Quantifying Impact of Mobility on Data Availability in Mobile Ad Hoc Networks

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Abstract—In mobile ad hoc networks, there are many applications in which mobile users share information, e.g., collaborative rescue operations at a disaster site and exchange of word-of-mouth information in a shopping mall. For such applications, improving data availability is a significant issue and various studies have been conducted with this aim. However, each of these conventional works assumed a particular mobility model and did not fully investigate the influence of the mobility on the proposed approach. In this paper, we aim to quantify the influences of mobility on data availability from various perspectives. We assume neither specific applications nor specific protocols but we propose and quantify several metrics that affect data availability. We also report results of some experiments that measure the proposed metrics assuming several typical mobility models.

Index Terms—Mobile ad hoc networks, data availability, data replication, data diffusion, pervasive computing.

1 Introduction

1.1 Background and Motivation

Recent advancements in wireless communication and the miniaturization of computers have led to a new concept called the *mobile ad hoc network (MANET)*, where two or more mobile nodes can form a temporary network without need of any existing network infrastructure or centralized administration [2], [3]. In MANETs, mobile nodes act as routers themselves, keeping route information to reach other mobile nodes, and helping forward data packets sent from one mobile node to another.

At the early stage of MANET research, most studies focused on routing protocols to support communications among mobile nodes connected to each other by one-hop/multihop links [7], [17], [26]. Such routing protocols are useful for applications in which mobile users directly communicate with each other, e.g., video conferencing systems. However, in MANETs, there are also many applications in which mobile nodes share data and access data held by other mobile nodes. Typical examples are collaborative rescue operations at a disaster site, military operations, sensor networks, and exchange of word-of-mouth information in a shopping mall.

For such applications, preventing the deterioration of data availability at the point of network partitioning is a very significant issue [10], [18]. More specifically, as mobile nodes move freely in MANETs, disconnections often occur, and this causes data in two separated networks to become inaccessible to each other. For example, in Fig. 1, when disconnection happens between two nodes, data item D_1 becomes inaccessible to mobile nodes on the right side, while data item D_2 becomes inaccessible to mobile nodes on the left side. There are two major research trends to address this issue: *data replication* [5], [9], [10], [11], [12], [23], [33] and *data diffusion (dissemination)* [13], [14], [18], [20], [24], [31], [34], [35]. The former topic addresses replication or caching of data items whose sizes are relatively large. It focuses on data allocation (relocation), consistency management (synchronization), location management (data looking up), etc. The latter topic addresses effective and efficient dissemination of data items whose sizes are relatively small in sparse and partitionable MANETs.

The results of these conventional works have revealed that mobility heavily affects data availability; high mobility sometimes increases data availability, e.g., a mobile node relays data between two separated (partitioned) networks, and it sometimes decreases, e.g., a mobile node that holds hot (popular) data disconnects from the network. However, most of the conventional works assumed a particular mobility model (movement pattern of mobile nodes) and only examined the influence of the mobility model on the performance of the proposed approach. In other words, they did not give any general insights on the relationship between mobility and data availability.

1.2 Contributions

In this paper, we aim to quantify the influences of mobility on data availability from various perspectives. We do not assume specific applications nor specific data replication or diffusion protocols, but propose several general metrics to quantify data availability. Since there are typically two approaches for improving data availability in MANET applications in which data are shared among mobile users or devices: 1) data replication and 2) data diffusion, the proposed metrics are defined to examine the impact of mobility on the performance of these two approaches.

For data replication protocols, significant factors that affect the performance are how many data items can be replicated on connected mobile nodes and how often and how much the groups of connected mobile nodes change. Therefore, we define few metrics that represent the total

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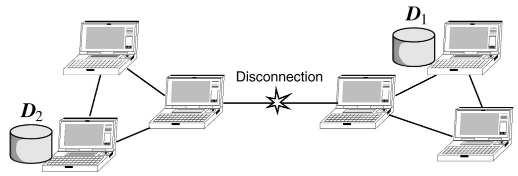


Fig. 1. Network partitioning and data access.

size of data storage of connected mobile nodes and the degree of change in the storage size. For data diffusion protocols, significant factors for performance are how fast data items can be distributed to a large number of mobile nodes. Therefore, we define few metrics that represent the number of mobile nodes to which a mobile node connects during a certain unit of time.

Then, we report the results of some experiments that measure the proposed metrics assuming several typical mobility models: random walk, random waypoint [3], Manhattan mobility, and reference point group mobility [15]. We also report the results of experiments using two kinds of real mobility traces: taxi cabs [4] and humans [28].

In summary, the contributions of this paper are as follows:

1. Because the proposed metrics for quantifying the impact of mobility on data availability are general and do not assume particular mobility models, they can be used for any applications in which mobile users or devices share data with each other. Therefore, these metrics would be helpful for system developers and researchers to design and examine data replication or data diffusion protocols by taking the impact of the mobility model into account.
2. The experiment part shows examples of how to apply the proposed metrics to the given mobility models and how to examine the impact of the mobility pattern. If the mobility pattern of the assumed application is just or almost same as a typical mobility model shown in this paper, our experimental results can be directly used for the design of the protocols for the application. Even if the mobility pattern of the assumed application is different from the typical ones shown in this paper, its impact on data availability can be examined in the same way as we did in our experiments using typical mobility models and real traces.
3. The experimental results would be useful for reviewing the performance of the conventional protocols on typical mobility models shown in this paper. Specifically, while the conventional works evaluated the proposed protocols in terms of particular performance metrics, the results have not been deeply examined in most cases. Here, our experimental results can give reasonable explanations on the performance of these conventional protocols and make their advantages and disadvantages more clear.

1.3 Paper Organization

The remainder of this paper is organized as follows: In Section 2, we introduce some related work. In Section 3, we define metrics to quantify the influences of mobility on data availability, some of which are new metrics proposed in this paper. In Section 4, we report the results of experiments that measure the proposed metrics on several typical mobility models. We conclude the paper in Section 5.

2 Related Work

In recent years, much research has been conducted to investigate the influences of mobility on network performance such as the efficiency of routing protocols [19], [21]. Because the main objectives of routing protocols are finding destinations and forwarding data packets with low message overhead in a dynamically changing network topology, it is known that mobility heavily affects protocol performance. These studies are similar to our work because both approaches aim at investigating the influence of mobility on system performance. However, these conventional works mainly concentrated on link stability and node distribution in the assumed area. This is because routing protocols support communications between two connected mobile nodes, and these two metrics directly affect how often and dynamically paths between nodes change, i.e., they affect protocol performance. On the contrary, data availability is affected by network partitioning; thus, other metrics to quantify network partitions are needed.

Related to the above research, various new mobility models that seem more realistic than the existing ones have been proposed [15], [16], [22], [25], [27]. These works also reported the results of experiments that measured the performance metrics on the proposed models. Since the proposal of mobility models is outside the scope of this paper, we choose several typical mobility models to examine our proposed metrics.

Some conventional works studied the influences of mobility on data availability in MANETs [1], [8]. In [1], the authors mathematically defined and analyzed some metrics that represent the impacts on information diffusion in MANETs. Among these metrics, the estimated number of encountered nodes is the measurement for representing how data are rapidly disseminated. Here, encountered nodes are defined for each node as nodes with which it experienced a direct connection by a one-hop wireless link, i.e., that are located within its communication range. However, this metric does not truly represent the rapidness of data dissemination because data can be transmitted not only to nodes within the communication range of each other, but also to nodes connected by multihop links. Our proposed metrics take this fact into account.

The conventional work that is most relevant to our work has been reported in [8]. To our best knowledge, this is the first and only work that aims to quantify network partitioning. In [8], the authors proposed five metrics. Three of them are network wide metrics: number of partitions, size of partitions, and partition change ratio. The rest are node-centric metrics: node partition change rate and node separation time. However, these metrics are not enough to fully examine the influences of mobility on data availability. In terms of data availability, the first two metrics represent the capacity of data storage (memory space) of each partition, e.g., the larger the partition is, the more data can be stored in it. The other three metrics just represent how frequently members of each partition change or how long before each pair of two nodes disconnects. More specifically, these metrics cannot distinguish whether only one node disconnects from the partition or the partition is split into two partitions with the same size. Also, they do not represent how many nodes each node connects with at a certain interval. Thus, they do not truly represent the dynamism of partitions. In terms of data availability, not only the capacity but also the dynamism is a significant factor. In this paper, we propose new metrics to represent the dynamism of partitions in MANETs.

In [30], the authors present three metrics that are complete and smallest for distinguishing between typical measured and canonical network topologies including the Internet. Then, these metrics were used for qualitatively matching these measured and canonical network topologies with topologies generated by several network generators. Although the paper [30] does not assume MANET, determining the complete and smallest set of performance metrics is also a significant issue in MANET. Finding the minimum set of metrics that can qualitatively distinguish between given network types is a problem that has a clear solution. On the other hand, we do not assume such a concrete (solvable) problem because requirements for quantifying the impact of mobility are different according to the applications and situations. Rather, we aim to quantify the impact of mobility on data availability to briefly grasp the qualitative characteristics (not qualitative distinctions) of any given mobility patterns. Therefore, it is impossible to provide the complete and smallest metrics. However, following the approach in [30], we might be able to qualitatively distinguish between and match movement patterns in real networks and typical mobility models by using performance metrics for quantifying the impact of mobility. We think that this is an interesting topic we should address in the future.

3 Metrics to Quantify Network Dynamism

In this section, we propose new metrics to quantify the influences of mobility on data availability.

3.1 Preliminary

First, we explain our assumed system model. m nodes exist in the entire network. The set of all mobile nodes in the system is denoted by $\boldsymbol{M} = \{M_1, M_2, \ldots, M_m\}$, where M_k $(k = 1, \ldots, m)$ is a *node identifier*.

The communication range of each mobile node is expressed by a circle with radius C, i.e., the communication ranges of all the nodes are of the same size; thus, every wireless link is bidirectional. This assumption is for simplicity, but we can deal with more realistic situations in which nodes may have different or noncircular communication ranges by ignoring unidirectional links as many network and application protocols do. The network can be partitioned only due to the limitation of a node's communication range. In this paper, a partition denotes a set of mobile nodes that have (one-hop/multihop) communication paths between two arbitrary nodes, and no path exists between any pair of nodes in different partitions. Here, we simply call mobile nodes in the same partition *connected mobile nodes*.

Based on the system model, we define the terms used in this paper. We observe the proposed metrics during time interval T. We further divide T into l fragments with the same size t, i.e., $T = l \cdot t$, and t_i denotes the time when the ith fragment in T begins $(i = 1, \ldots, l)$. We calculate the metrics as statistics of l times observations. n_i denotes the number of partitions that exist in the entire network at time t_i. We assume that each of the n_i partitions (n_i sets of nodes) is assigned a partition identifier $P_{i,j}$ $(j = 1, \ldots, n_i)$ in descending order of the number of nodes in the partition, i.e., $P_{i,1}$ contains the largest number of nodes at time t_i.

3.2 Metrics on Capacity and Stability

First, we define five metrics that represent the storage capacity and stability of partitions.

