Modelling Mobility based on Human Behaviour in Disaster Areas

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Abstract. Mobility models are used to mimic the realistic movement of entities. Mobility models for wireless networks feature different objectives and characteristics, most based on random behaviour. However, random based mobility models, e.g. Random Waypoint (RWP), are often not suitable to represent the reality of node mobility, particularly in disaster areas where the search time for victims is a critical factor. Moreover, the studied mobility models for disaster environments are either random based or not suitable for such scenarios. This work proposes a new mobility model based on Human Behaviour for Disaster Areas (HBDA) to properly evaluate the performance of mobile wireless networks in disaster environments. HBDA is designed to cover as much area as possible, regarding search time as an important factor. This work evaluates HBDA concerning movement and link performances. Results show that HBDA provides an even distribution of nodes, a high coverage area and an efficient routing performance.

Keywords: Mobile Wireless Networks, Mobility Model, Disaster Scenarios

1 Introduction

Post-disaster scenarios are typically considered to exist in deserts, forests or heavily damaged urban areas, often lacking operational network infrastructures. The establishment of a temporary communication system is crucial for the assistance of victims. Mobile wireless networks are often the only capable technology to answer to this type of demands. The evaluation of the network performance for such situations in a real world scenario is, in most cases infeasible, since the cost of the repeatability of the disaster scenario would be very high and extremely difficult to reproduce. Thus, simulation evaluation is the only feasible tool to study the behaviour and performance of mobile wireless networks in post-disaster environments. The results of a simulated performance evaluation strongly depend on the used mobility models. Since in post-disaster environments most nodes are mobile, the used mobility model has a crucial impact on the results. Despite of this fact, most performance evaluations existent in literature are simply based on random mobility models. This work proposes a new mobility model based on Human Behaviour for Disaster Areas (HBDA).

This model attempts to reproduce the human behaviour in search for victim operations.

The remaining of this document is organized as follows. Section 2 discusses the related work, covering some of the most significant mobility models in literature. Section 3 describes the HBDA mobility model. Section 4 performs a performance evaluation of HBDA, compared to the most common used mobility model: the Random Waypoint (RWP). Finally, Section 5 concludes this work and discusses future steps.

2 Related Work

Mobility models can be segmented according to node dependencies. Currently in literature there are two types of mobility models, namely *Entity Mobility Models* and *Group Mobility Models*. Entity Mobility models represent mobile nodes whose movements are independent of each other, whereas Group Mobility Models represent mobile nodes that have spatial dependencies, where the movement of a node influences the movement of at least one node around it. Regardless of

Table 1: Mobility Model Attributes

Attribute	**Description**
Random based	Node movement relies mainly in random decisions
Geographic restrictions	Nodes are restricted to a sub-area within the scenario
Target Area	Nodes have the objective of reaching a pre-determined point or area
Temporal dependencies	The node movement is influenced by its past movement
Constant velocity	Node velocities can not be modified during execution
Nodes join/leave	Leaving and joining the scenario is supported
Obstacles	The mobility model has obstacle avoidance mechanisms

their type, mobility models can be characterized according to their attributes, as shown in Table 1.

2.1 Entity Mobility Models

In this subsection several proposed entity mobility models are discussed. The Random Waypoint Mobility Model is the most common and used by researchers, thus its discussion is performed in more depth than the remaining.

The **Random Waypoint (RWP)** mobility model was first introduced in [1]. The RWM model is based on pause times between changes of direction and/or speed. Initially, nodes are placed within the scenario area in a random fashion. After deployment, nodes do not have any attachments or restrictions towards remaining nodes. Each node begins by staying in a location for a period of time. When this time expires, it travels in a random direction with a random speed $[Vmin, Vmax]$, whereas $Vmin$ and $Vmax$ are the minimum and maximum velocity of the node, respectively. After reaching a waypoint (a decision position), the node waits another constant period of time and repeats the previous procedure until it reaches another waypoint. This process is repeated endlessly until the execution is over. Due to its simplicity, the RWP is a widely used model in research and it is the foundation for many recent mobility models. However, it does not represent realistic movements [2], and its use should only be considered for general purpose scenarios.

