Traces b) Modeling contacts with the help of traces. The first part describes all the mobility traces which have been collected to date, type of devices and technology used and methodologies adapted for collecting such traces. The second part deals with studying and analyzing distribution curves obtained by plotting mobility parameters with respect to time. Analyzing the distribution curves enable researchers to analytically determine the efficiency of forwarding/routing algorithms in terms of delay, throughput, and overhead. We deal with the impact of mobility on the performance of opportunistic routing algorithms in the next section.

A. Trace Collection

The main idea behind trace collection is to understand realistic user behavior from operational wireless networks and mobile devices. The method of collecting traces can be classified into two types: 1) Polling-based method and, 2) Event based method.

1) Polling-based method: This method records the association of mobile nodes at periodic time-intervals using Simple Network Management Protocol (SNMP), or using an association tracking software on the MNs. In this, the device making the record constantly polls and records sample points of MN being associated at regular time intervals.
2) Event-based method: Event based methods uses online/offline events using logging server or encounter events by means of a software loaded in the MN. For example, whenever two devices come within the communication range of each other an association record is made; similarly when devices dissociate i.e., move out of each other's range, a dissociation record is made. Hence, all the records are event triggered.

We now provide a chronological survey of various mobility traces which were collected over a period of time by researchers for studying the above mentioned mobility parameters. The readers can find the summary of traces in Table III.

Dartmouth traces [2004]: This trace includes the SNMP logs from the APs for a period of over one year. To collect the traces, about 560 access points from Cisco Systems were installed in Dartmouth campus, each an Aironet model 3501, to provide 11 Mbps coverage to nearly the entire campus. Each access point (AP) had a range of about 130–350 feet indoors, so there were several APs in all but the smallest buildings. All APs shared the same network name (SSID), allowing wireless clients to roam seamlessly from one AP to another. Whenever clients associated and dissociated, a syslog message was recorded along with timestamp (in seconds) and MAC address of the client.

ZebraNet [2004–2005]: The data contained in this data set are movement traces collected from two real world ZebraNet deployments at Sweetwaters Game Reserve near Nanyuki, Kenya. The first deployment was in January 2004 and the second deployment was during summer of 2005. The data offer detailed animal position information using UTM (Unix Time-Stamp) format. The sensor nodes used in the deployments were based on the ZebraNet Test nodes. The nodes were built around a MSP430 processor and included a GPS module, a radio module, and a flash module.

TABLE III
SUMMARY OF MOBILITY TRACES

Name of Trace	Mobility Type	# of nodes	Duration (days)	Device Type	Network Interface
Cambridge1 [85]	Human	12	5	iMote	Bluetooth
Cambridge2 [85]	Human	54	55	iMote	Bluetooth
ZebraNet [5]	Animal	100	365	GPS	Short & long range radio
Intel [85]	Human	9	3	iMote	Bluetooth
Hong Kong [139]	Human	37	5	iMote	Bluetooth
Infocom, 2005 [85]	Human	41	4	iMote	Bluetooth
Infocom, 2006 [85]	Human	78	4	iMote	Bluetooth
Darthmouth [125]	Human	6,648	114	Laptop/PDA	Wi-Fi
UCSD [134]	Human	273	77	PDA	Wi-Fi
Toronto [133]	Human	23	16	PDA	Bluetooth
MIT BT [132]	Human	100	246	Cell phone	Bluetooth
MIT GSM [132]	Human	100	246	Cell phone	GSM
Shanghai [139]	Vehicle (Taxi)	2100	30	GPS	GPRS
SanFrancisco [137]	Vehicle (Taxi)	500	30	GPS	GPRS
UMassDieselNet [138]	Vehicle (Bus)	40	60	Ha-Com Open Brick with AP	802.11b
USC [136]	Human	4,528	30	WLAN Generic	802.11a
UF [140]	Human	32,695	30	WLAN Generic	802.11a

MIT reality [2005]: The MIT reality trace consists of 100 Nokia 6600 smart phones installed with custom software BlueAware that was developed at MIT Media laboratory. BlueAware is a software application to log BTIDs (a 12-digit hex Bluetooth MAC address), that runs passively on the background on MIDP2 enabled mobile phones. The researchers also used a Context application (developed at University of Helsinki) to record Bluetooth device proximity, cell tower IDs, and phone status (in use or idle). The dataset is available at: http://reality.media.mit.edu and http://crawdad.cs.dartmouth.edu/meta.php?name=mit/reality.

USC [2005]: This trace-set contains the trap log of the (switch port, MAC address) association when the user is online. This trace-set contains "association history" traces for individual MAC addresses, which consist of start times and end times of a MAC associated with various locations.

Toronto [2005]: To investigate whether a large-scale Bluetooth worm outbreak is viable in practice, the authors conducted controlled experiments where they gathered traces of Bluetooth activity in different urban environments to determine the feasibility of a worm infection. The University of Toronto trace set was collected using 23 Bluetooth-enabled PDAs carried by students for a period of 16 days. The authors used Palm Tungsten-T PDAs having 16MB of RAM with PalmOS version 5.0 to scan for Bluetooth devices. The Bluetooth radios of the PDAs were similar to the ones found in most commodity cellphones with a range of 10 meters approximately.

Infocom [2005]: This trace includes Bluetooth sightings by groups of users carrying small devices (iMotes) for four days in conference IEEE Infocom (March, 2005) in Grand Hyatt Miami. 54 iMotes were distributed among the students attending the conference, of which 41 yielded useful data, 11 did not contain useful data because of various failures with the battery and packaging, and two were not returned.

