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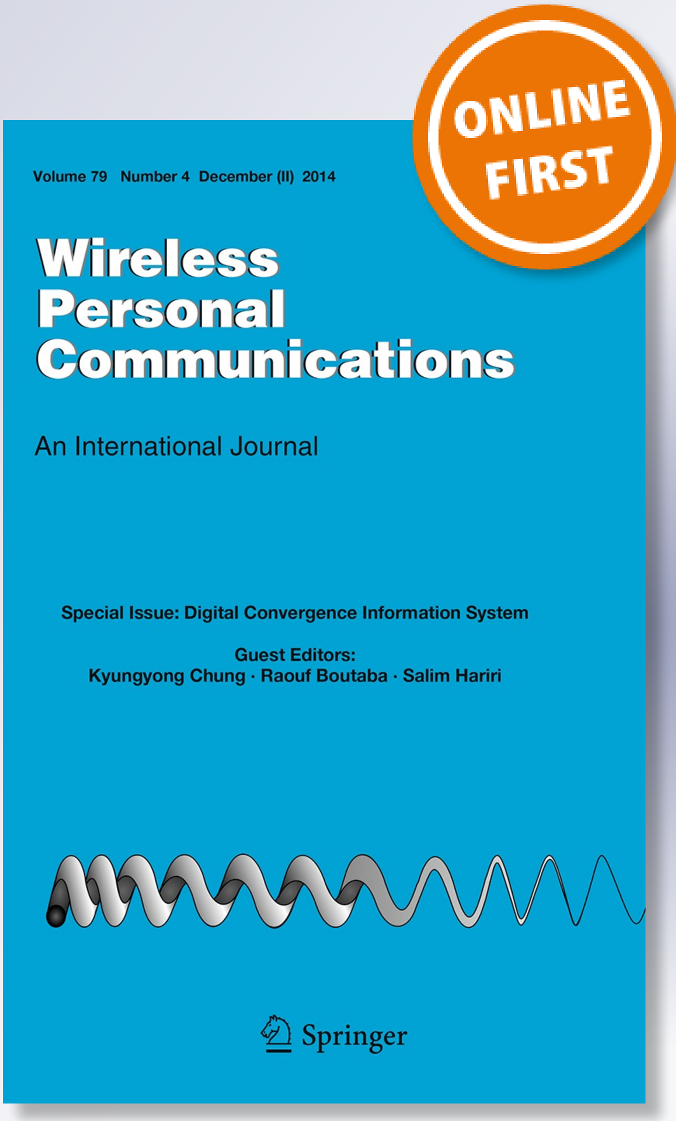
Wireless Personal Communications
An International Journal

ISSN 0929-6212

Wireless Pers Commun
DOI 10.1007/s11277-014-2235-8



Springer

Wireless Pers Commun
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Modelling Mobility Based on Obstacle-Aware Human Behaviour in Disaster Areas

Luís Conceição · Marilia Curado

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, such as the random waypoint, 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. This work studies the main existent mobility models able to suit disaster environments, according to specifically identified requirements. Moreover, a formal specification of the human behaviour for disaster areas (HBDA) mobility model is presented and an obstacle avoidance mechanism is introduced. Obstacle-aware HBDA is evaluated and compared with two existent mobility models, regarding its movement and network performances in different types of scenarios with variable network size and obstacle density. Obtained results show that obstacle-aware HBDA provides an even distribution of nodes, a efficient area coverage and a good transmission rate.

Keywords Mobile wireless networks · Mobility model · Disaster scenarios · Obstacles

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

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Published online: 19 December 2014

high and extremely difficult to reproduce. Thus, simulation evaluation allows the study of the behaviour and performance of mobile wireless networks in post-disaster environments.

The performance of mobile wireless networks strongly depend on the used mobility models [1]. Since in post-disaster environments most nodes are mobile, the used mobility model has a crucial impact on the results. Most performance evaluations existent in literature have modelled node mobility using the random waypoint model (RWP) [2,3]. Such model is easy to implement and visualize, however it is generally unrealistic for modelling real world scenarios due to the uneven distribution of nodes. The random waypoint with attraction points (RWAP) [4] attempts to solve this issue by creating "hot" areas where nodes have the tendency to remain longer. The clustered mobility (ClusM) [5] model extends RWAP by reducing the attraction to "hot" areas which have high density of nodes. However, considering the search for victim (SFV) in disaster scenarios, it becomes necessary a cooperation between mobile nodes in order to deliver an efficient area exploration. Group mobility models provide such cooperation, capable of movement coordination within groups of nodes. The reference point group mobility (RPGM) [6] combines the organized mobility of a group but also allows individual motion. The configuration of this model is highly adaptable, enabling different types of behaviour in individual and group motion. Three variations of RPGM were proposed [7] attempting to reproduce different mobility requirements. The column mobility model (COL) is one of the variation and distinguishes itself for its capability of wide area exploration.

COL enforces nodes to be positioned in a line formation, allowing each node to move freely within small area range. This method provides an organized mobility pattern, potentially suitable for quick area exploration. The disaster area (DA) [8], specifically designed for disaster environments, enforces the division of the scenario into several areas and establishes well defined mobility paths between them. The composite mobility (CoM) [9] model is a modification of RPGM model, replacing random mobility by the Levy-Walk model.

The human behaviour for disaster areas (HBDA) [10] reproduces the human behaviour in search for victim (SFV) operations. Nodes move towards a destination target, always keeping a considerable distance between their neighbours. This paradigm seamlessly enforces the spreading of nodes across the scenario, covering a larger area. Another important requisite of mobility in disaster scenarios is the blind area exploration. The map of post-disaster areas is typically unknown due to the scenario degradation. A correct mobility modelling must count with unexpected obstacles and ensure that nodes are able to bypass them. Thus, this work proposes an extension of the HBDA to provide obstacle avoidance.

To access the impact of obstacles in disaster areas, a comparative study between obstacle-aware HBDA, RWP and COL mobility models is conducted, featuring the mobility and network performances. The evaluation scenarios contain three types of obstacle density in order to determine which models are most affected by obstacles.

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 formally describes the obstacle-aware HBDA mobility model. Section 4 performs a performance evaluation of obstacle-aware HBDA in comparison with the RWP and COL models. Finally, Sect. 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 their type, mobility models must meet some requirements to accurately represent movement patterns in post-disaster areas. These requirements are described as follows.

- Coordination—the trajectories of nodes must not be entirely random. Random mobility may exist, however some form of mobility coordenation and constraints between nodes must be ensured.
- Obstacle avoidance—blind exploration of the area is required, enabling nodes to avoid obstacles
- Even node distribution—it is important an even distribution of nodes to enable a full area coverage.