One important problem of the RWP model is the uneven distribution of nodes. Several publications (e.g. [3]) have shown that, over execution time, nodes tend to accumulate in the middle of the simulation scenario. To overcome this issue, a variation of the RWP, called **Random Waypoint with Attraction Points (RWAP)** is proposed in [4]. This model generates more realistic non-equally distributed mobility. However, the probability of a node visiting an attraction point is larger than the random choice of other points, resulting in a larger concentration of nodes in the attraction points.

The **Mobility (ClusM) Model** [5] is very similar to the RWAP model, using RWP with attraction points to disaster areas. The main difference is that the attraction to the disaster area depends on concentration of nodes nearby. In other words, nodes are have a lower probability of moving towards attraction areas where there is already a high density of nodes. Thus, in a scenario with multiple disaster areas (in this case, used as attraction points), nodes tend to be evenly distributed across those areas.

2.2 Group Mobility Models

The previous subsection presented the mobility models whose nodes actions are completely independent of each other. However, there are situations where nodes must mutually coordinate to achieve a certain objective, such as search and rescue operations. In order to model cooperative situations, a group mobility model is required. The Reference Point Group Mobility (RPGM) [6] can be considered a reference model, as there are many improvements of it in literature.

The **Reference Point Group Mobility (RPGM)** [6] allows the random motion of a group and also enables the individual motion of a node within its group. Every group has a logical centre, which controls the mobility parameters, such as motion behaviour, location, speed and direction of the entire group. Furthermore, every group is confined to a well defined geographical scope, from where its nodes can not exit. Therefore, all nodes have spatial dependencies defined by the logical centre. Sánchez et al. proposed three variations of the RPGM model in order to cover distinct objectives, namely the Column Mobility Model (CM), the Nomadic Community Mobility Model (NCM) and the Pursue Mobility Model (PM) [7]. The **Column Mobility Model (CM)** can be used for searching purposes. A group of mobile nodes moves in a line formation (or column) towards a random direction. Each node is tied to a reference point and each reference point is followed by another, i.e. each reference point depends on another until the head of the column is reached. Within groups, each node can move randomly around its reference point, however not exceeding a pre-configured maximum distance. The CM Model can be useful for searching purposes, whereas several groups/columns move in distinct directions and nodes move randomly inside each column. This mobility model can be obtained using a variation of the RPGM model implementation. The **Nomadic Community Mobility Model (NCM)** is also a variation of the RPGM model. The community (or group) is defined as several nodes following only one reference point. A random direction and speed of the reference point is calculated. The group of nodes follows the reference point and can also move randomly around it, once more not exceeding a pre-configured maximum distance. The **Pursue Mobility Model (PM)** attempts to imitate the tracking of a certain target. A group of nodes follows one particular node, adjusting their speed and direction according to the target. Within the group, nodes can move randomly but can not exceed a pre-configured distance from each other. For example, to better illustrate, this model could represent a group of police officers attempting to catch an individual. Again, this mobility model can be obtained using a modified version of the RPGM model.

The authors in [8] designed a mobility model for disaster scenarios, namely **Disaster Area (DA)**. The work studied the displacement of civil protection forces in real life and developed a corresponding model. The simulation area is divided according to several categories (e.g. incident site, casualties treatment area, transport zone, hospital zone). Technically, the disaster area scenario consists of several sub-areas with different configurations. Each sub-area uses a visibility graph to avoid obstacles. Each node is manually assigned to one sub-area and it is not allowed to exit unless it belongs to the transport zone sub-area. In the transport zone sub-area, nodes are allowed to leave and join, in order to represent the transportation of injured patients to the hospital. Despite the effort of mimicking a real scenario, the mobility model is still quite unrealistic as movement of rescue agents is based on the Random Waypoint (RWP) mobility model, particularly in the disaster site sub-area, where agents are performing search-for-victim operations.

