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Research Article

DRT mobility model for search and rescue operations based on catastrophic intensity to improve the quality of services

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Abstract

Communication and coordination amongst rescue teams in post-disaster areas (DAs) are essential during search and rescue (SAR) operations. The physical infrastructure network may be partially or fully damaged due to the disaster's nature, hindering communication between rescue teams and delaying the broadcast of information. This paper aims to enhance the quality of services in post-DA by addressing the difficulties of network communication caused by the obstacles and tactical zones, and unrealistic node movement due to the mobility speed of the disaster rescue teams (DRT). Hence, a DRT mobility model is proposed and implemented to simulate DRTs' movement realistically in post-DA. This study modifies the previous DA model by separating the incident location (IL) into four risk-based zones based on catastrophic intensity (CI) values using network simulator 2 (NS2). The network performance of the DRT model outperformed the DA model, achieving a 2.5% improvement in throughput, a 5.4% improvement in PDR, an 83% reduction in overhead, a 5.4% improvement in packet loss rate, and a 0.3% improvement in E2E delay. As a result of improved routing protocol efficiency shown by the higher value of packet delivery ratio (PDR), there is less packet congestion and communication overhead between the rescue teams. This result shows that the proposed method is better in the effectiveness of the communication for the rescue teams to be applied in mobile ad hoc network (MANET). Recommendations for future work are outlined for this study to be extended by considering the movement of the victims in a post-DA.

Keywords

Mobile Ad-hoc network, Mobility model, Post-DA, Nodes mobility, Performance evaluation.

1.Introduction

Natural disasters (NDs) and man-made disasters have distinct characteristics and causative factors. NDs, such as earthquakes, floods, hurricanes, tornadoes, and wildfires, are caused by uncontrollable natural processes and are often unpredictable. They are frequently driven by geological, meteorological, or climatic factors. In contrast, man-made disasters, such as industrial accidents, transportation mishaps, nuclear incidents, and terrorist attacks, result from human actions or omissions.

While NDs have an inherent unpredictability, man-made disasters often stem from human error, technological failures, or deliberate acts with disastrous consequences. Comprehending the unique characteristics and causative factors associated with each type of disaster is crucial for effective disaster preparedness, response, and recovery efforts. This understanding is essential for minimizing the impact of these events on affected areas and populations.

The aftermath of a large-scale disaster presents a critical phase known as the "post-disaster area (DA)". This phase is characterized by the interaction between two key entities: disaster rescue teams (DRTs) and disaster victims. Rescue teams, comprising police, firefighters, medical personnel,

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and volunteers, face the primary challenge of establishing and maintaining reliable communication amidst disrupted infrastructure [1–4]. This is particularly important given that victims often lose contact with the outside world [5]. Rescue teams themselves encounter significant obstacles in securing stable connections due to the dynamic nature of their operations within the disaster zone, which ultimately impacts the effectiveness of search and rescue (SAR) operations [5].

Data confirms a significant surge in the demand for communication following a disaster, particularly within the post-DA. Efficient network communication can be customized to address diverse rescue operations and missions, potentially minimizing loss of life and property [2]. However, the severity of the disaster often leads to partial or complete destruction of physical infrastructure [1]. This necessitates deploying alternative solutions capable of restoring network communication in the face of such devastation.

To bridge the communication gap in the post-DA, an alternative network solution with decentralization and infrastructure-less capabilities is essential. Mobile ad hoc networks (MANETs) offer a potent solution by facilitating reliable communication even in the absence of established infrastructure [6, 7]. These self-organizing networks, formed by mobile devices dynamically, empower rescue teams to establish wireless connections on-the-fly, significantly enhancing communication capabilities within the challenging post-disaster environment [8, 9]. In addition to their crucial role during SAR operations, MANETs also play an important role in the construction of smart organizations, residents, campuses, and battlefields [10].

The effectiveness of SAR operations conducted by rescue teams is influenced by various factors. These include the dynamic movement patterns of team members, potential signal interference, and the presence of environmental obstacles. Traditionally, the previous DA model has been used to simulate rescue teams’ movement, drawing inspiration from concepts like room separation and civil defense tactics [11]. This work aims to refine this approach by introducing a novel DRT mobility model specifically designed to enhance network efficiency during SAR operations in the post-disaster context.

This study aims to refine the existing DA model by introducing a novel DRT mobility model, specifically designed to enhance network efficiency during SAR operations in post-disaster contexts. The research expands upon the previous model by segmenting the existing IL areas into four distinct risk-disaster zones based on varying catastrophic intensity (CI) values. This approach addresses two key limitations of the DA model: the insufficiency of a single isolation location category and the unrealistic movement patterns modeled for rescue teams. By incorporating zone-specific considerations and more nuanced movement dynamics, the DRT model aims to provide a more accurate representation of rescue teams' behavior in the complex and variable post-disaster environment.