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 [2] 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 [11], and its use should only be considered for general purpose scenarios.

The most important problem of the RWP model is the uneven distribution of nodes since, over execution time, nodes tend to accumulate in the middle of the simulation scenario [12]. Moreover, the assumption that waypoints are uniformly distributed is not feasible for most real applications. However, using different probability distributions, the RWP is able to distribute nodes impartially, highlighting certain regions of the scenario [13]. A variation of the RWP, called random waypoint with attraction points (RWAP) [4] 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 clustered 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 RPGM model 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 (COL), the nomadic community mobility model (NCM) and the pursue mobility model (PM) [7].

The column mobility model (COL) can be used for search 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 COL 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 disaster area (DA) [8] mobility model is specifically designed for disaster scenarios. The model is based on the displacement of civil protection forces in real life, containing different areas 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.

The composite mobility (CoM) [9] is also designed for disaster scenarios. It is a combination of several existing models to better represent human mobility in disaster areas. The original RPGM model is used, however for better realism the RWP is replaced by the Levy-Walk model [14]. 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,

Table 1 Requirements of mobility models for disaster areas

Model	Coordination	Obstacle avoidance	Even node distribution
RWP [2]	✖	✖	✖
RWAP [4]	✖	✖	✖
ClusM [5]	✖	✖	✔
RPGM [6]	✔	✖	✖
COL [7]	✔	✖	✔
NCM [7]	✔	✖	✖
PM [7]	✔	✖	✖
DA [8]	✔	✔	✖
CoM [9]	✔	✔	✖
BFBIGM [15]	✔	✔	✖
StrM [16]	✔	✖	✖
HBDA [10]	✔	✖	✔

✔: satisfies requirement, ✖: does not satisfy requirement

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.

The bird-flocking behaviour inspired group mobility (BFBIGM) [15] takes inspiration from the mobility of bird flocks, flying in group coordination. In this model, several distinct groups of nodes may exist (flocks), but all have the same destination, which is a common randomly defined target. Within each group, nodes move in formation and attempt to avoid collision by keeping a safe distance between neighbours. Nodes are also capable of avoiding obstacle collision by deviating their path upon obstacle detection. The stream mobility (StrM) model [16] has a similar mobility pattern, simulating nodes in moving water or wind. Each node chooses a random angle and speed. When a node moves, it shares its angle with its neighbours. The neighbors modify the angle by adding or reducing a randomly chosen degree between 0 and 30. Thus, each node influences the movement of its neighbours.

The human based mobility model (HBDA) [10] attempts to mimic human movement during SFV operations in disaster areas. Nodes start area exploration from a common start point and move across the scenario towards a final target area. During exploration, nodes tend to spread across the scenario maintaining at least a neighbour node in-range communicable. Thus method seamlessly forces nodes to evenly spread resulting in a high amount of covered area.

2.3 Summary of Mobility Models

This section studied some of the most relevant mobility models in literature, presented in Table 1. 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 node coordination. Regardless, the ClusM model can be considered to obtain an even distribution of nodes due to the avoidance of regions with a high density of nodes.

On the other hand, all 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. There are also a few group entity models designed specifically for disaster environments. The DA mobility model is not 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 uneven node distribution within sub-areas. CoM 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. The BFBIGM model does not require knowledge of the map and it is capable of blind navigation, since obstacle avoidance is supported. However, the behaviour of node mobility is not suitable for area exploration, since nodes travel from an initial point to destination as directly as possible, only deviating their path to avoid obstacle collision. In the StrM model, the moving angle of nodes is influenced by its neighbours. Ultimately, the first node to initiate movement is the leader of the group, resulting in a group of nodes following a single node.

The HBDA mobility model is based on human behaviour. Individuals explore the scenario maintaining a configurable distance between each other. This behaviour naturally forces the spread of nodes across the area, providing an even distribution of nodes.

By the analysis of Table 1 it can be concluded that none of the studied mobility models provide all the defined requirements suitable for modelling disaster areas. In the following section, a formal description of the obstacle-aware HBDA is provided.

3 Obstacle-Aware Human Based Mobility Model (OHBDA)

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. The studied mobility models for disaster areas are random based, such as disaster area (DA), which also uses the RWP inside each sub-area. In this section, a formal description of the obstacle-aware human behaviour for disaster areas (OHBDA) is provided. The OHBDA model is specifically focused in the disaster zone, disregarding periphery rescue coordination. In other words, the OHBDA is designed to model only search for victim operations inside a limited area.

3.1 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. During exploration, nodes are able avoid obstacle overlapping, in order to mimic real life obstacle collision avoidance.

3.1.1 Assumptions

To accurately represent the OHBDA model, a list of parameters is presented in Table 2.

Table 2 OHBDA motion parameters

Parameter	Description
x and y	Generic identifier of a node position in Cartesian coordinates (x, y)
$C_i(X_i, Y_i)$	Initial coordinate position of nodes
S_x	Horizontal scenario size divided by 2. In a Cartesian system, this variable represents the horizontal length of a quadrant
S_y	Vertical scenario size divided by 2. In a Cartesian system, this variable represents the vertical length of a quadrant
E	Scenario edge size
N	Number of nodes
μ	Connectivity distance or radius of nodes
$minV, maxV$	Minimum and maximum node velocity (in meters per second)

3.1.2 Start and Target Points

In the OHBDA model all nodes initiate their movement from a initial coordinate $C_i(X_i, Y_i)$ located in the edges of the scenario. The determination of such coordinates is random, i.e. nodes can start at any location as long as it is located within the scenario edges, such that the condition of Eqs. (1) or (2) is met.

$$X_i \in (|S_x - E|, |S_x|) \quad and \quad Y_i \in (0, |S_y|) \tag{1}$$

$$X_i \in (0, |S_x|) \quad and \quad Y_i \in (|S_y - E|, |S_y|) \tag{2}$$

The determination of X_i and Y_i follows a continuous uniform distribution U either on (1) or (2). An uniform distribution is used to deliver an equal probability to all possible coordinates. The determination of which equation to choose is based on a which follows a discrete uniform distribution on $[1, 2]$, defined in Eq. (3).

$$|X_i'| = \begin{cases} U(S_x - E, S_x), & a = 1 \\ U(0, S_x), & a = 2 \end{cases}$$
$$|Y_i'| = \begin{cases} U(0, S_y), & a = 1 \\ U(S_y - E, S_y), & a = 2 \end{cases} \tag{3}$$