Authors in [9] also proposed a **Composite Mobility (CoM)** model for disaster scenarios. It is a combination of several existing models to better represent human mobility in disaster areas. For group mobility the original RPGM model is used, however for better realism the RWP is replaced by the Levy-Walk model, proposed in [10]. The CoM model also concerns obstacle avoidance based on a modified Voronoï diagram. Thus, this model is based on a well known geographic map and is driven by a specific target, using the Dijkstra algorithm to calculate the shortest path between two points. However, in a disaster scenario it is very difficult to accurately obtain the current map, whereas its infrastructures may be modified or non existent. Therefore, following a known map of the area could not be sufficient to successfully perform search and rescue operations.

2.3 Summary of Mobility Models

This section studied some of the most relevant mobility models in literature, presented in table 2. The Entity Mobility Models do not establish any relationship between nodes, thus not being suitable to represent movements in disaster scenarios due to the lack of group coordination. On the other hand, the Group

Mobility Models provide node coordination. The RPGM model is widely used in literature and many proposals derive from it, due to its configuration versatility.

Table 2: Studied Mobility Models and their Attributes

Models	Random based	Geographic Restrictions	Temporal dependencies	Target Area	Constant velocity	Nodes join/leave	Obstacles
RWP[1]	✔				✚		
RWAP[4]	✔			✔			
ClusM[5]	✔			✚			
RPGM[6]				✚		✚	
CM[7]				✚		✚	
NCM[7]				✚		✚	
PM[7]							
DA[8]		✔	✔	✔		✔	✔
CoM[9]		✔		✔			✔

[1]**Note:** ✔represents explicitly supported and ✚represents not originally supported but can be modified to support

There are also a few Group Entity Models designed specifically for disaster environments. The DA mobility model is not mainly based in random movements, since it implements specific movements between the sub-areas of the scenario. However, within each sub-area the RWP model is used, ultimately resulting in the disaster sub-area being explored by the RWP. The CoM model uses the Levy-Walk model instead. Nonetheless, a map of the post-disaster area must be known in advance, which in most situations very difficult to obtain. Thus, to the best of our knowledge, there is no mobility model that is both not random based in disaster area exploration and Thus, to the best of our knowledge, there is no mobility model that provides blind (post-disaster area is unknown) exploration with non random major decisions.

3 Modelling Mobility based on Human Behaviour in Disaster Areas

In order to obtain accurate evaluation results in mobile wireless networks it is necessary to use a mobility model that is capable of reproducing as much as possible a real scenario. This work is focused on post-disaster areas whereas the typical mobility pattern is based in search for victim (SFV) operations. As previously studied, most of simulation evaluations are based on the Random Waypoint (RWP) model, which often does not represent the reality of node movements. Furthermore, the studied mobility models for disaster areas are random based, such as Disater Area (DA), which also uses the RWP inside each sub-area. Thus, it becomes necessary to develop a new model, not random based, capable of representing node movements in such scenarios.

This work proposes a new mobility model based on Human Behaviour for Disaster Areas (HBDA), aiming to mimic real node movements in search operations in order to properly evaluate the network performance.

3.1 Mobility Description

Regarding human behaviour, when a group of people is performing search operations, each person tends to physically separate from one another, in order to scout unexplored areas. On the other hand, each person typically maintains a line of sight (or in-range communicable) to at least one other person in order to be able to announce a possible victim discovery. The group of people start the area exploration from an initial position and step-by-step, each individual makes his way to a Target Position, constantly maintaining a light of sigh to another (*maximum distance*) and, at the same time, not becoming too close (*minimum distance*). This method of search seamlessly forces individuals to evenly spread across the scenario in order to cover as much area as possible.

To maintain a compromise between the minimum distance and maximum distance to neighbour nodes, the HBDA model uses a system based on force vectors. To better illustrate this process, Figure 1 shows an example of the resultant force vector for three neighbour nodes.