3.2.1 Average Size of Partitions

This metric is defined as the average number of mobile nodes in each partition, which was also used in [8]. Formally, it is expressed by the following equation:

$$AvgSize = l \cdot m \Bigg/ \sum_{i=1}^{l} n_i. \tag{1}$$

3.2.2 Distribution of Partition Sizes

We believe that the average size of partitions is not a very significant metric since it treats the two cases equally: 1) every partition has almost the same size and 2) one partition is very large and the others are very small. In terms of storage capacity of partitions, the distribution of partition sizes (numbers of nodes in partitions) is more significant than their average and is heavily affected by the adopted mobility model. Therefore, we define the distribution of partition sizes as a new metric by the following equation:

$$ParSize_h = \frac{\sum_{i=1}^{l}\sum_{j=1}^{n_i} eq(h, |P_{i,j}|)}{\sum_{i=1}^{l} n_i} \quad (h = 1, \ldots, m),$$
$$\text{where} \quad eq(x, y) = \begin{cases} 1, & \text{if } x = y, \\ 0, & \text{otherwise } (x \neq y). \end{cases} \tag{2}$$

Here, this metric corresponds to the histogram of occurrence ratios of partitions with each partition size.

3.2.3 Sizes of Partitions Belonged to

This metric is from the viewpoint of each mobile node and is defined as the histogram that represents the distribution of the sizes of the partitions to which the node belonged. This metric becomes almost equal to the distribution of partition sizes explained above if every mobile node randomly moves around in the whole area. However, if the movement patterns of mobile nodes have some locality or specific relationships with others, e.g., group mobility, this metric differs from the network-wide metric. This metric for mobile node M_k is expressed by the following equation:

$$SizeParBel_{k,h} = \frac{\sum_{i=1}^{l} eq(h, |bel(M_k, t_i)|)}{l} \quad (h = 1, \ldots, m). \tag{3}$$

Here, $bel(M_k, t_i)$ is a function to return a partition that contains M_k as a member at time t_i.

3.2.4 Change in Size of Partitions Belonged to

This metric is also from the viewpoint of each mobile node and is defined as the histogram that represents how much the sizes of the partitions to which the node has belonged change, where the value ranges from $1-m$ (negative value) to $m-1$. It aims at making a further consideration of the distribution of sizes of the partitions belonged to and helps to quantify their stability. The metric for mobile node M_k is expressed by the following equation:

$$ChgSizePar_{k,h} = \frac{\sum_{i=1}^{l-1} eq(h, |bel(M_k, t_{i+1})| - |bel(M_k, t_i)|)}{l-1} \quad (h = 1-m, \ldots, m-1). \tag{4}$$

3.2.5 Distribution of Connected Nodes

This metric is also from the viewpoint of each mobile node and is defined as the histogram representing the ratio of the duration during which the node is connected to each node to the entire observation time. This represents the stability of each node for sharing data. The metric for mobile node M_k is expressed by the following equation:

$$\begin{aligned} DistConnNode_{k,k'} &= \frac{\sum_{i=1}^{l} seq(bel(M_k, t_i), bel(M_{k'}, t_i))}{l} \quad (k' = 1, \ldots, m), \\ \text{where} \quad seq(X, Y) &= \begin{cases} 1, & \text{if } X = Y \quad (X, Y\text{: sets}), \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{5}$$

3.3 Metrics on Data Distribution

Next, we define two metrics that represent how rapidly data are distributed to mobile nodes in the network.

3.3.1 Total Number of Connected Nodes

This metric is from the viewpoint of each node and is defined as the total number of mobile nodes to which the node experienced a connection during a specific duration $l' \cdot t$ $(1 \leq l' \leq l)$. If this metric has a large value, the node can disseminate its data in a wide range (a large number of nodes), even when the sizes of the partitions are very small, i.e., the connectivity among nodes is very low in the short term. This metric represents to how many nodes each node can disseminate its own data when all data distributions must be directly done by the data owner. This kind of data distribution is used in applications in which data transmissions require authentication from the data owner.

Formally, this metric for mobile node M_k is expressed by the following equation:

$$NumConnNode_k = \left| \bigcup_{i=1}^{l'} bel(M_k, t_i) \right|. \tag{6}$$

3.3.2 Total Number of Data-Reachable Nodes

This metric is also from the viewpoint of each node and is defined as the total number of mobile nodes to which data sent by the node are reachable during a specific duration $l' \cdot t$. This metric covers cases in which data are transmitted to nodes that do not directly connect to the sender node but can be reachable with the help of other relaying nodes. For example, if mobile node A connects with node B but does not have a path to C, and then, A disconnects from B but B newly connects with C, this metric counts not only B but also C as data-reachable nodes from A. As for the total number of connected nodes defined above, C is not counted from A because A has never directly connected to C. This metric represents to how many nodes each node can disseminate its own data when data distributions do not need a direct authentication from the data owner, i.e., data can be relayed by other nodes even if the owner does not directly connect to the receiver.

Formally, this metric for mobile node M_k is expressed by the following equation:

$$\begin{aligned} NumReachNode_k &= \left| \bigcup_{i=1}^{l'} R_i \right|, \\ \text{where} \quad R_i &= \bigcup_{M_j \in N_i} C_{i,l',M_j}, \\ N_i &= bel(M_k, t_i) - C_{1,i-1,M_k}, \\ C_{s,f,M_j} &= \bigcup_{i'=s}^{f} bel(M_j, t_{i'}) \quad (s \leq f). \end{aligned} \tag{7}$$

Here, C_{s,f,M_j} denotes a set of mobile nodes that M_j have connected to during the duration from t_s to t_f. N_i denotes a set of mobile nodes that M_k first connected to at the beginning of t_i but have never connected to before that. Thus, R_i denotes a set of mobile nodes that mobile nodes in N_i connected to from the beginning of t_i until the end of the observation time $l' \cdot t$.

Note that these two metrics, the total numbers of connected nodes and data-reachable nodes, do not represent the actual numbers of nodes to which data can be distributed in a real environment. This is because these two metrics just count the numbers based on the existence of connections between nodes but take into account neither time for sending the data nor communication failures. Therefore, these two metrics represent the ideal numbers (upper bounds) of nodes to which data can be distributed. We adopt them in order to remove the influence of the underlying network protocols and network conditions.

3.4 Discussion

As mentioned in Section 2, our proposed metrics are neither the smallest nor complete for quantifying the impact of mobility on data availability. Also, our approach to quantifying data availability using only partitions and node connections has some limitations. In this section, we discuss these issues.

3.4.1 Redundancy and Correlation between the Metrics

There is an obvious redundancy between "average size of partitions" and "distribution of partition sizes" because the average size can be calculated from the histogram of sizes of partitions. Also, there are correlations between several pairs of metrics, i.e., 1) "sizes of partitions belonged to" and "change in size of partitions belonged to;" 2) "sizes of partitions belonged to" and "total number of connected nodes" ("total number of data-reachable nodes"); and 3) "total number of connected nodes" and "total number of data-reachable nodes." As mentioned in Section 2, we aim to briefly grasp the qualitative characteristics (not qualitative distinctions) of given mobility patterns. For this aim, we intentionally allow the redundancies and correlations among our metrics. For example, both the average and distribution of partition sizes are useful for protocol designers to intuitively grasp the characteristics of the mobility pattern. Moreover, correlations among metrics are very useful for grasping the qualitative characteristics by comparing these correlated metrics for different mobility patterns, i.e., correlations can be positively used. For example, as described later in Section 4, the MM model gives rapid growth of "total number of connected nodes" ("total number of data-reachable nodes"), while it gives relatively low "sizes of partitions belonged to." This fact is against the correlation between these metrics, and thus, well represents the characteristics of the MM model.

3.4.2 Limitations of the Metrics

Our proposed metrics do not take into account communication failures or time for sending the data, i.e., network bandwidths between nodes and sizes of exchanged data. We also do not take into account the status of connections between individual pairs of nodes, e.g., how steady each connection is. Taking these two factors into account might improve the accuracy of quantifying data availability. However, we ignore these factors to remove the influence of the underlying network protocols and to observe the influences of mobility on data availability in perspective. Thus, we have adopted our approach in order to quantify the influences of mobility and briefly grasp the qualitative characteristics of mobility patterns.

As mentioned in Section 2, while some conventional works use link status as a performance metric, data availability is affected by network partitioning but not only by connection or disconnection of a single wireless link. Therefore, we have proposed the metric "change in size of partitions belonged to" to quantify the stability of partitions (node groups) for data sharing in a large sense. Time during which a partition is stable is briefly estimated as the ratio of no change in size. Reliability of each node with which data are shared is estimated by the metric "distribution of connected nodes."

We believe that our approach makes sense to make clear the scope of this paper, i.e., quantifying the influences of mobility and briefly grasping the qualitative characteristics of mobility patterns. Of course, our proposed metrics have limitations and we cannot concretely calculate the performance criteria such as the success ratio of data requests and the traffic and delay of data diffusion by only using our proposed metrics. To concretely calculate these criteria, we have to provide other detailed conditions such as network bandwidth, hopping delay at each node, impact of radio signal interference, and size of data.

Here, there are trade-off relationships between the rapidness of data diffusion and the traffic (or overhead) for data diffusion protocols and between the success ratio of data access and the traffic (or energy consumption) for replication protocols. The trade-off points depend on the system or application requirements. Therefore, we cannot determine the trade-off points between performance criteria without the information on the system conditions and that on the system (application) requirements. This is the reason that we only provide the performance metrics to briefly grasp the qualitative characteristics of mobility patterns.

Note that our metrics are independent of the assumption that we do not consider some factors such as communication failures, time for sending the data, and status of connections of individual pairs of nodes. Thus, we can easily extend our approach by integrating our metrics and these factors, e.g., ignoring wireless links with lower stability, bandwidth, or connection time than the predetermined thresholds. We will consider such an extension and concrete protocol designs based on the extension in our future work.

4 Experiments

In this section, we report the results of some experiments that measure the proposed metrics assuming several typical mobility models: random walk, random waypoint, Manhattan mobility, and reference point group mobility. First, we explain these typical mobility models. Then, we show the experimental results. We also report the results of experiments using two kinds of real traces.

4.1 Mobility Models

4.1.1 Random Walk (RW)

This is one of the simplest mobility models and is often used in simulation experiments for MANETs. In this model, at every unit of experimental time, each mobile node randomly determines a movement direction from all directions, and randomly determines a movement speed from 0 to V [m/s]. It is known that in the long term, this model offers very low mobility similar to vibrating in the same position, because mobile nodes randomly change movement direction.

4.1.2 Random WayPoint (RWP)

This is one of the most popular mobility models for MANET researchers. In this model, each node remains stationary for a pause time S [s]. Then, it selects a random destination in the entire area and moves to the destination at a speed determined randomly between 0 and V [m/s]. After reaching the destination, it again pauses, and then, repeats this behavior. It is known that in this model, mobile nodes tend to gather at the center of the area, and the movement speed tends to converge to zero (very low).

4.1.3 Manhattan Mobility (MM)

This model emulates the node movement on streets where nodes only travel on the pathways in the map. Manhattan grid maps of horizontal and vertical streets are used to restrict the node movement. On each street, the mobile nodes move along the lanes in both directions. At each intersection, the mobile nodes choose their directions and speed (0 to V [m/s]) randomly.

