

On the Interactions between Mobility Models and Metrics in Mobile ad hoc Networks

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Abstract In this paper we investigate several gaps on the study of mobility models in Mobile ad hoc Networks (MANETs). We present a survey of taxonomies for mobility models, and introduce a novel taxonomy for mobility metrics, which is then employed for classifying the surveyed metrics. It is performed a comprehensive experimental study taking into account an heterogeneous set of mobility models and seven representative mobility metrics. As a first result, we show how effective metrics are on distinguishing among models. Additionally, our simulation findings reveal that, independently of the movement pattern of mobile nodes, there are similar relationships among node speed and several mobility metrics. Furthermore, we estimate the impact of each mobility model's parameter on the evaluated mobility metrics, revealing the variables that most impact the metrics. Lastly, through stepwise multiple linear regression analysis we created accurate models for predicting the value of link duration, node degree and network partitioning metrics from a proposed set of novel predictors. The results presented in this work provide significant insights on the comprehension of mobility models and metrics and the interactions between them in MANETs.

Keywords Mobility Model, Mobility Metric, Simulation, Regression Analysis, Mobile ad hoc network

1. Introduction

To support the growth and development of mobile ad hoc networks (MANETs), researchers from industry and academia have designed a variety of protocols, spanning the physical to the application layer. When it comes to evaluating such protocols, analytic modeling and simulation are amongst the most used methods. The former has limitations due to the lack of generalization, and the intrinsic high level of complexity[15]. The latter is by far the most used method for designing and evaluating MANET protocols[37].

A mobility model is one of the most important components in the simulation of MANETs. This component describes the movement pattern of mobile nodes (e.g., people, vehicles) and it has many impact factors such as: protocol performance[7, 12, 40, 55]; topology and network connectivity[10, 26, 59]; data replication[31]; and security [18]. Regarding the first factor, Bai et al.[7] demonstrated that the performance of a protocol can vary dramatically depending on the adopted mobility model.

A drawback on the current analysis of mobility models is that just a few variables (i.e., input parameters) are covered.

Among the analyzed parameters, the majority of studies just assess the impact of maximum speed[3, 7, 24, 31, 32, 39, 57, 63, 67, 77] for mobility and protocol performance metrics. Other studies also evaluate the impact caused by changing the values of radio communication range[24, 57], number of nodes[32, 63, 67], and node pause time[56]. Thus, there is plenty of space for analyzing the impact of other parameters, such as number of city blocks and number of mobile groups (when applicable).

After several mobility models had been proposed, there was a need for better analyzing and comparing them. For this reason, mobility metrics were introduced for classifying and measuring, quantitatively and qualitatively, any mobility model. However, there are disagreements over the quality of some mobility metrics. For instance, several authors[30, 52] argue that the number of link changes[30] is a good metric because it is able to differentiate among mobility models, while other authors[7, 64] disagree with that statement.

Some mobility metrics are directly related to the performance of routing protocols. Sadagopan et al.[57] demonstrated that there exists a linear relationship between the mobility metrics of link and path duration and the protocol performance in terms of throughput and routing overhead.

Considering that mobility models' input parameters have a direct impact on mobility metrics, it seems suitable to estimate the relationship between metrics and parameters. Understanding relationships among them allow developing

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accurate metrics' prediction models, while also guiding on the design of mobility aware protocols. Besides that, other works[35, 47] have shown that mobility metric predictive models may also be used for allowing researchers specifying rigorous MANET simulation scenarios for protocol evaluation.

From the points raised so far, we list the following Research Questions (RQ) regarding mobility aspects in mobile networks:

RQ1: How effective are the metrics on distinguishing models?

RQ2: Can mobility models from different classes exhibit similar behavior for the same metrics?

RQ3: Can mobility models belonging to the same class behave differently for the same metrics?

RQ4: What are the mobility variables that most impact on the metrics?

To investigate the aforementioned questions, we performed a comprehensive experimental study (Section 4) using six mobility models (Section 2) and seven well-known mobility metrics (Section 3). In section 2 we show a survey of taxonomies for mobility models, and in section 3 we introduce a novel taxonomy for mobility metrics, using it to classify the surveyed metrics. Results from related work are compared with ours in Section 5. Finally, the conclusions of this work are pointed out in Section 6.

2. Mobility Models

A mobility model can be defined as a mathematical model that describes the movement pattern of mobile nodes (e.g., people, vehicles). It determines how the movement components (e.g., speed) of nodes change over time, aiming at modeling the real behavior of mobile nodes. Mobility models can be classified in different ways (Figure 1): the level of mobility description[11]; the model building technique[17]; the type of mobility entity (user)[50]; the interdependence of nodes' movement[17]; the model internal characteristics[6]; and the degree of randomness in mobility pattern[79][62]. Some representative mobility models are described below.

Mainly due to its simple implementation, Random Waypoint (RW)[16] became the most widely employed model in the evaluation of MANET protocols[36]. The RW algorithm randomly chooses a destination point and a constant speed at which a node moves until it reaches that destination. Then the node may stay still for some time (in case a pause time is defined) before starting a new movement (Figure 2(a)). The RW model has only three input parameters: minimum speed, maximum speed, and maximum pause time. Node speed and pause time follows a uniform probability distribution.

Although it is one of the simplest mobility models, the RW model has at least two well-known drawbacks. The first is the non-uniform node distribution resulting from the edge effect[11]. The other is the average node speed decay during

the simulation[73]. Yoon et al.[73] estimated an approximation equation for the minimum speed in order to work around this problem.

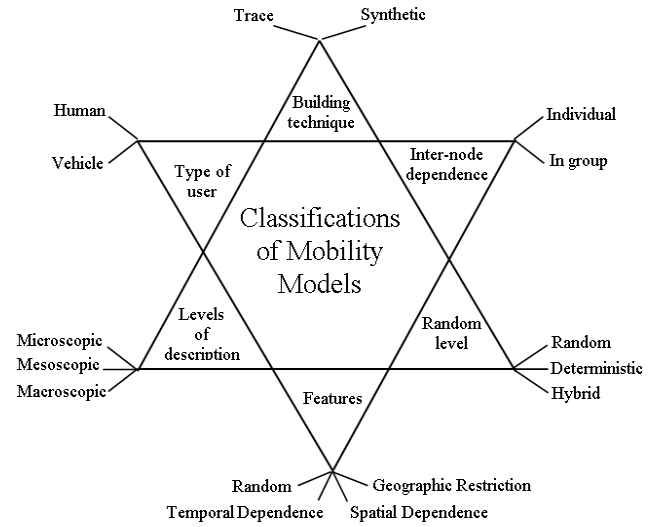


Figure 1. Classifications of mobility models

Hong et al.[30] proposed the Reference Point Group Mobility (RPGM) model and used it in a proposal for a routing protocol[53]. An applicable situation using this model is in the battle field, where soldiers move in unity following their leader. Another possible application for this model is in rescue operations during disasters.

In the RPGM model (Figure 2(b)), each group has a center point, which can be physical (i.e., geographic point on the map) or logical (i.e., the leader of the group). The movement of the leader of a group determines the movement of all its members.

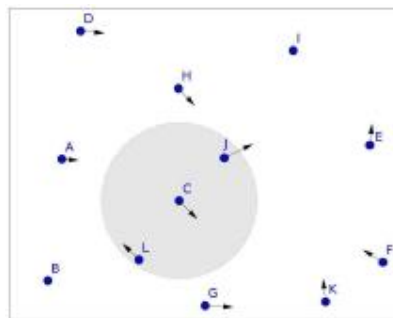
Liang and Haas[41] proposed the Gauss-Markov (GM) model. Initially, this model was proposed to model node mobility in mobile phone networks. However, this model has been used also in MANETs[17]. Using stochastic process to model node speed, this mobility model overcomes a limitation (i.e., abrupt speed changes) normally found in random models.

A grid-based model, Manhattan, was introduced by Bai et al.[7]. In this model, nodes follow specific paths (e.g., streets) distributed in a grid (Figure 2(c)). This model is more appropriate for describing the movement of pedestrians or vehicles in a city. Some of Manhattan's input parameters are the number of horizontal and vertical streets and the standard node speed deviation, since in this model the speed follows a Normal distribution.

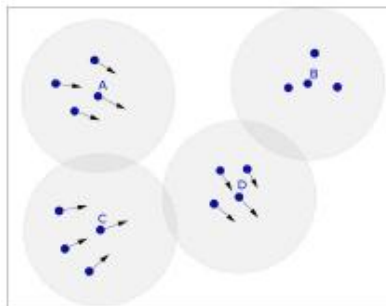
Zhao and Wang[76] designed the Semi-Markov Smooth (SMS) model. It uses the physical laws of kinematics to characterize nodes' movements. The authors considered that a moving object usually undergoes three movement phases: acceleration, speed stability, and slow down. Thus, the movement generated by the SMS model becomes smooth, showing a temporal correlation between the consecutive speeds of a node. This model is named Semi-Markov due to the speed stability phase, where velocity and direction are

similar to those from the Gauss-Markov model.

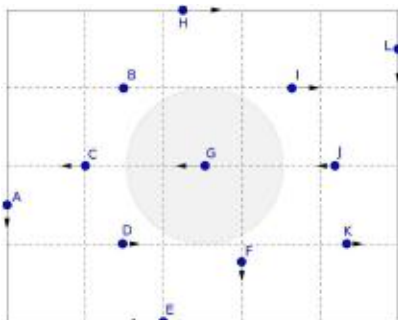
A mixed grid and group-based mobility model, the Community Based Mobility Model (CMM), was proposed by Musolesi and Mascolo[49]. It is based on the theory of social networks, taking into account how people come together and move according to their social relations, which is estimated from what the authors call the social attractiveness. This is a measure based on how many friends (i.e., neighbors) are in a same region of the grid. The authors take into account that in real life there are periodic repetitions in the movement pattern of people. The CMM model was validated through real movement traces provided by the Intel Research Lab[49].



(a) Random Waypoint



(b) Reference Point Group Mobility Model



(c) Manhattan

Figure 2. Visualization of RWP, RPGM and Manhattan mobility models in action

3. Mobility Metrics

Each affiliation must include, at the very least, the name of the company and the name of the country where the author is based (e.g. Causal Productions Pty Ltd, Australia).Email

address is compulsory for the corresponding author.

A mobility model can be seen as a simple input output process (Figure 3). The input consists of the mobility model's parameters. The output consists of mobility trace files each containing details about the movements of all nodes during the simulation. From these files one can compute the mobility metrics.

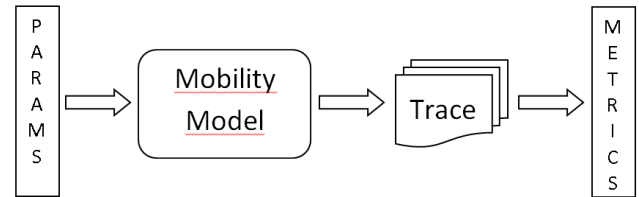


Figure 3. Mobility model seen as an input output process

Mobility metrics are usually based on four assumptions. First, the communication range between every pair of nodes is always bidirectional. Second, the transmission range (R) is constant and equal for all nodes. Third, the number of nodes (N) remains unchanged during the simulation. Lastly, the network scenario should have a two-dimensional rectangular geometry.

One of the most traditional and known mobility metric is the average node degree (ND). It accounts for the average number of nodes residing within the communication range of a given node. Thus, the degree of a node is the same as the degree of a vertex in a graph. As an example, node degree of node F is five in Figure 4 (top left side).