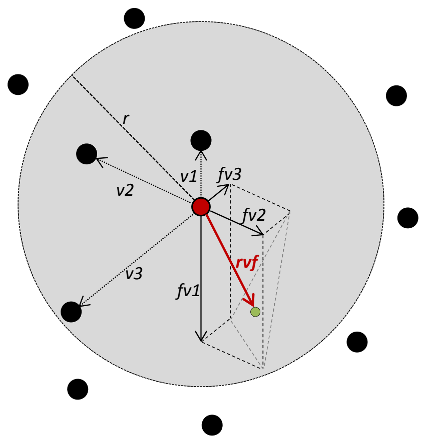

Fig. 1: Example of a Resultant Vorce Vector rfv

A node considers that another node is its neighbour if the distance is less than the maximum distance, represented in the Figure as r. During exploration, each node adjusts its position in order to become separated from its closest neighbours. To achieve this, first it is calculated a vector from the node position (represented in the middle) to each neighbour position ($v1$, $v2$ and $v3$). Afterwards, a force vector is calculated for each neighbour vector ($fv1$, $fv2$ and $fv3$). The force vectors always have the opposite direction of the neighbour vectors and their length is provided by the subtraction of the maximum distance (r) by the length of the neighbour vectors. This method allows closer neighbour nodes to have an higher opposite direction force. Finally, the sum of the force vector is computed, resulting in a single force vector (rfv).

Upon the arrival to the Target position, a new Target is determined for all nodes, which immediately start moving towards it. This process is repeated until the end of execution. The new Target is determined based on the previous by the inversion of the x or y positions, e.g. assuming a previous Target $PT(x, y)$, the new Target will be located in $NT(-x, y)$ or $NT(x, -y)$. The decision of inverting x or y is random with 50% of probability for each.

3.2 Algorithm Description

For a better comprehension of the HBDA model, this subsection discusses the main procedures of the algorithm. Table 3 describes the model of the system, including the parameters and functions used in the algorithm.

Table 3: HBDA Parameters and Functions

Parameters	
x and y	current position of a node (x, y)
$targetX$ and $targetY$	current position of the Target in the form $(targetX, targetY)$
$MinVelocity$ and $MaxVelocity$	minimum and maximum velocities of nodes
$MinDistance$ and $MaxDistance$	minimum and maximum distances that nodes separate from each other
$MinTravelTime$ and $MaxTravelTime$	minimum and maximum amount of time that a node travels towards a position
Rnd	object responsible for random generations. This object is initialized with a different seed for each execution
Auxiliary Functions	
$distance(n1, n2)$	determines the distance (in meters) between nodes $n1$ and $n2$
$getInRangeNodes(x, y)$	returns a list of nodes which distance less than $MaxDistance$ from the (x, y) position
$generateUnitVectors()$	generates a new random unit vector. This method is used in the network start up, allowing the nodes to distance from themselves in order to proceed to their objective.

The HBDA algorithm starts by determining the next node movement (Algorithm 1). In this function, a list of in-range nodes is obtained in order to determine if the node is optimal positioned towards its neighbours.

Algorithm 1 Determining next move - **determineNextMove()**

```
# {Obtain in-range neighbours}
optimalDistance ← true
inRangeNodes[] ← getInRangeNodes(x, y)
for i = 0 to length(inRangeNodes) do
   if distance(this, inRangeNodes[i]) < MinDistance then
      optimalDistance ← false
      break
   end if
end for

# {Determine if node is well positioned}
if optimalDistance and length(inRangeNodes) > 0 then
   followTarget()
else
   adjustPosition()
end if
```

A node is considered to be optimal positioned when its distance to all neighbours is comprehended between $MinDistance$ and $MaxDistance$. When a node is in optimal position, it follows the Target, otherwise it has to adjust its position. Regardless of the decision, the node will calculate a trajectory from its current position towards a new location, spending a certain amount of time, between $MinTravelTime$ to $MaxTravelTime$ to traverse it.