Infocom [2006]: This trace includes Bluetooth sightings by groups of users carrying small devices (iMotes) for four days in conference IEEE Infocom, 2006 at Princesa Sofia Gran Hotel, Barcelona, Spain. 78 iMotes were distributed among students and researchers attending the conference of which 2 iMotes did not deliver useful data, as a consequence of accidental hardware reset. Nodes with ID#1 through #17 were static long range iMotes which were deployed throughout the area. The three nodes with ID#18–#20 were long range iMotes that have been placed in lift of the hotel. Nodes #21–#98 were participants of the Infocom student workshop. Nodes with ID larger or equal than #100 denote external devices.

Cambridge [2005]: This trace includes Bluetooth sightings by groups of users carrying small devices (iMotes) for about two months in various locations that the authors expected many people to visit such as grocery stores, pubs, market places, and shopping centers in and around the city of Cambridge, UK. In the experiment that was performed, the authors were interested in tracking contacts between different mobile users, and also contacts between mobile users and various fixed locations. Mobile users in our experiment mainly consisted of students from Cambridge University who were asked to carry these iMotes with them at all times for the duration of the experiment. In addition to this, they deployed a number of stationary nodes in various locations that was expected to be visited by many people such as grocery stores, pubs, market places, and shopping centers in and around the city of Cambridge, UK. A stationary iMote was also placed at the reception of the Computer Lab, in which most of the experiment participants are students. Due to various hardware problems and the loss of some of the deployed iMotes, they were able to gather measurement data from 36 mobile participants and 18 fixed locations. The different types if iMotes that were deployed are:

- MSR-10: Mobile Short Range iMotes with an interval of 10 minutes between inquiries. These iMotes were given to a group of 40 students, mostly in the 3rd year at the Cambridge University Computer Lab. The devices were packaged in small boxes (dental floss boxes) to be easy to carry around in a pocket, and used a CR-2 battery (950 mAh) for power.
- FSR-10: Fixed Short Range iMotes with an interval of 10 minutes between inquiries. 15 of these iMotes were deployed in fixed locations such as pubs, shops or colleges' porter lodges. The researchers used exactly the same packaging and batteries as the MSR-10.
- FSR-6: Fixed Short Range iMotes with an inquiry interval of 6 minutes. These iMotes were equipped with a more powerful rechargeable battery providing 2200 mAh so that we were able to reduce the inquiry interval to 6 minutes. The researchers deployed 2 of these devices.
- FLR-2: Fixed Long Range iMotes with an interval of 2 minutes between inquiries. To increase the area in which these iMotes can discover other devices, four devices were equipped with an external antenna, which provided a communication range that was approximately twice that of b the short range iMotes. Furthermore, these iMotes were also equipped with 3 more powerful rechargeable batteries providing 2200 mAh so that we could reduce the inquiry interval to 2 minutes.

Intel [2006]: This trace includes Bluetooth sightings by groups of users carrying small devices (iMotes) for six days (but most of the traces lasted only three days) in Intel Research Cambridge Corporate Laboratory. Data from only 9 iMotes could be collected properly while the others suffered from hardware reset. Out of 9 iMotes, node 1 was stationary and nodes 2–9 were mobile nodes which were distributed among staff, researchers, and interns while the remaining were identified as external devices.

NCSU [2006]: Lee *et al.* [26] collected GPS traces from five different sites, including two university campuses (NCSU and KAIST), New York City, Disney World (Orlando), and North Carolina State fair. Garmin GPS 60CSx handheld receivers are used for data collections which are WAAS (Wide Area Augmentation System) capable with a position accuracy of better than three meters 95 percent of the time, in North America. The GPS receivers take reading of their current positions every 10 seconds and record them into a daily track log. The dataset is available at: http://crawdad.cs.dartmouth.edu/meta.php?name=ncsu/mobilitymodels. In NCSU campus, every week, 2 or 3 randomly chosen students of Computer Science department carried the GPS receivers for their daily regular activities. The New York City traces were obtained from 8 volunteers living in Manhattan or its vicinity. Most of the participants have offices in Manhattan. Their track logs contain relatively long distance travels because of their long commuting paths.

Shanghai taxi trace [2007]: This is also a vehicular trace, where the authors collected motion trace data from 2,100 taxies in Shanghai city during the whole month of February in 2007 (available at http://www.cse.ust.hk/dcrg). As a taxi runs along the roads in the city, it periodically sends a report back to a data centre via a GPRS channel. Due to the GPRS communication cost for data transmission, reports are sent at a time interval of one minute reports are sent at a time interval of one minute when a taxi is loaded and of about 15 seconds when it is vacant. The information contained in such a report includes: the taxi's ID, the longitude and latitude coordinates of the taxi's current location, report timestamp, the instant speed and heading angle of the taxi and the status of the taxi (i.e., whether the taxi has passengers onboard).

UMassDieselNet [2007]: The UMassDieselNet (http://prisms.cs.umass.edu/dome) is a vehicular DTN based testbed, operated by the UMass Amherst branch of the Pioneer Valley Transport Authority (PVTA), consisting of 40 buses, of which a subset is on the road each day. The transit buses service an area sparsely covering approximately 150 square miles. Each bus in DieselNet carries a small-form of desktop computer, 40 GB of storage, and a GPS device. The buses operate on 802.11b radio that scans for other buses 100 times a second and an 802.11b access point (AP) that accepts incoming connections. Once a bus is found, a connection is created to the remote AP. (It is likely that the remote bus then creates a connection to the discovered AP, which our software merges into one connection event.) The connection lasts until the radios are out of range. Traces are available at: http://traces.cs.umass.edu/index.php/Network/Network.

