Quantifying Network Partitioning in Mobile Ad Hoc Networks

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Abstract

The performance of distributed algorithms in mobile ad hoc networks is strongly influenced by the connectivity of the network. In cases where the connectivity is low, network partitioning occurs. The mobility and the density of network nodes as well as the communication technology are fundamental properties that have a large impact on partitioning. A detailed characterization of this behavior helps to improve the performance of distributed algorithms.

In this paper we introduce a set of metrics that characterize partitioning in mobile ad hoc networks. Based on an extensive simulation study we show the impact of node mobility, density and transmission range on the proposed metrics for a wide range of network scenarios.

1 Introduction

Many seminal algorithms for distributed data management used in wired networks assume that communication failures occur rarely and, therefore, treat them as failure with special recovery mechanisms [6]. In a distributed database, for example, a transaction is aborted due to the failure of a communication link and rolled back. In wired networks many innovations have led to large improvements regarding the stability of network connections, so that communication failures are kept to a minimum. This allows classical distributed algorithms to treat these rare occasions as transient failures from which they recover.

Wireless networks, especially mobile ad hoc networks (MANETs), are very different from the perspective of communication failures. On top of the wireless media, which is very error prone, node mobility leads to a new class of reasons for communication failures. In many application scenarios, mobile devices in such networks are carried by (human) users. In most cases, their movement cannot be influenced by the algorithms running on their devices. Thus, mobility in general leads to three main types of problems:

1. Communication links between pairs of devices may be established and lost without notification, yet not every link change leads to partition creation or merging.
2. Many nodes may be located inside of a small area resulting in high node density, which may lead to the so-called broadcast storms [8].
3. Low node density may lead to network partitions where nodes in different partitions are unable to communicate with one another.

Characterizations of both, the behavior of individual links and of broadcast storms, have been actively studied in the research performed in the past years, e.g., [1], [4], [8]. In this paper we concentrate on the third problem. We perform a systematic study of networks with low density which potentially lead to frequent network partitions and focus primarily on their impact on data management algorithms.

For example, if we consider data replication algorithms, every node is able to distribute update operations to those nodes in the network located in its own partition. Depending on the consistency model used, the system either ends up having to accept stale values, or the update operations have to be suspended until connectivity among all replicas has been restored. If algorithms are aware of network partitioning, they may take explicit precautions to cope with such situations. For instance, they may use knowledge about the average number of partitions in the network in order to approximate a reasonable number of replicas to be placed throughout the network. In the field of location-aware algorithms, the spatial properties of a node’s own network partition define the possible set of other nodes that may be accessed. When using geographic hash tables [10], for example, it may not be possible to retrieve some of the information if it was stored at a location that is not covered by any nodes of the same partition. Information about possible partitions may help in deriving a geographic hash function that stores information at appropriate locations. Data aggregation algorithms (e.g. [7]) are only as accurate as the available data is. On the one hand, relying on possibly stale replicated information may in turn lead to stale aggregates.
On the other hand, obtaining information by using query dissemination when data is not replicated, may lead to incomplete aggregates because only a fraction of the required information can be retrieved. In all of the above classes of algorithms, knowledge about the network’s partitioning behavior may help improve algorithm performance. For example, query and update intervals may be chosen on the basis of an expected partition change rate over time, while an appropriate number of replicas may be selected as a function of the number of partitions over time.

In the next section, we review related work with a focus on modeling the properties of mobile ad hoc networks. In Sec. 3, we state our system model and define the notion of network partitions. In Sec. 4, we introduce the set of partition metrics that we use to characterize different types of MANET scenarios. A comprehensive set of simulation experiments and the obtained results are discussed in Sec. 5. We conclude our paper in Sec. 6 and state future work.

2 Related Work

The impact of mobility on MANETs is an important characteristic that has been treated in previously published work at various levels. This work can be classified into the analysis of basic properties, e.g., link properties, and the analysis of higher-level properties beyond single links.