Algorithm 2 Following Target Position - **followTarget()**

{Determine vector to target from current position}
$vectorX \leftarrow (targetX - x)$
$vectorY \leftarrow (targetY - y)$

{Calc velocity between MinVelocity and MaxVelocity}
$velocity \leftarrow MinVelocity + (Rnd.NextDouble() \times MaxVelocity - MinVelocity)$
{Calc travel time between MinTravelTime and MaxTravelTime}
$travelTime \leftarrow MinTravelTime + (Rnd.NextInt() \times MaxTravelTime - MinTravelTime)$

{Normalize vectors}
$distanceToTarget \leftarrow \sqrt{(vectorX^2 + vectorY^2)}$
$unitVectorX \leftarrow vectorX/distanceToTarget$
$unitVectorY \leftarrow vectorY/distanceToTarget$

{Calc new positions}
$x \leftarrow x + (unitVectorX \times velocity \times travelTime)$
$y \leftarrow y + (unitVectorY \times velocity \times travelTime)$

Upon reaching its new location, and upon that time expires, a new node movement determination is performed. This process is repeated until the end of execution.

The Following Target procedure (Algorithm 2) will calculate a trajectory based on a vector from the current node location towards the target. It begins by determining the vector from the current node position (x, y). Afterwards a velocity between $MinVelocity$ and $MaxVelocity$ is randomly generated. Finally, based on the generated velocity and travel time, the unit vector is calculated and a new vector towards the next position is computed.

When nodes are not in optimal position they are required to adjust it (Algorithm 3). The adjustment towards an optimal position is based on force vectors, as previously described in subsection 3.1. This procedure starts by analysing if the current unit vectors are null, i.e. none have been previously generated. This only occurs in the network start up. Since all nodes start from the same position, new random unit vectors are generated allowing the nodes to spread apart.

For the remaining cases, a list of the in-range neighbours is obtained and a force vector is determined, based on the distances to neighbours. The resultant force vector is then normalized and a vector towards the next position is computed based on a randomly generated velocity between $MinVelocity$ and $MaxVelocity$. To be noted that this procedure always expends one second, disregarding both $MinTravelTime$ and $MaxTravelTime$. Nonetheless, the position adjustment can be called consecutively.

Algorithm 3 Adjusting To Optimal Position - **adjustPosition()**

```
# {If unit vectors are null, generate new (Startup)}
if unitVectorX = 0 and unitVectorY = 0 then
    generateUnitVectors()
else
    # {Obtain in-range neighbours}
    inRangeNodes[] ← getInRangeNodes(x, y)
    vectorX ← 0
    vectorY ← 0
    for i = 0 to length(inRangeNodes) do
        # {Obtain vector for each neighbour}
        nX ← inRangeNodes[i].getX()
        nY ← inRangeNodes[i].getY()
        distance(this, inRangeNodes[i])
        nVectorX ← (x − nX)/distance
        nVectorY ← (y − nY)/distance
        # {Add neighbour vector to overall force vector, based on distance}
        distance ← MaxDistance − distance
        vectorX ← vectorX + (nVectorX × distance)
        vectorY ← vectorY + (nVectorY × distance)
    end for
    # {Normalize vectors}
    distanceToTarget ← √(vectorX² + vectorY²)
    unitVectorX ← vectorX/distanceToTarget
    unitVectorY ← vectorY/distanceToTarget
end if
# {Calc velocity between MinVelocity and MaxVelocity}
velocity ← MinVelocity + (Rnd.NextDouble() × MaxVelocity − MinVelocity)
# {Calc new positions}
x ← x + (unitVectorX × velocity)
y ← y + (unitVectorY × velocity)
```

4 Evaluation and Results

In this section, an evaluation study of the HBDA model performance is conducted. The main objective of this evaluation is to assess the movement and performance differences between RWP and HBDA mobility models.

4.1 Environment and Parameters

The scenario and parameter variations utilized to evaluate HBDA were selected carefully, in the attempt of representing, as much as possible, realistic disaster environments. In this specification the evaluation parameters were divided in four groups (Table 4). The General Parameters and Traffic Generation Parameters are common to the HBDA and RWP models. The RWP Parameters and HBDA Parameters are specific to the RWP and HBDA models, respectively. The conducted simulations were performed using the OPNET Modeler [11]. Network sizes were varied between 25 and 100 nodes in order to assess the scalability of routing for the different models. In this evaluation it has been decided that a proactive routing protocol should be used in order to evaluate the impact of constant path establishment. The Optimized Link State Routing protocol (OLSR) [12] was utilized for this purpose.