Node degree is a quantity of interest due to its implication on capturing mobility dynamics[43] and on the success rate of various tasks in mobile ad hoc networks[34]. Ishibashi and Boutaba[32] showed the effects of the number of nodes, geographical area and transmission range on ND for the Random Waypoint mobility model. ND is still currently the subject of intensive investigation. For instance, Bouabdallah et al.[14] recently used ND for providing mobility-aware clustering schemes for wireless mesh networks.

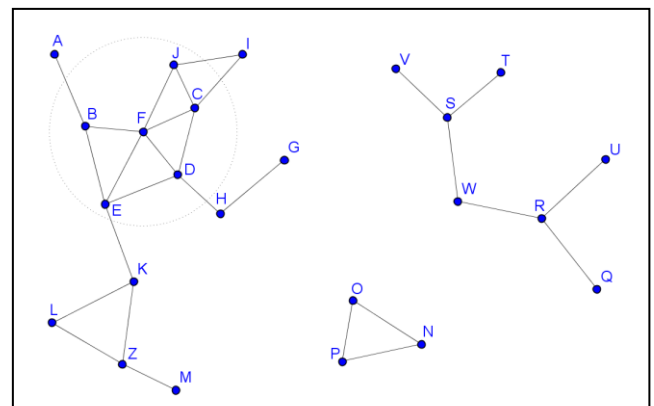


Figure 4. An illustration of a mobile ad hoc network

Number of network partitions (NP) is also a metric derived from graph theory. This metric indicates the connectivity network degree, which is related to the performance of routing protocols. Kurkowski et al.[35]

argues that this metric is important to enable researches following standards in MANET simulation. This metric is also subject of intense study, e.g., for network partition detection[70], prediction[66], and quantification[28, 29]. Moreover, Ahmed et al.[1] recently investigated partition caused by different mobility models in large network area. Figure 4 shows a mobile network where $NP=3$.

Hong et al.[30] proposed the number of link changes (LC) as a metric to distinguish the movement patterns of RW and RPGM models. It is based on the number of times a link between two nodes transitions from “down” to “up” and vice versa. According to Bai et al.[9], this metric was not able to differentiate between the several mobility patterns used in their study. Besides that, Tran et al.[64] states that LC cannot reflect accurately the dynamics of networks with different sizes since it depends on the number of nodes. Nevertheless, this metric has already been used in several analytical and simulation-based studies in MANETs[12, 22, 54, 77].

Link Duration (LD), also known as link lifetime or contact time, is another link-based mobility metric. It is the total amount of time where there is communication between pairs of nodes, i.e., when nodes are distant from each other up to R meters (where R is the communication range of node’s radio antenna). Boleng et al.[12] demonstrate that LD is an indicator of protocol performance and effectively enables adaptive MANET protocols. This metric is one of the most adopted in the literature[12, 20, 21, 23, 42, 57, 63, 72, 77].

Another well-known mobility metric is the relative speed (RS) between nodes[7]. We classify this metric as velocity-based since the relative speed between nodes i and j at time t is given by the difference between their instant velocities (i.e., $|V_i(t) - V_j(t)|$). However, RS is computed only for those nodes that are apart from each other at most $2R$ units. Bai et al.[8] demonstrate the effect of RS on the probability distribution function of path duration for RW, RPGM, Manhattan, and Freeway mobility models. This metric has been mainly used for mobility model designing [76], validation[65], and evaluation[44, 68], though there are other applications for this metric like routing protocol designing[74].

Since a mobile node may move according to other node’s movement, no matter if they are pedestrians or vehicles; it is opportune thinking about mobility metrics that measure this relationship. Related to this statement, Bai et al.[7] proposed the degree of spatial dependence (DSD), which indicates the similarity between the velocities of two nodes that are not too far apart (less than $2R$). DSD is high when the velocities (magnitude and direction) of two nodes are similar, what normally occurs when the movement of a node depends on the other’s. Thus, when applied to the whole wireless network, this metric reveals when nodes move in a group manner. Figure 5 (left side) shows an illustration for this spatial metric. DSD is computed based on nodes’ speed and the angle between them. For this example, $DSD(A,B) = \cos 30^\circ \cdot 1/2 \approx 0.72$. DSD values range from 1 to 1, where 1 means maximum

negative movement correlation (dependence), 0 means absence of spatial dependence, and 1 means maximum dependence (correlation).

A negative DSD occurs, for example, when a node is moving to North while other is moving to South. On the other hand, whenever a node is moving at close direction and velocity of another, then a positive DSD occurs.

Several works were based on DSD for a wide range of purposes, including geographic routing evaluation[61], mobility model design[44], validation[65] and evaluation [68, 72], performance analysis of routing protocols[7, 43], mobility-aware routing protocol analysis[25], and design of clustering algorithms[75].

Bai et al.[7] also proposed another velocity-based mobility metric, called degree of temporal dependence (DTD). It is similar to DSD, but considers the similarity between a node’s velocity at time t and the same velocity at time t' (where $|t - t'| > 0$). An illustration for DTD is shown in Figure 5 (right side), where three consecutive time steps of the position and velocity vector of a node is shown. The more similar are the vectors the higher is DTD, in the same way as for DSD. By definition, this metric can differentiate temporal models from others, and it has already been used for mobility model design[44] and evaluation[72].

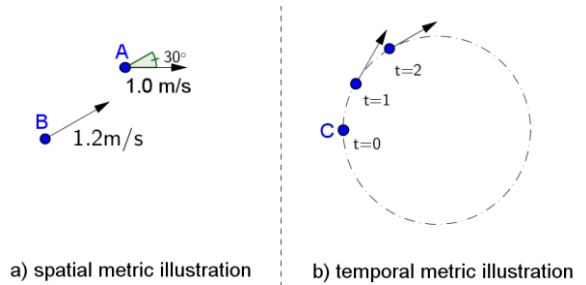


Figure 5. An illustration of spatial and temporal mobility metrics

Besides the aforementioned metrics, there are numerous others in the literature, such as probability of link path availability[45], path duration[57], probability of link change[64], and degree of node proximity[19]. Though other past works proposed classifications for mobility metrics in MANETs[9, 60, 69, 71], we believe that the nomenclature shown in Figure 6 covers all the current proposed metrics.

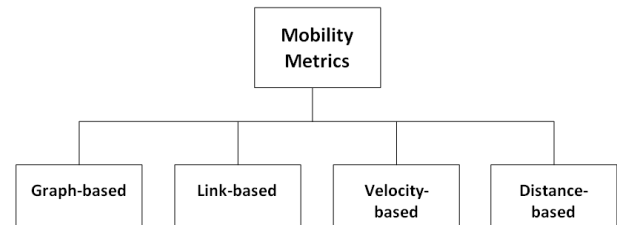


Figure 6. Classification of mobility metrics

We consider four categories of mobility metrics: graph-based, link-based, velocity-based, and distance-based. The first involves all metrics related to link (and path) time measurements, e.g., duration, availability, probability, or stability. The second group includes the metrics derived from Graph Theory (since a MANET topology is some sort

of graph) which are applicable for wireless networks. As we already introduced, node degree and network partitioning are examples of graph-based metrics. The third group contains metrics based on node velocity's components (i.e., speed and direction). RS, DSD, and DTD are velocity-based mobility metrics. Lastly, the metrics based on the distance between nodes compose the last group. Examples of distance-based metrics are the distance change rate[38] and the degree of node proximity[19].

4. Experimental Study

After introducing examples and taxonomies for mobility models and metrics, we focus on answering the four research questions introduced in Section 1.

Table 1. Classification of the mobility models used in the simulation

Classification	RW	RPGM	GM	MAN	SMS	CMM
Level of Details	Mi	Mi	Mi	Mi	Mi	Ma
Building technique	Synthetic					
Type of user	H, V	H, V	H, V	V	V	H
Inter-node dependence	I	G	I	I	I	G
Features	-	SD	TD	GR	TD	SD/GR
Randomlevel	R	R	H	R	H	H

^aMi/Ma: Micro/Macroscopic. ^bH: Human, V: Vehicle. ^cI: Individual, G: Group
^dSD: Spatial Dependence, TD: Temporal Dependence, GR: Geographic Restrictions

^eR: Random, D: Deterministic, H: Hybrid

We set up an experimental study involving all the mobility models and metrics aforementioned. Scenarios for

RW, RPGM, Manhattan, and Gauss-Markov were obtained from the BonnMotion tool[2]. Node movement scenarios for SMS and CMM were computed by running the code made publicly available by their authors[48, 78]. For computing the mobility metrics we used the BonnMotion and Trace Analyzer[5] MANET mobility tools. The latter is part of the well-known IMPORTANT framework[7].

A comparative board for the selected models is shown in Table 1: RW is a random model; GM and SMS are hybrid random temporal models; RPGM and CMM are group-based models; and MAN and CMM have geographic restrictions since are grid-based models.

4.1. Configuration

When comparing models that belong to a same class, it is paramount to ensure a fair scenario configuration. A special case for reaching this requirement is setting a correct speed configuration, since there are four parameters related to velocity: minimum speed (s), average speed (AS), maximum speed (S), and the speed standard deviation (SSD). Usually the speed probability distribution function (pdf) of any mobility model is uniform (i.e., $X \sim U(s, S)$) or normal (i.e., $X \sim N(AS, SSD)$). Thus, we ensured an equivalence of speed when using mobility models that have different speed pdfs.

Table 2 presents the configuration for all mobility models' input parameters considered in this work. The simulation time was set to 900 s, after disregarding the first 3600 s to avoid the statistics variations due to the simulation transient phase[51]. A total of 172.800 experiments were created, and each of them was repeated 10 times, changing the pseudo-random number generator (PRNG) seed.

Table 2. Configuration of the mobility models' input parameters

Parameter ^a	RW	RPGM	GM	MAN	SMS	CMM
Simulation time (T)				900		
Number of nodes (N)				50, 100		
Scenario's length (X)				1000, 1500		
Scenario's width (Y)				500, 1000		
Transmission range (R)				50, 100, 150		
Minimum speed (s)	^{*b}	0, 2, 4			0, 2, 4	
Maximum speed (S)		10, 20, 30			10, 20, 30	
Average speed (AS)			f(S) ^c	6, 11, 16 ^d		
Speed Std (SSD)			f(S, AS) ^e	f(s, AS) ^f		
Maximum pause time (MPT)		0, 50, 100		0, 50, 100		
Group size (GS)		5, 10				5, 10
Memory parameter (MP)			.2, .5, .8			.2, .5, .8
Number of rows (NR)				10, 20		10, 20
Number of columns (NC)				5, 20		5, 20
Average pause time (APT)					0, 25, 50 ^g	
Max. dist. from center (MDC)		R ^h				
Pause probability (PP)				5%		
Speed change probability (SCP)				10%, 20%		
Total number of scenarios	648	3,888	216	5,184	3,888	3,456
Total number of experiments	6,480	38,880	2,160	51,840	38,880	34,560

^a Time in seconds and distance in meters. ^b Values based on formulas proposed by Yoon et al.[73] ^c Depends on S.

^d $6 = [(10+0)/2 + (10+2)/2 + (10+4)/2]/3$. Similar to 11 and 16 ^e Depends on S and AS. ^f Depends on s and AS

^g Due to uniform pdf we have that $APT = MPT/2$. ^h The same value as the transmission range

4.2. Analysis

For a better presentation, we divided this Section according to the four research questions pointed out in the Introduction.

