Chapter 1
Identifying the Intertwined Links Between Mobility and Routing in Opportunistic Networks

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Abstract Mobility intertwines with routing protocols play a vital role in opportunistic networks. First and foremost, mobility creates opportunities for mobile nodes to connect and communicate when they encounter. A series of encounter opportunities can spread a message among many nodes and to a large area until eventual delivery. Further, mobility properties, when utilized by routing protocols, can greatly improve performance. This chapter will trace the research on mobility and mobility enabled message dissemination approaches, and will present a survey over mobility models, analytical results on motion characteristics, and routing strategies that largely rely on mobility. These three components intertwine and show a strong research agenda in opportunistic networks. The survey shows that analytical mobility properties and abstracted graphic features are significant to the success of some routing protocols. By emphasizing on the three components, the survey will help in developing novel integrated mobility and message dissemination solutions for opportunistic networks.

1.1 Introduction

Advances in wireless communication devices bring increasing opportunities for information sharing through new mobile applications. Opportunistic networks support these applications by enabling communications between two mobile nodes when

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they move into transmission range of each other, or when a multihop path is found between them. Such contact opportunities may spread a message among many moving nodes and eventually deliver to the designated destination. Although many of the contact behaviors are sporadic, and can be treated as stochastic processes, a person's social activities can explicitly or implicitly drive his motion, and often produce noticeable patterns, which if explored, will be of great help for message disseminations in opportunistic networks.

Often, due to mobility, short radio range, and a potential large network area, mobile nodes only form intermittent connections. A routing path may not exist between the source and the destination at an instant time. To tackle the intermittent connection problem, recent researches have proposed many routing schemes using the "store-carry-forward" principle. Inevitably, mobility has a significant impact on the success of message delivery using these routing protocols. A number of researches have treated mobility as an integral factor in their routing protocol design. For example, the abstraction of the analytical properties about mobility can be used to help message delivery. Here, mobility and mobility models play three significant roles. First, a realistic mobility model is a valuable evaluation tool. Second, analysis on mobility patterns help to develop better mobility models. Lastly, mobility characteristics help the design of routing protocols.

In this chapter, we discuss recent research in the areas of mobility models, mobility characteristics, and routing strategies in opportunistic networks. Through these three components, we emphasize the unique intertwining connections among mobility models, mobility characteristics, and routing strategies. Our classifications and discussions set this chapter apart from the survey papers in each related area. The chapter also reveals research agendas in each area, and a research trend that integrates the three areas together. Such integration helps deliver significant insights into the performance of the protocols and applications designed for opportunistic networks [37, 42].

For mobility models, we use a novel classification that captures the social role of mobile users and their geographical movements. Typically, the movement of a person is driven by his social activities and is constrained to a road surface. We classify a mobility model based on whether it uses the social intention of mobile nodes and whether it uses realistic geographic locations (maps). Early classifications have used the independence among mobile nodes (namely, the entity mobility models and the group mobility models [8]) and the degree of randomness (namely, trace-based models, constrained topology based models, and statistical models [60]). These classifications are feasible when mobility models are used as common and valuable components in simulations for protocol evaluations. For our purpose, using social role as classification criterion can better serve the evaluation need for the routing protocols that are designed taking social properties.

The further investigation is on the motion characteristics. The movement patterns, demonstrating through spacial properties and temporal behaviors, are important in forming connecting links. Also, the patterns can be abstracted to graph features. We classify existing analytical results using these aspects. These analytical results are scattered in many research papers and they have been offering insightful knowledge for realistic mobility models and routing protocols. For example, the concentration locations can help communications among nodes [46], the spacial Levy Walks mobility can help design optimal search patterns as routing strategies [47]. In this chapter, we emphasize the characteristics and the utilization of these characteristics.

For routing in opportunistic networks, we are interested in how mobility helps in generating efficient message disseminations. A routing protocol delivering better performance shows higher delivery rate, shorter delivery delay, and less energy consumption. We classify routing schemes into two main categories, namely, proactive routing and reactive routing in opportunistic networks. Different from the conventional definitions of these two terms in Mobile Ad Hoc Networks (MANETs), in this chapter, the proactive routing category describes the schemes that build upon the knowledge of all the mobile members and their movements over time; while the reactive routing describes the schemes that use collected contact information at each forwarding node. The proactive schemes could use offline and global knowledge. With reactive schemes, knowledge is collected contact by contact. Such information may be different with different mobile users. Routing decisions are made using partial knowledge. The reactive routing category is further classified into three subcategories. They are contact-based routing, community-based routing, and auxiliary node-based routing. These subcategories are based on whether the routing relies on statistics of contacts, or topology structural features (community), or auxiliary nodes and movements.

The relationships of the three components are illustrated in Fig. 1.1. The mobility models are the evaluation tools for routing protocols and the sources for analysis. Some analytical results can contribute to new mobility models with increased flexibility in reproducing the desired network scenarios. On the other hand, routing protocols can take underlying mobile topological structures from some results of mobility analysis. In summary, this chapter provides a systematical overview for mobility models, mobility analysis, and routing over recent work in opportunistic networks. And more important, it addresses the intertwining connections among the three areas. It also discusses the research trends and future directions.

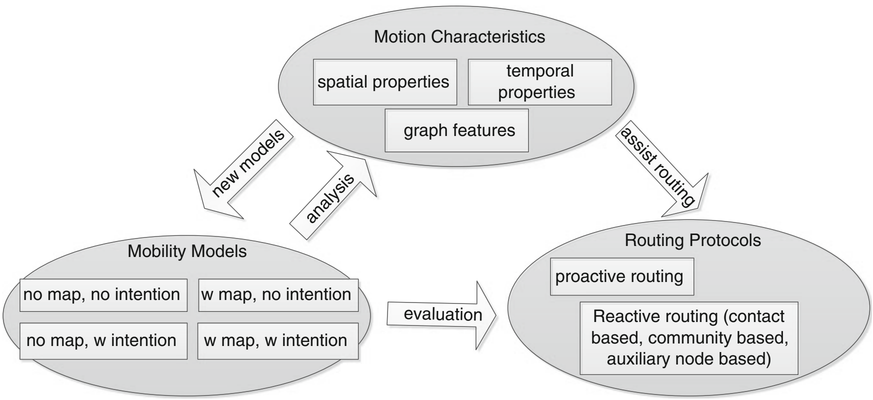

Fig. 1.1 Relationships of the three components

The rest of the chapter is organized as follows. In Sect. 1.2, we classify the mobility models into four categories with a combination of with or without intention and geographic constraints. We introduce the representative models respectively. Section 1.3 summarizes the analytical results on the motion characteristics including geographic, time related features, and graphic properties. In Sect. 1.4, brief overviews are given on several routing schemes for delay tolerant networks with a balance in coverage and focus. Future directions are discussed in Sect. 1.5. We summarize the chapter in Sect. 1.6.