Table 4: Simulation Parameters

General Parameters	
Simulator	OPNET Modeler 17.1
Simulation duration time (s)	900
Transmission range (m)	150
Network size (number of nodes)	25; 50; 75; 100
Area Size (m^2)	500×500
WLAN IEEE Standard	802.11g (54 Mbps)
Routing Protocol	OLSR
Mobility Model	HBDA; RWP
Traffic Generation Parameters (Per Node)	
Start-Stop Time (s)	50-End of Execution
Traffic pattern	Constant Bit Rate (CBR)
Transport Protocol	User Datagram Protocol (UDP)
Packet generation rate (s)	4
Packet Size (bits)	4096
Destination Node	Random
RWP Parameters	
Min-Max node speed (m/s)	1-5
Pause time (s)	None
HBDA Parameters	
Min-Max node speed (m/s)	1-5
Min-Max Distance Threshold (m)	50-100
Min-Max Travel Time	1-10

The metrics used to evaluate HBDA are divided in two categories, Mobility-based and Link-based. The Mobility-based metrics attempt to assess the movement characteristics produced by the mobility model. The Link-based metrics evaluate the network performance. The Mobility-based metrics are defined as follows.

- *Density Distribution of Nodes* - to study the distribution of nodes, the scenario area is divided in 25×25 sub-areas. At each second, the amount of nodes is measured inside each sub-area, in order to study the distribution of nodes during execution time.
- *Node Degree* - represents the amount of in-range nodes per node. In this evaluation, a node is considered to be in-range to another if they distance no more than 100 meters. Typically, a low mean node degree represents a low density network with poor connectivity. On the other hand, a high mean node degree symbolizes a high density network with potential for high connectivity.
- *Area Coverage* - represents the cumulative amount of covered area during execution time. For evaluation and comparison purposes, it has been considered that each node is able to cover 5 meters around it. Thus, a radius of 5 meters along the trajectory of each node is considered covered.

The Link-based metrics are defined as follows.

- *Topology Changes* - measures the amount of topology changes of the OLSR protocol. This metric assesses the performance of the routing protocol. Since each topology change leads to a route table recalculation, a big amount represents a poor performance efficiency.

– *Throughput* - represents the average rate at which data packets are successfully delivered from one node to another. This metric can be defined by Equation 1.

$$Throughput = \frac{Number\ Delivered\ Packets \times Packet\ Size(bits)}{Simulation\ Duration\ Time(s)} \tag{1}$$

4.2 Mobility-based Results

As previously stated, this evaluation studies the movement characteristics of the mobility model.

Density Distribution of Nodes Figure 2 shows the average density distribution of nodes for all network sizes, represented in two dimensions, i.e. across the x axis. This measurement is the result of 500 executions with different seeds, in order to produce a precise and even representation of the distribution.

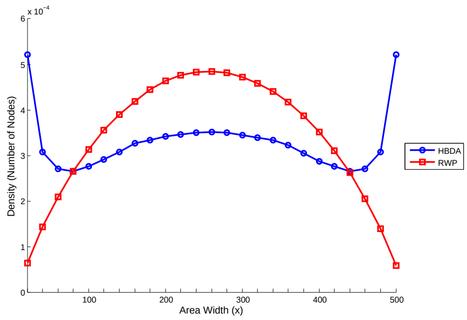

Fig. 2: Density Distribution of Nodes

As shown in the chart, the RWP model tends to concentrate nodes in the center of the scenario, producing an unbalanced distribution. This centralized distribution is characteristic of RWP and has already been demonstrated in several papers [9][2]. In contrast, the HBDA model tends to distribute its nodes more evenly across the scenario. However, it also shows a considerable density of nodes in the edges of the scenario. This fact only occurs because the start position of nodes is always located in the edges of the scenario.

Node Degree Figure 3 shows the average node degree for the different network sizes. The HBDA model presents a consistent node degree, i.e. it increases slightly along the network size. On the other hand, RWP presents a small node degree for the 25 node network and rapidly increases with network size, overcoming the HBDA model. This occurs due to the unbalanced distribution of nodes in RWP. For the 25 node network, the node density is low, and since most nodes keep losing connectivity due to its random mobility, the mean node degree is low. For the 100 node network, the mean node degree is remarkably high, mostly due to the high density of nodes but also due to the its unbalanced distribution.