4.2.1. First Research Question

In order to answer the first research question - How effective are the metrics on distinguishing mobility models? - we randomly¹ selected a sample of thirty mobility simulation scenarios from a universe composed by all the combinations of the following parameters' values: number of nodes (2), simulation area (4), transmission range (3), minimum speed (3), maximum speed (3), and maximum pause time (3), which results in a total of $2 \times 4 \times 3 \times 3 \times 3 \times 3$ 648 scenarios (see Table 2). The chosen scenarios are described in Table 3. Following the guidelines described by Kurkowski[36] on specifying rigorous scenarios for simulation of MANETs, node speed is expressed in terms of transmission range per second (R/s) whereas the simulation area in R^2 units.

The effectiveness of how the graph-based mobility metrics are on distinguishing among mobility models is shown in Figure 7(a). The node degree was able to clearly distinguish group-based models (i.e., RPGM and CMM) from others. However, in most scenarios this metric could not differentiate random from temporal and grid-based models. RW presented slightly higher values than GM, Manhattan, and SMS models for scenarios 14 to 23, corresponding to scenarios with higher node density (see Table 3). A somewhat similar result occurred for the other graph-based metric, network partitioning (Figure 7(b)). Group-based models presented the lowest values, while random, temporal, and grid models presented the highest scores. Again, the difference among the models is not perceptible in higher node density scenarios (i.e., density > 2.0 , Table 3).

The effectiveness that link-based mobility metrics have on distinguishing mobility models is illustrated in Figure 8. Except for the CMM model, there is a negligible difference on the number of link changes (LC) values in all scenarios with 50 nodes (1 to 13, Table 3), Figure 8(a). On the other hand, an opposite behavior is shown for the 100-nodes scenarios, where the results show a higher performance divergence between the models. In general, group-based models had higher number of link changes whereas random models the lowest. These results corroborate LC low ability on differentiating among mobility models[7, 30, 52, 64].

Differently from LC, the average link duration showed to be a better metric for distinguishing models (see Figure 8(b)). In 87% (26 out of 30) of the scenarios, the group-based model was set apart from the others with the highest LD value. Besides that, Manhattan and RW presented higher values than temporal models (SMS and

Gauss-Markov), the ones with the lowest LD scores.

Table 3. Configuration of the randomly selected mobility scenarios

#	N	Area (R^2)	Density	Node speed (R m/s)	Node pause time (s)
1	50	22.22	2.250	0.047	100
2	50	44.44	1.125	0.073	100
3	50	50	1.000	0.050	0
4	50	75	0.667	0.050	0
5	50	75	0.667	0.100	50
6	50	150	0.333	0.110	100
7	50	150	0.333	0.150	50
8	50	200	0.250	0.140	100
9	50	300	0.167	0.340	100
10	50	400	0.125	0.100	100
11	50	400	0.125	0.200	0
12	50	600	0.083	0.320	50
13	50	600	0.083	0.340	0
14	100	22.22	4.500	0.047	100
15	100	22.22	4.500	0.107	100
16	100	33.33	3.000	0.033	0
17	100	33.33	3.000	0.033	50
18	100	33.33	3.000	0.100	50
19	100	44.44	2.250	0.067	50
20	100	50	2.000	0.050	0
21	100	66.67	1.500	0.033	50
22	100	75	1.333	0.170	0
23	100	100	1.000	0.170	0
24	100	200	0.500	0.140	50
25	100	200	0.500	0.240	50
26	100	300	0.333	0.200	50
27	100	300	0.333	0.340	0
28	100	400	0.250	0.140	0
29	100	400	0.250	0.320	100
30	100	600	0.167	0.120	100

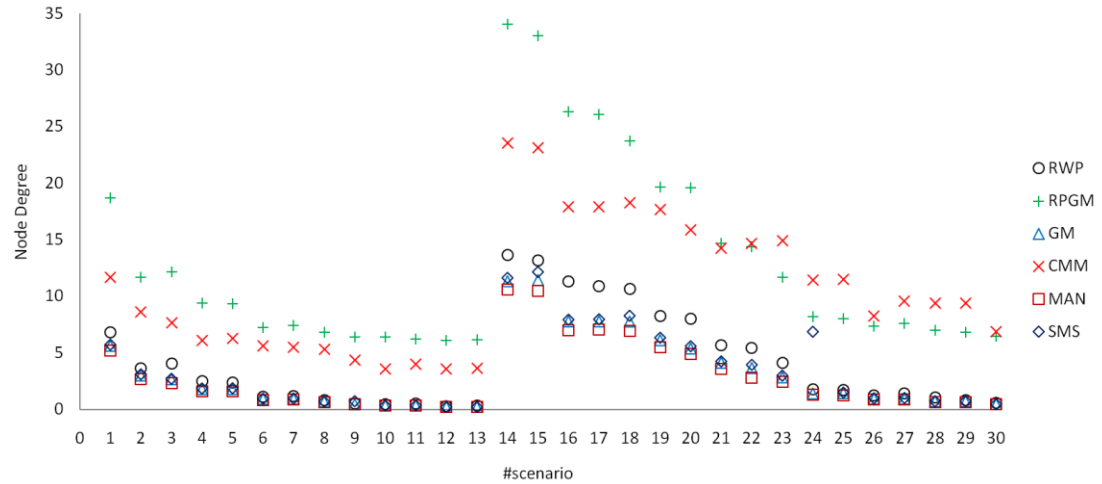
Lastly, the effectiveness of velocity-based metrics on distinguishing mobility models is depicted in Figure 9. The relative speed (RS) showed to be a good metric for distinguishing the models (see Figure 9(a)). Due to the low proximity among nodes in RPGM groups, RPGM had the lowest RS values. On the other hand, Gauss-Markov had the highest values, probably because in this model there is no pause time, making nodes move all the time. We can also notice that the presence of geographical constraints (e.g., streets), found in Manhattan and CMM, caused the nodes in the grid-based models to have higher RS values than in random models.

The degree of spatial dependence (DSD) presented similar results for all mobility models as depicted in Figure 9(b). Taking into account that, by definition, this metric should set group-based models apart from others, overall results are usually acceptable. However, there is a high variation in DSD values for the RPGM model. For instance, DSD varies from 0.56 (scenario 12) to 0.79 (scenario 13), even though the only difference between these scenarios is the pause time (respectively, 50 and 0 seconds). In fact, in another study[19] we have already pointed out that DSD

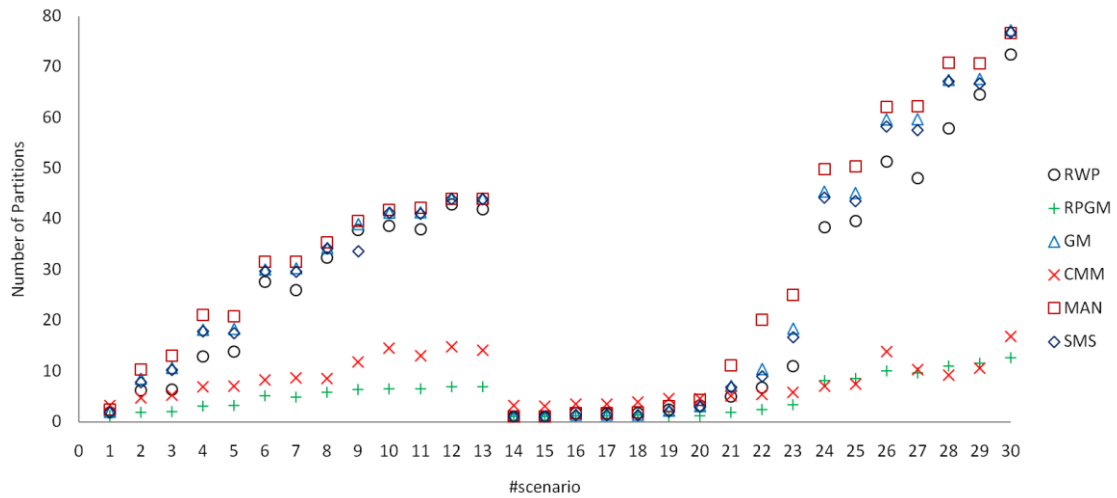
¹We use the true random number generator service provided by Haahr [27], which is based on atmospheric noise level for getting the random numbers.

erroneously decays as the node pause time increases. Anyway, DSD is at least able to distinguish group-based models from temporal and random ones. Another velocity-based metric, the degree of temporal dependence (DTD), provided a clear division among models (see Figure 9(c)). However, this division was not as expected, since

temporal models (e.g., Gauss-Markov and SMS) had not the highest values among the mobility models. According to Figure 9(c), the majority of the scenarios for SMS and Gauss-Markov showed DTD values between 0.3 and 0.5 whereas more than 80% of the scenarios for RW and RPGM presented DTD values higher than 0.5.