1.2 Mobility Models

Users' movements are most likely the explicit or implicit results of their social or personal activities. As mobility models, the movements can map to geographical locations and motion steps. In this section, we use a criterion to classify a mobility model depending on whether it uses road systems through maps and whether it captures the intention of mobile node. A map defines the available locations and paths where mobile nodes move. For example, mobile nodes may move freely among any spots in a field or may go along on certain fixed roads. As for the intention of mobile nodes, it dictates the motion behavior and trajectories, which, in return, generate the ever-changing topology of a network. Our criterion demonstrates both the objective constraint and the subjective intention, which reflect the essential features of a realistic mobility model in a social context. In this section, the two specific factors are combined to classify the mobility models.

1.2.1 Non-Map Without-Intention Models

In the non-map-without-intention category, the mobility models have no restrictions on paths nor intention of movement for mobile nodes.

1.2.1.1 Basic Model

The first basic mobility model is the Random Walk Model [8], which is sometimes referred to as Brownian Motion. A mobile node in a field moves at a certain speed and direction for a step and then changes to another speed and direction in the next step. The step can be a specific time interval or a distance. The model is memoryless, which means the current movement of the node is independent of the previous speed and direction [22]. Random Waypoint Model [28] adds a delay factor to simulate pauses during motion. Specifically, there will be a pause time between two straight line movements. The result suggests that long pause times will lead to stable network even at high speed [6]. Random Direction Mobility Model further adds treatments dealing with the movements hitting simulation boundary [43]. These models can generate unrealistic movements, such as sudden stops and sharp turns.

1.2.1.2 Realistic Model

To model reasonable movements, the Gauss-Markov Mobility Model is proposed where the current speed and direction are obtained based on the previous speed and direction [30]. The model further improves the previous models by simulating the acceleration and deceleration of mobile nodes to some extent. Moreover, the Heterogeneous Random Walk (HRW) model is able to simulate the clustered network [40]. In the model, every node performs an independent random walk with heterogeneous speed. The significant feature of the HRW model is that the occurrence clusters are guaranteed because of different speeds and not because of "popular locations". Besides that, the model is able to produce changing connectivity over time. The model uses a closed-form expression to describe the time-stationary distribution of nodes. It can generate various clustering phenomena by tuning the corresponding parameters. The result shows that the emergence of cluster is more like at the low speed areas.

1.2.2 Map Without-Intention Models

Mobility models in map-without-intention category reveal path restrictions in nodes' movements without their social intentions. The typical models are Freeway model [1] and City Block model [14]. The vertical and horizontal tracks of freeway confine the paths of movement for mobile node. Additionally, mobile nodes take random turns at the street crossings when they travel along street grid. The Street Random Waypoint mobility model uses real maps and simulates movement details for vehicular network by considering the intra-segment mobility and inter-segment mobility on street grid [11]. The vehicular movements include car following, traffic control, and turning behavior. Another mobility model for vehicular network covers the effects of stop signs, timed traffic lights, and control on next road [44].

1.2.3 Non-Map With-Intention Models

For the category of non-map-with-intention, there is no path restriction but nodes have special movement intentions. Such intentions can be individual or can be shared with other nodes.

1.2.3.1 Group-Based Model

The Reference Point Group Mobility Model (RPGM) [22] describes groups of nodes moving according to the paths of the group leaders. The path of a group leader is defined through a list of checkpoints. Members in one group add their own randomness around its leader's path. The model is general. It allows multiple groups and different methods in defining the paths for the groups. With the RPGM model, groups can move randomly within an area; they can move structurally according to a map; they can each occupy a sub-geographical area; they can also overlap partially or totally in geographical areas. The flexility of defining various motion patterns is achieved through the ways that the checkpoints are given. On the other hand, the nodes in a group have the intention to stay close in order to accomplish special missions such as battlefield situation, disaster recovery, and convention scenarios. Thus, the moving paths of these nodes are determined by the movement of their group leader.

In [34], an interaction-based mobility model with sheep and mavericks patterns characterizes the formation and disaggregation of hot spots at random times and locations. Specifically, the sheep movement pattern models the group behavior where the population at different locations serves as the influence probability. While the nodes with mavericks pattern play the role of disaggregation, the two patterns interact and cause the evolution of hot spots.

1.2.3.2 Community-Based Model

The community-based mobility model captures the feature that a number of hosts are grouped together at a certain time [35]. The model is implemented by making use of social network theory. The relationship between people is denoted as a connectivity matrix serving as the input of the model. Additionally, different types of relationships during certain times are included so as to represent the dynamics of the community.

With the assumption that each node moves independently and a node visits its own community more than others, the community model with cyclic pattern extends the community-based model by defining the repeating time period to model revisits to the same preferable locations [54]. Normal movement periods and concentration movement periods compose the time structure in this model. Specifically, in each period there are two different epochs: in local epoch the node only moves within its community and in roaming epoch the node can move anywhere. In order to match the synthetic data generated from model to the trace data, the multi-tier community model is developed to simulate the case that the neighboring areas around the community are visited frequently as well.

1.2.4 Map-With-Intention Models

The mobility models in this map-with-intention category show realistic features such as moving along paths and with intentions.

1.2.4.1 Trace-Based Model

By analyzing real mobility traces, we can obtain valuable insights into the realistic behaviors of mobile users. Many works are inspired to use trace data gathered in real scenarios for evaluation. In [2], data from a vehicular testbed of 40 buses were used to evaluate the proposed routing protocol. The buses form a Delay Tolerant Network (DTN). The impact of human mobility on message forwarding is discussed in [9]. The analysis on the data collected from six experimental traces suggests that the distribution of the inter-contact time is heavy-tail on a large range of values. Such results contradict with the exponential decay assumption implied by most mobility models.