San Francisco taxi trace [2008]: This dataset contains mobility traces of taxi cabs in San Francisco, USA. It contains GPS coordinates of approximately 500 taxis collected over 30 days in the San Francisco Bay Area. Each taxi is equipped with a GPS receiver and sends a location-update (timestamp, identifier, geo-coordinates) to a central server. The location-updates are quite fine-grained—the average time interval between two consecutive location updates is less than 10 sec, allowing us to accurately interpolate node positions between location-updates. Cab mobility traces are provided by the Exploratorium—the museum of science, art, and human perception through the cabspotting project: http://cabspotting.org.

Apart from the above traces, some researchers have collected macro-mobility traces. Macro-mobility traces gives us information about user movement when user moves from one cell to another. One of the most recent cellular traces was studied by Hoteit *et al.* [127] where they utilized the dataset to study and detect content consumption hotspots in Paris metropolitan area. For this the authors analyzed anonymized network probe data generated by mobile devices during Internet data exchange. The dataset is a two day data and covers almost 1.5 million users from "La Petite Couronne" area of Paris. Calabrese *et al.* [128] analyzed cellphone mobility data within an area of 15×15 km in Boston area during the period from 30th July to 12th Septemebr, 2009 to characterize the relationship between events and its attendees, more specifically of their home area. The dataset consists of anonymous cellular phone signaling data collected by AirSage, which turns this signaling data into anonymous locations over time for cellular devices. The dataset consists of 130 millions of anonymous location estimations—latitude and longitude—from close to 1 million devices.

B. Trace Formats

Network simulators (especially mobile adhoc network simulators) often come with added functionality of simulating mobile nodes. Simulation of mobile nodes may be performed either using dedicated modules within the simulator or may be read from trace files as input to the simulator. For the later part, the trace file should have certain semantics for the simulator to parse each line of the trace file and extract relevant fields and run accordingly. Unfortunately each simulator have their own format for accepting trace files; that is the same trace file may not be used as input to two different simulators and may have to be reconstructed to conform to other simulators. For example well known simulator like ns2 accepts trace file format as shown below:

$$\$ns\_\ at\langle time\rangle\$node\_(\langle id\rangle)\ setdest$$
$$\langle x\rangle\ \langle y\rangle\ \langle speed\rangle$$

example:

$$\$ns\_\ at\ 0.000000\ \$node\_2\ setdest$$
$$67.20830\ 130.66789\ 20.00575$$

However, the traces which are collected or are available in online repositories may not come in formats conforming to specific network simultors and researchers often have to modify the traces before using them as input to the simulator. One of the well-known repositories of mobility traces is CRAWDAD [125]. CRAWDAD is the Community Resource for Archiving Wireless Data At Dartmouth, a wireless network data resource for the research community. This repository stores wireless data, including mobility traces, collected from various sources and is freely available to be used by any researcher.

As mentioned before, mobility traces can be broadly classified to two types. First is the polling based method where locations or geo-coordinates of the devices are recorded. This method is generally used with GPS devices which could periodically record the location of the devices in form of latitudes and longitudes. One example for this could be the San Francisco taxi trace (see Section IV-B). The trace is of form $\langle latitude\ longitude\ time\ other\_values\rangle$, where time is in UNIX epoch format. This is a true mobility trace in the sense, that here the actual location of the mobile devices or nodes are recorded. This method relies on polling events where each device records its location after every fixed interval of time. Second is the event based method where only events such as contact, association or dissociation with certain devices are recorded. This method is used with normal wireless devices such that a contact log is created when two devices move within each other's range or away from each other. A ideal example for this case would be the Cambridge iMote trace. This trace contains the log of devices when they are *in-contact* or *out-of-contact* from each other. The trace file contains the following columns; $\langle id1\ id2\ time1\ time2\ value\ time3\rangle$. In this id1 and id2 are ids of the two devices, time1 and time2 are the start and end times of the contact period between the two devices; column value gives the count of the number of times a given pair of devices come in contact with each other within a given time period; and time3 is the inter-contact time between the given pair of devices. This method relies on event occurence and a log is created only on account of an event. In this case we do not get the actual physical location of the mobile device.

Before using any trace for evaluation, it is important to remove errorneous values and noisy data from the sample. For example, in GPS traces, change in direction may cause several short flights [26]. Rhee *et al.* in [26] suggest researchers to use three methods to preprocess a trace by combining the short flights made by mobile nodes into longer flights. Again, some traces may show false node movement when a node switches its association from oneAP to another without changing its actual physical location. This is known as the ping-pong effect [126]. The noise due to ping-pong effect can be removed by aggregating the data collected for different APs and then removing the reduntant data.

C. Modeling Contacts From Traces

The analysis of underlying probabilistic distribution of contact times (CT) and inter-contact times (ICT) of all the collected traces have helped researchers in developing theoretical foundations for opportunistic forwarding algorithms. Researchers have repeatedly analyzed different mobility traces (both human and vehicular) and tried to understand the nature of mobility exhibited by the nodes. The most important feature which impacts opportunistic forwarding in MON is the inter-contact time (ICT). It has been observed that the ICT distribution in the real-world human mobility traces displays a dichotomy: it initially obeys a power law, but it has an exponential tail for relatively large time values. We give a brief description (for the sake of completeness) of power law and exponential distribution:

1) Heavy-tailed Distribution: Heavy-tailed distributions are the distributions whose tails are not bounded or they have heavier tails comparing to exponential-tailed distributions, e.g., normal distribution, exponential distribution. In other words, the distribution of a random variable X in (5) has the heavy-tailed property when,

$$\lim_{x\to\infty} \exp^{\lambda x} P[X > x] = \infty\ for\ all\ \lambda > 0 \qquad (5)$$