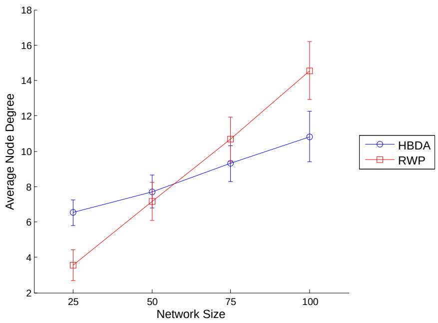

Fig. 3: Average Node Degree

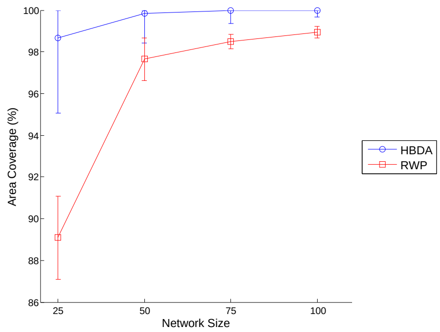

Fig. 4: Average Area Coverage

Area Coverage Figure 4 shows the average area coverage for different network sizes. Clearly, the HBDA model covers significantly more area when compared to RWP, reaching 100% coverage for the 100 node network. Despite of the superior coverage of the HBDA model, it has higher deviations from its mean, when compared to the RWP, particularly in smaller networks.

4.3 Link-based Results

The Link-based evaluation covers the evaluation of network performance. This evaluation mainly assesses the routing efficiency for the different scenarios.

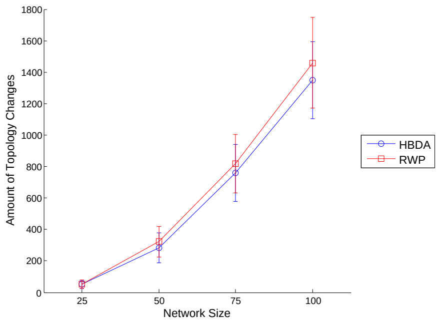

Fig. 5: Average Topology Changes

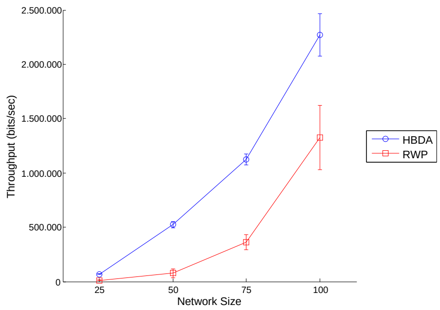

Fig. 6: Average Throughput

Topology Changes Figure 5 depicts the average amount of topology changes for the different network sizes. As shown, the number of topology changes grow significantly with the network size, particularly for networks larger than 50 nodes. This means that the OLSR protocol is performing a high amount of route recalculations, potentially having a big overhead.

Throughput Concerning that in the HBDA model nodes start from the same position, they would be capable of transmitting information even before the routing protocol calculate the paths, since they are at 1-Hop of distance. Considering this fact, the throughput of the network was only measured from the first 120 seconds of execution. After 120 seconds of execution in the HBDA model, it has been empirically observed, in all cases, that nodes already been completely spread. Figure 6 shows the average throughput over network size, for the entire network. As depicted in the figure, the average throughput significantly increases for larger networks. Since each node periodically generates a fixed amount of traffic, the overall throughput is higher for larger networks. Furthermore, HBDA offers a superior mean network throughput, when compared to the RWP model. The random movement of nodes in RWP is constantly disrupting node connections, resulting in a higher packet loss.

To be noted that the measured throughput complies both generated traffic and routing control traffic. Therefore, by the analysis of the chart, it can be observed that the mean throughput increases almost exponentially for larger networks. Despite the fact that more nodes are transmitting in larger networks, the amount of generated traffic per node is always the same. Regarding this fact, the mean throughput should grow proportionally to the network size. However, the chart confirms that the control traffic of the routing protocol strongly increases for networks larger than 75 nodes.