4.1.4 Reference Point Group Mobility (RPGM)

This model is used to model group mobility. Each group has a logical "center" called a *reference point* and group members

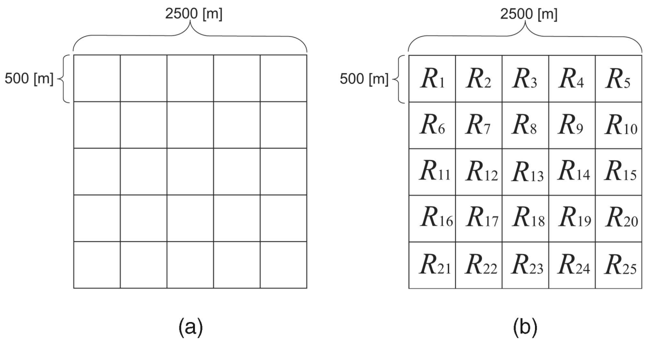


Fig. 2. Grid road map used in MM and home areas for RWP-L.

(nodes). Each reference point moves according to the RWP model with V' [m/s] (maximum speed) and S' [s] (pause time). In each group, nodes are uniformly distributed within a certain radius R from the reference point. To achieve this, we assume that each node moves according to the RW model with V [m/s] (maximum speed) within that range. Specifically, a node's movement vector is composed by adding the movement vector based on the RW model for the node to that based on the RWP model for the reference point.

4.1.5 Random WayPoint with Locality (RWP-L)

This model is same as the RWP model except for the way to choose destinations. In this model, each mobile node has a home area, which is a subarea in the entire area. When determining a destination, it chooses a random destination inside the home area with high probability H and one outside the region with probability $1 - H$. We call H the home area ratio.

4.2 Simulation Setting

Mobile nodes exist in an area $2{,}500\ [\mathrm{m}] \times 2{,}500\ [\mathrm{m}]$. The number of mobile nodes in the entire network is m ($M = M_1, M_2, \ldots, M_m$). For the MM model, we use a grid road map with six vertical and horizontal streets, i.e., 25 blocks of the same size ($500\ [\mathrm{m}] \times 500\ [\mathrm{m}]$), as shown in Fig. 2a. For the RPGM model, we assume that there are 25 reference points $rp_1, \ldots, rp_{25}$, and $M_j (j = 1, \ldots, m)$ sets its reference point as $rp_{\lceil j/(m/25) \rceil}$. For the RWP-L model, the area is divided into 25 regions of $500\ [\mathrm{m}] \times 500\ [\mathrm{m}]$, $R_1, \ldots, R_{25}$, as shown in Fig. 2b, and $M_j (j = 1, \ldots, m)$ sets its home area as region $R_{\lceil j/(m/25) \rceil}$.

At the beginning of the simulations, the initial position of each mobile node is randomly determined in the space where the node can exist, i.e., on a road in the MM model

TABLE 1
Parameter Configuration

parameter	symbol	value	range
Number of nodes	m	300	(300, 500)
Node movement speed	V	4 [m/s]	(4, 10 [m/s])
Group movement speed (RPGM)	V'	4 [m/s]	(4, 10 [m/s])
Radius of group (RPGM)	R	250 [m]	
Node pause time	S	10 [s]	
Group pause time (RPGM)	S'	10 [s]	
Communication range	C	100 [m]	
Home area ratio	H	0.9	
Duration factor	l'		$(1 \sim 100{,}000)$

TABLE 2
Average Size of Partitions ($m = 300$, $V = 4\ [m/s]$)

RW	RWP	MM	RPGM	RWP-L
2.21	2.88	3.59	5.30	2.54

and within the home area in the RWP-L model. We set T as 10,000,000 [s] and t as 1 [s], i.e., $l = 10{,}000{,}000$. We neglect the first 1,000 [s] to remove the impact of the initial state and observe our proposed metrics during 10,000,000 [s], i.e., from time 1,000 [s] to 10,001,000 [s].

Table 1 summarizes the parameters and their values used in the simulation experiments. The parameters are basically fixed to constant values, but some are changed in a range represented by the parenthetic values in each of the simulation experiments.

4.3 Results in Default Setting

4.3.1 Simulation Results

First, we show the experimental results in the default setting, i.e., $m = 300$, $V = V' = 4$ [m/s]. Table 2 and Fig. 3 show the average size of partitions and the distribution of partition sizes in the five mobility models. In Fig. 3, the horizontal axis indicates the partition size and the vertical axis indicates the ratio of partitions with the corresponding partition size to all the partitions formed during the entire observation time T. We separately show the results as two graphs where the scales of the vertical and horizontal axes are changed due to the skew of distribution.

Table 2 shows that the average size of partitions is much affected by the adopted mobility model. The average size in the RWP model is larger than the RW model due to the well-known characteristic of the RWP model that nodes tend to gather in the center of the area, which results in the formation of a large partition. This fact can also be seen in Fig. 3, i.e., the RWP model experienced large partitions with more than 20 nodes more often than the RW model. To confirm this, we pick the size of the largest partition formed during the whole observation time T and the ratio of partitions with only one node in Table 3. In this table, the first row shows the ratio of partitions with one node and the second row shows the maximum size. It can be seen that the maximum size in the RWP model is much larger than the RW model, whereas the ratios of partitions with one node are almost the same.

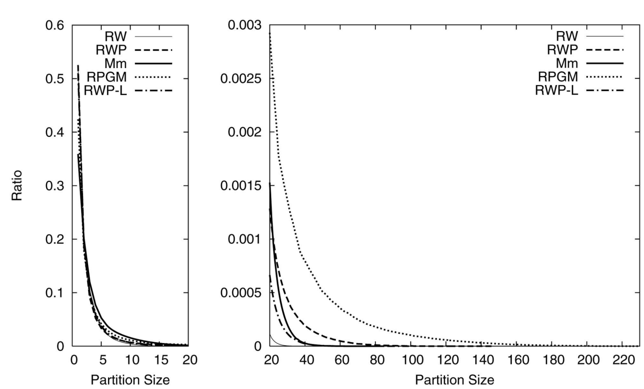


Fig. 3. Distribution of partition sizes ($m = 300$, $V = 4$ [m/s]).

TABLE 3
Ratio of Partitions with One Node and Maximum Partition Size ($m = 300$, $V = 4$ $[m/s]$)

RW	RWP	MM	RPGM	RWP-L
0.522 (52)	0.525 (146)	0.359 (85)	0.424 (274)	0.510 (99)

Comparing the RWP and the RWP-L models, partitions formed in the RWP-L model tend to be smaller than the RWP model, as shown in Tables 2 and 3 and Fig. 3. This is because in the RWP-L model, nodes that have the same home area tend to gather in the center of the home area, but those with different home areas tend to be disconnected. As expected, the RPGM model forms much larger partitions than other models. In addition to high connectivity among nodes in the same group, the reference points tend to gather in the center of the area because they move according to the RWP model, which results in the formation of very large partitions.

An interesting fact can be seen for the MM model. It provides higher average partition size than the RW, RWP, and RWP-L models as shown in Table 2, while the maximum partition size is not large (second lowest) as shown in Table 3. Thus, the MM model forms a large number of partitions with modest numbers of nodes, as is clearly shown in Fig. 3. These characteristics are due to the highly restricted mobility in the MM model. Since mobile nodes are allowed to move only in vertical or horizontal directions, they tend to connect in line. This is advantageous to avoid nodes being isolated, i.e., forming partitions with only one node, but harmful to forming large partitions since the node density is rarely high.

Next, we move on to the metrics for each mobile node. Since nodes that have a different home area in the RWP-L model behave in different ways, we pick two different nodes M_1 and M_{145}. The home areas of M_1 and M_{145} are R_1 (a corner in the entire area) and R_{13} (the center), respectively, in the RWP-L model. These two nodes are also in different groups rp_1 and rp_{13} in the RPGM model. Here, it should be noted that we have checked the results for all mobile nodes in our experiments and found that all nodes in the RW, RWP, MM, and RPGM models and nodes with the same home area in the RWP-L model show almost the same results for every metric. As for the RWP-L model, nodes with different home areas behave differently, especially, the results show the biggest difference between the two extreme cases of the home area being at a corner and the center. Thus, we chose the two extreme cases and a node in each of the two cases randomly.

Fig. 4 shows the sizes of the partitions M_1 and M_{145} belonged to in the five mobility models. In Fig. 4, the horizontal axis indicates the partition size and the vertical axis indicates the ratio of time that the node belonged to partitions with the corresponding partition size to the entire observation time T. From Figs. 4a and 4b, in the four mobility models except the RWP-L model, both M_1 and M_{145} show almost the same characteristics as the global one, although the characteristics in Fig. 3 are much clearer due to the statistical effect. This is because in each of the four

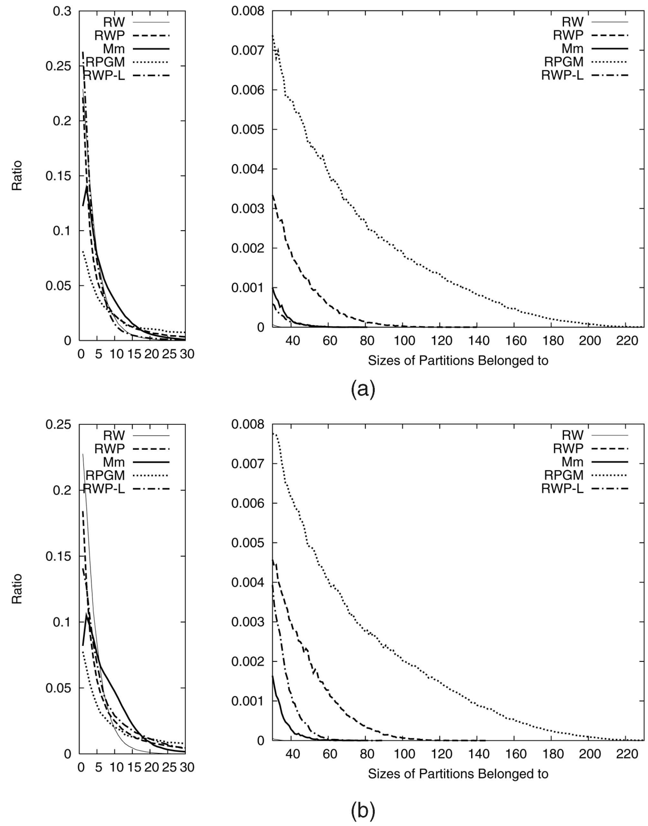


Fig. 4. Sizes of partitions belonged to ($m = 300$, $V = 4$ [m/s]). (a) M_1. (b) M_{145}.

models, every mobile node moves according to the same rule. As for the RWP-L model, M_1 and M_{145} behave in different ways. Specifically, it can be seen from the right graphs that M_{145} often belonged to larger partitions than M_1. This is because M_{145} often located near the center of the area and had more chances to connect to other nodes than M_1, whose home area is a corner of the area.