2) Power Law Distribution: A power law is a functional relationship between two variables. For example, if the frequency (with which an event occurs) varies as a power of some attribute of that event (e.g., its size), the frequency is said to follow a power law. Power law is generally used to describe phenomenon where large events are rare, but small ones are quiet common. For example, there are few large earthquakes but many small ones. Power law

distribution is just another form of Pareto distribution. Pareto's law is given in terms of cumulative distribution function (CDF), i.e., the number of events larger than x is an inverse power of x,

$$P[X > x] \sim x^{-k}$$

However, power law gives how many events are exactly equal to x. That is,

$$P[X = x] = C(x) \times x^{-(k+1)} = C(x) \times x^{-\alpha} \qquad (6)$$

where $C(x)$ in (6) is a slowly varying function and $\alpha > 1$ (known as the *shape parameter*), which is indeed a requirement for a power-law form to normalize. It can be shown that, when $1 < \alpha < 2$, the first moment (the mean or average) is infinite, along with all the higher moments. When $2 < \alpha < 3$, the first moment is finite, but the second (the variance) and higher moments are infinite.

Power law is best described by plotting the distribution on a log-log scale, which gives us a straight line, or by Pareto quantile-quantile plots (Pareto Q-Q plots). This method consists of plotting the logarithm of an estimator of the probability that a particular number of the distribution occurs versus the logarithm of that particular number. Usually, this estimator is the proportion of times that the number occurs in the data set. If the points in the plot tend to 'converge' to a straight line for large numbers in the x axis, then the researcher concludes that the distribution has a power-law tail.

3) Zipf's Law: Zipf's law (also called the zeta distribution) is a discrete power-law distribution that indicates the number of occurrences of an event is inversely proportional to its rank in number of occurrences as shown in the equation below. That is, the first rank event occurs most often. r is the event's rank, and s is the Zipf exponent.

$$p(r) = r^{-s}$$

4) Truncated Power Law: The power-law distribution that is bounded to represent the limits of dataset is known as the truncated (or bounded) power law distribution. There are different ways of truncations. The one used in this work is bounded Pareto distribution where L denotes the minimal value, and H denotes the maximal value, and k is considered as the shape parameter of the Pareto distribution.

$$\frac{kL^k x^{-k-1}}{1 - \left(\frac{L}{H}\right)^k} \; where\ L \leq x \leq H\ and\ k > 0 \qquad (7)$$

Owing to the popularity of mobility models, researchers have identified a number of mobility properties or parameters; and based on these properties mobility has been classified along three major axis [80] viz., spatial property, temporal property and connectivity property (Fig. 6). Spatial properties pertain to behavior of individuals in physical space such flight length. Temporal properties refer to the time varying features of an individual like return time. And connectivity properties refer to

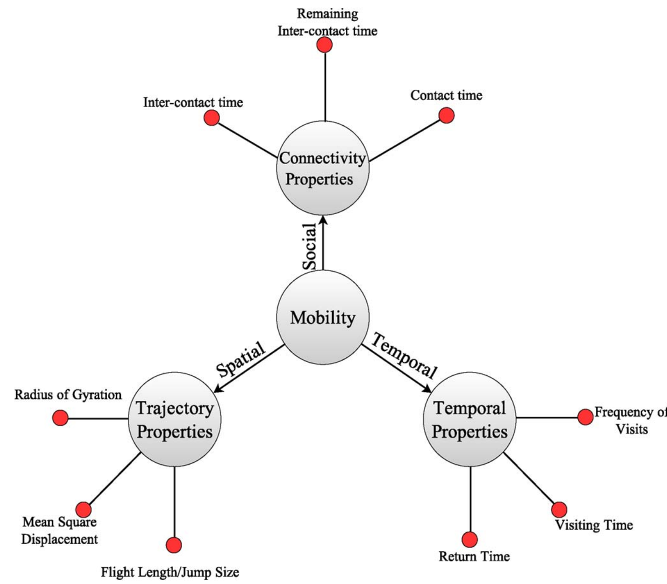

Fig. 6. Properties of human mobility. Diagram adopted from [80].

the encounter events like meeting and hitting rate. Previously a number of researchers have analyzed synthetic mobility models and analytically derived the mobility characteristics like spatial node distribution, inter-contact time, and flight length. However, a rigorous study of human mobility models based on real life traces was lacking until 2006. By analyzing a large data trace of bank note circulation and assuming them to be the main criteria for human mobility, Brockman *et al.* [81] showed that travel distances (also known as flight distance or jump size) of individuals follow a power law distribution where the exponent k is less than 2. Known as Lévy flight, a random model with such distance distribution was previously observed in dispersal ecology as an approximation of migration trajectories among different animal species [82]. By studying traces from mobile phone users, Gonzalez *et al.* [83] supported the above idea by suggesting that there exists an exponential cut-off and that individual truncated Lévy trajectories coexist with population based heterogeneity. This heterogeneity was measured in terms of the radius of gyration (r_g) which depicts the characteristic distance travelled by a user. It was shown that radius of gyration can be approximated by a truncated power-law,

$$P(r_g) = \left(r_g + r_g^0\right)^{\beta_r} exp\left(-\frac{r_g}{k}\right) \qquad (8)$$

where $\beta_r = 1.65 \pm 0.15$, $r_g^0 = 5.8$ km and $k = 350$ km. In other words most people usually travel in close vicinity to their home location, while a few frequently make long journeys. Gonzalez *et al.* [83] also detected that people tend to return to their previously visited site based on the *popularity* of a location. Song *et al.* [84] measured the visiting time distribution and concluded that it can be approximated by a truncated power law with an exponent value of 0.8 $\pm$ 0.1 and cut-off of $\Delta t =$ 17 hours, which the authors connected with the typical awake period of humans. The authors also found that the frequency with which a user visits its k^{th} most visited location follows a

Zip's law (a class of discreet power law p.d.f) ($f_k \sim k^{-\zeta}$) with parameter $\zeta \approx 1.2 \pm 0.1$.