The author of [1] provides an analytical model for minimum node degree and graph connectivity. The analysis of k-connectivity shows a relationship between the transmission range of nodes and the probability of the graph being k-connected for different k. The analytical model has been compared with simulation results. However, the results do not allow an interpretation concerning the number and size of partitions. In [2] the author analyzes the connectivity of an ad hoc network regarding the transmission range and number of nodes for the random waypoint mobility model. However, the results do not allow an interpretation of partitioning characteristics in mobile ad hoc networks. The authors of [4] only consider the duration of links between adjacent nodes. All of these analytical studies provide a detailed insight into the nature of mobility, node distribution, and the properties of individual links in mobile networks. However, the cause for partitions in general is due to temporal aggregations of link failures between different pairs of nodes and requires a more abstract set of parameters.

Some previous work has been conducted that examines network properties that go beyond the state of individual links. The authors of [8] consider MANETs where nodes are distributed with high density. They concentrate on the fact that message flooding leads to an increasing number of collision in such dense networks (broadcast storms) and propose optimizations to effectively reduce flooding overhead. In contrast, we focus on the impact of low node density on network connectivity. The authors of [5], introduce an algorithm to overcome partitioning in MANETs by increasing the transmission power of the wireless interfaces in the presence of network partitions. The authors’ evaluation only gives results on whether partitions were present at all in the given scenarios. In our work we went further by examining, among others, the number of partitions over time and the frequency of changes in partitioning.

3 System Model

We assume a mobile ad hoc network comprising a set of n mobile nodes. Each node occupies a position (x, y) inside of a fixed geographic area, denoted by A. The transmission properties of all nodes are based on the unit disc model, in accordance with the free space radio propagation model. Thus, two nodes n1, n2 are within transmission range rtx, if the Euclidean distance d(n1, n2) between n1 and n2 is less than rtx. The topology graph G(N, E) consists of a set of vertices, denoted by N, representing the nodes of the network, and the set E of undirected edges, corresponding to communication links between nodes. An undirected edge {n1, n2} ∈ E exists, iff d(n1, n2) ≤ rtx. A network partition is a subset P ⊆ N where i) a path exists between all pairs of vertices n1, n2 ∈ P, and ii) no path exists between any pair of vertices ni ∈ P, nj ∈ N \ P. Finally, by PART(G) we denote the set of partitions in G.

4 Methodology

In this section we state the motivation and formal definition of the set of metrics used for quantifying the partitioning behavior in MANETs. We focus on metrics that best describe the impact of partition characteristics on data management algorithms and reveal correlations that exist between the proposed metrics. To the best of our knowledge, no methodologies similar to our set of partitioning metrics have been treated in previously published work.

We consider two groups of metrics: network-wide partition metrics and node-centric partition metrics. The first group addresses the questions of the number and size of partitions as well as the frequency at which partitions change. Node-centric partition metrics are concerned with how many partition changes a single node experiences over time, and how long the separation time of two nodes located in disjunct partitions is.

In Sec. 4.1 we first introduce preliminary notations used in our methodology. Network-wide and node-centric partition metrics are defined in Sec. 4.2 and Sec. 4.3, respectively. Finally, our simulation study in Sec. 5 investigates the impact of node density and transmission range on each of the proposed metrics according to the given definitions.
4.1 Preliminaries

Let \( T = (t_{\text{min}}, t_{\text{max}}) \) denote a physical time interval. The topology graphs at \( t_{\text{min}} \) and \( t_{\text{max}} \) are defined to be \( G_{\text{min}} \) and \( G_{\text{max}} \), respectively. A partition event \( e \) occurring at a discrete point in time \( t \in T \) is defined by a tuple \( e = (\text{type}, t, P_1, P_2, G, G') \). The \textit{type} attribute is either \textit{split} or \textit{join}, indicating that partitions \( P_1 \) and \( P_2 \) involved in the event are split or joined, respectively. \( G \) and \( G' \) are the topology graphs before and after the occurrence of the event. For a join event, both partitions \( P_1 \) and \( P_2 \) are contained in set \( \text{PART}(G) \) and \( P_1 \cup P_2 \) is in \( G' \). For split events the opposite holds.