In return, some trace-based models make use of the characteristics extracted from the trace to reproduce the trajectories for mobile nodes. Tuduce et al. [51] present a framework describing the spatial process and temporal process for the mobility model. Their WLAN mobility model is derived from the combination of spatial distributions, session length distributions, and movement decisions. They also studied the relationship between the above parameters and the impact on mobility model. The result shows that their WLAN model can simulate the real movement with a very small error. Additionally, Weighted waypoint model is presented based on the trace analysis in the campus [23]. The model captures the preferences of visiting location, pause duration, and weights for choosing next destination. The critical parameters extracted from the trace include the pause time distribution, time-varying transition probability, and wireless network usage.

The Agenda-Driven Mobility model [59] takes initiatives of people's social and personal activities in generating mobility. Specifically, it focuses on the personal agenda of activities (when, where, and what) and combines these activities to geographic locations and movements. The main components of the model involve a series of activities during a certain period of time, a map with various social sites such as schools and malls, and motion generation algorithms. It can be used to characterize many opportunistic network scenarios. In this work, the authors used the data from National Household Travel Survey (NHTS) to extract personal travel demographic characteristics such as activities, occupation types, and driving distances.

1.2.4.2 Graph-Based Model

The Area Graph-based mobility model [4] is derived from a directed and weighted graph. The vertices denote the locations with the corresponding waiting time and the edges are the paths connecting the locations with a chosen probability. During the waiting time, the node will stay inside the vertex and move according to the random waypoint model. Once the waiting is finished, the node has to pick a path to proceed. The different probability for each path will lead to the heterogeneous distribution of nodes. Such results greatly resemble the clustering phenomenon in the realistic mobile networks.

1.2.4.3 Levy Walk-Based Model

The Levy Walk is a type of random walk in which the movement increments are distributed according to a heavy-tail distribution [48]. By analyzing trace data, the authors in [41] found that human mobility is similar to Levy walk in terms of the heavy-tail distribution of flight lengths, pause times, and mean squared displacement. The deviation may arise from the map constraints such as the buildings, roads, and traffic. Based on their findings, they present a Truncated Levy Walk model that emulates human movement patterns in outdoor mobile environments with geographical constraints. This model can produce power-law inter-contact time distribution which matches the statistic feature in trace data. The movement caused by human interests or popularity of locations people visit is also implemented in the model.

1.2.5 Summary of Mobility Models

In summary, the trend of mobility modeling has moved towards being more realistic by taking considerations of both social intentions and geographical features. Early mobility models introduce randomness to motion speeds and directions. Later works have added map constraints and/or intention constraints respectively. The trace-based models can produce both features through replaying the real data. More recently, social behaviors or biological species movements are all studied in the literature. These works further spark the need for analyzing the motion patterns—the aggregated characteristics revealed in the realistic mobility. We review these properties in the following section.

Noticeably, some models are able to generate the concentrations (or called clusters) of mobile nodes. These models can be effective evaluation tools and also play an important role for message forwarding in opportunistic networks. We recap these models here: *heterogeneous random walk model*, *time-variant community mobility model*, *weighted waypoint model*, and *area graph-based mobility model*. The implementations of the models are different. In the *heterogeneous random walk model*, different speeds of mobile nodes lead to emergence of high density areas. In the other models, the preferences of locations are used to represent the popular locations. Furthermore, when the *agenda-driven mobility model* takes the daily activities and their locations, geographic concentrations are observed in their simulation results [59].

Moreover, a more explicit approach in modeling the relationships among mobile nodes can be very useful. Some models presented here are *reference point group mobility model (RPGM)*, *interaction-based mobility model* , and *community-based mobility model*. The models consider the attractions among mobile nodes. Again, the attractions are another important reason for concentrations. In some scenarios, the concentrations can have great influence on the network topology.

1.3 Mobility Characteristics

Various mobility models have been analyzed over the years and the analytical results have contributed to performance evaluation, simulation calibration, and routings protocol design. In this section, we introduce these analyses in four categories, namely, spatial characteristics, temporal characteristics, spatial-temporal analysis, and graph characteristics. The characteristics specifically include moving distance, spatial locality distribution, temporal properties, movement correlations, and graph-related features. At the end of this section, the impact of mobility models on evaluation results is discussed.

1.3.1 Characteristics of Flight

The flight length is defined as the longest straight line trip from one location to another. The probability density distribution of flight in Levy Walk mobility model [47] is expressed as follows:

$$p(l) = |l|^{-(1+\alpha)} \tag{1.1}$$

where α has a value between 0 and 2, l denotes the flight length. When $\alpha \geq 2$, the model becomes Brownian Motion. As for the property of flight in Random Waypoint Model [28] with a rectangle area $a \times b$, the probability density function is

$$f(l) = \frac{4l}{a^2b^2} f_0(l) \tag{1.2}$$

where the detailed expression of $f_0(l)$ is shown in [3]. The flight characteristics can reflect the diffusivity of mobility which is defined as the variance of translation between two waypoints. The conclusion about diffusivity suggests that the Random Waypoint model is the most diffusive model, the Brownian Motion is least, and the diffusivity of Levy Walk model is in-between [41].

The feature of flight is also mentioned in other mobility models. Specifically, the flight during each mobility epoch in community-based model is obtained as an exponential distribution with an average length. In the social network theory-based community model [35], the communities are mapped to locations in certain topographical space, hence the flight distribution heavily depends on the underlying map and relationships among communities.

For routing purpose, flight can be applied to discover the nodes that are helpful for relaying message. For example, in order to simulate the optimal search pattern, the nodes moving similar to Levy walk are selected for relaying message. In addition, the diffusive nodes with average longer flight can be employed to implement fast message dissemination [47].

1.3.2 Locality Distribution

Different movement patterns can lead to various spatial locality distributions. In general, we say that the scattering of nodes is either uniform or heterogeneous. The uniform distribution denotes the scenario that every node has the equal chance to visit each location in the network. With heterogeneous scattering, clustering phenomenon appears at some locations.