As mentioned earlier that contact time and inter-contact time acts as the deciding factor over the performance of opportunistic message forwarding; since messages can only be forwarded or replicated only when two nodes are within each other's communication range. Thats is, connectivity properties plays a vital role in message propagation across the network in a MON. With idea of opportunistic forwarding, Chaintreau *et al.* [85] for the very first time analyzed a large number of human mobility traces (Infocom, Toronto, Cambridge, Hong Kong, MIT BT, Dartmouth) and by analyzing the ICT of the nodes, arrived at the following conclusions:

- In the three iMote based experiments (Infocom, Cambridge, and Hong Kong), 17 to 30 percent of ICTs were greater than 1 hour and 3 to 7 percent of all ICTs were greater than 1 day.
- In Toronto data sets, 14 percent of ICT last more than a day and 8 percent more than week.
- Large ICTs were more frequent in UCSD, Dartmouth and MIT traces. In MIT BT traces, upto 60 percent of ICTs observed were above 1 day.
- In the region between 10 minutes and 1 day, the CCDF slowly varies and it is lower bounded by the CCDF of power law distribution. This contradicts the exponential decay of the tail which characterizes the most commonly found mobility models in literature.
- To justify the above claim, they studied the quantile-quantile ($Q - Q$) plot comparison between the empirical distributions and three parametric model viz. exponential, log-normal and power law. They found that only the power distribution remains close to the empirical distribution for upto 18 hours.

These observations motivated Chaintreau *et al.* [85] to propose the hypothesis that the ICT has a CCDF with power law tail. Under this assumption they also proved that for any forwarding scheme the mean packet delay is infinite, if power law exponent of the ICT is smaller than or equal to 1. However, this hypothesis was later proved to be over pessimistic by Karagiannis *et al.* [86]. They also analyzed a number of mobility traces (both human and vehicular) and arrived at the following conclusion:

- The aggregate CCDF of the ICT features a dichotomy; it varies slowly and follows a straight line thus suggesting power law upto a characteristic time (see Fig. 7). This time was found to be of order half a day.
- Beyond this characteristic time, the CCDF drops abruptly faster thus exhibiting an exponential decay.
- The datasets mean ICT is of same order as the characteristic time, and thus the exponential cannot be ignored by the time separation argument.
- The presence of exponential tail entirely eliminates the issue of infinite delay for opportunistic packet forwarding.
- The return time of mobile devices to its home location features the same dichotomy as of ICT.

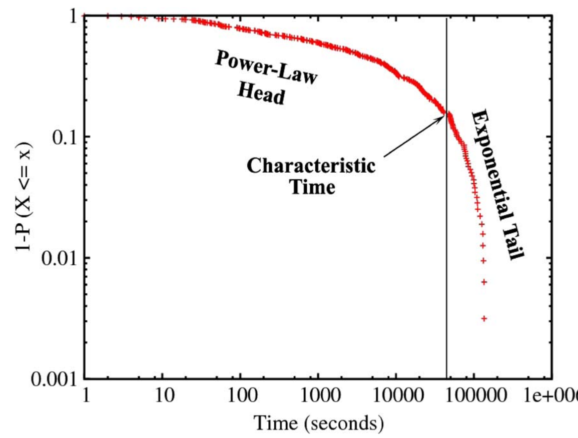

Fig. 7. Power-law + Exponential Dichotomy of ICT of Infocom (2005) trace.

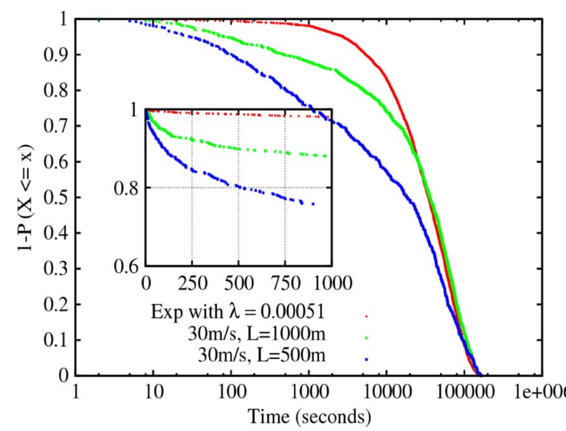

Fig. 8. Log-linear plot of CCDF of ICT (30 m/s).

They also analytically proved that simple mobility models such as simple random walk and random waypoint exhibit same qualitative properties as was observed in empirical traces. Motivated by the above findings Cai and Eun [87] they performed a stochastic analysis of the observed distribution and arrived at the following conclusion:

- Mobility models with strong correlated movement patterns have heavier power law head[3] than with weaker correlations.
- Mobility with shorter flight distance leads to higher motion correlation, leading to heavier power law head.
- Moreover, the average inter-meeting time is invariant with respect to degree of correlations.
- This invariance result holds not only for the inter-meeting time but also for many other variants of the contact-based metrics including contact time, inter-hitting time, inter-any-contact time, both under Boolean (distance based) model and under physical interference models.

From Fig. 8 we can observe that a flight length of $\mathrm{L} = 500$ meters leads to heavier power law head, (that is more curved towards the head) compared to $\mathrm{L} = 1000$ meters, which is almost a straight line.