The effect of events with equal timestamps on the topology graph is commutative, i.e., it leads to the same topology graph, independent from the order in which these events are applied.\(^1\) Informally, removing an edge \( e_1 \in E \) and adding a different edge \( e_2 \in E \) for a given topology graph \( G \) at the same time will result in the same topology graph \( G' \) independent of the order in which these edges are modified. Therefore, we can arrange all events linearly according to a total order \( <_o \) based on timestamps and a particular (arbitrary) order for events that occur at the same time.

By \( E_{\text{part}}(T) = \{ e \mid e.t \in T \} \) we denote the set of partition events in \( T \). The indexing function \( \epsilon : \{1, \ldots, |E_{\text{part}}(T)|\} \rightarrow E_{\text{part}}(T) \) is the bijection that preserves the total order on \( E_{\text{part}}(T) \), i.e., \( \forall i, j \in \{1, \ldots, |E_{\text{part}}(T)|\} : i < j \iff \epsilon(i) <_o \epsilon(j) \).

The two types of events indicated by the \textit{type} attribute are defined as follows: A partition \textit{join} event \( e = (\text{join}, t, P_1, P_2, G, G') \), or join event for short, is a partition event in \( E_{\text{part}} \) transforming a topology graph \( G \) into \( G' \) such that \( P_1, P_2 \in \text{PART}(G) \) and \( \exists P \in \text{PART}(G') \) for which \( P = P_1 \cup P_2 \). A partition \textit{split} event \( e = (\text{split}, t, P_1, P_2, G, G') \), or split event for short, is a partition event transforming a topology graph \( G \) into \( G' \) such that \( P_1, P_2 \in \text{PART}(G') \) and \( \exists P \in \text{PART}(G) \) for which \( P = P_1 \cup P_2 \).

4.2 Network-Wide Partition Metrics

Network-wide partition metrics characterize the partitioning situation in a MANET viewed as a single entity. We propose the following three metrics: the number of partitions, the size of partitions, and the partition change rate.

4.2.1 Number of Partitions

Let \( \Pi(e) = \text{PART}(e, G') \) be the set of partitions that exist after a given event \( e \) has occurred. If the \textit{number of partitions} that exist in the network after the occurrence of event \( e \) is denoted as \( |\Pi(e)| \), then the average number of partitions over the time interval \( T \) is defined as follows:

\[
|\Pi|_{\text{avg}}(T) = \frac{1}{|\Pi|_{\text{avg}}(T)} \sum_{i=1}^{E_{\text{part}}(T)} (e(i+1), t - e(i), t) \cdot |\Pi(e(i))|
\]

In other words, the average number of partitions is the time-weighted average of all partitions that exist in the system after each (split or join) event. For ease of exposition, we have not explicitly stated the number of partitions before the first event and after the last event in the above equation, although we have considered these corner cases in the simulation study.

The relevance of this metric is motivated as follows. Given an ad hoc networking scenario, the average number of partitions \( |\Pi|_{\text{avg}}(T) \) is the primary metric needed to identify how many partitions are to be expected. Many distributed algorithms, e.g. replication and distributed aggregation, rely on communication primitives such as broadcasting or multicasting which operate best in the presence of high connectivity within the network. For this metric, the optimum case is defined as \( |\Pi|_{\text{avg}}(T) = 1 \), that is, all nodes are contained in a single partition and are connected at all times. The worst case occurs if \( |\Pi|_{\text{avg}}(T) = n \), that is, every node \( n_k \in N \) is isolated.

More precisely, in the case of replication, the average number of partitions is an important indicator for the number of replicas that should be created in a particular network scenario. Obviously, if the number of replicas is much smaller than the average number of partitions, there is a high probability that some nodes will not be able to access any replica in the system. On the other hand, if the number of replicas is greater than the average number of partitions, the probability of reaching at least one replica in a partition is much higher. If the number of replicas is much larger than the number of partitions, too many redundant replicas might be available that may not be required.

Furthermore, the distribution of the number of partitions gives additional information which can be of use, for example, for broadcast protocols. If the distribution of \( \Pi(e) \) indicates that the network is never fully connected, that is, \( \forall e \in E_{\text{part}} : |\Pi(e)| > 1 \), a complete broadcast will never be possible without buffering the broadcast message.