Fig. 5 shows the change in size of the partitions M_1 and M_{145} belonged to in the five mobility models. In Fig. 5, the horizontal axis indicates the change in partition size and the vertical axis indicates the ratio of time that the node experienced the corresponding change to the entire observation time T. Table 4 shows the ratio of not changing in size, i.e., $ChgSizePar_{k,0}$ ($k = 1, 145$), in the first row, and the maximum changes in both cases, increase and decrease, that the node experienced in the second row. The results show that in the two models based on random waypoint in the entire area, RWP and RPGM, nodes often experienced large changes in size of their partitions. Especially, since in the RPGM model, nodes form very large partitions and move in groups, they experienced much larger changes than nodes in other models. The ratio of not changing in size is very high in the MM model because nodes moving in line form partitions and their connectivity is high. In the RW model, while the ratio of no change is not very high, the maximum changes are the smallest among the five models. This is because this model provides very low mobility, i.e., nodes stay at almost the same position in the long term. Thus, nodes often experienced small changes but the global network topology rarely changed. Similar to the result in

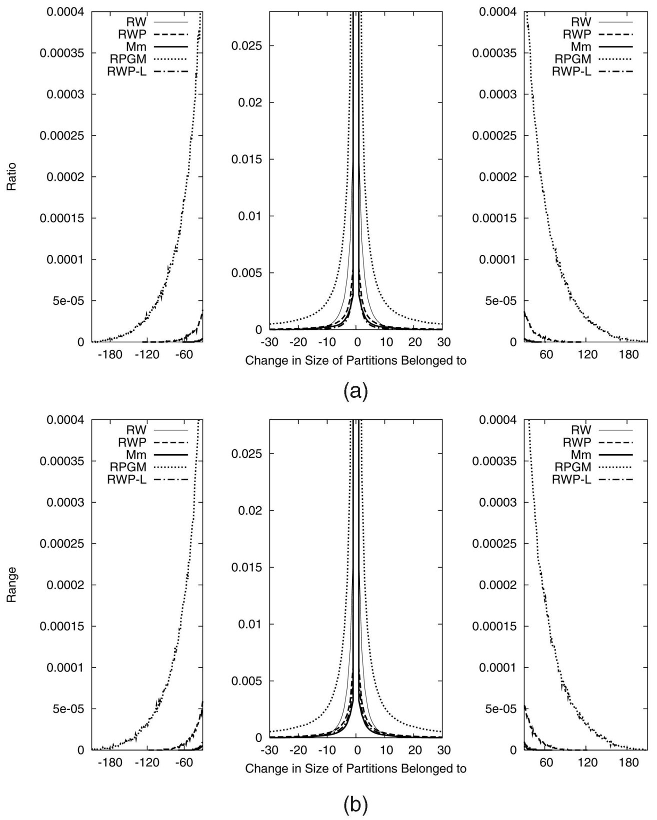


Fig. 5. Change in size of partitions belonged to ($m = 300$, $V = 4$ [m/s]). (a) M_1. (b) M_{145}.

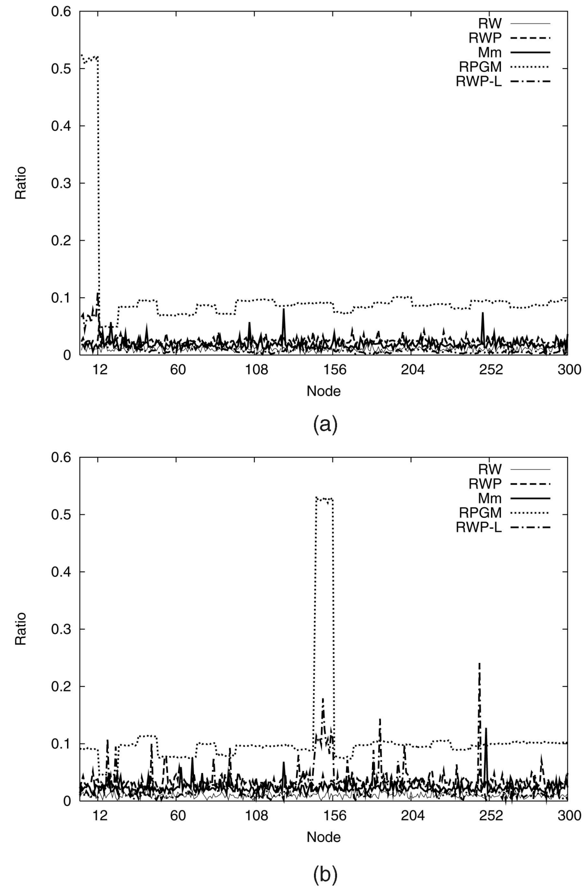


Fig. 6. Distribution of connected nodes ($m = 300$, $V = 4$ [m/s]). (a) M_1. (b) M_{145}.

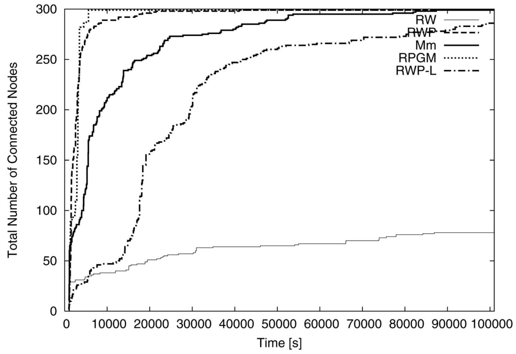
Fig. 4, except for the RWP-L model, two nodes M_1 and M_{145} give almost the same characteristics. In the RWP-L model, nodes whose home area is located at an area corner, e.g., M_1, form small partitions, and thus, the changes in size become small.

Fig. 6 shows the distribution of connected nodes for M_1 and M_{145} in the five models. The horizontal axis indicates the suffix of a node identifier, e.g., 12 denotes node M_{12}, and the vertical axis indicates the ratio of time that node M_1 or M_{145} is connected to the corresponding node to the entire observation time T. The result shows that in the RW, MM, and RWP models, since each node moves independently of the others, M_1 and M_{145} connected almost uniformly to all nodes. In the RPGM model, M_1 belonged to a group consisting of 12 nodes $M_1, \ldots, M_{12}$, and M_{145} belonged to a group consisting of $M_{145}, \ldots M_{156}$. Thus, both M_1 and M_{145} were connected to nodes in the same group for a long time. In the RWP-L model, M_{145} connected to nodes with the same home area for a long time. M_1 also shows the same feature but it is not conspicuous compared with M_{145}. This is due to low connectivity in the area. Here, M_{145} also connected to some other nodes, e.g., M_{246}, for a long time. From a detailed investigation of the simulation result, we found that this accidentally happened by M_{145} and these nodes choosing very slow moving speeds when they were close to each other.

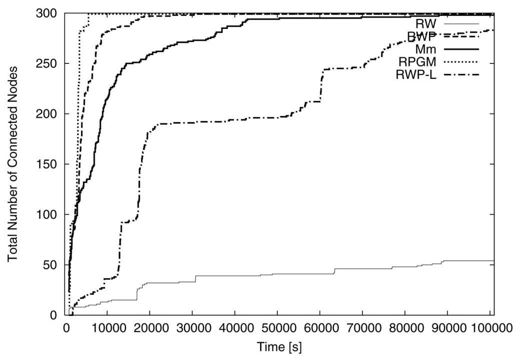
Next, we show the results of the two metrics on data distribution. Fig. 7 shows the total number of connected nodes for M_1 and M_{145} in the five mobility models when varying the observation time $l' \cdot t$. Here, since this metric is heavily affected by the nodes' initial positions and movement at an early stage, we show the results for M_2 and M_{146} for reference, where M_2 and M_{146} in the RWP-L model have the same home area as M_1 and M_{145}, respectively. In this figure, the horizontal axis indicates the observation time $l' \cdot t$, and the vertical axis indicates the total number of nodes to which M_1, M_2, M_{145}, and M_{146} connected during the observation time. From the result, while different nodes show different characteristics as expected, we can also observe several interesting common facts. First, the RW model gives a much lower number of connected nodes than others for all the nodes. This is due to low mobility in this model. The two models, RWP and RPGM, based on random waypoint in the entire area give higher values than others due to the two advantages of high mobility and large partitions. As for the RWP-L model, M_1 and M_2 with the home position at a corner were slow to grow the total number of connected nodes because they had little chance to connect to others, e.g., the

TABLE 4
Ratio of No Change in Size and Maximum Change ($m = 300$, $V = 4$ $[m/s]$)

	RW	RWP	MM	RPGM	RWP-L
M_1	0.924 (-31,33)	0.965 (-128,117)	0.980 (-63,51)	0.665 (-256,256)	0.983 (-63,63)
M_{145}	0.925 (-37,37)	0.958 (-118,122)	0.978 (-70,71)	0.645 (-239,239)	0.970 (-63,63)



(a)



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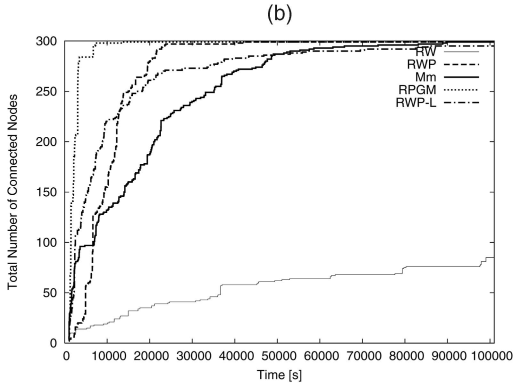

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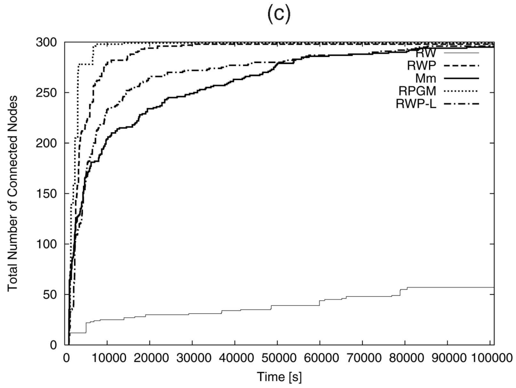
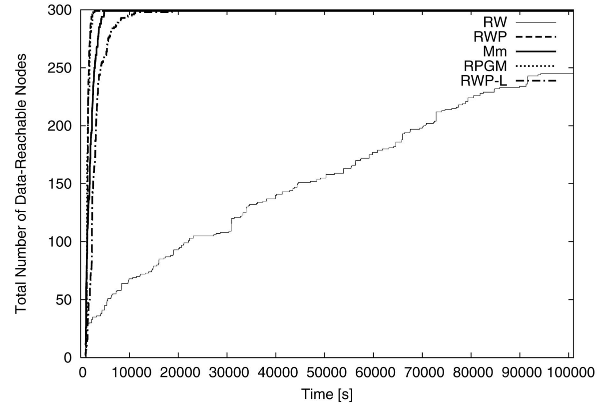


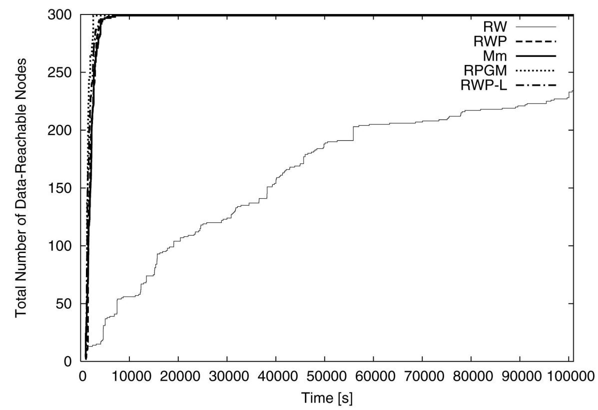
(d)

Fig. 7. Total number of connected nodes ($m = 300$, $V = 4$ [m/s]). (a) M_1. (b) M_2. (c) M_{145}. (d) M_{146}.

case when they moved beyond the home area (10 percent). On the contrary, M_{145} and M_{146} in the RWP-L model were fast to grow the total number of connected nodes. This is because nodes at the center area have high connectivity and many nodes that go beyond their home area pass through the center area, which is a characteristic of random waypoint that nodes tend to gather at the center of the area. In Figs. 7c and 7d, the RWP-L model grows faster than the MM model but is caught up to afterward. This is because in the RWP-L model, it is very difficult for nodes to visit all areas due to the locality of mobility. On the contrary, since the MM model forms a large number of small partitions, it is difficult to drastically grow the number of connected nodes in a short period but it can make a steady increase. It should also be noted that the two models RPGM and RWP-L, which form groups with high connectivity, often experienced a sudden increase in the total number of connected nodes, i.e., a step in the graph. This signifies that the node encountered another group.