[3]Portion of the curve before the characteristic time is the head and later portion denotes the tail (see Fig. 7)

Super-diffusive behavior [88]: For a class of isotropic random walks with finite step-length variance, the MSD will grow linearly with t, that is, $M(t) \sim O(t)$. On the other hand, when the step-length variance is infinite such as Lévy Walks, the mobile node tends to spread out faster than $O(t)$ since much longer step-lengths appear more often. In such cases $M(t) \sim O(t^{\gamma})$, where $\gamma > 1$ (generally). This is the very nature of super-diffusive pattern which was observed in the mobility traces by Kim *et al.* [88]. As the value of γ increases, the mobility pattern is more diffusive and has greater step-length. The varying degrees of diffusive properties of mobile nodes can be conveniently captured by the slope γ of $M(t)$ in a log-log scale (i.e., $M(t) \sim t^{\gamma}$).

Hossman *et al.* [89] represented mobility as weighted contact graph, where tie strength denotes how long and often a pair of nodes remains in contact. Besides confirming the small-world properties of social network, they showed that contacts are strongly modular i.e., there are communities in which individuals have strong and correlated mobility pattern. Most of the communities have small number of members and very few communities with large number of members. Moreover, communities are composed of several smaller communities. This finding conforms to the self-similar structure [90] of contact graph across different scales.

Although several researchers have analyzed the mobility traces and arrived at concrete inferences, there has been some underlying faults which have been overlooked before. The most important of them is the censorship issue which leads to strongly skewed distribution of ICTs. By observing the distribution of ICT, the authors classified the data points into uncensored and censored ICT. An ICT period is said to be censored if it starts during the measurement period, but terminates after the end of the measurement. They found that 7% and 1.3% of the ICT measurements in the UCSD and Dartmouth trace respectively are censored. The authors also showed that traces exhibit strong self-similarity.

V. Impact of Mobility on Opportunistic Routing Algorithms

Glossglausser and Tse [11] in their seminal paper showed that in a highly dynamic network where topology changes are frequent, the capacity (per-node throughput) can significantly increase when nodes are mobile rather than when they are fixed. However, throughput and delay is significantly affected by mobility characteristics of the nodes especially the inter-contact time (ICT). Since, messages are transferred in a hop-by-hop manner and when two nodes are in contact with each other, the ICT becomes the basic delay component. Another important factor that directly impacts the forwarding/replication is the diameter of the opportunistic network. The diameter of a network is an upper bound on the number of intermediate hops needed to find at least one path between any two nodes [15]. Chaintreau *et al.* [15] showed that the diameter grows slowly with network size in a simple random case. After analyzing multiple human contact traces, the authors observed that network diameter generally varies between 3 and 6 hops for node population from 40 to 100. This result holds for sparse and dense networks, and the diameter varies only a little when contacts are removed. Hence, Chaintreau *et al.* [15] once more established the existence of "small world" phenomenon with respect to mobile opportunistic networks. The above inferences suggest that messages can be discarded after a few numbers of hops without incurring more than a marginal performance cost. Having established the fact that a destination was reachable within few hops, the question that still remained to be answered was: what is the nature of delay and throughput that is observed in such networks? How does the nature of mobility affect delay and throughput?

The above questions are answered by two separate ideas with respect to ICT; 1) when the CCDF of ICT follows a power law distribution upto an order of a day and contradicts the exponential decay of tail, which characterizes most mobility model, and 2) when the CCDF of ICT features a dichotomy that is, power law head up to a characteristics time and exponential decay beyond. Although (1) was later discarded and (2) was adopted to be the most appropriate distribution of ICT, yet we include the results when Chaintreau *et al.* [85] considered (1) to be the plausible distribution of ICT. The authors arrived at the following conclusion based on the index (α) of power law distribution ():

- For $\alpha > 2$, any algorithm from the class of oblivious forwarding algorithms [85], achieves a delay with finite mean.
- If $1 < \alpha < 2$, the delay in two-hop relaying algorithm [11] does not have finite expectation.
- It is possible to design an oblivious forwarding algorithm that achieves a delay with finite mean. To achieve a finite mean delay, m duplicate copies of data should be produced and forwarded, where $m > \frac{1}{(\alpha-1)}$ and the network must contain at least $\frac{2}{(\alpha-1)}$ devices.
- If $\alpha < 1$, none of these algorithms, including flooding, can achieve a delay with finite expectation.

The above conclusions were quiet pessimistic, in that they suggested that finite expected delay cannot be guaranteed for any class of forwarding algorithms. For all the traces collected by the authors, the power law index (α) was less than 1 and hence the order of delay should be at least an order of a day. However, Karaignas *et al.* [86] later showed that CCDF of ICT followed a dichotomy and therefore, the idea of infinite expected delay was discarded.

With the establishment of optimistic idea that delay in most cases is finite, researchers sought the answers for the scaling properties of DTNs with respect to delay and capacity (per-node throughput). It was shown in [10] that when transmission range scales below critical connectivity threshold $\Theta\left(\sqrt{\frac{\log N}{N}}\right)$, the network becomes disconnected with high probability. In such cases the ICT becomes the main delay component. Groenvelt *et al.* [91] showed that for exponential inter-contact time $(1/\lambda)$ the distribution of the mean ICT is proportional to the radio range and node speed. Under such circumstances, inter-contact rate (λ) is mainly characterized by radio range and node speed. Lee *et al.* [92] arrived at the following conclusions in a DTN scenario that consists of n nodes in a unit square area with radio range $r = O(1/\sqrt{n})$, and average flight distance of $\Omega(r)$, where nodes travel in the order of its radio range $r = O(1/\sqrt{n})$:

- The per-node throughput scales $\Theta(nr^2)$ which suggests that node speed and degree of correlation in motion pattern do not affect the achievable network capacity.
- The average delay of two-hop relay routing is in the range of $\left[\Theta\left(\frac{1}{\lambda}\right), \Theta\left(\frac{\log n}{\lambda}\right)\right]$ depending on the degree of motion correlation. The lower bound is for the case when the degree of motion correlation is least and the upper bound is form the case when a strong correlation is motion pattern is observed.
- The increase in delay due to increase in motion correlation (i.e., decrease in flight distance) can be bounded by $\Theta(\log n)$.
- The two-hop relay routing requires buffer space ranging in $\left[\Theta(nrv), \Theta\left(\frac{n \log n}{rv}\right)\right]$; the stronger the correlation in motion pattern, the higher the amount of buffer space.
- For a buffer size of K (i.e., a node buffer can hold at most K packets/messages), the per-node throughput is in the range $\left[\Theta\left(\frac{rvK}{\log n}\right), \Theta(rvK)\right]$, with lower bound corresponding to lower degree of correlation in mobility pattern.