The distributions for Brownian Motion and Random Waypoint Model are analyzed in [5]. The result shows that Brownian Motion can always produce uniform position distribution. However, the space border can make an effect on the distribution in Random Waypoint model because of its diffusivity. If the pause time or pause probability increases, the border effect becomes weak and the mobile nodes can distribute in the space uniformly. The distribution of node position in Random Waypoint model can be found in [3]. Since there are only three states in the model: static, moving, and pausing, the probability density function is

$$\begin{aligned} f(x, y) = &\ f_{\text{initial}}(x, y) p_s \\ &+ f_{\text{pause}}(x, y) p_p (1 - p_s) \\ &+ f_{\text{move}}(x, y)(1 - p_p)(1 - p_s) \end{aligned}$$

where p_s is the probability of being static and p_p is the probability of pausing. The concrete derived formula is given in [3].

In the Heterogeneous Random Walk [40], the node's position in a stationary regime shows in the following pdf:

$$f(x, y) = \begin{cases} c_1 = \frac{a}{\sigma_1^2} \text{ if } (x, y) \in C \\ c_2 = \frac{a}{\sigma_2^2} \text{ if } (x, y) \in \overline{C} \end{cases}, a = \frac{1}{\frac{|C|}{\sigma_1^2} + \frac{|\overline{C}|}{\sigma_2^2}} \tag{1.3}$$

where $|C|$ and $|\overline{C}|$ are the sizes of the area C and $\overline{C}$. C and $\overline{C}$ have different nodes' density, σ_1 and σ_2. They are instantaneous variances of diffusion process which reflects the speed for each area. Since the average speed is slower in C, movement beginning with the distribution will lead to the appearance of clustering in C.

The social network-based model studies the relationship between individuals for the distribution of node positions [36]. An Interaction Matrix is used to express the social relations. The derived Connectivity Matrix can reveal clusters by identifying the groups of nonzero entries. In another work [51], analysis on the trace data shows that wireless users stay at a few locations for most of the time and only a small part of connections last for a long time. A user location at the next time step could be one of the three possible areas which are the current cell, neighboring cell, and non-neighboring cell. Similar concentration points are also identified when a taxi trace is analyzed [46]. Further, the location-dependent pause duration and preference in choosing next destination can be found in a survey-based trace data [23].

1.3.3 Temporal Characteristics

Several temporal characteristics are proposed to show the relationship between time and mobility. The probability density distribution of pause time in Levy Walked mobility model is shown in the following equation [41]:

$$\varphi(t) = t^{-(1+\beta)}, 0 \leq \beta \leq 2 \tag{1.4}$$

where t is the pause time. In Random Waypoint mobility model, the pause time of mobile node is uniformly picked from a range of time [28]. A general conclusion is that the longer the pause time, the smaller the mobility [38].

The hitting time is used to express the average time when a node starts from the stationary distribution to move into another arbitrary location. When there are several areas with higher visiting rates in the network, the hitting time for these areas is critical in selecting one for communications purpose. Additionally, the meeting time is defined as the expected time before two nodes meet with each other. The derivation of hitting time and meeting time is given with the Time-variant Community mobility model [54]. Based on the two-state Markov model and geometric distribution, the expected hitting time and meeting time are derived. The hitting time in Random Waypoint model defines the time that a host takes to move between two consecutive waypoints. The probability density function is [3]

$$f_T(t) = \begin{cases} \int_{v_{\min}}^{v_{\max}} v f_L(vt) f_V(v) dv & \text{if } t \in [0, l_{\max}/l_{\min}] \\ 0 & \text{otherwise} \end{cases} \tag{1.5}$$

where $f_L(l)$ is the probability density function of transition length and $f_V(v)$ denotes the probability density function of speed.

The inter-contact time denotes the time gap separating two contacts between the same pair of mobile nodes. Based on the observations on eight distinct experimental data sets, Chaintreau et al. show that the inter-contact time can be approximated by a heavy-tail distribution instead of a light-tailed distribution, though the latter is common to most of the mobility models [9]. The impact on packet delivery from various values of the distribution parameter is studied as well. The concept of $k - vicinity$ extends the contact between two mobile nodes to contacts that are within k-hop range [39]. The observation is that high percentage of contacts occur within k hops in mobile opportunistic networks. Building on $k-vicinity$, $k-contact$, and $k-intercontact$ are defined. The former characterizes the property that two nodes are within k hops in the $k-vicinity$, and the latter describes the inter-contact time of two nodes based on the contact states of the two disjoint k-vicinities each belongs to. These two metrics capture more contact opportunities for message sharing and also explain the social behavior of the community-based mobility model.

The authors in [45] provide an analytical framework to derive the statistics for link lifetime, new link inter-arrival time, link breakage inter-arrival time, and link change inter-arrival time. They are functions of node's speed, transmission range, and density. For the link inter-arrival time, the density can be denoted as

$$f_{\text{change}}(t) = \lambda e^{-\lambda t},$$

where λ is the mean link change rate which is a function of node velocity. This result is applied to adaptive periodic updating interval for a proactive routing protocol in mobile ad hoc networks.

Another routing relevant temporal feature is *encounter frequency*. It can be obtained from encounter history during a certain period. This statistical data is used as a metric to predict the encounter probability in the future. A couple of protocols such as [31, 49] make use of counter frequency as the simple and effective routing metrics. The above contact properties are also analyzed in [61] with special efforts for two distinct groups of people. One group of people visit a specific area periodically, while the other group shows random visits and occurs at the specific areas rarely.

With the interaction-based mobility model [34], the *filling time* and *scattering time* are proposed to describe the dynamics of hot spots. The filling time denotes the time when an expanding hot spot becomes stable and the scattering time indicates the time when the hot spot disappears. The two metrics describe the graph evolution when formation and disaggregation of hot spots change at random.

1.3.4 Joint Spatial and Temporal Analysis

The temporal and spatial properties are often studied jointly. In [29], the relationships among vehicles are analyzed by first creating a mobility profile of each node, which includes a series of times and locations of its movement. Then an entropy-based metric using the node profiles is proposed to compute the group similarity . Given a grouping threshold, the metric helps to determine whether two mobile nodes are neighbors or not at a given time.

A different approach is introduced in Mobyspace [27]. This work computes the similarity of mobile traces using a set of metrics including Euclidean distance, Canberra distance, Cosine angle separation, and Matching distance. The results associated with these metrics map each individual mobility into a high-dimension space, where the group similarity is found.