Being the absolute values of X_i and Y_i determined, the Cartesian quadrant on which C_i is located is determined by q which follows a discrete uniform distribution on $[1, 4]$, represented in Eq. (4).

$$X_i'' = \begin{cases} |X_i'|, & q = 1 \; or \; q = 4 \\ -|X_i'|, & q = 2 \; or \; q = 3 \end{cases}$$
$$Y_i'' = \begin{cases} |Y_i'|, & q = 1 \; or \; q = 2 \\ -|Y_i'|, & q = 3 \; or \; q = 4 \end{cases} \tag{4}$$

And the initial coordinate C_i is (X_i, Y_i), where $X_i = X_i''$ and $Y_i = Y_i''$. The destination or final coordinate of nodes $C_f(X_f, Y_f)$ is the symmetric inverse position of C_i defined in Eq. (5).

$$C_f = (-X_i, -Y_i) \tag{5}$$

3.2 Initial Movement

The position matrix $P_{m,n}$ represents the current coordinates of all nodes. m is a constant and is equal to 2, since the mobility model is working in 2 dimensions. n is equal to the number of nodes on the scenario. Thus, every column of P represents a coordinate $(p_{x,n}, p_{y,n)})$ for a node n, represented in Eq. (6).

$$P_{2,n} = \begin{array}{c} \\ x \\ y \end{array} \begin{array}{c} \begin{array}{ccccc} Node\,1 & Node\,2 & Node\,3 & \cdots & Node\,n \end{array} \\ \left[\begin{array}{ccccc} p_{x,1} & p_{x,2} & p_{x,3} & \cdots & p_{x,n} \\ p_{y,1} & p_{y,2} & p_{y,3} & \cdots & p_{y,n} \end{array} \right] \end{array} \tag{6}$$

As previously mentioned, the first position of all nodes is $C_i(X_i, Y_i)$, thus $P_{x,n} = X_i$ and $P_{y,n} = Y_i, \quad \forall n \in [1, N]$.

The first movement of nodes, at time step $t = 1$, is generated randomly. For each node, a unit vector $\hat{u_i} = (u_{x_i}, u_{y_i})$ and a velocity scalar v_i are generated. Its multiplication results in a vector which will provide the first position of nodes.

3.2.1 Initial Unit Vectors

Each unit vector $\hat{u_i}$ is determined following a continuous uniform distribution U. As known, $||\hat{u_i}|| = 1$, thus $\sqrt{u_{i_x}^2 + u_{i_y}^2} = 1$. Decomposing, two possibilities take place, Eqs. (7) or (8).

$$u'_{i_x} \in U(0,1) \quad and\,consequently;\; u'_{i_y} = \left(\sqrt{1 - u_{i_x}^2}\right) \tag{7}$$

or

$$u'_{i_y} \in U(0,1) \quad and\,consequently;\; u'_{i_x} = \left(\sqrt{1 - u_{i_y}^2}\right) \tag{8}$$

The choice between (7) and (8) follows a discrete uniform distribution p on [1, 2].

Furthermore, it is necessary to determine the signal of u_{i_x} and u_{i_Y}, as defined in Eq. (9). q follows a discrete uniform distribution on [1, 4].

$$\begin{aligned} u''_{i_x} &= \begin{cases} u'_{i_x}, & q = 1 \; or \; q = 4 \\ -u'_{i_x}, & q = 2 \; or \; q = 3 \end{cases} \\ u''_{i_Y} &= \begin{cases} u'_{i_Y}, & q = 1 \; or \; q = 2 \\ -u'_{i_Y}, & q = 3 \; or \; q = 4 \end{cases} \end{aligned} \tag{9}$$

The result is $\hat{u_i}(u_{i_x}, u_{i_y})$ with $u_{i_x} = u''_{i_x}$ and $u_{i_y} = u''_{i_y}$.

3.2.2 Initial Motion Vectors

A motion vector $\overrightarrow{v_i}$ for each node i is determined in Eq. (10).

$$\overrightarrow{v_i} = \hat{u_i}.v_i \tag{10}$$

whereas v_i is determined following a continuous uniform distribution on $[minV, maxV]$.

The generated vectors for all nodes are represented by the matrix $V_{m,n}$ [Eq. (11)]. Similarly to the position matrix, m is a constant equal to 2 and n is the number of nodes.

$$V_{2,n} = \begin{array}{c} \\ x \\ y \end{array} \begin{array}{c} \begin{array}{ccccc} Node\,1 & Node\,2 & Node\,3 & \cdots & Node\,n \end{array} \\ \left[\begin{array}{ccccc} v_{x,1} & v_{x,2} & v_{x,3} & \cdots & v_{x,n} \\ v_{y,1} & v_{y,2} & v_{y,3} & \cdots & v_{y,n} \end{array} \right] \end{array} \tag{11}$$

Having determined the vectors the new matrix position of nodes $P_{t=1}$ is calculated by the summing the last position $P_{t=0}$ and motion vector matrices, according to Eq. (12).

$$P_{(t=1)} = P_{(t=0)} + V \tag{12}$$

3.3 Determination of Movement

Node movement is determined at each time step t based on the current position of nodes. The coordinate of a node i at a time step t is denoted by the position matrix $P_{(t)}(p_{x,i}, p_{y,i})$.

The position of nodes for the next time step $P_{(t+1)}$ is calculated deterministically, based on two force matrices I and T and a scalar λ, according to Eq. (13).

$$P_{(t+1)} = I_{(t)} + \lambda \cdot T_{(t)} \tag{13}$$

The $I_{(t)}$ matrix represents the independence force vectors, which is calculated according to the proximity of neighbour nodes. A node n_1 is considered neighbour of node n_2 if the distance d between them is less or equal to the connectivity radius μ. If neighbour nodes do not exist, the resulting $I_{(t)}$ matrix is null. The $T_{(t)}$ matrix represents the Target (or final destination) of nodes, which is calculated based on the position of the Target. The scalar λ must be equal to one of two constants, 0 or 1, according to whether $I_{(t)}$ is not null (0) or otherwise (1). This scalar allows the exclusivity between $I_{(t)}$ and $T_{(t)}$. In other words, each node either attempts to separate from its neighbours or moves towards the Target.

3.3.1 Independence Force Matrix

The independence force of a node is based on the sum of the vectors towards its neighbours. In robot motion planing, obstacles represent unwanted positions in order to avoid collision [17]. Thus, negative forces vectors are generated towards the obstacles in order to avoid them. Similarly, the movement towards the position of neighbour nodes is undesirable, since the their area is already explored.