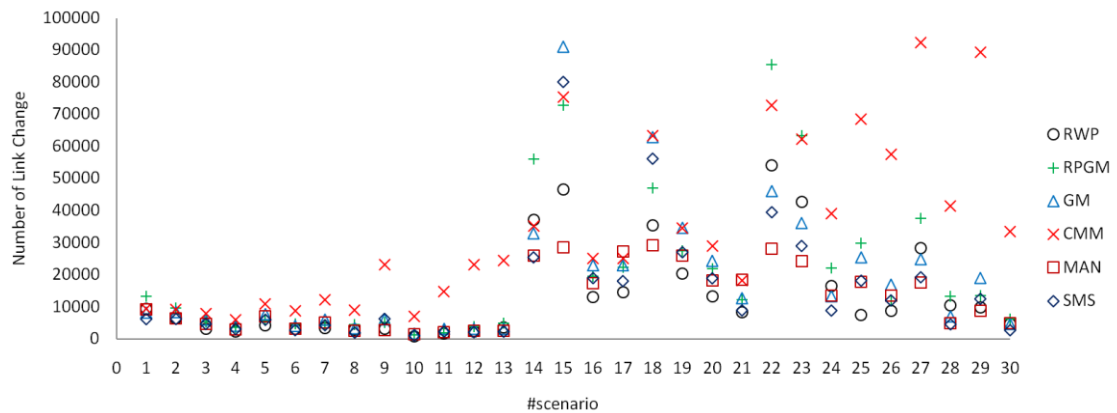


a) Node Degree

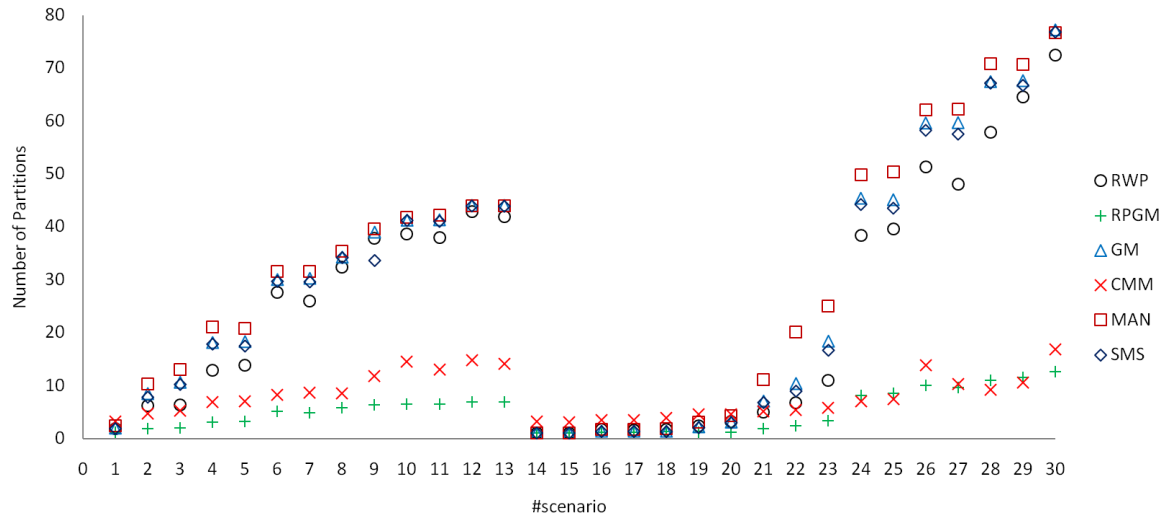


b) Number of Partitions

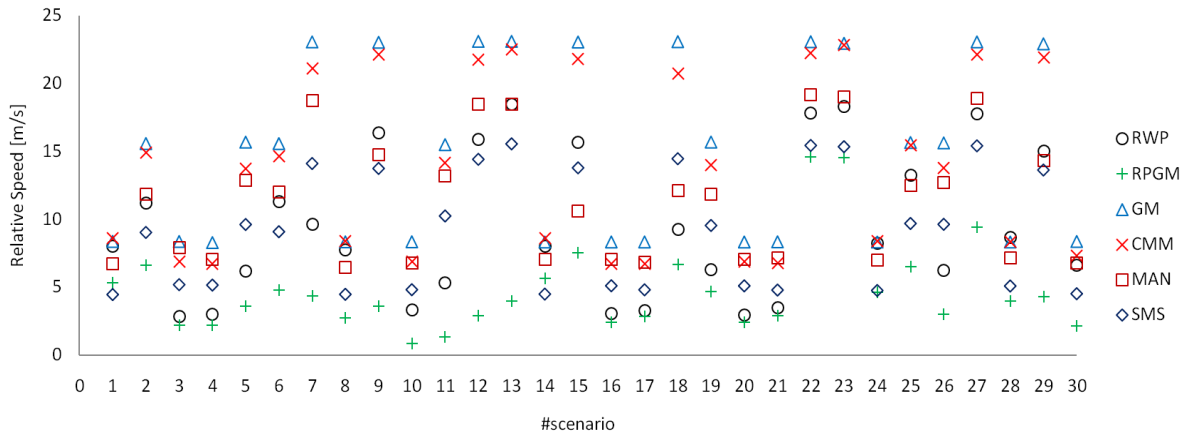
Figure 7. Effectiveness of graph-based metrics for distinguishing mobility models



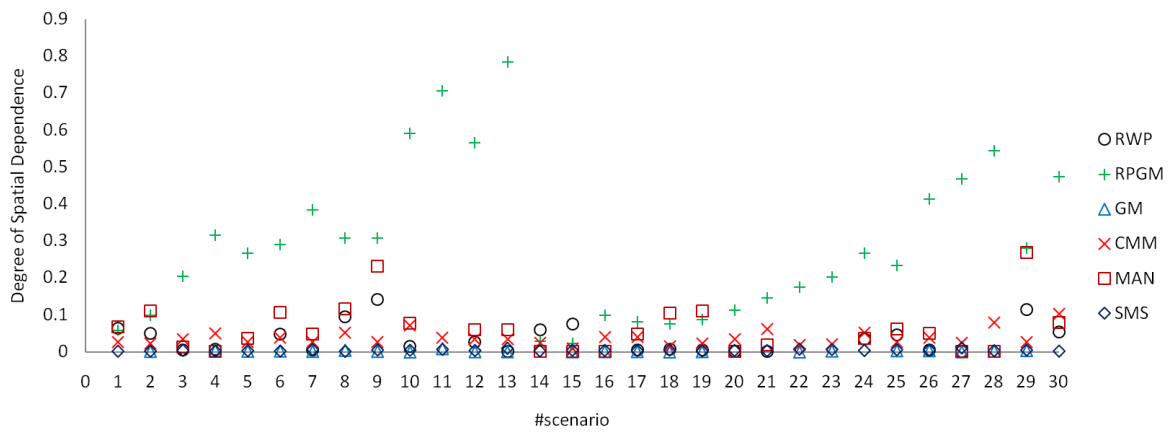
a) Node Degree



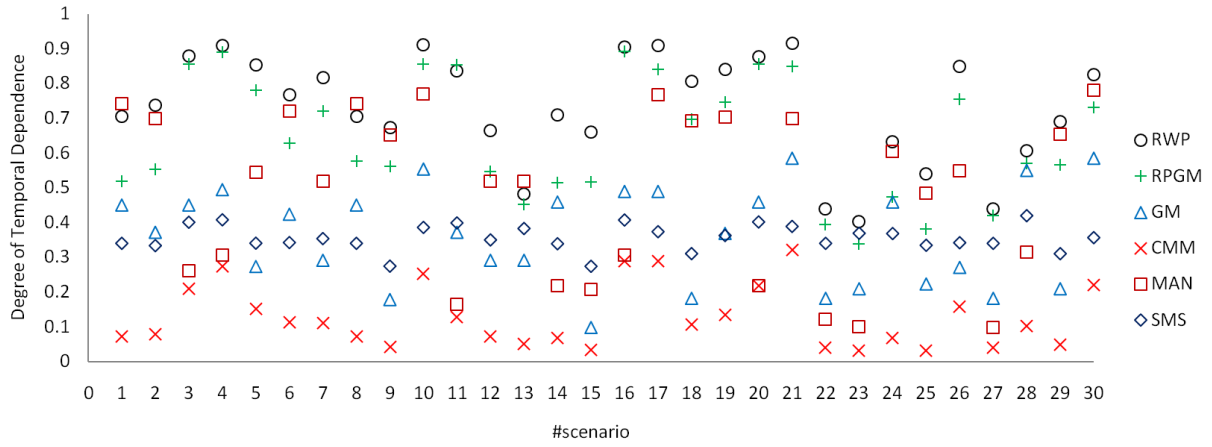
b) Number of Partitions

Figure 8. Effectiveness of link-based metrics for distinguishing mobility models

a) Relative Speed



b) Degree of Spatial Dependence

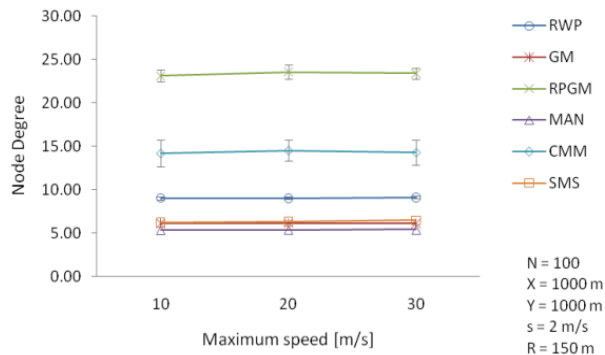


c) Degree of Temporal Dependence

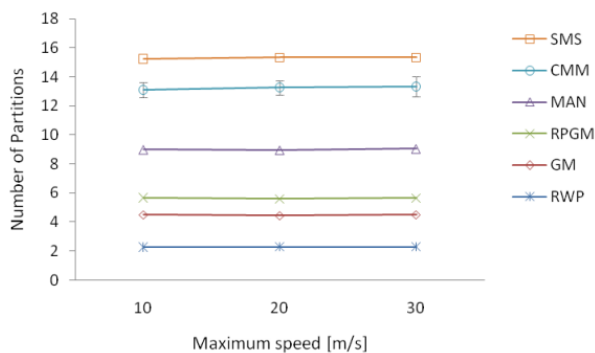
Figure 9. Effectiveness of velocity-based metrics for distinguishing mobility models

4.2.2. Second and Third Research Questions

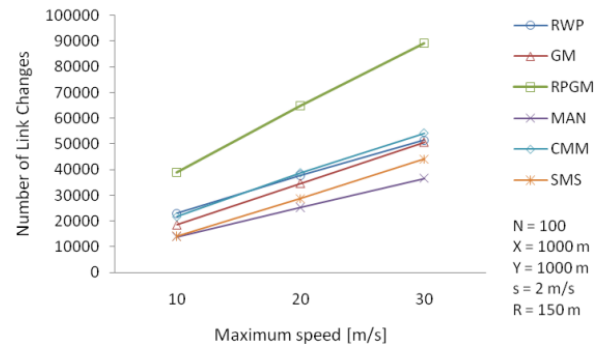
To answer the second research question we searched for similarities in the performance of mobility metrics for all mobility models under consideration. From now on, all graphs present results with a confidence level of 99%. In many situations, the interval length is smaller than the symbol used in the legend, making it barely visible.



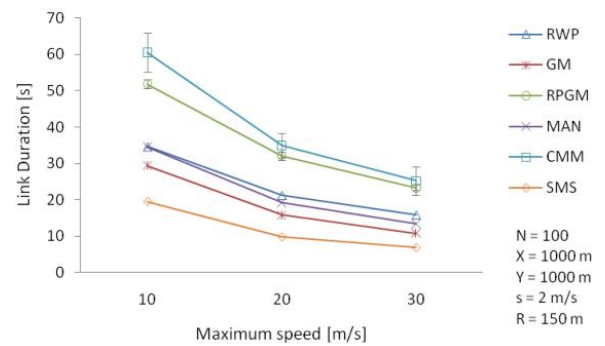
(a) Similarity in the impact of node speed over node degree



(b) Similarity in the impact of node speed over network partitions



(c) Similarity in the impact of node speed over number of link changes



(d) Similarity in the impact of node speed over link duration

Figure 10. Similarities in the performance of link-based and graph-based mobility metrics for different mobility models

Although all evaluated models present different features, they all showed the same behavior concerning the impact that maximum node speed cause on graph-based mobility metrics. Increasing node speed resulted on no node degree or network partitioning variation (Figures 10(a) and 10(d)).

As a result, the Person correlations between this parameter and these metrics, $\rho(S, \phi_{GN})$ and $\rho(S, \phi_{NP})$, were close to zero for all mobility models (Table 5).

Regarding the link-based metrics, link duration and number of link changes, there are also similar behaviors for the models. First, a linear positive relationship exists between node speed and link changes (Figure 10(c)), and an exponential-like decreasing pattern between node speed and link duration.

We also look for differences in the performance of mobility metrics for random, group, and grid-based mobility models, in order to answer RQ3. The RW and SMS models were selected for the comparison of random models². We observed that increasing node pause time rather affected the number of link changes in the SMS model, but it provoked a significant reduction on this metric in the RW model (Figure 11(a)). This result is corroborated by the correlation level between pause time and number of link changes for RWP and SMS, respectively 0.263 and 0.043.

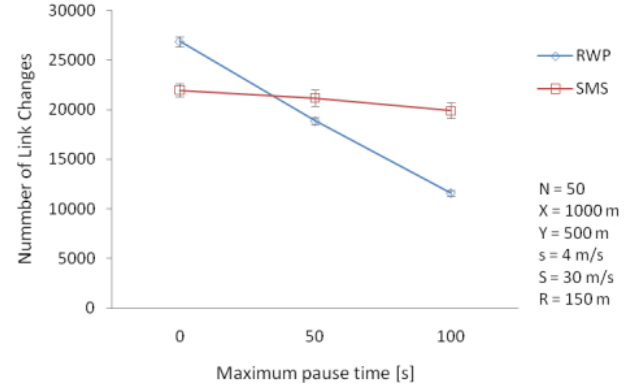
The temporal models, GM and SMS, were compared concerning the effect that memory parameter causes on the degree of temporal dependence (DTD). GM showed a positive linear relation between these variables, differently from SMS performance (Figure 11(b)).