4.2.2 Size of Partitions

Let \( |P| \) denote the \textit{size of a partition} \( P \), that is, the number of nodes in that partition. The average size of partitions, written \( S_{\text{avg}}(e) \), that exist in the system after a given event \( e \) can be derived from the average number of partitions by computing \( n/|\Pi(e)| \). Thus, the average size of partitions over \( T \) is

\[
S_{\text{avg}}(T) = \frac{n}{|\Pi|_{\text{avg}}(T)}
\]
For given size $x$, the number of partitions with size $x$ over the interval $T$ is calculated as:

$$H(x, T) = |\{ P \in \text{PART}(G_{\text{min}}) \mid |P| = x\}| +
\{|e| e.\text{type} = \text{join} \land |e.\text{P}_1 \cup e.\text{P}_2| = x\}| +
\{|e| e.\text{type} = \text{split} \land |e.\text{P}_1| = x\}| +
\{|e| e.\text{type} = \text{split} \land |e.\text{P}_2| = x\}|$$

(3)

where $e \in E_{\text{part}}(T)$. Obviously, the domain of $x$ is $\{1, \ldots, n\}$, because the minimum and maximum size of a partition is 1 and $n$, respectively. The graph of $H(x, T)$ is the frequency distribution of partition sizes within time interval $T$. With $H(x, T)$ it is possible to identify characteristic distributions of partition sizes. For example, peaks in the graph defined by $H$ indicate that many partitions are nearly equally sized, e.g. many small and few large partitions.

Concerning the impact on data management algorithms, a distribution of partition sizes that reveals many large partitions implies high connectivity of the network. This enables a single node to reach many nodes with a high probability, e.g., during a message broadcast or when addressing a replication quorum. If, however, many small partitions exist, many nodes are isolated and cannot be reached. For the particular case of broadcast algorithms, this metric can be used to determine whether or not simple flooding or gossiping mechanisms are sufficient, or whether or not different (more sophisticated) algorithms such as Hyper Flooding are optimized for settings where many partitions exist, are necessary.

### 4.2.3 Partition Change Rate

The **average partition change rate** $R_{\text{part}}(T)$ is defined as the number of partition events that have occurred over time interval $T$ divided by $t_{\text{max}} - t_{\text{min}}$:

$$R_{\text{part}}(T) = \frac{|E_{\text{part}}(T)|}{t_{\text{max}} - t_{\text{min}}}$$

(4)

The partition change rate is an indicator for the frequency of partition changes in general. On one hand, high partition change rates are beneficial for data dissemination algorithms in order to deliver data to nodes in different partitions. The higher the rate, the more contacts between different partitions occur per unit of time. On the other hand, low partition change rates are beneficial for algorithms that require a relatively stable topological structure, such as broadcast or aggregation trees. Here, any partition split event may damage the tree if the structure extends over multiple partitions after a split. These two examples show that the interpretation of the partition change rate strongly depends on the concrete application scenario.

### 4.3 Node-Centric Partition Metrics

In this section we present metrics that characterize the partitioning behavior from the perspective of individual nodes. The metrics defined here are the node partition change rate and the node separation time.

#### 4.3.1 Node Partition Change Rate

For this metric, we first determine the number of partition events that a node $n_k$ experiences. For a partition event $e$ to be counted, it must hold that $n_k \in e.\text{P}_1 \cup e.\text{P}_2$, where $e.\text{P}_1$ and $e.\text{P}_2$ are the partitions involved in the event $e$. We define the set of partition events that a node $n_k$ is involved in over time interval $T$ by $E_{\text{part}}(n_k, T) = \{e \in E_{\text{part}}(T) \mid n_k \in e.\text{P}_1 \cup e.\text{P}_2\}$. We define the node partition change rate for a node $n_k$ as follows:

$$R_n(n_k, T) = \frac{|E_{\text{part}}(n_k, T)|}{t_{\text{max}} - t_{\text{min}}}$$

(5)