(a)



(b)

Fig. 8. Total number of data-reachable nodes ($m = 300$, $V = 4$ [m/s]). (a) M_1. (c) M_{145}.

Fig. 8 shows the total number of data-reachable nodes for M_1 and M_{145} in the five mobility models when varying the observation time $l' \cdot t$. Since M_2 and M_{146} show almost the same results as M_1 and M_{145}, respectively, we omit their results here. In this figure, the horizontal axis indicates the observation time $l' \cdot t$, and the vertical axis indicates the total number of data-reachable nodes during the observation time. This result shows that in all the mobility models, the growing speed of the total number of data-reachable nodes is much faster than that of the total number of connected nodes. Thus, aggressive data dissemination using other nodes is very effective for rapidly distributing data. We can also observe an interesting fact by comparing the RWP and RPGM models that group mobility does not much contribute

TABLE 5
Average Size of Partitions in Other Settings

	RW	RWP	MM	RPGM	RWP-L
$m = 300$, $V = 10$	2.21	2.88	3.56	5.40	2.53
$m = 500$, $V = 4$	4.15	6.06	7.85	15.43	5.11

to the increase of the total number of data-reachable nodes, i.e., it is not very helpful for rapidly distributing data. On the contrary, the MM model was very fast to grow the total number of data-reachable nodes, while it was relatively slow to grow the total number of connected nodes.

4.3.2 Convergence of the Results

In our experiments, we measured our proposed metrics to quantify the influence of mobility on data availability and briefly grasp the qualitative characteristics of the mobility patterns. The values themselves obtained by the experiments are not very important but their qualitative characteristics are important. However, we realize that it is better to examine the reliability of the simulation results, i.e., the confidence intervals for the results. Therefore, we calculated breadths of 90 percent confidence intervals for the simulation results using the *Batch Means method* [6], where the batch size is 1,000,000 units of time and the number of batches is 10. Here, all of our metrics except for "average size of partitions" are histograms or snapshots of certain observations. As for snapshots, i.e., "total number of connected nodes" and "total number of data-reachable nodes," we cannot calculate the confidence intervals. As for histograms, we can calculate the confidence intervals of the observations (ratios of the corresponding values). Of course, the confidence intervals of the observations that rarely occur obviously become very large and it is impossible to run the simulations for a long enough time to obtain converged results with low confidence intervals for all possible observations.

Due to the limitation of space, we briefly explain the examination results as follows. The results show that the simulations were sufficiently converged for "average size of partitions," where the breadths of the confidence intervals were at most a few percent of the average values for all the mobility models. As for histograms for the entire network, "distribution of partition sizes," breadths of the confidence intervals were a few percent in most cases and at most 10 percent of the average values for the observations that often occurred, i.e., where the partition sizes were less than 20. When the partition sizes were very large, the breadths of the confidence intervals were also large. This is obvious because such cases rarely occurred in the simulations.

As for histograms for each mobile node, "sizes of partitions belonged to," "change in size of partitions belonged to," and "distribution of connected nodes," the breadths of the confidence intervals were relatively large and more than 10 percent of the average values in most cases. Specifically, as for "sizes of partitions belonged to," we observed only a few cases in the RW, RWP, and RWP-L models where breadths of the confidence intervals were less than 5 percent of the average values. In the RPGM and MM models, the breadths of the confidence intervals were more than 10 percent in all cases. As for "change in size of partitions belonged to," breadths of the confidence intervals were less than 5 percent of the average values in almost every mobility model only where the change in size is zero. As for "distribution of connected node," the breadths of the confidence intervals were less than 5 percent of the average values only for mobile nodes in the same group in the RPGM model.

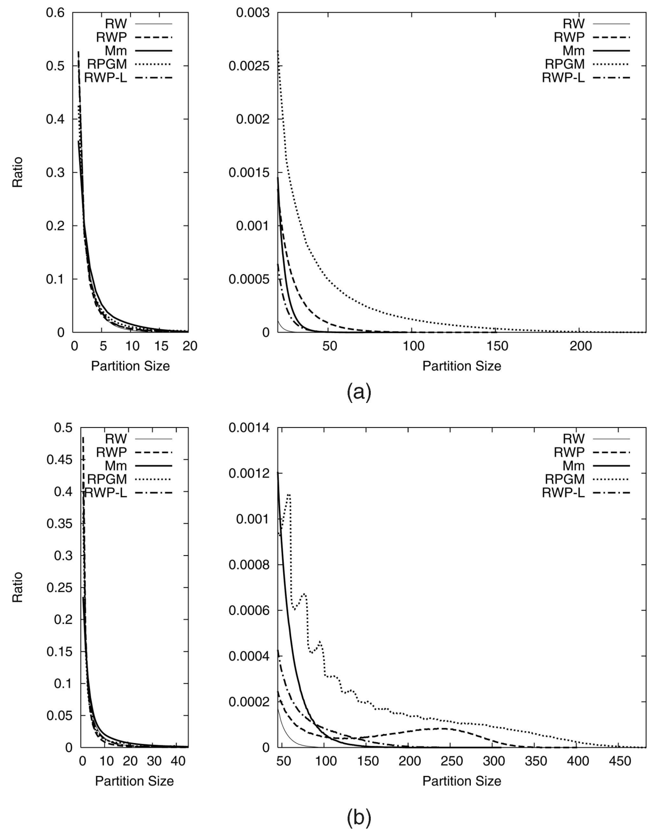


Fig. 9. Distribution of partition sizes in other settings. (a) $m = 300$, $V = 10$ [m/s]. (b) $m = 500$, $V = 4$ [m/s].

4.4 Results in Other Settings

Next, we show the experimental results when changing the setting of the number of nodes m and the movement speed V and V'. We examine two cases: one is for examining the impact of the movement speed, $m = 300$ and $V = V' = 10$ [m/s], and the other is for examining the impact of the node density, $m = 500$ and $V = V' = 4$ [m/s].

Table 5 and Fig. 9, respectively, show the average partition size and the distribution of partition sizes in the five mobility models for both cases. We also show the ratio of partitions with one node and the maximum partition size in Table 6. By comparing the default setting ($m = 300$, $V = V' = 4$ [m/s]) and the case with higher speed ($m = 300$, $V = V' = 10$ [m/s]), every mobility model gives almost the same results in both cases, and thus, we can confirm that the movement speed has little impact on the partition sizes. On the contrary, by comparing the default setting and the case with more mobile nodes ($m = 500$, $V = V' = 4$ [m/s]), it is shown that the number of mobile nodes, i.e., node density, greatly affects the partition sizes. However, the characteristics of the five models described in the previous section were basically

TABLE 6
Ratio of Partitions with One Node and Maximum Partition Size in Other Settings

	RW	RWP	MM	RPGM	RWP-L
$m = 300$	0.521	0.527	0.360	0.425	0.510
$V = 10$	(56)	(151)	(97)	(273)	(91)
$m = 500$	0.382	0.485	0.235	0.366	0.415
$V = 4$	(168)	(401)	(311)	(494)	(288)

preserved in the case with more nodes except that the RWP model often forms a large group of mobile nodes.

Fig. 10 shows the distribution of sizes of partitions mobile node $M_{145}(\in R_{13})$ belonged to in the case with higher speed ($m = 300$, $V = V' = 10$ [m/s]) and that for $M_{241}(\in R_{13})$ in the case with more nodes ($m = 500$, $V = V' = 4$ [m/s]). In the following, we focus on only one node that has been randomly chosen among nodes whose home area is the center of the entire area in the RWP-L model. These results show almost the same characteristics as the global ones shown in Fig. 9. Fig. 10a shows similar but clearer characteristics than Fig. 4b because higher mobility provides faster convergence of the simulation results.

Fig. 11 shows the change in size of partitions M_{145} belonged to in the case with higher speed ($m = 300$, $V = V' = 10$ [m/s]) and that for M_{241} in the case with more nodes ($m = 500$, $V = V' = 4$ [m/s]). We also show the ratio of not changing the partition size and maximum change in the five models in Table 7. From these results, we can confirm that both the movement speed and the node density greatly affect the change in the size of the partitions belonged to. By comparing Figs. 11a and 5b, relative differences among the mobility models are preserved independent of the movement speed, while higher speed basically gives a larger change in size. On the other hand, it is shown by Fig. 11b and Table 7 that the increase in nodes has relatively lower impact on the RPGM and MM models; thus, the results of the RW, RWP, and RWP-L models got closer to those of the RPGM model as shown in the center graph of Fig. 11b. Moreover, a large group of mobile nodes formed in the RW model (as shown in Figs. 9b and 10b) causes more frequent big changes in the partition size.

Fig. 12 shows the distribution of connected nodes for M_{145} in the case with higher speed ($m = 300$, $V = V' = 10$ [m/s]) and that for M_{241} in the case with more nodes ($m = 500$, $V = V' = 4$ [m/s]). Fig. 12a shows a similar result to that in Figs. 6b. Fig. 12b shows that while the characteristics of each model are preserved, the values just become higher.

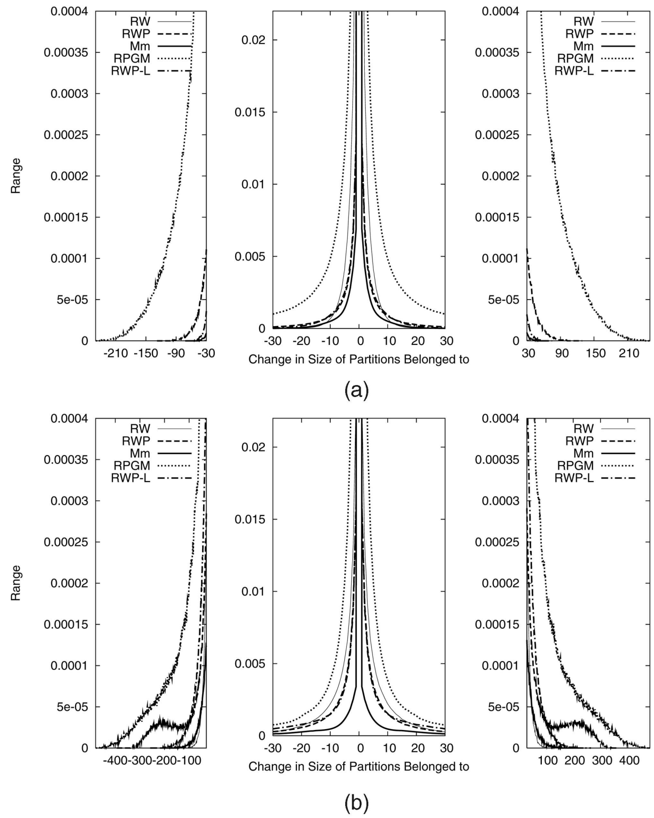


Fig. 11. Change in size of partitions belonged to in other settings. (a) $m = 300$, $V = 10$ [m/s]. (b) $m = 500$, $V = 4$ [m/s].