Let the matrix $N_i(t)$ represent the position of the neighbours of each node i at each time step t.

The vectors from $P_i(t)$ to each $N_i(t)$ are computed and represented by $\overrightarrow{Fi}(t)$.

At each time step t, a resultant force vector $\overrightarrow{F_R}(t)$ is computed for each node. For better illustration, Fig. 1 shows an example of a resultant force vector $\overrightarrow{F_R}(t)$ for three neighbor nodes. Each force vector $\overrightarrow{F_R}(t)$ is calculated for the each neighbour node, according to Eq. (14).

$$\overrightarrow{F_R}(t) = \sum_{i=1}^{m} \left(\mu - \overrightarrow{Fi}(t)\right) \tag{14}$$

where m is the number of neighbours, μ represents the connectivity radius and $\overrightarrow{F_i}(t)$ is the computed vector between $P_i(t)$ and each neighbour $N_i(t)$.

The resultant vector $\overrightarrow{F_R}(t)$ cannot be applied directly to the node movement, since the velocity must be controlled between $[minV, maxV]$ and randomly generated. Thus, the unit vector $\hat{F_R}(t)$ is computed following Eq. (15).

$$\hat{F_R}(t) = \frac{\overrightarrow{F_R}(t)}{||\overrightarrow{F_R}(t)||} \iff \hat{F_R}(t)\left(\frac{F_{R_x}}{\sqrt{F_{R_x}^2 + F_{R_y}^2}}, \frac{F_{R_y}}{\sqrt{F_{R_x}^2 + F_{R_y}^2}}\right) \tag{15}$$

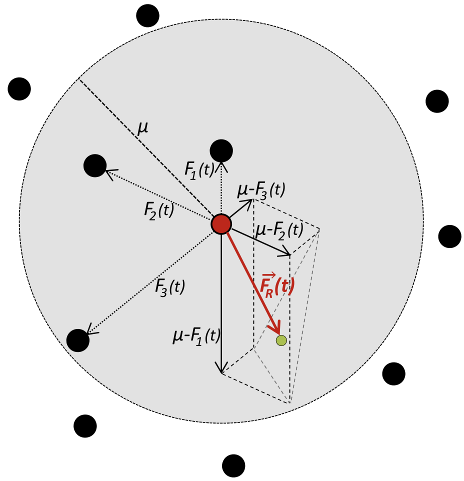

Fig. 1 Example of a resultant force vector

In order to determine the motion vector, the velocity scalar v is calculated following a discrete uniform distribution on $[minV, maxV]$ and the new independence vector is determined according to Eq. (16).

$$\overrightarrow{I_i}(t) = Pi_{(t)}.\hat{F_R}(t).v \tag{16}$$

The collation of all independence vectors $\overrightarrow{I_i}(t)$ results in the final independence matrix $I_{(t)}$.

3.3.2 Target Force Matrix

In order to determine the Target force for each node, the vector towards Target t_i is calculated according to Eq. (17).

$$\overrightarrow{t_i} = Cf - Pi_{(t)} \iff \overrightarrow{t_i}\left(Cf_x - P_{x,i}(t), Cf_y - P_{y,i}(t)\right) \tag{17}$$

Following this, the unit vector towards the Target is computed in Eq. (18).

$$\hat{t_i} = \frac{\overrightarrow{t_i}}{||\overrightarrow{t_i}||} \iff \hat{t_i}\left(\frac{t_{i_x}}{\sqrt{t_{i_x}^2 + t_{i_y}^2}}, \frac{t_{i_y}}{\sqrt{t_{i_x}^2 + t_{i_y}^2}}\right) \tag{18}$$

Finally, the velocity scalar v is calculated following a discrete uniform distribution on $[minV, maxV]$ and the new vector towards Target is determined according to Eq. (19).

$$\overrightarrow{T_i} = Pi_{(t)} \cdot \hat{t_i} \cdot v \tag{19}$$

The matrix $T_{(t)}$ represents the current determined forces of all nodes towards the Target.

3.4 Obstacle Avoidance

A node will collide with an obstacle if the vector $\overrightarrow{C}(t)$ intersects the matrix $O_{2,n}$. The vector $\overrightarrow{C}(t)$ is calculated regarding the current (t) position of the node and its future position $(t+1)$, according to Eq. (20).

$$\overrightarrow{C}(t) = P_{(t+1)} - P_{(t)} \tag{20}$$

The obstacle matrix is defined as Eq. (21).

$$O_{2,n} = \begin{array}{c} \\ x \\ y \end{array} \begin{array}{c} \begin{array}{ccccc} Vertex\,1 & Vertex\,2 & Vertex\,3 & \cdots & Vertex\,n \end{array} \\ \begin{bmatrix} v_{x,1} & v_{x,2} & v_{x,3} & \cdots & v_{x,n} \\ v_{y,1} & v_{y,2} & v_{y,3} & \cdots & v_{y,n} \end{bmatrix} \end{array} \tag{21}$$

Upon detection of obstacle collision, nodes reset their execution and assume an initial movement, as previously described in Sect. 3.2. Similarly, an initial unit vector and an initial motion vector is generated. This behaviour enables nodes to assume a temporarily random movement, discarding the influence of the independence force and target force matrixes. In other words, upon obstacle collision detection, nodes move randomly regardless of their neighbours, in order to obtain a trajectory suitable to avoid obstacle collision.

4 Evaluation and Results

In this section the performance of OHBDA was assessed and compared with the random waypoint (RWP) and column (COL) mobility models. This evaluation is mainly focused on the movement characteristics and network performance delivered by these models.

4.1 Environment and Parameters

The scenario and parameter variations utilized to evaluate OHBDA 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 3).

The general parameters and traffic generation parameters are common to the OHBDA and RWP models. The RWP parameters and OHBDA parameters are specific to the RWP and OHBDA models, respectively. The conducted simulations were performed using the OPNET Modeler [18]. The free-space propagation model was used and configured with a transmitting power and reception power threshold equivalent to a path loss distance of 150 m. 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) [19] was utilized for this purpose. To access link performance, each node generates a packet of 4,096 bits every 4 s. Upon packet transmission its destination is a randomly chosen node in the network.