We also compared the joint impact that the number of groups (NG) and the group size (GS) caused on link duration (LD) and node degree (ND) for the RPGM and CMM group-based models³. Considering LD as the performance criteria, Figure 11(c) shows that RPGM presented better performance when you have few large groups, while CMM surpasses when there are many small groups. Furthermore, we also observed a divergence regarding these parameters and node degree (Figure 12(a)). This result may be related to the fact that CMM poses geographical restrictions to node movement.

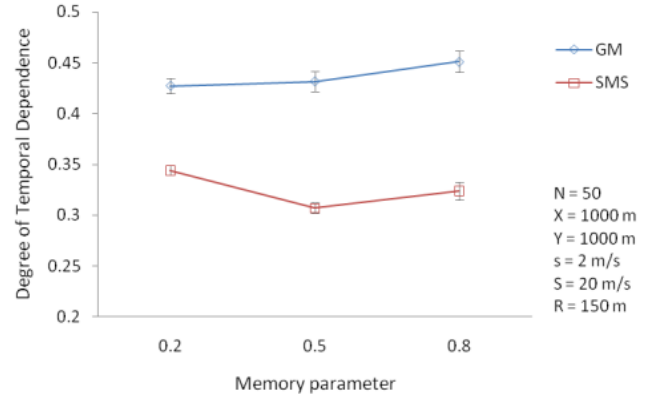
The last comparison was for the grid-based models (i.e., Manhattan and CMM). It was observed an opposite behavior concerning the degree of spatial dependence variation due to increasing node speed. When node speed is increased from 10 m/s to 30 m/s DSD increased linearly from 0.04 to 0.14 for Manhattan, and it dropped from 0.06 to 0.02 in the CMM model (Figure 12(b)). This result is also corroborated by the correlation level between node speed and DSD for these models, $\rho(S, \phi_{DSD}^{CMM}) = 0.643$ and $\rho(S, \phi_{DSD}^{MAN}) = 0.382$.

Additionally, we also noticed a different performance when varying the number of rows (NR) and columns (NC) (which may represent streets in a city) over link duration (Figure 12(c)). Clearly, for higher NC and NR values, lower

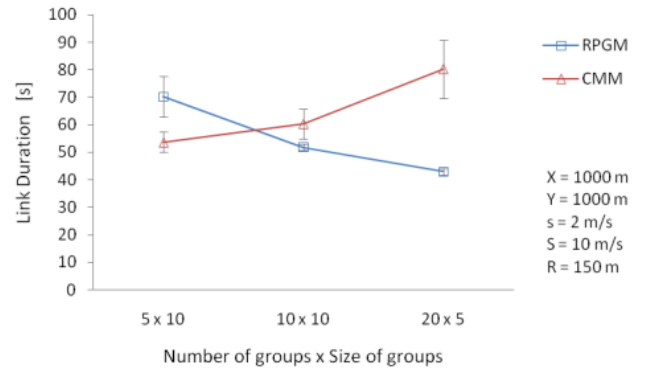
is the size of each city block, and hence higher is the amount of blocks within the communication range (R) of nodes⁴. As there are fewer rows and columns in the scenario, there are fewer larger blocks. In this situation, the link duration decreases in CMM, while increasing in Manhattan.



a) Differences in the impact of pause time over the number of link changes



b) Differences in the impact of the memory parameter over the degree of temporal dependence.



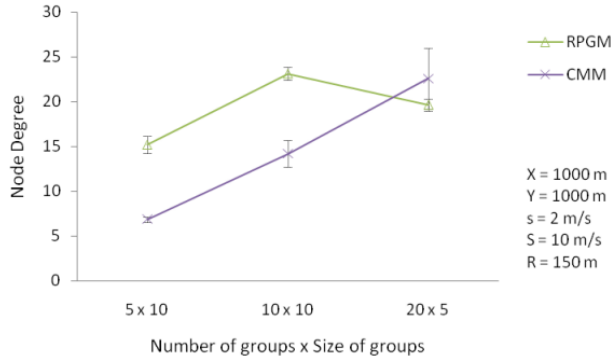
c) Differences in the joint impact of number of groups and group size over link duration in group-based mobility models

Figure 11. Differences in the performance of mobility metrics for random, group, and grid-based mobility models (1/2)

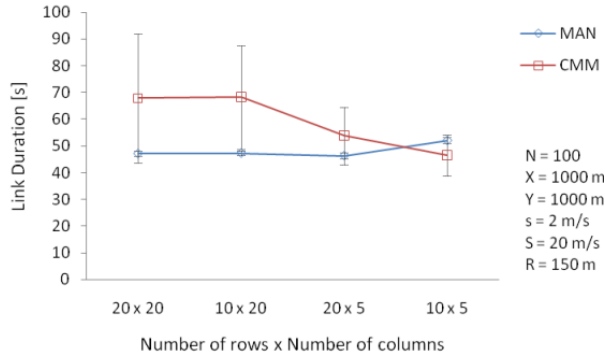
²Even though SMS is a temporal model by default, when its memory parameter α is properly set, the model behaves like a random model [76].

³To get the number of groups (NG), we simply divide the number of nodes (N) by the group size (GS).

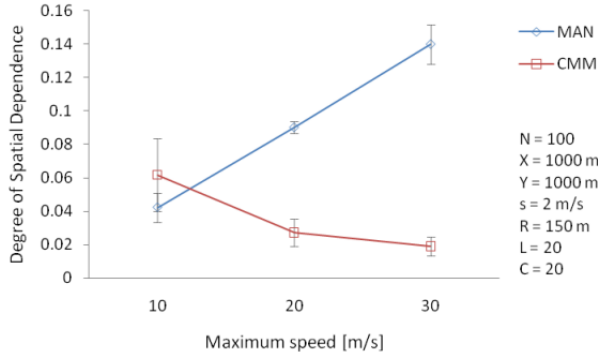
⁴For instance, if the scenario is a square of 1000 m and NR=NC=11, then there will be 100 square blocks of 100 m. On the other hand, if NR=6 and NC=5, there will be 20 rectangular blocks of 200 m x 250 m. An example is depicted in Figure 13.



a) Differences in the joint impact of number of groups and group size over node degree in group-based mobility models



b) Differences in the impact of node speed over degree of spatial dependence in grid-based mobility models



c) Differences in the joint impact of number of rows and columns over link duration in grid-based mobility models

Figure 12. Differences in the performance of mobility metrics for random, group, and grid-based mobility models (2/2)

4.2.3. Fourth Research Question

As already used before, let $\rho(M_i^p, \phi_m)$ indicates the correlation between the p -th parameter of mobility model M_i and metric m . To discover which mobility parameters most impact the mobility metrics we measured the correlation level between each mobility model's input parameter and every mobility metric under consideration, what is called correlation matrix. This information is shown in Table 5.

From the correlation matrix we highlighted the most impacting parameters of each mobility model, summarizing them at Table 4, by including only variables that showed reasonable correlation $\rho(M_i^p, \phi_m) > 0.2$. The '+' and '-' signals means the correlation is either positive or negative.

Since the variables that have a direct effect on mobility metrics are the mobility models' parameters, it seems opportune thinking on the development of models for predicting the metrics from the parameters. For this reason, as an addition to the last research question, in the next section we provide models for predicting some mobility metrics from the aforementioned list of variables that most impact the metrics.

Table 4. Input parameters that most impacted mobility metrics.^{ab}

Metric	RW	RPGM	GM
LD	+R +P -s -S	-N -s -S	+R -S
ND	+N +R -A	+N -A +R +GS	+N -A +R
RS	+s +S	+R +s +S -P	+S
LC	+N +R +s +S -P	+N -A +R +s +S	+N -A +R +S
DSD	+s +S +P	-N +A -R -P +GS	+S
DTD	-s -S +P	-s -S	+A -S
NP	+A -P	-R -GS	+A -R
Metric	MAN	CMM	SMS
LD	+R -S -P	+R -S -GS +NB	+R -S
ND	+N -A +R	+N -GS	+N -A +R
RS	+AS -P	+S	+S
LC	+N -P	+N -R +S -GS	+N -A +R +S
DSD	-R +S	+A -R -S -GS	+S -P +MP
DTD	-S +P	-s -S	+A -S -P
NP	+A -R	-R +GS	+A -R

^a 'S' represents average speed (AS) or maximum speed (S). ^b 'P' represents average pause time (mPT) or maximum pause time (MPT)

Table 5. Predictors' configuration for the regression analysis

Predictor	Values
Number of nodes (N)	50, 75, 100, 125, 150
Simulation area (A)	16, 36, 64, 100, 144
Averagespeed (S)	0.4, 0.8, 0.12, 0.16, 0.20
Group Size (GS)	5, 10, 25
Number of Blocks (NB)	50, 100, 200
Averagepausetime (P)	25, 125, 250, 375, 500

4.3. Analysis

According to Montgomery and Runger[46], multiple linear regression is one of the most used techniques to predict the value of one dependent variable (i.e., response variable) from a set of independent variables (i.e., predictors). This technique has already been used for predicting mobility metrics from mobility model's input parameters[20, 35, 47]. There are at least two main purposes for this approach. First, for allowing researchers specifying rigorous and standard MANET simulation scenarios for protocol evaluation[35, 47]. Second, for supporting designing mobility-adaptive protocols[20].

Let $\phi_m^{M_i} = \alpha + \beta_1^{M_i^1} + \beta_2^{M_i^2} + \dots + \beta_{n-1}^{M_i^{n-1}} + \beta_n^{M_i^n}$ represent the estimated value (by multiple regression) of mobility metric m for the mobility model M_i . Parameters $M_i^1 + M_i^2 + \dots + M_i^{n-1} + M_i^n$ should be mutually independent.

We applied stepwise regression, for which the first step is to choose the predictor that produces the best-fitting linear regression model with the response variable. In each

succeeding step, the predictor that most improves the fit of the linear model is added to the model, in case the improvement exceeds a predetermined threshold. Then, any predictor in the model that can be dropped without reducing the fit by more than a predetermined amount is removed. This process is iterated until no variable that is not in the model may improve the fit by an amount exceeding the threshold, and no predictor that is in the model can be removed without reducing the fit by more than the predetermined threshold.

4.3.1. Response and Predictor Variables

We selected three mobility metrics as response variables for the regression analysis: average link duration, average node degree, and average network partitioning. Boleng et al.[12] demonstrate that link duration is an indicator of protocol performance and effectively enables adaptive MANET protocols. Node degree is a quantity of interest due to its implication on the success rate of various tasks in mobile ad hoc networks[34]. Lastly, Kurkowski et al.[35] argue that network partitioning is an essential metric for designing MANET standard simulation scenarios.

We considered two possible sets of predictor variables: input and derived parameters. The first contains the mobility models' input parameters (the same as factors), as detailed in Table 2. A derived parameter is a combination of two or more input parameters. We tried various possible subsets of the predictor variables to find a subset that gives significant parameters and explains a high percentage of the observed metric value variation.