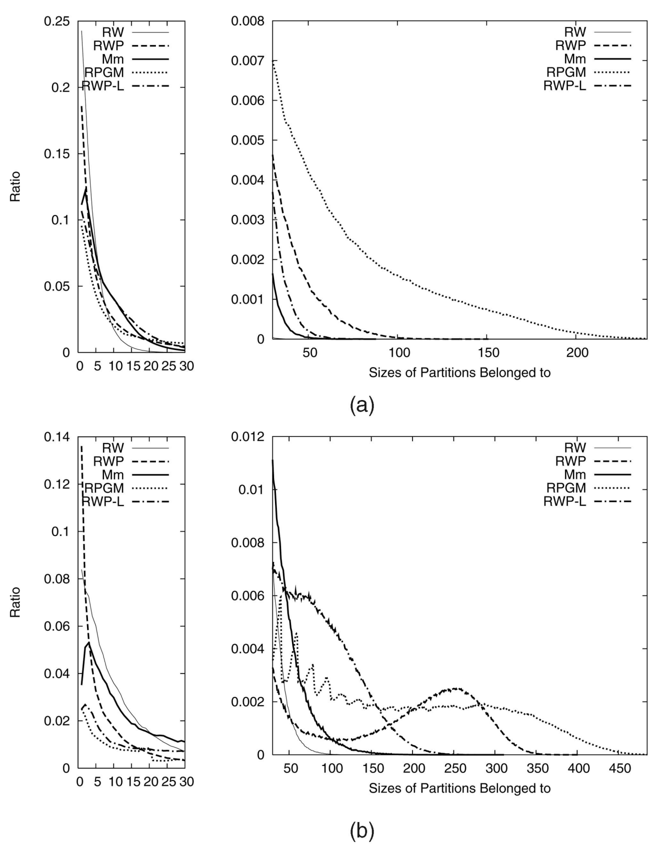
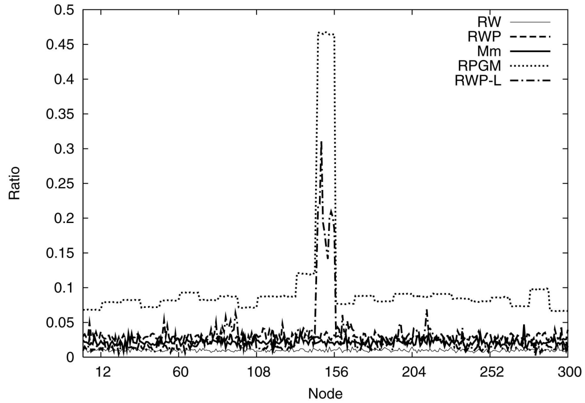


Fig. 10. Sizes of partitions belonged to in other settings. (a) $m = 300$, $V = 10$ [m/s]. (b) $m = 500$, $V = 4$ [m/s].

TABLE 7
Ratio of No Change in Size and Maximum Change in Other Settings

	RW	RWP	MM	RPGM	RWP-L
$m = 300$	0.833	0.919	0.954	0.412	0.962
$V = 10$	(-41,40)	(-116,127)	(-68,55)	(-261,266)	(-61,66)
$m = 500$	0.828	0.812	0.952	0.459	0.939
$V = 4$	(-123,127)	(-362,368)	(-222,235)	(-487,487)	(-256,249)



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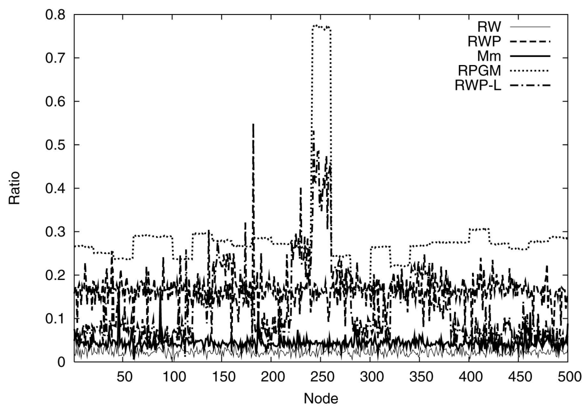
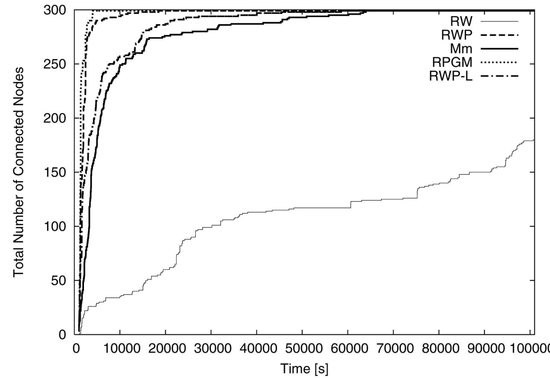


(b)

Fig. 12. Distribution of connected nodes in other settings. (a) $m = 300$, $V = 10$ [m/s]. (b) $m = 500$, $V = 4$ [m/s].



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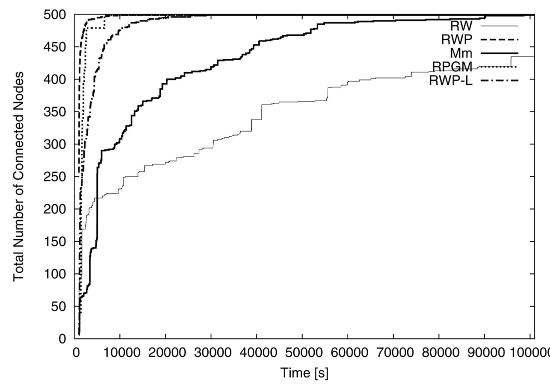


(b)

Fig. 13. Total number of connected nodes in other settings. (a) $m = 300$, $V = 10$ [m/s]. (b) $m = 500$, $V = 4$ [m/s].

Fig. 13 shows the total number of nodes to which M_{145} and M_{241} connected. Fig. 14 shows the total number of data-reachable nodes for these two nodes. From Figs. 13a and 14a, it is confirmed that higher movement speed is effective for data distribution, while relative differences among the mobility models are preserved. From Figs. 13b and 14b, it can be seen that the increase in node density is effective for the RW, RWP, and RWP-L models. The RWP model outperforms the RPGM model, and the RWP-L model gives closer performance to the RPGM model than that in the default setting. The RW model benefits most from the increase in node density.

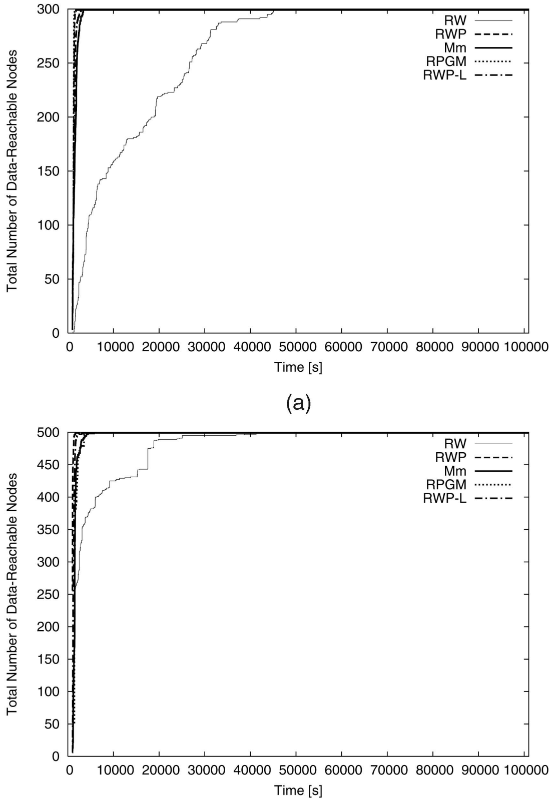
4.5 Experiments Using Real Traces

As mentioned in Section 1, the main contribution of this paper is a proposal of the performance metrics to quantify the impact of mobility on data availability, where we do not assume any specific mobility models nor specific movement patterns. Therefore, our experiments using some well-known mobility models are just examples of how to apply the proposed metrics to a given mobility model and how to examine the impact of the mobility pattern. In this section, we present the results of some experiments using real mobility traces as other examples of applying our proposed metrics.

In these experiments, we used two kinds of real traces: taxi cabs and humans. The first traces were given by the Cabspotting project [4] and contain GPS mobility traces of 300 taxi cabs traveling throughout the Bay Area of San Francisco for 50 hours. The second traces were given by the NCSU Mobility and DTN Group [28], and contain GPS mobility traces of 82 people walking on the campus of the Korea Advanced Institute of Science and Technology (KAIST) for 384.5 minutes. We calibrated the time and spatial scale in these traces to achieve almost the same node density and movement speed as our experiments in Section 4.3, i.e., (300 nodes in an area $2{,}500\ [\mathrm{m}] \times 2{,}500\ [\mathrm{m}]$ and 2 [m/s] on average).

Tables 8, 9, and 10 and Figs. 15, 16, 17, 18, 19, and 20 show the experimental results. As for the metrics for each mobile node, we selected three typical nodes that behaved differently from each other.

In summary, we can confirm that the two kinds of real traces basically show different characteristics from all the typical mobility models used in our experiments. The biggest reason is that there is a strong hot spot in the area for both real traces, i.e., the central downtown in the cab traces and the department building in the human traces. Specifically, there constantly exist a large number of mobile nodes in a specific region, which results in forming a very large group of mobile nodes. This fact can be seen from the results in Figs. 15 and 16, and Table 9, where there exists a group with a large number of nodes (about 70-80 percent of all nodes) with relatively high ratios. Since the ratio of partition with one node is high, it is shown that nodes basically stayed in a specific area and formed a large group, and sometimes, moved to another area alone, e.g., brought a



(a)

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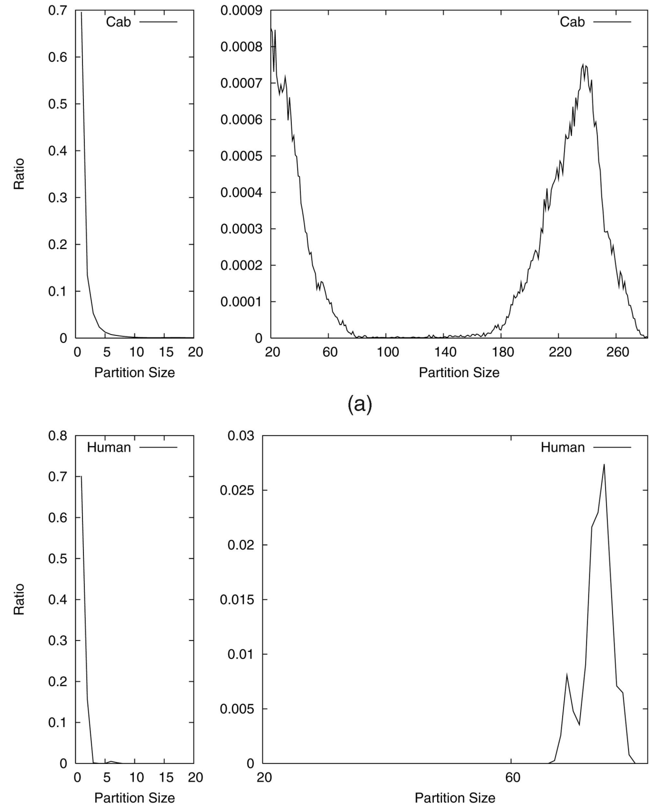
Fig. 14. Total number of data-reachable nodes in other settings. (a) $m = 300$, $V = 10$ [m/s]. (b) $m = 500$, $V = 4$ [m/s].