4.1.1 Obstacles

A post disaster scenario typically consists of an area in an unknown condition or status. Regardless of its geographic map, it becomes very challenging to obtain an accurate map of the affected area [20], which necessarily forces a blind mobility across the scenario. Concerning this issue, the evaluated scenarios were populated with randomly defined obstacles. Each obstacle can be represented by a polygon characterized by the matrix O (21), with an amount of vertices n, randomly generated between $minV$ and $maxV$. For each obstacle, vertex positions (Vx, Vy) are randomly generated with two main constraints. The resulting shape sides must not intersect and the length of the shape sides l must lie between $minLen$ and $maxLen$. Following this approach, resultant obstacles are irregular polygons, with different sides and shapes. Furthermore, in order to further assess the behaviour of mobility models, two density levels of obstacles were utilized, namely *Den 1* and *Den 2* representing a low

Table 3 Simulation parameters

General parameters	
Simulator	OPNET Modeler 17.5
Simulation duration time (s)	900
RF propagation model	Free-space
Path loss distance (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	OHBDA; RWP; COL
Obstacle density	Clears; Den 1 (low); Den 2 (high)
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)	4,096
Destination node	Random
Obstacle generation parameters	
Min-Max obstacle amount	Den 1: 5–15; Den 2: 10–30
Min-Max vertex amount	Den 1: 3–10; Den 2: 5–30
Min-Max side length (m)	Den1: 1–5; Den2: 3–15
COL parameters	
Min-Max node speed (m/s)	1–5
Neighbour distance (m)	50
RWP parameters	
Min-Max node speed (m/s)	1–5
Pause time (s)	None
OHBDA parameters	
Min-Max node speed (m/s)	1–5
Min-Max distance threshold (m)	50–100
Min-Max travel time	1–10

and high density, respectively. Figure 2 shows examples of scenarios for the three possible obstacle densities, Clear, i.e. no obstacles, *Den 1* and *Den 2*. As represented in Table 3, the amount of deployed obstacles, the number of vertices for each obstacle and the length of each obstacle side varies according to the obstacle density.

Since that the COL and RWP models are not capable of obstacle avoidance, it was implemented, for both, the same mechanism used in OHBDA. Just before obstacle collision, the movement of node is interrupted and a new random trajectory is generated. This implemented obstacle avoidance mechanism does not significantly affect the behaviour of RWP, since it is an entity model moving according to random trajectories. However, OHBDA and COL are likely to suffer from unplanned trajectories, leading to link failure between nodes.

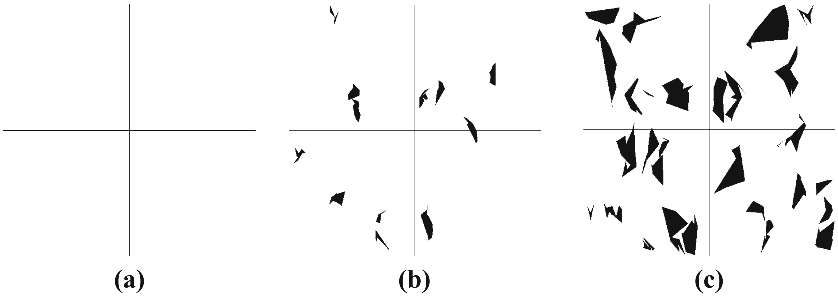

Fig. 2 Examples of scenarios with different obstacle densities. **a** Clear, **b** Den 1, **c** Den 2

4.1.2 Metrics

The metrics used to evaluate OHBDA 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.

- *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 m around it. It was empirically observed that a 5 m radius is sufficiently granular in order to analyse the different coverage provided by the mobility models. Moreover, a lower value would not be realistic, since it must be considered that in SFV operations humans are able to "see" an amount of area around them. Thus, a radius of 5 m along the trajectory of each node is considered covered.
- *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 the distance between them is at most 100 m. Typically, in a wireless multi-hop network, a low mean node degree represents a low density network with poor connectivity [21]. On the other hand, a high mean node degree symbolizes a high density network with potential for high connectivity.

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.
- *Goodput*—represents the average rate at which application data packets are successfully delivered from one node to another.
- *Packet loss*—amount of lost packets for the total amount of transmitted packets
- *Delay*—End-to-end delay of packet transmission from source to destination. The delay is measured only for the packets that arrive to the destination, i.e. successfully transmitted packets.

4.2 Mobility-Based Results

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

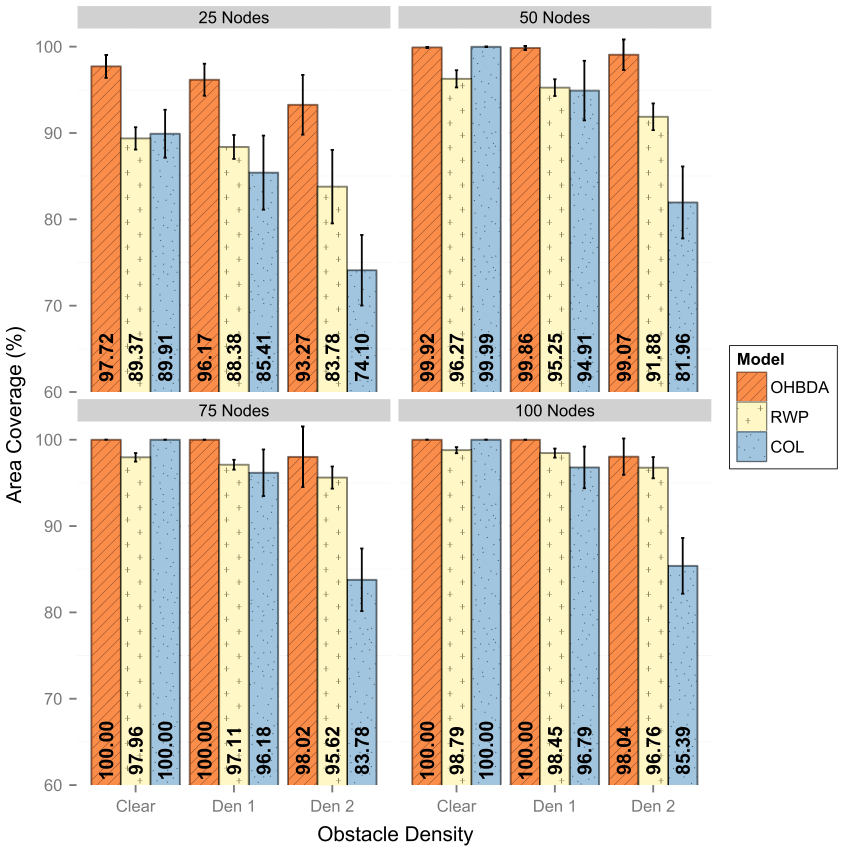

Fig. 3 Scenario area coverage in percentage

4.2.1 Coverage

The coverage represents the amount of explored area during the movement of nodes. A higher amount of coverage lead to a higher probability of finding victims in a disaster scenario.