The time-dependent link properties at different locations are studied in [19]. The analysis identifies popular locations in mobile networks and trajectory segments between each pair of these locations. The corresponding time-dependent graph is formed and the aggregated mobile segments are analyzed for each link to derive the link delay and capacity. The probabilistic analysis under the similar network scenario is given in [20, 21]. In these works, the movement duration is discretized into steps and the forwarding strategy is modeled as a probabilistic value. The analysis uses matrix to calculate communication latency for different forwarding strategies.

1.3.5 Graph Characteristics

It is interesting to note that some trace-based mobility models have given rise to a new type of analysis, i.e, the potential indication of social networks. Typically, when nodes visit common places, or they move close to each other, the wireless devices can pick up the connections in proximity. In recent works, researchers have analyzed these connections to identify graph-related characteristics. The existence of nodes bearing the graph structural properties cannot be ignored since they can make a strong impact on message delivery, for example, a node showing centrality in the network can be applied to bridge the gap between two distant nodes.

Centrality [17] is used to measure the importance of node in terms of the network structure. The three common metrics are degree centrality, closeness centrality, and betweenness centrality. Specifically, degree centrality is defined based on the number of direct links of a given node. The closeness centrality measures the distance of each direct link. A shorter average distance of a node implies a higher closeness centrality. To measure the betweenness centrality, the shortest paths between any other nodes yet containing a given node are counted. Nodes with high centrality act as the central nodes. They can play an essential role of message relay. Generally, these central features are not proposed for network with dynamic topology because the derivation of central nodes needs global network information. Thus, it is necessary to search and compute the centrality locally.

Additionally, the concept of clique community is proposed to classify mobile nodes in a network for efficient routing. Specifically, the mobile nodes in the same community become the favorable message relays. A distributed algorithm [25] is provided for identifying k-clique community. The first step is to build a familiar set for each node which consists of its contact neighbors, and then the local community is generated by combining the related familiar sets subject to specific admission condition.

Given the importance of the connectivity of a network graph formed by mobile nodes, a measurement is proposed in a continuum framework [10]. The continuum space consists of two dimensions: the average node density and the average node speed. According to different combinations of density and speed, three classes of networks are found, which are the total connected network, disrupted network, and partitioned network. The building of their framework starts from each node pair and the node pairs are classified into different types based on the connection duration. Finally, the percentage of node pairs with a certain type is used to determine the whole network connectivity.

1.3.6 Simulation-Related Issues

Contact traces usually contain link information of encountering nodes but not the location coordinates of these nodes. The usage of a contact trace is thus limited to the environment where the trace is acquired. In order to improve the usability of the contact trace, e.g., transferring a Bluetooth trace for a WiFi contact environment, Whitbeck et al. [55] try to derive mobility information (position data) from a wireless contact trace. As a result, a single trace can generate more network scenarios for simulation. The authors use the constraints of speed and contact event, and an online force-based dynamic graph layout algorithm to calculate (infer) future node contacts. Their evaluation results show that reliable high frequency contact trace is helpful to derive accurate prediction. And using additional reference nodes can further increase the precision.

Several unexpected problems have emerged regarding to a certain mobility models. The issues are that the simulations using these models may bring inaccurate results in terms of evaluation. Taking the Random Waypoint model as an example, the first problem is the decay of speed [56], i.e, the average speed will decay to 0 when the speed range sets to [0, x]. Another problem is that the density at the center region will be higher than that around the boundary [3]. Jean-Yves Le Boudec applied Palm calculus to explain above problems [7]. The stationary distribution of nodes is also derived which can be used to start the simulation directly, eliminating the need for a long warm-up running time to reach the stable state.

1.3.7 Summary of Characteristic Analysis

The analysis on motion patterns has revealed many salient properties in spatial, temporal domains, and nodal graphic characteristics. These analysis results are being used in many areas. Some of the spatial and temporal properties from trace analysis are used in new mobility models, e.g., the power law distribution in flight length and flight time as in the Truncated Levy Walk model. Some results are used in analytical evaluations of latency and delivery ratio for routing protocols. The trustworthiness of simulation is also analyzed using the nodal spatial distribution for random waypoint mobility model. Warnings are given based on the results regarding the minimum speed and the treatments on the boundaries. The graph-related properties can suggest specific roles that the nodes may perform in forwarding messages. Those nodes with strong graph structural properties play an important role in expediting the forwarding and offering efficiency. Many characteristics are used by routing protocols directly, for example, interarrival time can be used to tune message broadcast interval, centrality and similarity can be used for forwarder selection, diffusivity can be used for forwarder selection as well. These analysis results are summarized in Table 1.1.

1.4 Routing Strategies

Disseminating messages with the "store-carry-forward" routing principle has been greatly studied as Delay Tolerant Network (DTN). We classify the various routing strategies into two categories: proactive routing and reactive routing. The proactive

Table 1.1 Summary of mobility characteristics

Categories	Mobility characteristics	Features for routing
Flight length	Longest straight line trip from one location to next location; node diffusivity	Message forwarder adopts Levy walk, high diffusive nodes for fast dissemination
Locality distribution	Distribution of node positions during moving process is either uniform or heterogeneous	Cluster-based routing is suitable in network with heterogeneous distribution
Temporal characteristics	Encounter frequency, pause time, hitting time, meeting time, inter-contact time, filling time, scattering time	Encounter history for choosing next forwarder; the other time metrics for estimating message delay and delivery rate
Joint spatial-temporal	Time and location relationships of groups, trajectory similarity	Routing uses clusters or high similarity nodes
Graph characteristics	Degree centrality, closeness centrality, betweenness centrality, k-clique community	Node with higher centrality as forwarder; community helps to group mobile nodes; connectivity analysis and evolution for performance

routings use the centralized or offline knowledge about the mobile network to make the routing decision. In the reactive routing, nodes derive the forwarding strategies through the contact history, without a global or predetermined knowledge of the occurrences of future (maybe better) links. Most DTN routing protocols fall into the reactive category. We further classify them based on the types of mobility characteristics or the usage of assistant nodes. It is worth noting that graph-related characteristics are regarded as important enablers for performance improvements, and thus are used by the protocols in both categories. Given the rich literature resources, we could only select representative routing protocols in our discussions.