(a)

(b)

Fig. 15. Distribution of partition sizes (real traces). (a) Cab traces. (b) Human traces.

TABLE 8
Average Size of Partitions (Real Traces)

Cab traces ($m = 300$)	Human traces ($m = 82$)
9.50	11.18

TABLE 9
Ratio of Partitions with One Node and Maximum Partition Size (Real Traces)

Cab traces ($m = 300$)	Human traces ($m = 82$)
0.696 (282)	0.701 (79)

TABLE 10
Ratio of No Change in Size and Maximum Change (Real Traces)

	Cab traces ($m = 300$)	Human traces ($m = 82$)
M_1	0.422 (-276,274)	0.112 (-8,8)
M_2	0.416 (-269,267)	0.112 (-73,73)
M_3	0.508 (-274,264)	0.207 (-75,75)
M_4	0.410 (-263,262)	0.843 (-74,74)

passenger somewhere in the cab case. This fact also can be seen from the results in Fig. 17 and Table 10, where nodes frequently experienced a small change in partition size, i.e., other nodes left a big group, and sometimes a big change, i.e, the nodes themselves left a big group. Therefore, every mobile node experienced a sudden increase in the total numbers of connected and data-reachable nodes when it connected to the large group (see Figs. 19 and 20).

Big differences in distribution of connected nodes between three nodes in the human traces are due to the short tracking time, where person M_1 always stayed in the big group, while person M_3 did not come back to the group during the tracking time.

Among the typical mobility models, only the RWP model when the node density is high ($m = 500$) showed slightly similar characteristics to the real traces because it also forms a large group of mobile nodes at the center of the area.

4.6 Discussions

In this section, we summarize the experimental results and discuss their outcomes.

4.6.1 RW Model

The RW model forms many small partitions but rarely forms large ones when the node density is not very high. Moreover, since the mobility of nodes is very low in the long term, it shows the worst results for the two metrics on data distribution (i.e., the total number of connected nodes and that of data-reachable nodes). Thus, this model is not good in terms of both aspects, storage capacity and data distribution, although these drawbacks can be alleviated by the increase of node density. The low mobility of this model is advantageous in terms of the stability of partitions.

Therefore, when a researcher or engineer designs a data replication protocol and the movement pattern in the assumed environment follows the RW model, the protocol should not rely on data sharing with a large number of

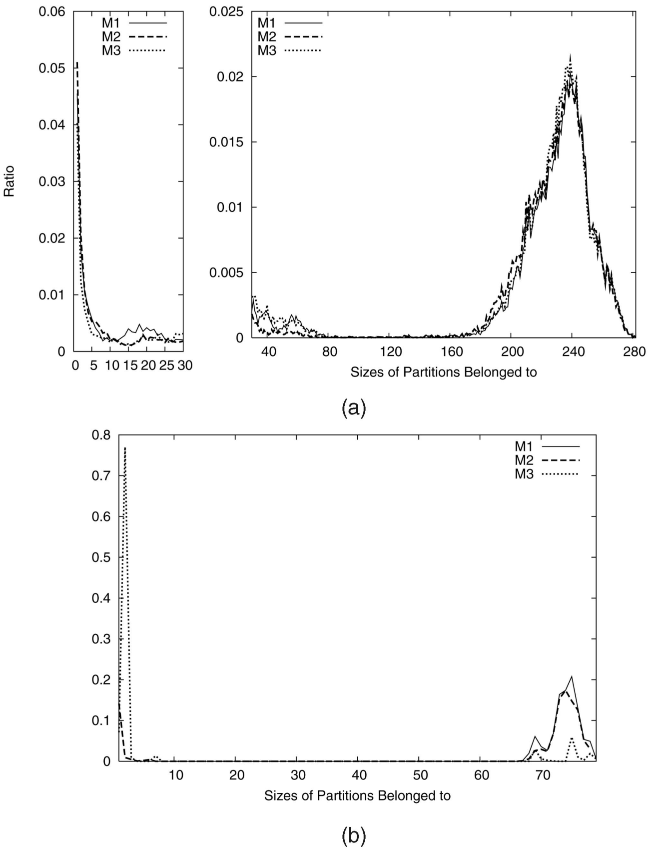


Fig. 16. Sizes of partitions belonged to (real traces). (a) Cab traces. (b) Human traces.

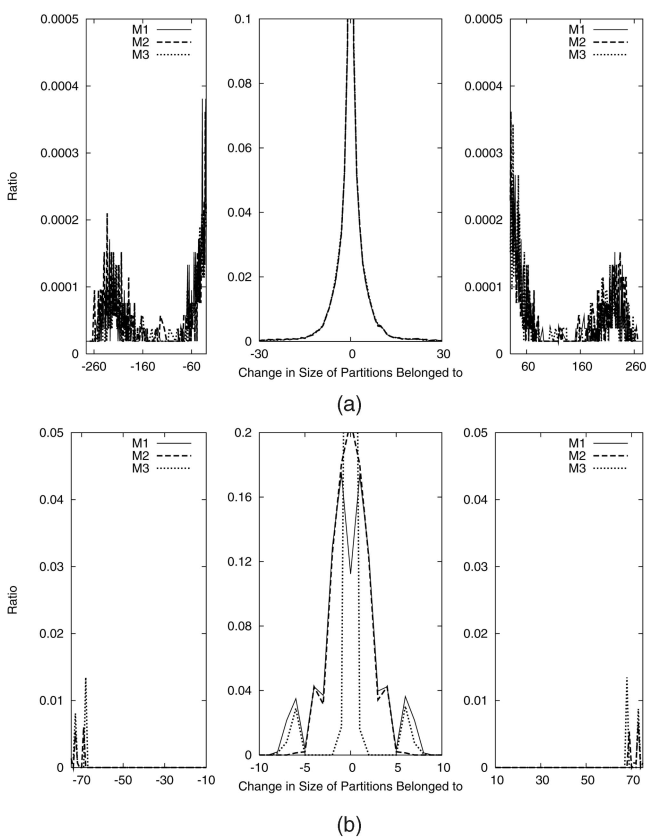


Fig. 17. Change in size of partitions belonged to (real traces). (a) Cab traces. (b) Human traces.

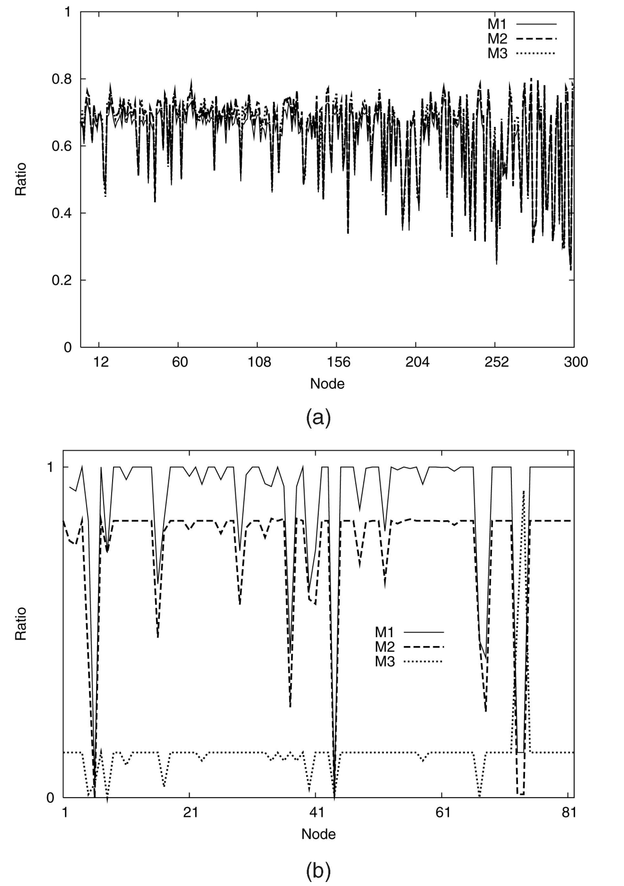


Fig. 18. Distribution of connected nodes (real traces). (a) Cab traces. (b) Human traces.

nodes but should share data with a small number of connected nodes.

When designing a data diffusion protocol, it should aggressively disseminate data to connected mobile nodes at the sacrifice of the increase of traffic. Moreover, if nodes can control their communication range by changing the radio signal strength, the communication range should be set longer in order to increase the node density. Of course, when the node density is very high, blind data disseminations might cause a big problem; thus, the protocol should consider effective data disseminations to reduce the traffic.

4.6.2 RWP Model

The RWP model often forms a few large partitions because nodes tend to gather in the center of the area. However, this model also causes many isolated nodes that do not connect to any other nodes. This fact can be seen from the experimental results, which showed a high ratio of partitions with one node and a very large maximum partition size for this model. Thus, in terms of data storage capacity, this model is good when the node belongs to a large partition. However, this model sometimes experiences big changes in partitions.

When designing a data replication protocol where the movement pattern follows the RWP model, each node should carefully determine with which nodes it shares data by considering several factors such as the number of neighboring nodes and the stability of wireless links.

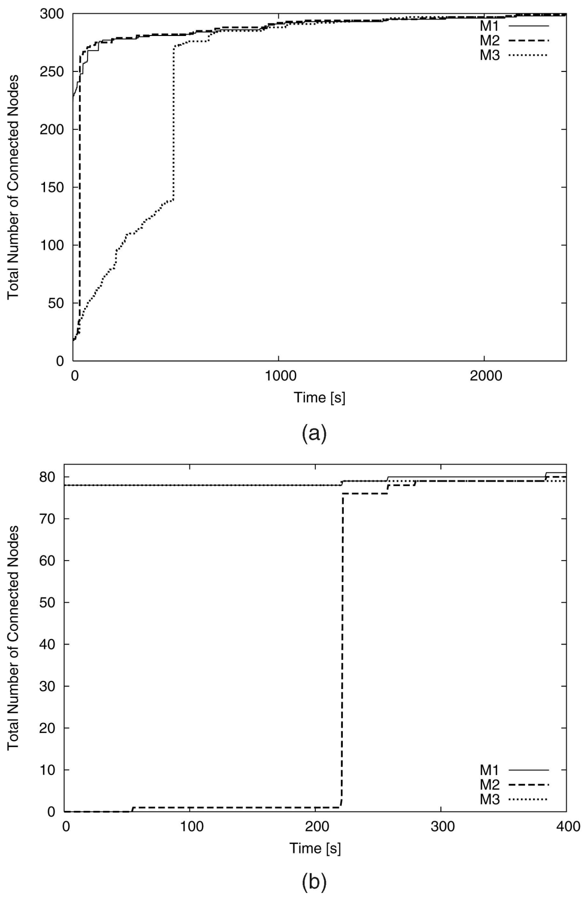


Fig. 19. Total number of connected nodes (real traces). (a) Cab traces. (b) Human traces.