Lenders *et al.* [93] studied the impact of mobility on link duration and link failures using random waypoint and reference point group mobility model. They analyzed the data gathered from real adhoc networks of 20 PDAs connected via 802.11b and showed that for smaller routes or smaller number of hops, the effect of mobility dominates the effect of collision or interference errors. They also showed that there exists an optimum ratio of:

$$\frac{number\ of\ groups}{number\ of\ members\ in\ a\ group}$$

which leads to the best performance of such networks. A higher ratio leads to performance degradation due to link failures (due to highly uncorrelated node movement) while a low ratio is unrealistic and does not reflect true nature of human mobility.

Rhee *et al.* study the impact of Lévy walks on the performance of DTN simultaneously studying the impact of other mobility models such as Brownian motion (BM) and RWP. They find that BM tends to have larger delays, RWP have smallest delays while Lévy walk have delays somewhere in between, depending on the parameter α. As α is increased the delay gets closer to BM and as α is a decreased delay approach near to RWP. Shorter delay in RWP is attributed to the large number of nodes having long flight lengths. They also find that delay has a heavy-tailed distribution which implies that many nodes experience long routing delays and increasing the number of message copies may not improve the delay performance. They also find that (for one relay case) there exists with high probability, some nodes within the communication range of the source node which make long trips thereby drastically improving the delay performance for Lévy walks.

Boldrini *et al.* [94] simulated the impact of social mobility on opportunistic routing algorithms and found that greater the degree of sociability, greater is the packet delivery probability with lower delay. They also showed that HCMM performs better than CMM because the former incorporates repeated and periodic visits to popular locations and routing protocols which can exploit this nature of node movement naturally yields better results.

Ciullo *et al.* [95] analyzed the effect of node correlation on throughput and delay performance. The authors measured the impact with respect to RPG mobility model, where they analyzed the impact of clustered movement on opportunistic routing algorithm. They showed that for a sparse but highly clustered node distribution, throughput is reduced. On the other hand, delay is improved by the effect of clustering, since the nodes belonging to the destination cluster which meet the destination at the highest frequency, can be effectively exploited as last hop relays.

Wang *et al.* [96] studied the impact of social structure on the performance of social-based opportunistic routing algorithms like LABEL [97], RANK [98] and BUBBLE [98]. They studied the impact in terms of community and centrality. Community is a group of co-located individuals for a given time period. There are a number of community detection algorithms which have been proposed with respect to complex networks. K-Clique [99], and Fiedler [100] are two centralized community detection algorithms. Centrality indicates the popularity of one or more individuals within a given community. By using real-life human mobility traces on social-based forwarding algorithms, the authors concluded that social structure has great impact on the performance of such networks. Moreover, a complex social structure has greater impact on performance than a simple one. Centrality plays a vital role in packet delivery since it has largest degree in the social network. Hence, it can be used to quickly deliver a message within a community than other nodes with lower degree.

Becchetti *et al.* [102] for the first time, studied the impact of realistic mobility model on flooding time[4] in opportunistic network. That is they studied the delay performance under power law + exponential dichotomy. Previously MONs had been studied under mobility models depicting exponential ICTs only. The authors used Home-MEG model and showed that flooding time is much faster than what was predicted based on simple generic mobility models which do not reproduce dichotomy. They showed that flooding time in a network with n nodes moving under Home-MEG model grows unboundedly with n, but with a rate which is logarithmic in n.

Baccelli *et al.* [103] studied the information propagation speed in a bi-directional vehicular delay tolerant network. Information propagation speed determines the delay experienced by destination nodes in such networks. The authors analytically prove that there exists a threshold of vehicular density above which information propagation speed increases significantly with respect to vehicle speed. Below this threshold information is propagated at same speed as vehicle. The authors also show

[4]Flooding time denotes the minimum time that is required to spread a message across the whole network starting from the source node.

that DTN routing under threshold provides a gain in propagation distance, which follows a sub-linear power law with respect to elapsed time. Earlier works such as [104] show that when a 2-D network is not percolated, the latency scales linearly with the Euclidean distance between the sender and the receiver.

Authors in [88] show that faster diffusive behavior of mobile nodes lead to greater number of encounters which effectively leads to higher delivery ratio under same transmission range. The authors also studied performance by adding pause time to the CTRW mobility model. They found that pause time leads to slower diffusion which in turn leads to lower throughput. The authors also suggest that if diffusive property is not properly captured, it can lead to over optimistic or over pessimistic performance result.

There have been several other interesting areas of research with respect to MON where mobility plays a key role. One such area is the impact of mobility on content distribution in MON. In [105] the authors propose OPAN (Opportunistic temporal Pairing Access Network)-a mobile peer-to-peer opportunistic content distribution architecture which is basically an enhancement of Bit-torrent [106]. They infer that mobility pattern with high node clustering is more beneficial for content distribution due to higher chance of forming direct pairing between nodes. Others have tried to predict/forecast MON performance under homogeneous and heterogeneous mobility characteristics by mapping mobility models into Markovian chain traversal over relevant solution space.