Figure 3 shows the mean area coverage for the different network sizes and obstacle densities. A broad analysis of the results indicate a high amount of coverage for all models and scenarios, whereas the minimum mean of coverage is 74.10 %. This indicates that during execution time, the trajectories of nodes provide a high coverage, even in low density scenarios with 25 nodes. Regardless, the OHBDA model presents an overall higher coverage in all scenarios. This difference is more noticeable in the 25 node network, due to the uniform dispersion of nodes provided by OHBDA. On the other hand, the Column model ”sweeps” the scenario with a group of nodes organized in a column fashion, which should provide a higher coverage. However, in the 25 node network, the formed column is not sufficiently wide to cover the full scenario, hence the lower coverage. The Column model offers high coverage, however it is strongly affected by obstacles, presenting significant coverage decrease in those scenarios. The random waypoint model is also affected by obstacles, since the premature interruption of in course random paths results in a slight lower area coverage. Finally, the OHBDA is the model least affected by obstacles, presenting a consistent high coverage percentage.

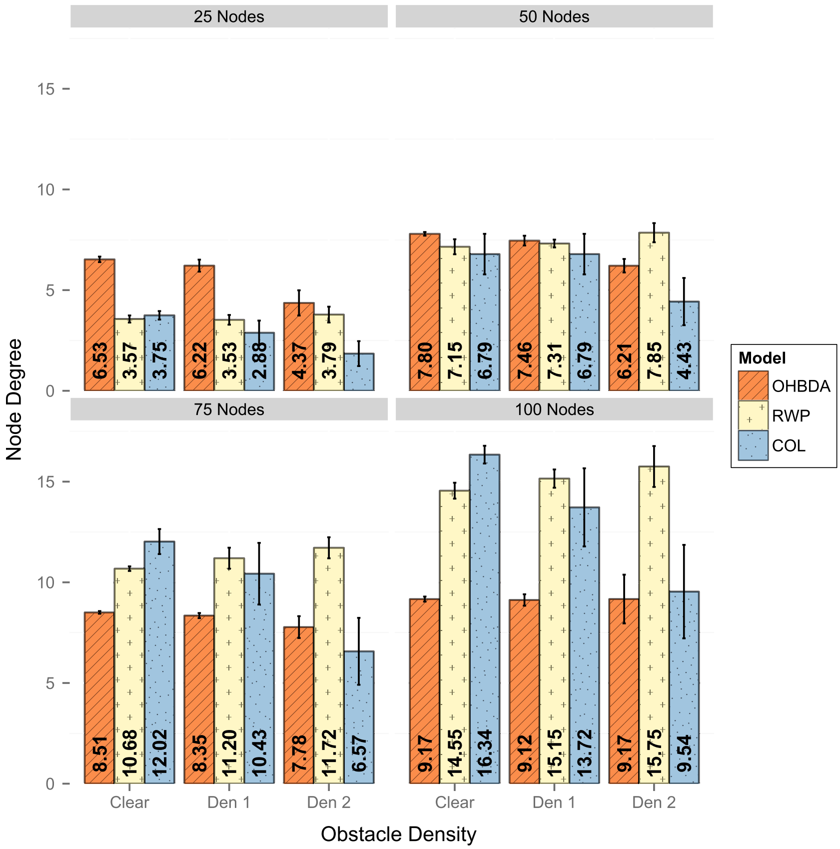

Fig. 4 Mean node degree

4.2.2 Node Degree

Typically in mobile networks, a high node degree leads to a higher amount of path recalculations, which may decrease the performance of the routing protocol, consequently leading to packet loss.

A high node degree may also represent good network connectivity, providing a more resilient network. However, a low node degree normally represents bad connectivity, particularly in high density scenarios. The optimal node degree for a given scenario is extremely difficult to determine, since it depends on many factors [22], e.g. routing protocol, node density, node speed, transmission range, scenario interferences. Thus, the evaluation of the node degree must be based on the variation of node degree for the different scenarios. Figure 4 shows the node degree for the evaluated scenarios. It can be concluded that the node degree from OHBDA and COL models decreases for higher obstacle densities, and the opposite occurs to RWP. In OHBDA and COL models the movement of nodes is organized, i.e. nodes move according to a determined vector capable of maintaining connectivity of between nodes. Upon obstacle interference, movement vectors must be recalculated, occasionally leading to non-optimal paths, which may result in connection losses and consequently a decrease of node degree. The RWP node movement is entirely random, regardless of neighbour nodes.

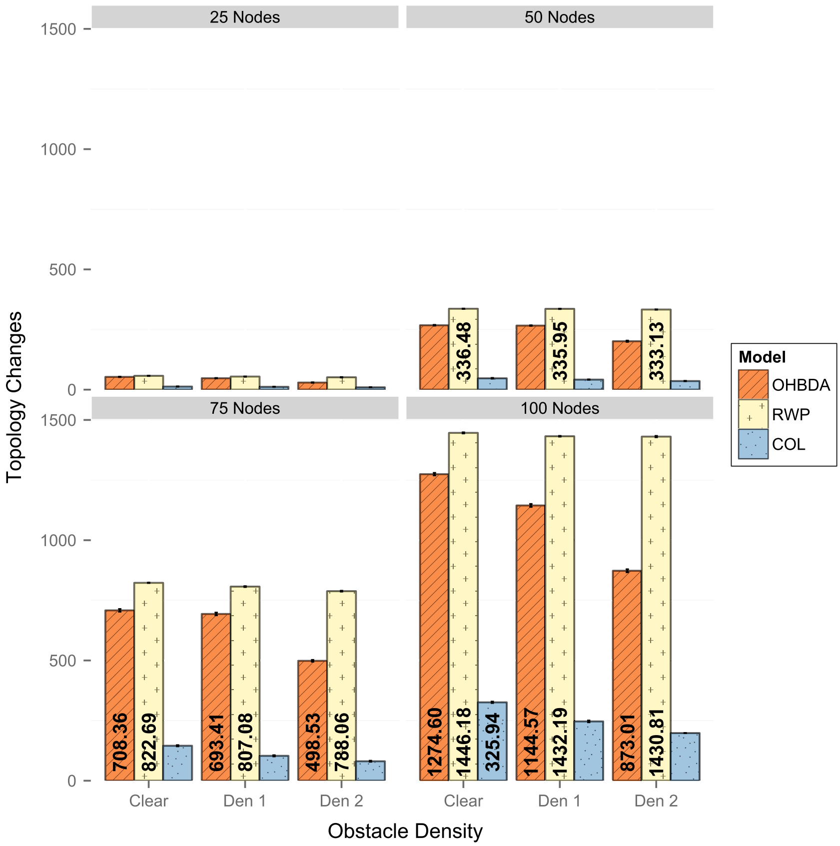

Fig. 5 Number of topology changes

The increase of node degree is therefore explained due to the reduction of usable area and the increase of node density. Analyzing the results across the different network sizes, there is a general increase of the node degree, particularly in the 100 nodes scenario. Moreover, the COL model is strongly affected by obstacle interference, whereas OHBDA is significantly more constant in all network sizes.