For every node $n_k$, it holds that $R_n(n_k, T) \leq R_{\text{part}}(T)$, because $E_{\text{part}}(n_k, T) \subseteq E_{\text{part}}(T)$. The average node partition change rate for interval $T$ is

$$R_{\text{avg}}(T) = \frac{1}{n} \sum_{k=1}^{n} R_n(n_k, T)$$

(6)

and will be used in comparison to the network-wide partition change rate $R_{\text{part}}(T)$ (cf. Sec. 4.2.3). Patterns in the distribution of node change rates may provide helpful insights into the characteristics of algorithms operating in a given geometric area. For example, if the network-wide partition change rate $R_{\text{part}}(T)$ is high, the node partition change rate is able to reveal e.g. if a few nodes being involved in frequent partition changes dominate the global rate, while other nodes may experience only a few partition changes. Especially the latter case would indicate stable, but isolated partitions.

#### 4.3.2 Node Separation Time

The **node separation time**, denoted by $\tau_{\text{sep}}(n_1, n_2, T)$ and defined between pairs of nodes $n_1, n_2$ during time interval $T$, describes the time for which nodes are located in different partitions and thus, cannot communicate with each other. To derive this node-centric metric, two events $e_1, e_2$ have to be found for which the following is true: $e_1.\text{type} = \text{split}$ and $e_2.\text{type} = \text{join}$ and $n_1 \in e_1.\text{P}_1$ and $n_2 \in e_1.\text{P}_2$ (w.l.g.) and the next join event $e_2 \in E_{\text{part}}(T)$ for which $n_1, n_2 \in (e_2.\text{P}_1 \cup e_2.\text{P}_2)$. The set of all such pairs of events is denoted as $E_{\text{sep}}(T)$. The sum of all node separation times during interval $T$ is defined as follows:

$$\tau_{\text{sep}}(n_1, n_2, T) = \sum_{(e_1, e_2) \in E_{\text{sep}}(T)} e_2.t - e_1.t$$

(7)
and the number of nodes. The mobility model the nodes follow, and the transmission range of the wireless communication technology. The spatial node density is defined by the size of the spatial area and the number of nodes.

We assume that all network nodes are mobile, thus inducing changes in the topology graph over time. We use two mobility models in our experiments: the random waypoint mobility model [3] and the graph-based mobility model [12], which model typical scenarios in an open field and urban area, respectively. In the random waypoint model, nodes move on straight lines inside of the simulation area by repetitively selecting a random destination and random speed. Because this model has the property of a steadily decreasing average node speed over time [13], we choose the random speed from an interval (\(v_{\text{min}}, v_{\text{max}}\)), with \(v_{\text{min}} > 0\).

In the graph-based model, the mobility of nodes is spatially constrained by a graph. Each vertex in the graph represents a particular location \((x, y)\) within a geographic region, such as points of interest or road intersections. Graph edges connect these locations, and represent routes in the region, such as streets. Each node chooses a vertex of the graph as its destination and a speed from a given interval randomly and moves to that destination on the shortest path of the graph at the chosen speed. In contrast to the random waypoint mobility model, the graph based random walk mobility model is more restrictive and prohibits completely arbitrary movement, reflecting more closely scenarios in urban areas.

5 Simulation Study

The key parameters for performance evaluation of algorithms in MANETs are the spatial area in which the mobile nodes may move, the number of nodes in the network, the mobility model the nodes follow, and the transmission range of the wireless communication technology. The spatial node density is defined by the size of the spatial area and the number of nodes.

While for a large number of connections, the aggregated total connection time may be high, the intervals for each connection and may still be small. Therefore, we also examine the number of node separations \(K_{\text{sep}}(n_1, n_2, T)\) and connections \(K_{\text{con}}(n_1, n_2, T)\) per node pairs, which define the number of separations and connections that occur during time interval \(T\), respectively.