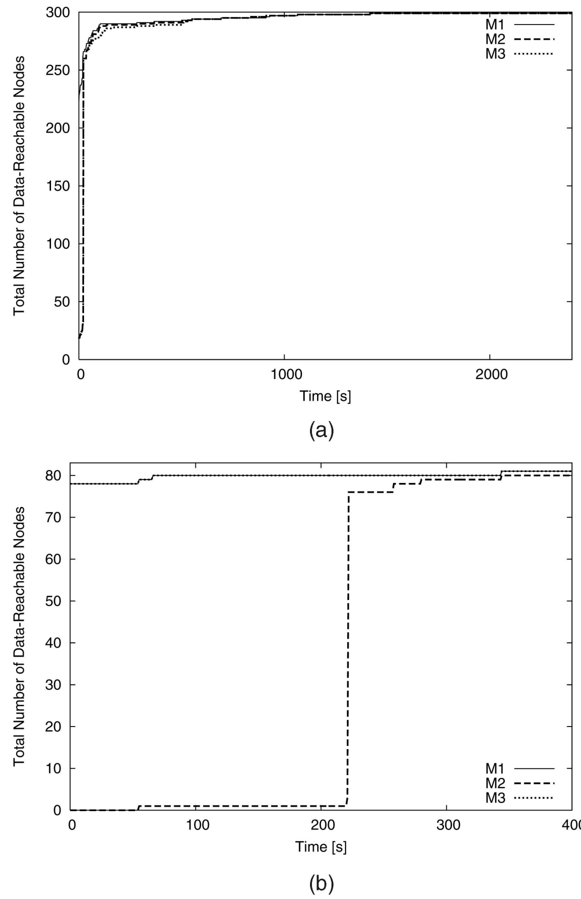


Fig. 20. Total number of data-reachable nodes (real traces). (a) Cab traces. (b) Human traces.

On the other hand, this model is very effective in terms of data distribution because nodes choose the destinations to move randomly in the entire area; thus, they move around in a wide range. When designing a data diffusion protocol, the designer does not need to be very nervous for the performance in terms of distribution rapidness. Rather, the protocol should address the reduction of unnecessary data redistribution when mobile nodes newly connect with each other in order to reduce excessive data traffic.

4.6.3 MM Model

The MM model showed several interesting features due to its restricted mobility. First, similar to the RW model, this model forms many small partitions but rarely forms large ones when the node density is not very high. However, this model causes much fewer isolated nodes than other models; thus, the average partition size is relatively large. Moreover, the ratio of not changing the size of partitions is very high and the maximum changes in size are small. Totally, this model works well in terms of data storage capacity and partition stability, while the maximum capacity is small. Therefore, when designing a data replication protocol where the movement pattern follows the MM model, it is effective to share data among nodes in the same partition.

In terms of data distribution, the MM model basically gives a modest total number of connected nodes, which is lower than those in the RWP and RPGM models that form large partitions. In addition, the total number of connected nodes shows a steady increase as time passes in this model. As for the total number of data-reachable nodes, it gives good results similar to the RWP and RPGM models.

When a data diffusion protocol is designed and the node density is not very high, aggressive data dissemination is effective in terms of distribution rapidness. Contrary to the RWP model, the protocol designer does not need to be very nervous to reduce data redistribution because the maximum capacity of partitions is basically small in this model. Rather, the protocol should address how each mobile node effectively distributes data items to nodes moving on the incoming lane and to other nodes that the node meets at an intersection within a limited time when the wireless connection is available. This issue includes a problem how to effectively select significant data items to be distributed. Of course, when the node density is very high, blind data disseminations might cause a big problem; thus, the protocol should consider effective data disseminations to reduce the traffic.

4.6.4 RPGM Model

The RPGM model gives a much higher average and maximum partition size than other models and the second lowest ratio of partitions with one node (following the MM model). These features are due to the combined advantages of random waypoint and group mobility and show that this model is the best in terms of data storage capacity. As a negative effect of the large partition size, nodes often experienced big changes in partitions. However, as the experimental results on the distribution of connected nodes showed, it provides very high connectivity among nodes in the same group. Therefore, when designing a data replication protocol where the movement pattern follows the RPGM model, it is effective to share data among nodes in the same group. It should be careful to share data with nodes in other groups.

In terms of data distribution, this model gives good performance due to its two advantages: high mobility and large partitions. Similar to the RWP model, when designing a data diffusion protocol, the designer does not need to be very nervous for the performance in terms of distribution rapidness. Rather, the protocol should address the reduction of unnecessary data redistribution.

4.6.5 RWP-L Model

The RWP-L model basically gives relatively low average and maximum partition sizes due to low connectivity among nodes in different home areas. Thus, in terms of data storage capacity, this model is not very good. However, it gives lower change in size of partitions. The most remarkable feature of this model is unfairness among nodes according to their home areas. For all the metrics, the node whose home area is the center of the entire area gave better performance than the node whose home area is a corner of the entire area.

Therefore, when designing a data replication protocol where the movement pattern follows the RWP-L model and the node density is not very high, it is effective to share data among nodes in the same partition, especially, those having the same home area. Moreover, it is preferable that mobile nodes with different home areas adopt different policies for data replication. For example, since mobile nodes whose home area is the center of the entire area have a strong connectivity with other nodes, they can rely on the connected nodes for sharing data more than those at a corner.

In terms of data distribution, this model basically has the weakness that nodes have difficulty connecting to all nodes due to the movement locality. Moreover, the total number of connected nodes is greatly affected by the increase in node density because the increased number of nodes can bridge isolated partitions. Therefore, when designing a data diffusion protocol, similar to the RW model, it should aggressively disseminate data to connected mobile nodes, especially for those with different home areas. Moreover, if nodes can control their communication range, it should be set longer in order to increase the node density. Of course, when the node density is very high, the protocol should consider effective data disseminations to reduce the traffic.

4.6.6 Examination of a Data Diffusion Protocol

To examine the above discussions, we show the result of a simulation experiment regarding the performance evaluation of a data diffusion protocol for the five typical mobility models. Due to the limitation of space, we only show the performance of a data diffusion protocol under a specific network configuration, i.e., the default setting in Section 4.3.

In this experiment, we evaluated the performance of a simple data diffusion protocol in which data items are reflooded with a certain probability (*reflooding probability*) when two mobile nodes newly connect with each other. More specifically, each mobile node receives all data items held by the newly connected node and refloods them in the entire network based on the reflooding probability.

Every mobile node generates a new data item at every 10,000 units of simulation time and the data item becomes invalid (expired) after 10,000 units of time. We assume that all data items are very small and every mobile node has enough storage to store all data items. For the purpose of simplicity, communication times for these data items are short enough to be negligible.

We measured two performance metrics, *average ratio of having valid data* and *total traffic for data diffusion*, where we varied the reflooding probability. Here, for each node and each data item, we define the ratio of having a valid data item as the ratio of the time period during which the valid data item is held by the node to the entire valid time, i.e., 10,000 units of time. Therefore, the average ratio of having valid data is defined as the average of the ratios of having a valid data item for all nodes and all data items generated during the entire simulation time. This metric represents the rapidness of data diffusion. The total traffic for data diffusion is defined as the total hop count for all data transmissions occurring during the entire simulation time.

TABLE 11
Performance of Data Diffusion Protocol

	Re-flooding probability			
	0.001	0.01	0.1	1.0
RW	0.0268	0.0452	0.1396	0.2630
RWP	0.0919	0.4037	0.8412	0.9666
MM	0.0623	0.2819	0.8026	0.9327
RPGM	1 (0.5958)	1 (0.8587)	1 (0.9310)	1 (0.9493)
RWP-L	0.0384	0.1111	0.6458	0.9115

(a)

	Re-flooding probability			
	0.001	0.01	0.1	1.0
RW	0.0005	0.0007	0.0018	0.0031
RWP	0.0022	0.0083	0.0152	0.0166
MM	0.0016	0.0056	0.0137	0.0153
RPGM ($\times 10^{10}$)	1 (0.1737)	1 (2.279)	1 (23.92)	1 (241.7)
RWP-L	0.0005	0.0009	0.0043	0.0055

(b)

(a) Average ratio of having valid data. (b) Total traffic for data diffusion.

Table 11 shows the simulation result. In this table, we generalized the result of each mobility model based on that of the RPGM model (represented as 1). The values between parentheses denote the actual values of the two metrics for the RPGM model. The result shows that the MM and RWP-L models provide lower traffic for data diffusion than the RPGM and RWP models, and the data diffusion rapidness in these models is more sensitive to the reflooding probability, i.e., aggressiveness of data diffusion.

Consequently, we can confirm the validity of some discussions above. We realize that we need more extensive experiments to apply our proposed metrics to designing concrete data diffusion and replication protocols. However, we leave it for future work since it is beyond the scope of this paper.

4.6.7 Real Traces

The two kinds of real traces used in our experiments form a large node group. This shows that nodes basically stayed in a specific area and formed a large group, and sometimes, moved to another area alone. In such a case, a data replication protocol should consider efficient allocation of replicas in the large group with low traffic. Also, each node should precisely detect the timing of disconnection from the group and effectively relocate necessary replicas. As for a data diffusion protocol, it does not need to deal with fast diffusion of data items generated in the large group but should rapidly detect a node newly connected to the group and one that will be disconnected soon.

Here, we cannot say from the results using the real traces that all real networks have the same features because the movement patterns heavily depend on the situations and applications. Specifically, the two kinds of real traces used in our experiments are just instances of two specific real situations, where mobile nodes basically move independently of others and they do not collaborate. While information sharing for a collaborative work such as rescue operations and military affairs is a typical MANET application, the two traces do not represent movement patterns in such an application. Experiments using various kinds of real traces will be the first priority in our future work.

5 Conclusion

In this paper, we proposed seven metrics to quantify the influence of node mobility on data availability. Our proposed metrics can be categorized from two different perspectives: 1) global or node-centric and 2) capacity/stability or data diffusion. We also reported results of experiments that measured the proposed metrics assuming five typical mobility models: RW, RWP, MM, RPGM, and RWP-L. From the results, we can confirm that the proposed metrics are greatly affected by both the mobility model and system characteristics. The number of nodes, i.e., node density, greatly affects the data storage capacity and the movement speed greatly affects the data diffusion. Moreover, there is basically a trade-off relationship between the stability of partitions and the rapidness of data diffusion. Here, due to restricted mobility, the MM and RPGM models break this trade-off relationship and achieve both at the same time. We also reported results of experiments using two kinds of real traces.

We believe that the experimental results and knowledge obtained from the results are very useful for researchers and engineers for designing various protocols for data sharing and data diffusion on these typical mobility models. Even if the mobility pattern of the assumed application is different from these typical mobility models, its impact on data availability can be examined in the same way as we did in our experiments.

As mentioned in Section 3.4, our proposed metrics are neither the smallest nor complete for quantifying the impact of mobility on data availability. Also, our approach to quantifying data availability using only partitions and node connections has some limitations. As part of future work, we will further investigate these facts and reconsider the metrics for some concrete problems. We also plan to address a issue to qualitatively distinguish between and match movement patterns in real networks and typical mobility models by using performance metrics for quantifying the impact of mobility.

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