1.4.1 Proactive Routing

Using the knowledge about the mobile network such as nodes' contacts history, queueing length and traffic demands, a network graph can be obtained in advance. The graph includes edges with time-varying capacity and propagation delay. Jain et al. [26] proposed a framework of routing which takes different levels of knowledge modeled after the graph to calculate minimum delay path for message delivery and trade-offs. The work shows that the more knowledge acquired by the routing protocol the better the performance. The authors in [2] treat the message routing as a resource allocation problem. Packets in the buffers will be forwarded based on the decisions on whether to be replicated or not in order to optimize a specific routing metric. A per-packet utility function is derived from the routing metric designed by administrator. After the information for utility is received from control channel of node, the inference algorithm in the protocol will estimate the utility for each packet and the result will be used to pick up the corresponding packet to be replicated and sent. The distributed estimation procedure can be found in [2] which assumes that the inter-meeting time between nodes is exponentially distributed.

Taken the fact that cyclic movement patterns occur in real mobility scenarios, the mobile network can be modeled as a stochastic contact graph where every node is a vertex and each link has the contact probability and expected latency [32]. In routing, Markov decision process is applied to search the path with expected minimum cost for message routing.

The cyclic movement pattern is also considered in the network scenario where static throw-boxes are deployed [19]. The mobile nodes traveling between throw-boxes form network links that carry the temporally stored messages from one box to another. Multiple cyclic movement patterns are multiplexed to form a contact graph with time-dependent metric states at each link. A capacity-aware routing protocol is proposed which searches the shortest path that considers the time-varying delay and capacity of the virtual links for each box pairs. A Markov model is used to describe the evolution of the real-time link delay and capacity between two throw-boxes. The routing decision is made for each Markov state at each link.

Mobyspace [27] describes a generic routing scheme using high-dimensional Euclidean space with the assumption of full knowledge at each node about other nodes' mobility patterns. The main routing idea is that the packet should be forwarded to the node which has the similar pattern of destination. Several metrics are proposed to compute the similarity of mobility models including Euclidean distance, canberra distance, cosine angle separation, and matching distance. Based on the results of similarity, each node can efficiently route the message to the right forwarder.

1.4.2 Reactive Routing

The reactive routing category further divides into three subcategories as the contact-based routing, community-based routing and the auxiliary node-based routing. In the contact-based routing, communication is achieved by a series of encounters among mobile nodes. Specifically, when two nodes contact with each other, they can decide to exchange messages according to a predefined metric. The community-based schemes typically identify and use a special group of nodes. Messages will be sent to this group of nodes. This special group is formed by the nodes with better sociability, frequent contacts with the destinations, or attached to a hot location. By identifying the communities, messages can be quickly transmitted to the destination. In auxiliary node-based routing, extra nodes are introduced to act as message forwarders. These nodes may move with favorable trajectories or stay at specific locations.

1.4.2.1 Contact-Based Routing

Epidemic routing [52] is the basic contact-based routing in DTN. In this scheme, when two nodes encounter, the message called summary vector is exchanged in order to detect the missing contents in each other. Once a node finds the discrepancy, it will request the unseen message. The epidemic routing will flood a message with the expense of wasting huge resources such as bandwidth and buffer sizes. Based on the epidemic routing, PROPHET [31] employs a probabilistic metric called delivery predictability to narrow the scope of message flooding. The delivery predictability indicates the likelihood of the encountering node being able to deliver the message to the destination. Three equations are used to predict the delivery probability. The equation for probability updating is:

$$P_{(a,b)} = P_{(a,b)_{\text{old}}} + (1 - P_{(a,b)_{\text{old}}}) \times P_{\text{init}} \tag{1.6}$$

where $P_{(a,b)} \in [0, 1]$ means the contact probability at node a for destination b and $P_{\text{init}} \in [0, 1]$ is an initialization constant. The equation for aging is:

$$P_{(a,b)} = P_{(a,b)_{\text{old}}} \times \gamma^k \tag{1.7}$$

where γ is aging constant and k is the number of time units that have elapsed. The last one is to measure the transitivity which is for the case that if node A frequently meets node B and node B frequently encounters node C, then node A is a good candidate to relay message to C(through B) even if A rarely sees C.

$$P_{(a,c)} = P_{(a,c)_{\text{old}}} + (1 - P_{(a,c)_{\text{old}}}) \times P_{(a,b)} \times P_{(b,c)} \times \beta \tag{1.8}$$

where β is the scaling constant to decide the impact of transitivity on the delivery predictability. Therefore the forwarding happens only when the delivery predictability of neighboring node is high.

The Spray and Wait protocol [49] significantly reduces the transmission overhead of flooding-based scheme by spraying only a fixed number of copies of message into network and then wait until the nodes that carry these messages encounter the destination node. The number of copies used by the protocol is determined through an equation based on the relationship between the number of nodes and the amount of copies. The Spray and Focus is also proposed in [49] which aims at improving Spray and Wait for mobile users with localized mobility. The difference between the above two protocols is that the message carrier in Spray and Focus will forward the copy to another suitable neighbor if they have not encountered the destination for a long time. The Seek and Focus is a hybrid protocol which includes utility-based routing and randomized routing. It builds on the Spray and Focus protocol to conquer the slow-start phase problem. The initial step of this protocol discovers the potential relay neighbor by using the utility-based approach. It then uses the randomized routing in the re-seek phase in order to avoid routing jamming for a long time at local maxima of utility.

A data item and interests on the data item can be another decisional factor in message exchanging among contacts [42]. Such consideration is important for data-centric opportunistic networks. Data can be described using a set of tags; and a user's interest on data can use the same tagging attributes. A *relevance score* measures the strength of a node's interest on a data item through the matching attributes between user's interest space and data's metadata. A data item with a higher score will have higher priority and being transferred earlier. However, trade-offs exist in terms of local interest versus global interest. The work introduces five strategies that detail various preferences at the times of data exchanges. Extensive comparisons are made to understand the performance under the strategies, the mobility patterns, and the data interest model.