The following derived parameters are proposed as candidates for predictor variables. Each one of them was applied in an attempt to achieve a better prediction model.

i. *Speed(S)*: for mobility models that have uniform speed probability distribution function (i.e., $X \sim U(s, S)$), where X is the speed random variable, then we call *speed* as the derived parameter which value is the arithmetic mean between the minimum (s) and maximum speed (S). Logically, both *speed* and the input parameter AS means the average node speed. S is expressed in units of transmission range by seconds, R/s .

ii. *Area (A)*: is the simulation area, given by the product of width (X) and length (Y) of the scenario, and expressed in terms of the square of transmission range, R^2 .

iii. *Density (D)*: is the average amount of nodes per area unit (i.e., nodes R^2).

iv. *Node coverage (NC)*: is the area covered by a node's transmission range. NC of node P is πR^2 (see Figure 13).

v. *Pause (P)*: for mobility models that have uniform node pause time probability distribution function (i.e., $X \sim U(mPT, MPT)$), where X is the pause random variable, then we call *pause* as the derived parameter which value is the arithmetic mean between the minimum (mPT) and maximum node pause time (MPT). Logically, both *pause* and the input parameter APT means the average node speed.

vi. *Number of Groups (NG)*: is defined as the ratio

between the number of nodes (N) and the group size (GS) (i.e., $NG=N/GS$). It is applicable for group-based mobility models.

vii. *Number of Blocks (NB)*: is the product of the number of rows minus one and the number of columns minus one (i.e., $NB = (NR - 1) \cdot (NC - 1)$). This derived parameter is suitable for grid-based models (e.g., Manhattan). For instance, Figure 13 shows a grid-based simulation scenario with three horizontal streets and four vertical streets (i.e., $NR=5$, $NC=6$). In this example we have that $NB = (5-1) \times (6-1)=20$.

viii. *Percentage Block Area (PBA)*: is the percentage of the simulation area covered by a block. In Figure 13, the area of the block B (BA) is R^2 , where R is the radio transmission range of node P . Thus, the percentage block area is given by $PBA = BA/\text{area} = R^2 / 20R^2 = 5\%$. It is also true that $PBA = 1/NB$.

ix. $\log_{GS} N$: for group-based mobility models we have found that the logarithm of N to the base GS may be satisfactorily used for predicting some mobility metrics.

Values for the predictor variables used in the regression analysis are shown in Table 5. Simulation time was set to 1000 seconds and the node's radio transmission range to 250 meters. A wide range of values for the proposed predictors are used in order to accurately detect their relationship (e.g., logarithmic, quadratic) to the response variables through scatter plots analysis.

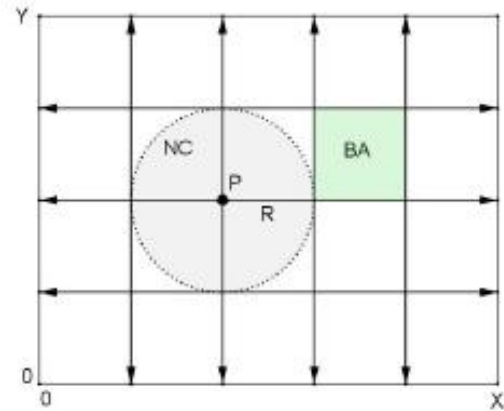


Figure 13. Node coverage and percentage block area derived parameters in a grid-based mobility scenario

4.3.2. Assumptions

A predictive model obtained by multiple linear regression is valid only if the following assumptions are met[33, 46]:

i. Linearity between predictors and response variables. To ensure this assumption we made nonlinear transformations in several predictor variables.

ii. Normality of residuals (i.e., the residuals are normally distributed). Residual is calculated as the difference between the observed value of the variable and the value suggested by the regression model. The normality of residuals assumption is checked through the Normal Q-Q plot, and the measures of skewness and kurtosis of the residual distribution

iii. Absence of multicollinearity⁵ between selected predictor variables. We set the variance inflation factor (VIF=5) as the threshold for disregarding a predictor from the regression model.

iv. Homoscedasticity (i.e., the variance of the residuals is homogeneous). We ensure this property through visual check of the residual plots.

v. Treatment of outliers. We use Mahalanobis and Cook's distance for detecting outliers[13].

We have also applied BoxCox transformation (i.e., power transformation) on the majority of dependent variables in order to make them more Normal distribution-like[58]. Though it is not an assumption for regression validation, in some cases it helped us achieving normality of residuals. The formula applied for transformation was $Y = (\gamma - 1)/\gamma$, where Y is the dependent variable (i.e., the mobility metric). The values used for the parameter γ are detailed in Table 6.

Table 6. Power parameter's values for Box-Cox transformation

Model	Dependent Variable		
	LD	ND	NP
RW	0.25	-0.12	0.25
RPGM	0.25	-0.06	-0.5
GM	-1.5	-0.12	*
MAN	0.5	*	*
SMS	*	*	*
CMM	-0.09	0.06	-0.12

* Transformation was not applied

4.3.3. Metric Prediction

Recalling that ϕ_{LD}^{RW} represents the estimated link duration for the Random Waypoint model, we can predict it from the following parameters: area, speed and pause time (Eq. 1). However, for better predicting this metric for RPGM (Equation 2, it is also necessary to know some group information (i.e., GS). The link duration prediction formulas for the other mobility models are show in Equations 3 to 5. The proposed derived parameters, percentage block area (PBA), is useful for predicting LD for CMM. For all models, the speed predictor contributes negatively on the metric value, which is in accordance to previous analysis (Figure 10(d)).

The node density (D) is the only predictor necessary to estimate the average node degree (ND) in the model RWP and GM, as stated in Equations 6 and 8. Besides node density, the group size information is again crucial for accurately predicting node degree for RPGM model 7.

Node density and group size are also the derived parameters approved for predicting network partitioning (NP) for RW, GM and RPGM models. Unfortunately, we could not obtain validated regression models for predicting ND and NP for SMS and CMM since they failed in one or more assumptions.

$$\phi_{LD}^{RW} = -0.801 \ln A - 1.05 \ln S \quad (1)$$

$$\phi_{LD}^{RPGM} = -0.178 \log_{GS} N + 0.143 \ln P \quad (2)$$

$$\phi_{LD}^{MAN} = -0.27S + 0.332 \ln P + 1.171 \quad (3)$$

$$\phi_{LD}^{SMS} = -0.253 \ln S - 1.013 \quad (4)$$

$$\phi_{LD}^{CMM} = -0.162 \ln S - 0.205 \ln GS \quad (5)$$

$$\phi_{ND}^{RW} = 0.759 \ln D + 1.074 \quad (6)$$

$$\phi_{ND}^{RPGM} = 0.172 \ln GS + 0.2 \ln D + 0.446 \quad (7)$$

$$\phi_{ND}^{GM} = 0.947 \ln D + 1.032 \quad (8)$$

$$\phi_{ND}^{MAN} = 1.015 \ln N - 0.986 \ln A + 0.75 \quad (9)$$

$$\phi_{NP}^{RW} = -0.434D + 2.024 \quad (10)$$

$$\phi_{NP}^{RPGM} = 0.516 \ln A - 0.007GS - 1.258 \quad (11)$$

$$\phi_{NP}^{GM} = -1.965 \ln D + 2.477 \quad (12)$$

The adjusted coefficient of determination (R^2) and the standard error of the estimate for all the predictive models are shown in Table 9. R^2 ($0 < R^2 < 1$) states the amount of variability in the data explained or accounted for by the regression model.

These results show that, as it could be expected, it is easier to build predictive models for simpler mobility models (e.g., Random Waypoint or Manhattan) than for more complex synthetic models like SMS and CMM. Additionally, according to R^2 statistical measure (goodness of fit), the accuracy for predicting mobility metrics for random and temporal models is higher than for group-based models, even when specific predictors are taken into account (e.g., group size).

Information about the standard errors and confidence interval for the predictor's coefficients are detailed in Table 8.

5. Related Works

Bai et al.[7] reported results showing the effects that maximum speed causes on metrics relative speed, degree of spatial dependence, and degree of temporal dependence for the models RW, RPGM, and Manhattan. Table 10 shows a comparison between theirs and ours results. The values found in the matrix correlation (Table 7) are in consonance with the results presented by Bai et al.

Ishibashi and Boutaba[32] show the effects that number of nodes, the length and width of the simulation area, and transmission range cause on node degree. They considered only scenarios with square geometry (i.e., $X=Y$), and used only the Random Waypoint model. Table 11 presents a comparative of the authors' results against ours. They found that an increase in the number of nodes causes a linear increase in node degree. This result is consistent with ours as the value of the correlation between N and ND is moderate, $\rho(M_{RW}^N, \phi_{ND}^{RW}) = 0.362$ (Table 5).

⁵ Multicollinearity exists when two or more predictor variables in a multiple regression model are highly correlated

Table 7. Mobility parameters versus mobility metrics correlation matrix

Metric	Model	N	Area	R	s	S, AS	APT	NNG	MDC	PM	NB
LD	RWP	-0.001	-0.060	0.711	-0.532	-0.553	0.244				
	RPGM	-0.279	0.165	0.164	-0.507	-0.398	0.109	0.169	0.164		
	GM	0.000	-0.016	0.681		-0.652				0.000	
	MAN	-0.001	-0.011	0.571	-0.013	-0.469	-0.571				-0.017
	CMM	0.089	-0.044	0.312	0.049	-0.161		-0.318			0.245
	SMS	-0.001	-0.032	0.670	0.000	-0.647	0.093			0.002	
ND	RWP	0.362	-0.264	0.729	-0.026	-0.026	-0.104				
	RPGM	0.326	-0.264	0.670	-0.014	-0.015	-0.068	0.274	0.670		
	GM	0.370	-0.271	0.734		0.001				0.000	
	MAN	0.364	-0.270	0.725	0.000	-0.002	0.000				0.022
	CMM	0.442	-0.062	0.193	0.038	0.015		-0.446			0.070
	SMS	0.367	-0.275	0.730	0.000	0.017	-0.004			0.000	
RS	RWP	0.002	0.019	0.030	0.899	0.978	0.104				
	RPGM	0.160	-0.083	0.481	0.495	0.459	-0.253	-0.186	0.481		
	GM	0.000	-0.001	0.001		1.000				0.000	
	MAN	0.096	-0.078	0.028	0.017	0.834	-0.347				-0.038
	CMM	-0.018	-0.006	0.005	0.102	0.992		0.011			0.017
	SMS	0.000	-0.003	-0.002	0.000	0.991	-0.119			-0.005	
LC	RWP	0.590	-0.212	0.384	0.248	0.267	-0.263				
	RPGM	0.542	-0.218	0.388	0.243	0.225	-0.187	0.001	0.388		
	GM	0.612	-0.245	0.355		0.387				0.000	
	MAN	0.614	0.096	0.005	0.008	0.039	-0.504				0.077
	CMM	0.389	0.010	-0.237	0.037	0.212		-0.224			-0.117
	SMS	0.553	-0.250	0.379	0.000	0.384	-0.043			-0.001	
DSD	RWP	-0.002	-0.080	-0.163	0.378	0.378	0.776				
	RPGM	-0.261	0.222	-0.749	-0.095	-0.066	-0.239	0.293	-0.749		
	GM	0.145	-0.004	-0.107		0.228				0.127	
	MAN	0.037	-0.126	-0.294	0.110	0.382	0.448				0.004
	CMM	0.114	0.246	-0.237	0.008	-0.643		-0.340			0.026
	SMS	-0.066	-0.038	-0.213	-0.009	0.264	-0.217			0.634	
DTD	RWP	0.000	0.193	0.000	-0.637	-0.639	0.625				
	RPGM	0.002	0.184	-0.123	-0.792	-0.347	0.123	0.002	-0.123		
	GM	0.001	0.287	0.000		-0.884				0.082	
	MAN	0.113	-0.024	0.000	0.048	-0.275	0.785				-0.151
	CMM	0.024	0.216	0.000	-0.553	-0.668		0.005			-0.037
	SMS	0.000	0.240	0.000	0.000	-0.559	-0.619			-0.197	
NP	RWP	0.095	0.208	-0.854	0.016	0.017	0.060				
	RPGM	0.171	0.184	-0.769	0.013	0.011	0.044	-0.255	-0.769		
	GM	0.106	0.214	-0.855		0.001				0.000	
	MAN	0.131	0.213	-0.854	0.001	0.006	-0.004				-0.011
	CMM	-0.120	0.168	-0.536	-0.098	-0.008		0.509			-0.057
	SMS	0.101	0.216	-0.853	0.000	-0.009	0.005			0.000	