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.

4.3.1 Topology Changes

In OLSR protocol each topology change leads to recalculation of the routing table, which causes network flooding. A topology change occurs when a link fails, thus highly dynamic networks typically result in a bigger amount of topology changes. From the analysis of Fig. 5, it can be seen that RWP model causes more topology changes than the remaining models. Once again, this fact is due to its characteristic uncoordinated movement, leading

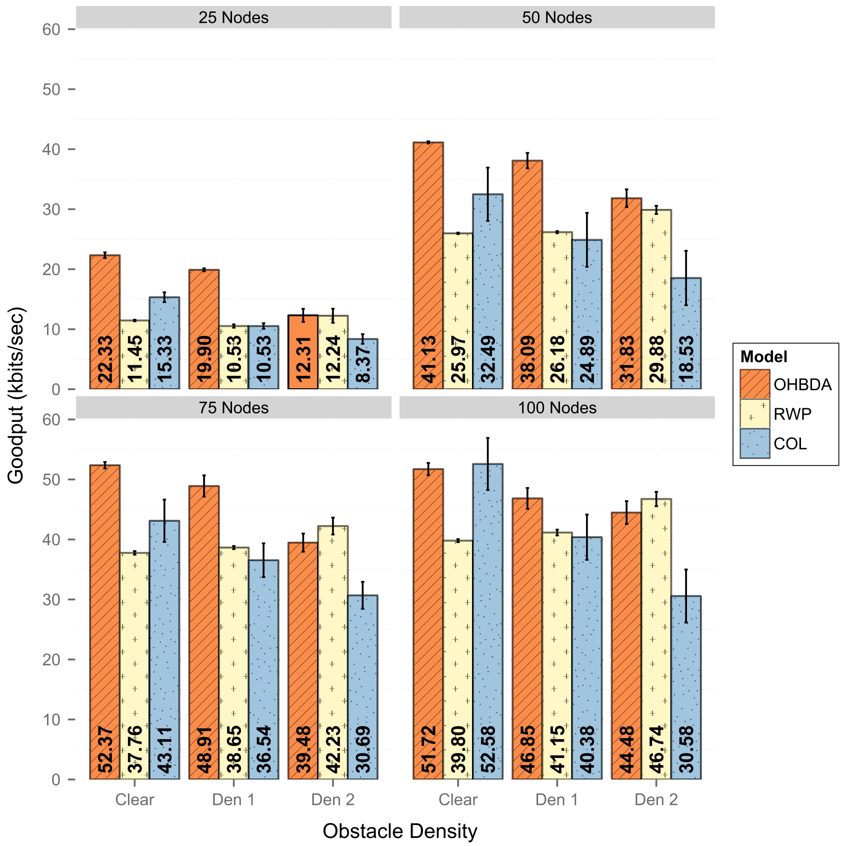

Fig. 6 Network Goodput

to constant link failures. It can also be observed in RWP model that the density of obstacles has practically no influence in the amount of topology changes. On the other hand, OHBDA and COL models are significantly influenced by obstacle density.

In the presence of obstacles, OHBDA and COL models tend to decrease connectivity (as evaluated in node degree) which results in smaller amounts of neighbours per node. Thus, the probability of loosing a link with a neighbour node decreases, which results in lower topology changes for higher obstacle density.

Regardless of this fact, the COL model presents the lower amount of topology changes, due to the column fashion organization of nodes.

4.3.2 Goodput

The goodput represents the application level throughput, in this case the generated traffic successfully transmitted and received by each node. Figure 6 depicts the overall network goodput for the different evaluated scenarios. Similarly to the results of node degree, the RWP model presents an increase of goodput for scenarios with higher obstacle density. Once more, due to the increase of node density caused by obstacles, the RWP provides better connectivity, resulting in a higher goodput. The OHBDA model provides better overall

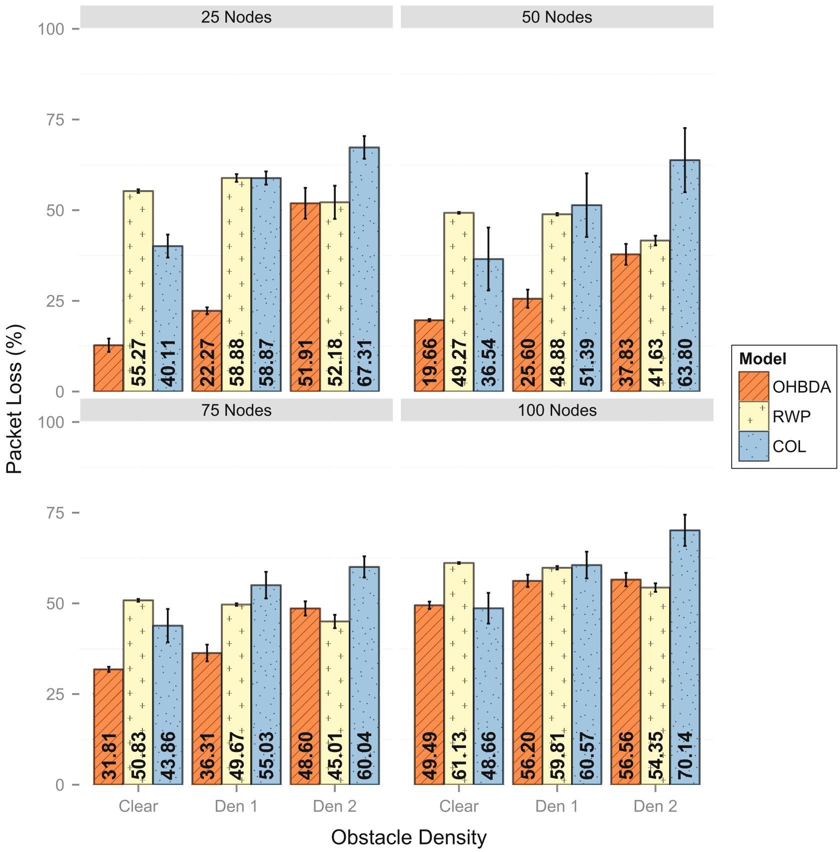

Fig. 7 Overall packet loss in percentage

goodput. COL model is able to overcome OHBDA in the 100 nodes scenario with no obstacles. Since COL model organizes nodes in a column fashion, the network topology is very stable (as previously seen in the routing topology changes), reducing the routing overhead and increasing the amount of successfully transmitted data. However, the COL model heavily affected by the presence of obstacles, presenting significant lower goodput in these scenarios.