1.4.2.2 Community-Based Routing

Various analysis on mobility patterns have shown that a certain group of mobile nodes can be at more helpful positions topology-wise. For example, mobile nodes with better sociability or having similar location preferences or motion trajectories. Such groups can be identified through various metrics, and are called communities. Many routing protocols well utilize the identified community for passing messages to achieve better performance.

The concept of centrality can be used to identify the nodes with high betweenness centrality which measures the importance of node on the communication paths. In addition, the similarity of nodes can be measured to find the nodes closest to destination. With these two metrics, the central nodes will first forward the messages to the possible node groups that contain the destination and then some nodes in the group will hand over the messages to destination.

Daly et al. provide a distributed method to identify central nodes and utilize them to forward messages [13]. The authors utilize the idea from ego network to measure the centrality in a distributed way. In addition, the similarity between nodes is calculated based on neighbor set so as to obtain the nodes close to destination. With the centrality and the similarity, the weighted metric is defined and used to choose next forwarder. In another work [24], the forwarding algorithm makes use of the averaged degree of node as approximate metric to find the forwarder with higher centrality.

In [18], an efficient multi-casting mechanism is proposed by using social characteristics including community and centrality. It determines the message forwarders subject to certain delivery ratio. A new centrality metric considering the contact frequency among nodes is provided as the weight of each node in [25]. A distributed algorithm is used to identify the communities in the network using the metric. The transmission among communities is achieved by exchanging message through the gateway nodes belonging to multiple communities.

Island Hopping [46] relies on the cluster-based mobility model. The authors introduce a novel network entity called Concentration Points (CP), which are locations where many nodes stay for a while. Nodes can communicate within the same CP.

A mobile node will carry messages from one CP to another. The routing algorithm first discovers the whole network graph collaboratively in order to calculate a sequence of CPs to forward the message. The Last Encounter Table is used to estimate the position of destination for the shortest path. One-hop acknowledgment is used in Island Hopping for reliability. Thus a message will have a few copies at the previous CP. These copies will be suppressed after an acknowledgment is received.

The protocol [33] for VANET makes full use of the underlying road map to achieve the efficient message dissemination among dynamic vehicles. In their design, the intersection graph is created first where each road segment becomes the vertex and the intersection linking any two segments is the edge. Based on that, the corresponding connected dominating set (CDS) is derived, which develops into the information search area. At the same time, the nodes only in that CDS form a special community and become the forwarders to disseminate messages.

1.4.2.3 Auxiliary Node-Based Routing

Some of the DTN routing protocols use a set of special nodes to help message dissemination. The mobile ones are called message ferries. The trajectories of the message ferries are controlled in order to maximize the chances of message delivery. The Levy message ferries are proposed in [47], where the ferries move using the Truncated Levy Walk mobility model with a smaller value of α (inducing higher diffusivity). An optimal routing scheme, using Levy Walk searching strategies, achieves better performance for sparsely and randomly distributed targets [53].

A well-known message ferry approach is discussed in [57]. There are two different message ferry schemes described in that paper: Node-Initialed MF scheme and Ferry-Initiated MF scheme. The first scheme takes advantage of the fixed routes of ferries to collect data from mobile nodes. When the nodes periodically move close to the route of the message ferry to send message, the deviation of their original path will degrade performance on the tasks they need to finish. So the balance between performance gain in data delivery and performance degradation in assigned tasks should be considered. Another scheme is initiated by ferry in which ferry takes proactive movement to contact nodes for communication. In this scheme, each node is equipped with a long range radio which is used for contact control and a short range radio for message exchange. In addition, the goal of trajectory control of the ferry is to minimize the message drops. A follow-up work employs multiple ferries to improve the data delivery performance.

Stationary device known as throwbox is another type of auxiliary node that can be deployed in order to facilitate message exchange [58]. Based on the degree of available information, three modes for deployments are presented: contact and traffic-based mode, contact-based mode, and oblivious mode. Intensive simulations suggest that throw-boxes are effective in improving throughput and delay when multi-path routing and regular movement are employed.

1.4.3 Summary of Routing Strategies

In this section, we introduced many representative DTN routing schemes. We also tried to identify the noticeable trend that explores the underlying network mobility. The helpful mobility features demonstrated not only in geographical phenomena but also in social network implications. Brief summaries and comparisons of the routing schemes are given in Tables 1.2 and 1.3 for proactive and reactive routing protocols respectively. We use a column *Mobility Model and Feature* to reflect the influence from mobility. It includes the movement patterns and potential mobility features that the protocols rely on. The column of *Applicable Environment* expresses the scenarios where a protocol can perform better according to the original papers. As indicated in the tables, while each protocol can be applied to general opportunistic network scenarios, applicable situations exist for many protocols in order to fully utilize their design strengthes.

1.5 Future Directions

Future investigations can go in several directions. One direction is the social network-related analysis and its connection with opportunistic networks. As pointed out by Conti et al. [12], the translation from social network relationships to geographical distance bounded contacts is not a trivial issue. In this regard, mobile social networks can provide useful insights. Contact traces, on the other hand, still warrant for in-depth investigations. The work presented in [61] claims that traces from general users and all kinds of devices are highly desired. The work itself also proposes a method to identify the more socialized population at a specific area against rare and random occurrences. To be noted are the the graph-related characteristics, they shall still be of the most importance in the analysis of social behaviors. More study can investigate graph characteristics associated with temporal properties and subgraphs.

Many of the movement characteristics are closely related to the real fields where the data are obtained. As such, some most recent work has focused on vehicle movements within a road system. The unique geographical constraints and movement constraints pose great challenges to network connectivity, partition, and message persistency. These are all interesting topics for further research.

A step further will be the novel message dissemination schemes that explore more social network properties. For example, the social-aware content sharing scheme exchanges mutual interested contents when a node moves into a new community [15]. The scheme relies on closely coupled social communities to their physical device contact patterns.