Table 8. Lower and upper bound of coefficients' values with 99% confidence interval

Eq.	Pred.	SE ^a	Lower	Upper	Eq.	Pred.	SE	Lower	Upper	Eq.	Pred.	SE	Lower	Upper
1	B_0	0.105	6.537	7.08	2	B_0	0.17	1.612	1.698	5	B_0	0.014	1.401	1.475
	$\ln A$	0.02	-0.853	-0.75		$\log_{GS} N$	0.004	-0.187	-0.169		$\ln S$	0.004	-0.173	-0.15
	$\ln S$	0.027	-1.12	-0.979		$\ln S$	0.004	-0.108	-0.088		$\log_{GS} N$	0.004	-0.215	-0.195
	P	0	0.002	0.004		$\ln(P)$	0.002	0.138	0.149		PBA	0.398	-9.478	-7.426
3	B_0	0.008	1.149	1.192	9	B_0	0.021	0.695	0.805	7	B_0	0.067	1.641	1.984
	S	-0.027	-0.028	-0.026		$\ln N$	0.004	1.004	1.027		$\ln A$	0.006	-0.669	-0.636
	$\ln(P)$	0.332	0.328	0.335		$\ln A$	0.002	-0.991	-0.98		$\ln GS$	0.008	0.465	0.504
											$\ln N$	0.013	0.536	0.602
4	B_0	0.007	-1.019	-1.007	8	B_0	0.003	1.023	1.04	11	B_0	0.038	-1.357	-1.158
	$\ln S$	0.003	-0.267	-0.239		$\ln D$	0.003	0.939	0.955		$\ln A$	0.009	0.493	0.539
											GS	0	-0.008	-0.006
10	B_0	0.009	2.001	2.047	12	B_0	0.057	2.322	2.632	6	B_0	0.004	1.063	1.086
	D	0.005	-0.446	-0.421		$\ln D$	0.067	-2.145	-1.784		$\ln D$	0.004	0.748	0.771

Table 9. Regression models' summary

Model	Link Duration		Node Degree		Net. Partitioning	
	R ² adj.	SEE ^a	R ² adj.	SEE	R ² adj.	SEE
RW	93.0%	.388	97.9%	.096	94.0%	.109
RPGM	80.9%	.095	87.8%	.077	75.4%	.133
GM	*	*	99.9%	.031	95.7%	.127
MAN	97.8%	.061	99.3%	.722	*	*
SMS	96.4%	.120	*	*	*	*
CMM	81.0%	.083	*	*	*	*

^aSEE: Standard Error of the Estimate. * Means we could not find a model that met all the assumptions

Table 10. Comparison results related to findings reported in[7]

Met.	Effect caused by node speed reported in[7]	Correlation		
		RW	RPGM	MAN
RS	Linear positive for all models	.978	.459	1
DSD	Linear negative for RPGM and constant for RW and MAN	.378	-.066	.382
LD	Linear negative in all models	-.553	-.398	-.469

Furthermore, Ishibashi and Boutaba found that increasing the values of X and Y produces an exponential decay in ND. Our results are consistent with theirs since $\rho(M_{RW}^{Area})$ is negative. Finally, the authors found that transmission range caused an almost exponential growth in ND. This growth is justified due to the high correlation value between the input parameter R and the metric ND for the RW model, which is $\rho(M_{RW}^R, \phi_{ND}^{RW}) = 0.729$.

The effect that the number of nodes causes on link duration in several mobility models is presented by Theoleyre et al.[63]. In almost all models, N does not affect LD. The only exception occurred in the group-based model Nomadic Community (similar to RPGM), where LD decays with the increase of N. These results are also consistent with the correlations presented in Table 7: in RW and Gauss-Markov the correlation is practically zero, while it is 0.279 for RPGM.

Table 11. Comparison results related to findings reported in[32]

Var.	Met.	Effect reported in[32]	Correlation
N		Linear positive on RW	0.362
A	ND	Exponential negative on RW	-0.264
R		Approx. exponential positive on RW	0.729

Kurkowski et al.[35] also used the technique of linear regression in order to build models able to predict the metrics average path size and network partitioning from the input parameters. They proposed several prediction models suitable for scenarios rectangular and square geometry. In addition, the authors carried out a consistent validation of metrics' predictive models; concluding that node speed and node pause time have little effect on the average number of partitions NP. This result is also consistent with the Equation 10 and the correlation values we have found $\rho(\phi_{RW}^{RS}, NP) = 0.17$ and $\rho(\phi_{RW}^{MPT}, NP) = 0.6$ (Table 7). However, one limitation of their work is that only two metrics were considered, and only for the Random Waypoint model.

6. Conclusions

In this paper we investigated several gaps on the study of mobility in MANETs, by taking into account six representative mobility models (random, temporal, grid-based and group-based) and seven mobility metrics (link-based, graph-based, and velocity-based).

First of all, we showed that the ability of metrics on distinguishing different mobility models is variable, which depends on the mobility scenario configuration, such as the node density. This finding may explain, for example, the divergences found in the literature over the effectiveness that the metric number of link changes has on distinguishing mobility models[9, 30, 52, 64]. As described

in the experimental study (Section 4.2.1), depending on the node density this metric may or not be able to distinguish models.

Secondly, we show that, independently of the mobility model, node speed cause no impact on average node degree neither on the number of network partitions. Besides that, for all mobility scenarios evaluated our simulation results point out the existence of a linear positive relation between node speed and number of link changes between nodes in a MANET. On the other hand, only negative correlations were found between node speed and link lifetime (duration). The results presented in this paper also show differences in the performance of metrics for mobility models belonging to the same class (e.g., group-based).

Through correlation analysis we estimate the mobility variables that most impact the mobility metrics for each class of mobility model. Lastly, we proposed and used several derived parameters as potential predictors in several stepwise multiple linear regressions to obtain predictive models for link duration, node degree, and network partitioning metrics.

As future work, we intend to investigate how to design mobility aware protocols with the findings reported in this paper, with special attention to the mobility metrics' predictive models.

REFERENCES

- [1] S. Ahmed, G. C. Karmakar, J. Kamruzzaman, An environment-aware mobility model for wireless ad hoc network, *Comput. Netw.* 54 (2010) 1470–1489.
- [2] N. Aschenbruck, R. Ernst, E. Gerhards-Padilla, M. Schwamborn, BonnMotion: a mobility scenario generation and analysis tool, in: *Proc. of the 3rd SIMUTools, ICST*, Brussels, Belgium, 2010, pp. 51:1–51:10.
- [3] N. Aschenbruck, E. Gerhards-Padilla, M. Gerharz, M. Frank, P. Martini, Modelling mobility in disaster area scenarios, in: *Proceedings of the 10th MSWiM*, Chania, Crete Island, Greece, October 22–26, 2007, ACM, 2007, pp. 4–12.
- [4] Waleed Alasmari e Weihua Zhuang, Mobility impact in IEEE 802.11p infrastructureless vehicular networks. *Ad Hoc Networks*, 10(2):222–230, 2012.
- [5] F. Bai, N. Sadagopan, A. Helmy, User Manual for IMPORTANT Mobility Tool Generators in ns-2 Simulator, University of Southern California (February 2004).
- [6] F. Bai, A. Helmy, *Wireless Ad Hoc and Sensor Networks*, Kluwer Academic Publishers, 2004, Ch. A Survey of Mobility Modeling and Analysis in Wireless Adhoc Networks.
- [7] F. Bai, N. Sadagopan, A. Helmy, IMPORTANT: A framework to systematically analyze the impact of mobility on performance of routing protocols for adhoc networks, in: *INFOCOM*, IEEE, San Francisco, CA, USA, 2003, pp. 825–835.
- [8] F. Bai, N. Sadagopan, B. Krishnamachari, A. Helmy, Modeling path duration distributions in manets and their impact on reactive routing protocols, *IEEE Journal on Selected Areas in Communications* 22 (2004) 1357–1373.
- [9] F. Bai, N. Sadagopan, A. Helmy, The important framework for analyzing the impact of mobility on performance of routing protocols for adhoc networks, *Ad Hoc Networks* 1 (4) (2003) 383–403.
- [10] C. Bettstetter, On the connectivity of ad hoc networks, *The Computer Journal* 47 (4) (2004) 432–447.
- [11] C. Bettstetter, Mobility modeling in wireless networks: categorization, smooth movement, and border effects, *Mobile Computing and Communications Review* 5 (3) (2001) 55–66.
- [12] J. Boleng, W. Navidi, T. Camp, Metrics to enable adaptive protocols for mobile ad hoc networks, in: *Proc. Int. Conf. on Wireless Networks (ICWN)*, Las Vegas, Nev, USA, 2002, pp. 293–298.
- [13] K. A. Bollen, R. Jackman, *Modern Methods of Data Analysis*, Sage Publications, 1990, Ch. Regression diagnostics: An expository treatment of outliers and influential case, pp. 257–91.
- [14] N. Bouabdallah, R. Langar, R. Boutaba, Design and analysis of mobility-aware clustering algorithms for wireless mesh networks, *IEEE ACM Transaction on Networking* 18 (6) (2010) 1677–1690.
- [15] A. Boukerche, L. Bononi, Simulation and modeling of wireless, mobile and ad hoc networks, in: *Mobile Ad Hoc Networking*, Wiley-IEEE Press, 2004, pp. 373–410.
- [16] J. Bronch, D. Maltz, D. Johnson, Y.-C. Hu, J. Jetcheva, A performance comparison of multi-hop wireless ad hoc network routing protocols, in: *MobiCom*, ACM IEEE, 1998, pp. 85–97.
- [17] T. Camp, J. Boleng, V. Davies, A survey of mobility models for ad hoc network research, *Wireless Communications and Mobile Computing* 2 (5) (2002) 483–502.
- [18] S. Capkun, J.-P. Hubaux, L. Buttyan, Mobility helps peer-to-peer security, *IEEE Transactions on Mobile Computing* 5 (1) (2006) 43–51.
- [19] E. R. Cavalcanti, M. A. Spohn, Degree of Node Proximity: a Spatial Mobility Metric for MANETs. In: *Proceedings of the 9th ACM International Symposium on Mobility Management and Wireless Access (MobiWac)*, Oct. 31 - Nov. 4, 2011, Miami Beach, FL, USA. ACM, 2011, p. 61–68.
- [20] E. R. Cavalcanti, M. A. Spohn, Predicting mobility metrics through regression analysis for random, group, and grid-based mobility models in manets, in: *Proceedings of the 15th IEEE Symposium on Computers and Communications (ISCC)*, Riccione, Italy, 2010, pp. 443–448.
- [21] E. R. Cavalcanti, M. A. Spohn, Estimating the impact of mobility models's parameters on mobility metrics in manets, in: *Proceedings of the 8th IEEE International Symposium on Network Computing and Applications (NCA)*, Cambridge, MA, USA, 2009, pp. 227–233.
- [22] S. Cho, J. P. Hayes, Impact of mobility on connection stability in ad hoc networks, in: *Proc. of Wireless Communication and Networking Conference (WCNC)*, IEEE Computer Society, 2005, pp. 1650–1656.
- [23] M. Fiore, J. Härri, The networking shape of vehicular