5.1 Simulation Results

To conduct our experiments, we have used an event-based simulator which, given a mobility trace, constructs and alters the topology graph over time. The event-based approach is able to capture every occurring state of the topology graph over time. The mobility traces were obtained using the simulation environment presented in [11]. The random waypoint model operates on an area of \(2 \times 2\) km\(^2\). For the graph-based random walk mobility model, we have modelled two graphs, representing a typical Central European city and Midtown Manhattan. Both graphs, depicted in Figure 1, span a total area of approximately \(2.5 \times 1.8\) km\(^2\). The similar areas of the mobility models allow us to compare the simulation results for different mobility patterns with one another. The speed of nodes was randomly chosen from the interval \((0.5, 2.0)\) km/s. The total simulation time was 3600 s.

5.1.1 Number of Partitions

Figure 2 shows the results for the average number of partitions \(\Pi_{\text{avg}}(T)\) as a function of the number of nodes in the network. For small networks, \(\Pi_{\text{avg}}(T)\) is mostly determined by the number of nodes in the network, which defines the upper bound of the number of partitions. Once the node density is higher than 75 nodes/km\(^2\), which corresponds to 300 nodes in our simulations, \(\Pi_{\text{avg}}(T)\) steadily decreases. However, even for larger networks with a density of 600 nodes/km\(^2\), i.e., 2400 nodes, the relatively high number of partitions (5 to 10 on average) still needs to be taken into account, especially for the implementation of algorithms, such as reliable broadcast techniques, that require the reachability of all nodes in the network.
Figure 2. Average number of partitions $|\Pi|_{\text{avg}}(T)$ as a function of the number of nodes $n$ for $r_{\text{tx}} = 100$ m and all three mobility models.

Figure 3. Frequency distribution of the number of partitions $|\Pi(c)|$ for $n = 400$ nodes, $r_{\text{tx}} = 100$ m and the random waypoint mobility model.

Figure 4. Frequency distribution of the partition size $H(x,T)$ over the number of nodes $n$ for $r_{\text{tx}} = 100$ m and random waypoint mobility.

Figure 5. Average partition change rate $R_{\text{part}}(T)$ over the number of nodes $n$ for $r_{\text{tx}} = 100$ m and all three mobility models.

Figure 3 shows an example of the frequency distribution of the number of partitions for 400 nodes. For the graph-based models, we have observed a very similar distribution with respect to the averages in the number of partitions. A key observation is the fact that no arbitrary number of partitions occur for any selected number of nodes. In addition, with increasing number of nodes, the distribution is even more distinct around the average. Assuming that nodes are able to detect the node density in their vicinity, the selection of a matching distribution allows us to reason about the number of partitions in regions of the network for the presented mobility models.

5.1.2 Size of Partitions

Figure 4 shows the distribution of partition sizes for different node densities. In all scenarios, the occurrence of very small partitions, e.g., isolated nodes and partitions of up to 5 nodes, is very common. For low densities, these small sizes dominate the distribution. With increasing density, the occurrence of very large partitions becomes more frequent and leads to a large standard deviation for the size of partitions.

The result that average sized partitions are rare leads to the conclusion that, if a node is not located inside a small partition, there is a high probability that it is located in a large partition. Detecting whether or not a node is in a small partition is possible with relatively low communication overhead by calculating the $k$-hop neighborhood, where, for example, $k = 4$ to decide whether or not a node is in a partition with at most 5 nodes. In our results, simply checking for partitions of size smaller than 5 would allow us to determine with a high probability ($\geq 80\%$) whether or not a node is located in a large partition. This information could be valuable for many data management algorithms involving, for example, multicasting or broadcasting, where it would be useful to send important information while being inside a large partition.

5.1.3 Network and Node Partition Change Rate

Figure 5 shows the average partition change rate $R_{\text{part}}(T)$ over the number of nodes. From the results, we can distin-
guish two classes of network sizes: for a very small number of nodes, the partition change rate is low and increases with the number of nodes until the network comprises approximately 300 nodes. For this low density, the number of partitions containing only one or a few nodes is high. Such partitions are connected with a small number of links only. Therefore, a link change leads to a partition change very frequently. Partitions become connected with more links as the number of nodes increases further, leading to partitions which are more robust against link changes. As a consequence, the partition change rate decreases.