VI. Open Issues

Mobility, being an interdisciplinary subject, has been regarded highly by researchers from various fields. Albeit a vast amount of literature available on mobility and its analysis, researchers still harness a great deal of interest in studying mobility, especially with regard to humans. Scientists are still trying to understand the complex nature of human mobility. For example, it has been observed that individuals never belong to same community or social network every day and may change or be attracted to different communities over a period of time. This is quiet unlike animals that tend to remain confined to their own herd and rarely change groups. Humans however tend to remain confined to their own geographic location (known as home location) and their location rarely shows a large variation. However, their home location may be quiet large compared to animals. These features are yet to be captured in mobility models. Mobility also depends on classes of individuals and very few works have been done considering the role of a person in the society. Another important parameter of mobility is the pause time which has often been neglected or discriminately studied. Pause time can affect inter-contact time (ICT) directly and performance indirectly. Pause has been observed in human mobility as individuals remain at a given location for a brief time period before moving to a new location. Sometimes pause times can be large enough and distribution of pause time and its effect on ICT can be an interesting area of study. Very few works like [26], [56] have considered the nature of flight lengths and pause time while designing a mobility model. Even traces which have been collected do not reveal much about the nature of pause times and flight lengths. Another interesting area of research may be mobility prediction based on recent history. Mobility predictions and their comparison with empirical data may help understand human motion in a better way. One might be tempted to say that if we are able to predict human mobility within a given error percentage, we have been able to understand a lot about human mobility and can be represented mathematically.

People are often attracted to popular places and the popularity of a given location significantly determines their frequency of visit to such areas. Such places can act as attraction points and individuals may repeatedly visit such places. Although traces have been collected to represented general human mobility in a confined region like conference or university, sufficient statistics are still unavailable regarding the frequency of visits made by individuals to a given location. For example, devices could be installed at well-known popular places and traces can be recorded regarding the frequency of visits made by a particular device over a given time period. Although most of the research work concerning MON has been directed towards designing new routing algorithms, very few works [113], [114] have taken mobility into account while proposing such algorithms. Most researchers have used available mobility traces for evaluating the performance of their routing algorithms, but they fail to take into account the very nature of mobility before proposing a new algorithm. We recommend that mobility and its inherent characteristics should be the very basis of a routing algorithm. Before designing a new routing algorithm, researchers should perform a statistical analysis of appropriate mobility model or ensemble mobility parameters from mobility traces. For example, if one intends to evaluate the performance of a routing protocol based on mobility traces, they should collect statistical data of ICT, contact time, flight length, and pause time. Statistical data may include probability density function (p.d.f), cumulative distribution function (CDF), expected value or mean, variance. Some other important areas for proposing new mobility models can be improved algorithms for user-area selection based on distance from the current location. An ideal situation would be to combine the community based mobility models (CMM or HCMM) with realistic mobility models such Lévy Walk or SLAW since human mobility is largely influenced by community formation or strong inter-dependence/attraction between individuals belonging to the same community. Finally, to comment on some of the mobility models;

- Many authors and even we recommend avoiding mobility models such random waypoint, random direction or random walk since they do not reflect the true nature of mobility as observed in real life.
- RWP has its inherent anomalies, RD is unrealistic because it is unlikely that people would spread themselves evenly throughout an area and RW suffers from sub-diffusive nature of mobility.
- BSA has undesired side effects that occur since it allows the MNs to move around a torus.
- With GM, PRW, ECR and RPGM difficulty arises from selecting the correct parameter which would be suitable for a given scenario.

VII. Conclusion

Studying mobility and proposing mobility models has been an active area of research since late 1990s. We believe that this paper provides detailed survey and state-of-the-art researches in mobility and its impact on opportunistic routing algorithms. We have performed an extensive research on the topic and have highlighted the major findings to date. But we believe that "Mobility" is a subject of its own and there *still* exists tons of literature which would be quiet interesting to go through. We divide the entire survey into three major sections. The first part (Section II) provides a detailed survey of almost all the well-known mobility models available in literature to date. Mobility greatly influences the performance of opportunistic routing algorithms and different models have different effect on the performance metric. Even same mobility model but with different parameters such as speed, pause time, flight length, etc may reflect different performance characteristics. Since mobility has a significant impact, the performance of dynamic network should be evaluated with mobility that closely matches the real-life scenario in which the network is deployed. For example, if the network is deployed in disaster management scenario, performance is best evaluated with event-driven and role based mobility model. Similarly, if it is vehicular DTN then nodes should follow vehicular mobility model.

The second part of the paper deals with mobility traces (Section III) which researchers have collected in different scenarios (like conferences, university campus, public places) to study the movement pattern of human, wildlife and vehicles. A large part of trace collection has been dedicated to human mobility since individuals carrying hand-held devices can exchange information opportunistically when they meet or move from one community to other. One of the important parameter which characterizes mobility is the inter-contact time (ICT), since ICT forms a major component of delay experienced by the nodes in such networks. Although ICT was first approximated by power law distribution, it was later found that ICT has a power law head followed by an exponential tail. This finding led the researchers to prove that expected delay in such networks is not infinite.

The third part deals with the impact of mobility on opportunistic routing algorithms. The effect of mobility can be best judged by selecting an appropriate mobility model. Social based mobility models have community structure and nodes have highly correlated movement patterns. Mobility parameters like speed and pause times have direct effect on link breaks, ICT and contact times. For example, in vehicular DTN, message propagation speed is largely determined by vehicle density and vehicle speed. Therefore a suitable framework is desirable to correctly assess the performance of routing protocols. Bai *et al.* [115] propose a framework called "IMPORTANT" for analyzing the impact of mobility on ad hoc routing protocols.

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