Moreover, the management of opportunistic networks can take a great leap when cognitions on network traffic, radio resources, and mobility conditions are devised [50]. As illustrated in the paper, a broad range of applications can be developed. Examples include extending coverage, capacity, and traffic aggregation when

Table 1.2 Summary of proactive DTN routing schemes

Protocol	Category	Main routing strategy	Mobility model and feature	Applicable environment
Knowledge-based routing schemes [26]	Proactive	Use modified Dijkstra with cost function from different oracles	Trace data derived topology, graph characteristic of time varying link delays	Communication opportunities are known or predictable
RAPID [2]	Proactive	Estimate utility function from routing metric and route the messages with highest utilities	Vehicular DTN traces with power-law meeting probabilities, meeting time	Nodes contact with an exponential inter-meeting time
Routing in cyclic mobile space [32]	Proactive	Derive optimal routing with stochastic graph-based on Markov decision process	Trace data with cyclic pattern, contacts	Cyclic contact pattern between two nodes
Capacity-aware routing using throw-boxes [19]	Proactive	Derive optimal routing path among throw-boxes where time-varying links are formed by mobile nodes	Trace data with cyclic pattern, derived graph with contacts and time varying links	Cyclic movement pattern between two throw-boxes
Mobyspace [27]	Proactive	Forward to node having similar mobility pattern with destination	Session durations and frequencies of location visits following power-law distribution, high dimension temporal-spatial distribution	Assume the mobility pattern of destination is known

Table 1.3 Summary of reactive DTN routing schemes

Protocol	Category	Main routing strategy	Mobility model and feature	Applicable environment
Epidemic [52]	Reactive, contact	Message flooding	Any mobility model, contacts	General mobile network
PROPHET [31]	Reactive, contact	Predicting the delivery probability of relay nodes	Community-based mobility, encounter frequency	General mobile network
Seek and focus [49]	Reactive, contact	Use randomized forwarding utility-based routing and geographical routing	Community-based mobility, encounter frequency	General mobile network
Spray and wait, spray and focus [49]	Reactive, contact	Limit the number of nodes to flood message	Community-based mobility, encounter frequency	The former prefers network with diffusive nodes; the latter prefers network with localized mobility
Social network-based routing [13], Bubble rap [24]	Reactive, community	Select the central node and similar node for routing	Trace data with some nodes showing network structural properties, graph characteristics of centrality and similarity	General mobile network
Social network-based multi-casting [18]	Reactive, community	Select the central node and community in multicast	Trace data named reality [16], graph characteristics of centrality and similarity	General mobile network
Island hopping [46]	Reactive, community	Use clusters to forward message	Random walk with exponentially distributed pause and move time, spatial locality	Rely on the presence of stable clusters
Routing in VANET [33]	Reactive, community	Rely on the nodes in the CDS of the intersection graph	Trace data of taxi in urban area, graph characteristics connected dominating set	General mobile network
Scale-free Levy message ferries [47]	Reactive, auxiliary	Select the node with high diffusivity to relay message	Flight length following truncated Levy Walk, flight length	General mobile network, message ferries in Levy walk
Message ferries [57]	Reactive, auxiliary	Use message ferries to move and pick messages	Area-based model, temporal and spatial location distribution	Ferries move in proactive manner for communication
Throwboxes [58]	Reactive, auxiliary	Use static relay devices to help forwarding	Trace-based model from bus network, spatial locality	Special static nodes are needed

concentration of users in a certain service area occurs. Much work can be done in investigating the routing strategies for the cognitive tasks.

1.6 Summary

This chapter presents a survey over mobility models, analytical results on motion characteristics, and routing strategies that largely rely on mobility. The three components embedded an intertwining research agenda ranging from early separate research on mobility models till the latest results where analytical properties about mobility are abstracted and utilized in many routing protocols. Figure 1.2 illustrates the relationship of the contents covered in this chapter. At the bottom, various mobility

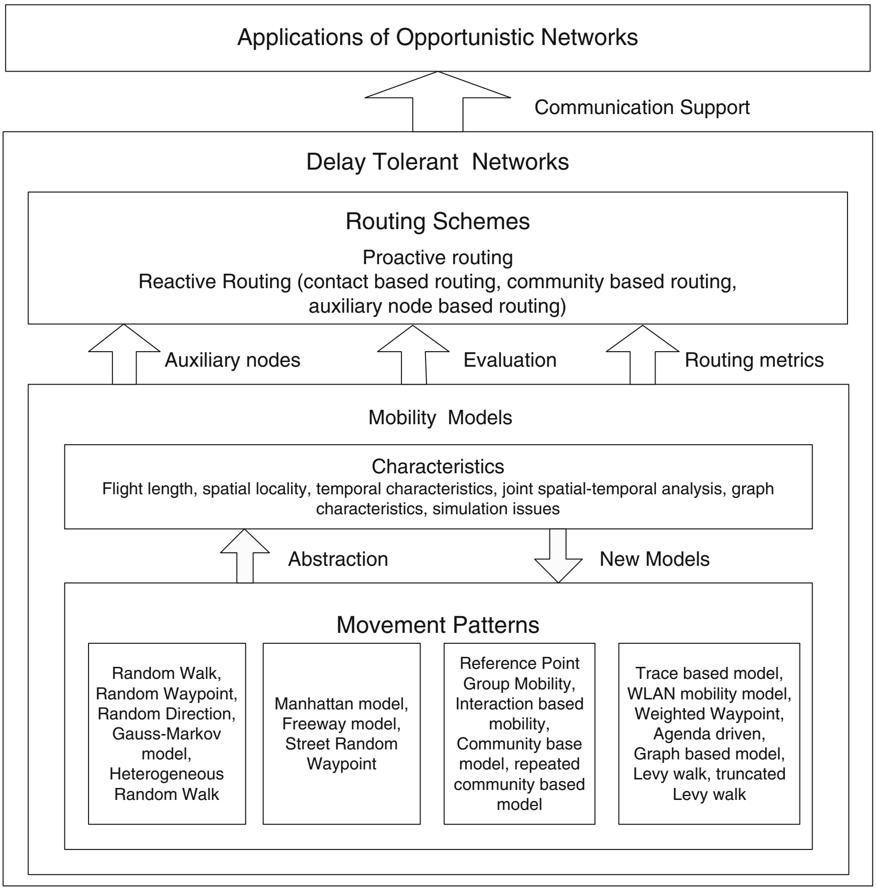

Fig. 1.2 Intertwined links between mobility and routing

patterns are listed. They are abstracted into analytical characteristics. The two parts together are under the huge scope of mobility models. The figure also shows several connections between mobility and routing schemes. On top of the routing protocols (the opportunistic network layer), distributed applications can be supported.

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