- mobility, in: *MobiHoc*, ACM, 2008, pp. 261–272.
- [24] M. Ghassemian, V. Friderikos, A. Aghvami, On mobility metrics applied for ad hoc network protocol evaluation, in: 7th IFIP International Conference on Mobile and Wireless Communications Networks (MWCN), 2005, pp. 435–444.
- [25] J. Ghosh, S. J. Philip, C. Qiao, Sociological orbit aware location approximation and routing (SOLAR) in manet, *Ad Hoc Networks* 5 (2) (2007) 189–209.
- [26] M. Grossglaube, D. Tse, Mobility increases the capacity of ad-hoc wireless networks, *IEEE ACM Transactions on Networking* 10 (4) (2001) 477–486.
- [27] M. Haahr, Random.org (2011). URL <http://www.random.org>
- [28] J. Hahner, D. Dudkowski, P. J. Marron, K. Rothermel, Quantifying network partitioning in mobile ad hoc networks. In: *Proceedings of the 2007 International Conference on Mobile Data Management*, IEEE, Washington, DC, USA, 2007, pp. 174–181.
- [29] T. Hara, Quantifying impact of mobility on data availability in mobile ad hoc networks, *IEEE Transactions on Mobile Computing* 9 (2010) 241–258.
- [30] X. Hong, M. Gerla, G. Pei, C.-C. Chiang, A group mobility model for ad hoc wireless networks, in: *Proc. 2nd ACM MSWiM*, Seattle, Washington, United States, 1999, pp. 53–60.
- [31] J. L. Huang, M. S. Chen, On the effect of group mobility to data replication in ad hoc networks, *IEEE Transactions on Mobile Computing* 5 (5) (2006) 492–507.
- [32] B. Ishibashi, R. Boutaba, Topology and mobility considerations in mobile ad hoc networks, *Ad Hoc Networks* 3 (6) (2005) 762–776.
- [33] R. K. Jain, *The Art of Computer Systems Performance Analysis*, Wiley-Interscience, New York, NY, USA, 1991.
- [34] P. Krishna, N. Vaidya, M. C. D. Pradhan, A cluster-based approach for routing in dynamic networks, *SIGCOMM Comput. Commun. Rev.* 27 (2) (1997) 49–64.
- [35] S. Kurkowski, W. Navidi, T. Camp, Constructing manet simulation scenarios that meet standards, in: *IEEE International Conference on Mobile Adhoc and Sensor Systems (MASS 2007)*, 2007, pp. 1–9.
- [36] S. Kurkowski, *Credible mobile ad hoc network simulation-based studies*, Ph.D. thesis, Colorado School of Mines (2006).
- [37] S. Kurkowski, T. Camp, M. Colagrosso, MANET simulation studies: The incredibles, *ACM's Mobile Computing and Communications Review* 9 (4) (2005) 50–61.
- [38] Byung-jae Kwak, Nah-oak Song, Leonard E. Miller, A mobility measure for mobile ad-hoc networks, *IEEE Communications Letters* 7 (2003) 379–381.
- [39] Byung-jae Kwak, Nah-oak Song, Leonard E. Miller, A standard measure of mobility for evaluating mobile ad hoc network performance, *IEICE Transactions on Communications* 86 (11) (2003) 3236–3243.
- [40] V. Lenders, J. Wagner, M. May, Analyzing the impact of mobility in ad hoc networks, in: *Proc. 2nd Int. Workshop on Multi-hop ad hoc networks: from theory to reality, REALMAN '06*, ACM, Florence, Italy, 2006, pp. 39–46.
- [41] B. Liang, Z. Haas, Predictive distance-based mobility management for pcs networks, in: *INFOCOM*, IEEE, 1999, pp. 1377–1384.
- [42] Q. Liang, T. Kunz, Mobility metrics to enable adaptive routing in manet, in: *IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, IEEE, 2006, pp. 1–8.
- [43] Y. Lu, H. Lin, Y. Gu, A. Helmy, Towards mobility-rich performance analysis of routing protocols in ad hoc networks: Using contraction, expansion and hybrid models, in: *Proc. Int. Conf. on Communications (ICC)*, IEEE, 2004, pp. 4346–4351.
- [44] K. Maeda, K. Sato, K. Konishi, A. Yamasaki, A. Uchiyama, H. Yamaguchi, K. Yasumoto, T. Higashino, Getting urban pedestrian flow from simple observation: realistic mobility generation in wireless network simulation, in: *Proc. 8th ACM Int. Symp. on Modeling, Analysis and Simulation of Wireless and Mobile Systems, MSWiM '05*, ACM, Montreal, Quebec, Canada, 2005, pp. 151–158.
- [45] A. McDonald, T. Znati, A path availability model for wireless ad-hoc networks, in: *IEEE WCNC*, IEEE, New Orleans, LA, USA, 1999, pp. 35–40.
- [46] D. Montgomery, G. Runger, *Applied Statistics and Probability for Engineers*, 3rd Edition, Wiley, 2002.
- [47] A. Munjal, T. Camp, W. Navidi, Constructing rigorous manet simulation scenarios with realistic mobility, in: *European Wireless Conference (EW)*, 2010, pp. 817–824.
- [48] M. Musolesi, C. Mascolo, *Social Network Founded Mobility Models for Ad Hoc Network Research*, University of Cambridge, <http://www.cl.cam.ac.uk>, February 2009.
- [49] M. Musolesi, C. Mascolo, Designing mobility models based on social network theory, *Mobile Computing and Communications Review* 11 (3) (2007) 59–70.
- [50] S. Nousiainen, K. Kordybach, P. Kemppi, User distribution and mobility model framework for cellular network simulations, in: *VTT Information Technology*, 2002, pp. 518–522.
- [51] S. PalChaudhuri, J.-Y. L. Boudec, M. Vojnovic, Perfect simulations for random trip mobility models, in: *Annual Simulation Symposium*, IEEE Computer Society, 2005, pp. 72–79.
- [52] M. Pandey, D. Zappala, The effects of mobility on multicast routing in mobile ad hoc networks, *Tech. Rep. UO-CIS-TR-2004-2*, Brigham Young University, Utah (2004).
- [53] G. Pei, M. Gerla, X. Hong, C.-C. Chiang, A wireless hierarchical routing protocol with group mobility, in: *IEEE WCNC*, 1999, pp. 1538–1542.
- [54] X. Costa, C. Bettstetter, H. Hartenstein, Toward a mobility metric for comparable & reproducible results in ad hoc networks research, *MC2R* 7 (4) (2003) 58–60.
- [55] G. Ravirikan, S. Singh, Influence of mobility models on the performance of routing protocols in ad-hoc wireless networks, in: *Proc. 59th IEEE Vehicular Technology Conference*, Milan, Italy, 2004, pp. 2185–2189.

- [56] S. Ray, Realistic mobility for manet simulation, Master's thesis, Department of Computer Science - The University of British Columbia (December 2003).
- [57] N. Sadagopan, F. Bai, B. Krishnamachari, A. Helmy, PATHS: analysis of path duration statistics and their impact on reactive manet routing protocols, in: *MobiHoc*, ACM, 2003, pp. 245–256.
- [58] R. Sakia, The box-cox transformation technique: a review, *Journal of the Royal Statistical Society. Series D (The Statistician)* 41 (2) (1992) 169–178.
- [59] P. Santi, *Topology Control in Wireless Ad Hoc and Sensor Networks*, Wiley, 2005.
- [60] P. Sommer, Design and analysis of realistic mobility models for wireless mesh networks, Master's thesis, Department of Information Technology and Electrical Engineering – ETH Zürich (September 2007).
- [61] D. Son, A. Helmy, B. Krishnamachari, The effect of mobility-induced location errors on geographic routing in mobile ad hoc and sensor networks: Analysis and improvement using mobility prediction, *IEEE Transactions on Mobile Computing* 3 (3) (2004) 233–245.
- [62] I. Stepanov, Integrating realistic mobility models in mobile ad hoc network simulation, Master's thesis, University Stuttgart (Jan. 2002).
- [63] F. Theoleyre, R. Tout, F. Valois, New metrics to evaluate mobility models properties, 2nd International Symposium on Wireless Pervasive Computing.
- [64] Q.-M. Tran, A. Dadej, S. Perreau, Link change and generalized mobility metric for mobile ad-hoc networks, in: *Military Communications Conference, 2006. MILCOM 2006*, 2006, pp. 1–7.
- [65] C. Tuduze, T. Gross, A mobility model based on wlan traces and its validation, in: *INFOCOM*, IEEE, 2005, pp. 664–674.
- [66] K. Wang, B. Li, Group mobility and partition prediction in wireless ad-hoc networks, in: *Proc. IEEE ICC*, New York, USA, 2002, pp. 1017–1021.
- [67] N.-C. Wang, Y.-F. Huang, J.-C. Chen, A stable weight-based on-demand routing protocol for mobile ad hoc networks, *Information Sciences* 177 (24) (2007) 5522–5537.
- [68] S. Williams, D. Hua, A group force mobility model, *Simulation Series* 38 (2) (2006) 333–340.
- [69] S. Xu, Mobility metrics for routing in manets, PhD in doctor of philosophy, The Australian National University (June 2007).
- [70] Q. Xue, A. Ganz, Ad hoc qos on-demand routing (aqor) in mobile ad hoc networks, *J. Parallel Distrib. Comput.* 63 (2003) 154–165.
- [71] C. Yawut, B. Paillassa, R. Dhaou, Mobility metrics evaluation for self-adaptive protocols, *Journal of Networks* 3 (1) (2008) 53–64.
- [72] Y. Lu, H. Lin, Y. Gu, A. Helmy, Towards mobility-rich analysis in ad hoc networks: Using contraction, expansion and hybrid models, in: *ICC*, IEEE, 2004, pp. 4346–4351.
- [73] J. Yoon, M. Liu, B. Noble, Random waypoint considered harmful, in: *Proc. IEEE INFOCOM*, 2003, pp. 1312 – 1321.
- [74] M. Yoshida, K. Arai, S. Asami, T. Miki, Relative speed-based routing (RSR) for vehicle ad-hoc networks, *Electronics and Communications in Japan* 89 (2006) 1–11.
- [75] Y. Zhang, J. Ng, C. Low, A distributed group mobility adaptive clustering algorithm for mobile ad hoc networks, *Computer Communication* 32 (1) (2009) 189–202.
- [76] M. Zhao, W. Wang, A unified mobility model for analysis and simulation of mobile wireless networks, *ACM-Springer Wireless Networks (WINET)* 15 (3) (2009) 365–389.
- [77] M. Zhao, W. Wang, Joint effects of radio channels and node mobility on link dynamics in wireless networks, in: *INFOCOM*, IEEE, 2008, pp. 933–941.
- [78] M. Zhao, SMS Mobility Model Description, North Carolina State University, [http: www.ece.ncsu.edu netwis mobility model](http://www.ece.ncsu.edu/netwis/mobility_model) (2009).
- [79] Q. Zheng, X. Hong, S. Ray, Recent advances in mobility modeling for mobile ad hoc network research, in: S.-M. Yoo, L. H. Etzkorn (Eds.), *Proceedings of the 42nd Annual Southeast Regional Conference*, 2004, Huntsville, Alabama, USA, ACM, 2004, pp. 70–75.