Figure 6 displays the results of the average node partition change rate $R_{\text{avg}}(T)$ as a function of the number of nodes. The change rate as experienced by individual nodes on average, shows the same characteristic behavior as the network-wide partition change rate in Figure 5. This indicates that the characteristics of the partition changes over networks of different sizes are similar to those experienced by individual nodes. On average, $R_{\text{avg}}(T)$ is lower than the network-wide partition change rate, because not every node is affected by every change. Nevertheless, as the size of the network increases, the difference between the node rate and the system-wide rate becomes smaller.

5.1.4 Node Separation Time

Figure 7 shows the average of the sum of node separation times $\tau_{\text{sep}}$ over the number of nodes. For the evaluation, we selected $n/2$ disjunct node pairs for each experiment at random, i.e. every node is contained in exactly one of the pairs. As the number of nodes in the network increases, the average node separation time decreases. For networks between 300 and 500 nodes the slope is very steep. This is associated with the decreasing partition change rate presented in Figure 5 which leads to more stable partitions in networks with a larger number of nodes.

Figure 8 shows an example for the distribution of node separation times of 400 nodes. About 75% of the occurrences are below 50 seconds, about 35% are even below 10 seconds. This information is very valuable for algorithms that need to estimate when a node will be reachable again after a communication failure has occurred. For example, a node that has not succeeded in sending information to a particular other node may retry to initiate communication after 10 and 20 seconds, because 35% and 55% of all separations in a network with 400 nodes are shorter than 10 and 20 seconds, respectively.

5.1.5 Comparison of the Mobility Models

When comparing the results of the different mobility models used in the experiments, i.e. the random waypoint mobility model and the two instances of the graph based random walk mobility model, it is noticeable that they share the same characteristic behavior for all metrics examined. However, the particular results measured vary significantly in quantitative terms. In general, it can be observed that
the quantities obtained for the random waypoint experiments are between those used for the two graphs (Figure 1). Taking the results for the average number of partitions $|Π|_{\text{avg}}(T)$ as an example, the Manhattan graph reveals a significantly higher average number of partitions than the other two mobility models, which becomes more prominent for network sizes between 500 and 1500 nodes. The comparison of the two graphs reveals that the Manhattan graph has a longer total length of edges while having approximately the same number of vertices. Additionally, the European city graph has a lower average number of edges originating at vertices. Both graphs have approximately a base of 4 km$. In the Manhattan graph the movement of nodes is restricted to an almost regular grid pattern with distances in between those grid rows that are larger than the assumed transmission range. As a consequence, nodes moving on parallel grid rows/columns are separated for longer periods of time. The results obtained with the two different city graphs underline that the partitioning behavior depends on the spatial structure of the system’s environment. Further research will be necessary in order to distinguish between individual parameters of the spatial environment that influence the network topology.

6 Summary and Future Work

In this paper we have provided an in-depth study of the partitioning behavior in mobile ad hoc networks. In order to quantify partitioning, we have defined a set of metrics which helps during the process of design and improvement of distributed algorithms in mobile ad hoc networks. Our metrics describe characteristics such as the number and size of partitions, the separation times for pairs of nodes, and the rate at which partition changes occur.

In our simulation study, we have investigated the effect of different node densities on partitioning and quantified these effects by applying our set of metrics. The results show that network partitions occur frequently even in networks with reasonably high node densities. For example, in a network containing 800 nodes on a 4 km$^2$ area and a transmission range of 100 m, we found more than 20 partitions on average. For such scenarios, the partitioning situation should not be neglected in the design of distributed algorithms for mobile ad hoc networks. The separation time between pairs of nodes showed to be significant even in scenarios with high node densities.

Future work will include a more detailed analysis of the impact of different parameter sets of the mobility models on the partitioning behavior. The observation that different graph structures in the graph-based random walk model lead to significant variations in the measured values of our metrics raises the question which key parameters of the spatial environment account for the dynamics in network partitions. Additionally, spatially structured environments will most likely induce a location dependent effect on network partitioning, which may have great impact on applications of mobile ad hoc networks in, for example, urban areas.

References