4.3.3 Packet Loss

The amount of lost packets is strongly tied with the goodput. Figure 7 shows the overall percentage of lost packets, regarding the amount of transmitted packets by all nodes. Similarly to goodput, the RWP model loses fewer packets in the presence of obstacles, whereas OHBDA and COL models lose a higher amount in these scenarios. Once more, the COL model is the most affected by obstacles, reaching a 70 % packet loss in the 100 node network with high density obstacles.

4.3.4 Delay

This metric measures end-to-end delay of generated application packets in seconds for the entire network between the transmission up to the reception of packets. The delay of lost

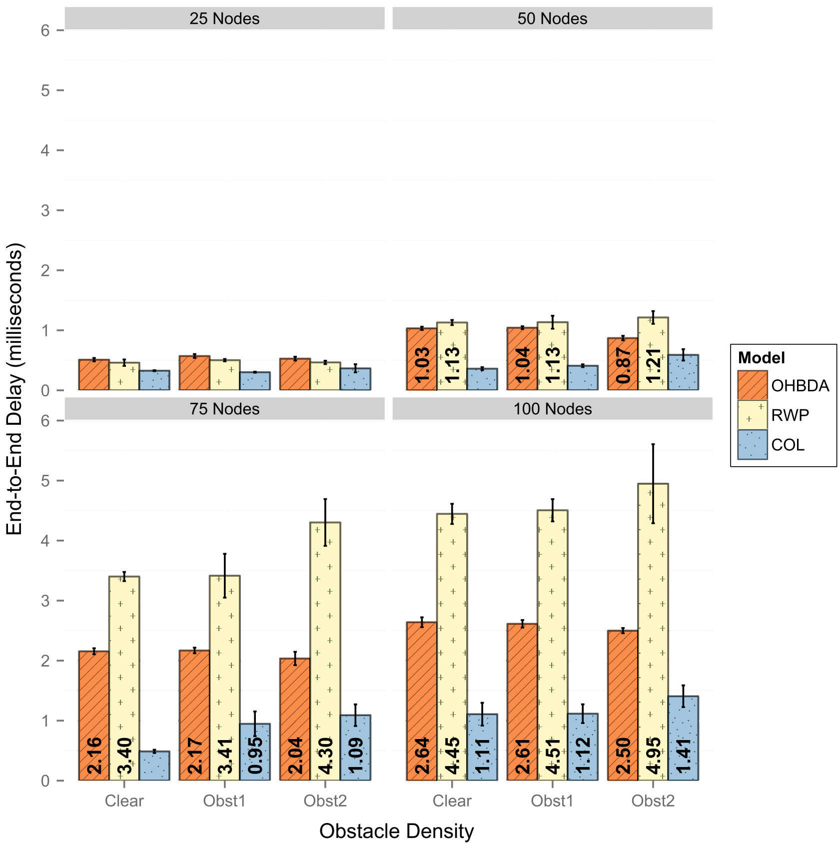

Fig. 8 End-to-end delay of application traffic

packets is discarded. Packets are individually generated by each node and their destination is a random node of the network. This paradigm provides a full delay evaluation regardless of node location and distance between transmitter and receiver.

Figure 8 shows the measured delay for the evaluated scenarios. Generally, the RWP model takes the biggest amount of time to deliver packets. This is caused by the constant link failure inherent to random mobility, since packets are typically stored in node queues for longer until being forwarded. Nodes were configured with a queue buffer of 256,000 bits, thus it is capable of holding up to 62 packets before discarding any. Previous evaluation with lower capacity queues shown a significant increase of packet loss in RWP model. The COL model offers the less delay. Since nodes are organized in a line fashion and there is a big amount of packet loss (as previously seen) the successfully transmitted packets are often quickly delivered. OHBDA sits in the average of the previous models.

4.4 Evaluation Summary

Table 4 summarizes the best, average and worst results of the evaluated models in each metric. The OHBDA model outperforms the remaining in most evaluation metrics, presenting a broader coverage, a more constant node degree, higher goodput and lower packet loss. The COL model, on the other hand, obtains either the best results or the worst, but never in the

Table 4 Summary comparison of models

	Best	Average	Worst
Coverage	OHBDA	RWP	COL
Node degree	OHBDA	RWP	COL
Topology changes	COL	OHBDA	RWP
Goodput	OHBDA	RWP	COL
Packet loss	OHBDA	RWP	COL
Delay	COL	OHBDA	RWP

middle. Its results show less topology changes and a low end-to-end delay. As previously observed, this occurs due to the disposition of nodes in a line, keeping the network topology more stable.

However, in the remaining metrics, the COL model has a great negative impact due to the presence of obstacles. Its coverage, node degree and goodput drop drastically in the presence of obstacles. The RWP model is never the best, obtaining in most metrics an average result.

Considering all the evaluated scenarios, OHBDA is capable of wider area coverage and rate of data transmission at the cost of delay, when compared to COL. COL however, obtains very good results scenarios free from obstacles and provides fast data delivery.

5 Conclusion

In this work, a study of the existent mobility models was conducted, concerning necessary requirements to model post-disaster scenarios. A formal description of the OHBDA model was presented and a obstacle avoidance mechanism was proposed. The OHBDA, RWP and COL models were evaluated, considering different types of scenarios, particularly focusing the network size and density of obstacles. In most metrics, results demonstrated significant differences between OHBDA, RWP and COL. Generally, OHBDA proved to be the most suitable model to handle disaster scenarios, providing better coverage efficiency and higher transmission rate. It presents, however, higher delivery delay and higher routing overhead, when compared with COL. The RWP model obtained average results in most metrics.

In conclusion, the OHBDA and COL mobility models provide a real mobility modelling 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 This work was partially supported by the Portuguese Foundation for Science and Technology (FCT) under a Ph.D. Scholarship (SFRH/BD/81829/2011) and the by the iCIS Project (CENTRO-07-ST24-FEDER-002003), co-financed by QREN, in the scope of the Mais Centro Program and European Unions FEDER. The authors would like to thank the Riverbed Modeler University Program for the licenses provided for the OPNET Modeler Wireless Suite R.

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