5 Conclusion and Future Work

In this work, a study of the existent mobility models was conducted and a new mobility model for disaster areas was proposed. The simulation evaluation demonstrated significant movement and performance differences between HBDA and RWP models. Concerning mobility-based evaluation, results demonstrated that HBDA provides better node distribution across the scenario area, in contrast with the RWP centralization of nodes. The node degree is also more consistent, proving that the HBDA connectivity is more balanced. The HBDA mobility model also performs a better area coverage, however at the cost of a higher standard deviation, when compared to RWP. Regarding the Link-based evaluation, the routing protocol generally is more efficient when the HBDA model is used, providing a lower End-to-End delay and a higher throughput. However, it can be concluded that the routing algorithm has a significant performance decrease for networks larger than 50 nodes.

Summarizing, the proposed mobility model provides a more real simulation possibility for disaster scenarios, instead of random based movement decisions. The future of this work concerns the scalability of the network. In order to enable the simulation of more than 100 nodes it is necessary to create a network hierarchy, allowing the routing protocol to scale. Thus, the next steps of this work will contemplate the integration of a clustering algorithm for mobile wireless networks, providing an hierarchical structure for the routing protocol.

Acknowledgments

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References

1. D. Johnson and D. Maltz, "Dynamic source routing in ad hoc wireless networks," *Mobile computing*, 1996. [Online]. Available: http://www.springerlink.com/index/QG8843V474571123.pdf
2. S. Kumar, S. C. Sharma, and B. Suman, "Mobility Metrics Based Classification & Analysis of Mobility Model for Tactical Network," *International Journal of Next-Generation Networks*, vol. 2, no. 3, pp. 39–51, Sep. 2010. [Online]. Available: http://www.airccse.org/journal/ijngn/papers/0910ijngn05.pdf
3. C. Bettstetter, S. Member, G. Resta, and P. Santi, "The Node Distribution of the Random Waypoint Mobility Model for Wireless Ad Hoc Networks," vol. 2, no. 3, pp. 257–269, 2003.
4. C. Bettstetter and C. Wagner, "The spatial node distribution of the random waypoint mobility model," *German Workshop on Mobile Ad Hoc . . .* , 2002. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.93.1351&rep=rep1&type=pdf
5. S. Lim, C. Yu, and C. Das, "Clustered Mobility Model for Scale-Free Wireless Networks," *Proceedings. 2006 31st IEEE Conference on Local Computer Networks*, pp. 231–238, Nov. 2006. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4116552
6. M. G. Xiaoyan Hong, "A group mobility model for ad hoc wireless networks," 1999. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.138.971
7. M. Sanchéz. Mobility models @ONLINE. page last accessed in 30th december 2012. [Online]. Available: http://www.disca.upv.es/misan/mobmodel.htm
8. N. Aschenbruck, E. Gerhards-Padilla, M. Gerharz, M. Frank, and P. Martini, "Modelling mobility in disaster area scenarios," *Proceedings of the 10th ACM Symposium on Modeling, analysis, and simulation of wireless and mobile systems - MSWiM '07*, p. 4, 2007. [Online]. Available: http://portal.acm.org/citation.cfm?doid=1298126.1298131
9. S. Pomportes, J. Tomasik, and V. Vèque, "A Composite Mobility Model for Ad Hoc Networks in Disaster Areas," vol. 1, no. 1, pp. 62–68, 2011.
10. I. Rhee, M. Shin, S. Hong, K. Lee, and S. Chong, "On the Levy-Walk Nature of Human Mobility," *2008 IEEE INFOCOM - The 27th Conference on Computer Communications*, pp. 924–932, Apr. 2008. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4509740
11. OPNET, "Opnet simulator," 1986, http://www.opnet.com/. [Online]. Available: http://www.opnet.com/
12. P. Jacquet, P. Mhlethaler, T. Clausen, A. Laouiti, A. Qayyum, and L. Viennot, "Optimized link state routing protocol for ad hoc networks," 2001, pp. 62–68.