The scope of this study primarily focuses on computer simulations designed to evaluate the DRT model's efficacy. The research acknowledges the importance of including both rescue teams and disaster victims in simulations, but the initial phase concentrates solely on the rescue teams' movement and the presence of a single obstacle within the designated areas. This decision allows for a more focused exploration of the DRT model's core functionalities and sets the groundwork for future iterations that incorporate additional complexities.

The investigation centers around three critical research questions aimed at evaluating the proposed DRT model and its potential to improve network efficiency in SAR operations. Firstly, the study examines the relevance of identified movement characteristics. Can these characteristics, carefully chosen to reflect the dynamic and context-dependent nature of rescue teams' movement in disaster zones, be effectively integrated into mobility models designed for such scenarios? Secondly, the research explores into the realism of the DRT model itself. Does this novel approach accurately capture the nuanced movements and decision-making processes of DRTs operating in challenging post-disaster environments? Finally, the study seeks to quantify the impact of the DRT model on network efficiency. To what extent does the enhanced realism translate into improved communication reliability and performance for the rescue teams as they carry out crucial SAR operations? By addressing these multifaceted questions, this research aims to provide a comprehensive evaluation of the DRT model's effectiveness in supporting vital network communication during disaster response efforts.

This work offers three major contributions to the field of disaster preparedness and communication.

Firstly, it identifies and characterizes key DRT mobility features specific to the post-disaster context. This characterization lays the foundation for developing more realistic and context-aware mobility models for future research and applications. Secondly, the study proposes the novel DRT model, a refined approach to MANETs mobility modeling that explicitly considers the movement patterns and behavior of rescue teams within disaster zones. This model represents a significant step forward in tailoring network simulations to accurately reflect the unique challenges and dynamic environment of post-disaster scenarios. Finally, through comparative simulations involving the DRT and the previous DA model, the research provides valuable insights into the efficacy of the DRT model. Evaluating key metrics such as communication reliability and efficiency sheds light on the potential benefits of this novel approach for enhancing network performance and supporting effective SAR operations in the aftermath of disasters. These combined contributions advance the understanding of rescue teams' movement and network communication in post-disaster scenarios, paving the way for more targeted and effective disaster response strategies that rely on reliable and efficient communication infrastructure.

The paper structure is organized into sections. Section 2 describes the review of earlier study findings. Section 3 provides a thorough explanation of the proposed study approach. Section 4 analyses the results obtained through section 3, with tables and supporting graphics. Section 5 discusses a comparative analysis of the DRT and DA models, including the limitations of the study and future recommendations. Section 6 states the conclusions drawn from this study.

2.Literature review

2.1Alternative approaches for disaster recovery networks

For the past years, there have been improvements made by the researchers in terms of the disaster recovery networks. The improvements are made to ensure that the communication can be established successfully within a short time despite having such scenarios such as during the disaster struck. During the SAR operations, it is crucial to have a good communication network which is robust, reliable, and fast deployment. Good communication network will increase the performance of the mobility as the information can be delivered and received well by the rescue teams. Thus, the SAR operations can be conducted smoothly even in the DA scenario.

In a DA scenario, there are some disaster resilient communication networks that can be established to act as the recovery networks. However, each of the disaster resilient communication networks need to consider a few factors such as harsh environment, obstacles, noise signal, implementation costing, etc. Examples of disaster resilient communication networks are flying ad hoc networks (FANETs) [12 – 15], MANETs [16 – 19] and movable and deployable resource units (MDRUs) [20, 21].

The use of unmanned aerial vehicles (UAVs), or drones, has been explored in several studies for improvement of communication on disaster scenarios. He et al. [12] introduced a three-dimensional (3D) group mobility model based on a spiral line for aerial backbone networks in post-earthquake emergency communication, demonstrating improved coverage and capacity compared to traditional methods. Wang and Guo [13] proposed a four-quadrant mobility model-based routing protocol for post-earthquake emergency communication networks, resulting in an enhanced packet delivery ratio (PDR) and end-to-end (E2E) delay performance. Azmi et al. [14] presented a flying ad hoc coverage area mobility model for post-DA communication using two drones, showing improved coverage and capacity in disaster scenarios. Lastly, Ganazhapa et al. [15] discussed the use of drones as mobile network nodes for connectivity support in disaster recovery, resulting in better network connectivity and coverage.

Despite these advancements, there are limitations in each study. He et al. [12] did not consider environmental factors affecting drone movement, while Wang and Guo [13] overlooked the potential impact of network congestion on their routing protocol. Azmi et al. [14] failed to account for weather conditions impacting drone movement and communication, and Ganazhapa et al. [15] did not examine the consequences of drone failure on network performance. Addressing these limitations could further enhance the effectiveness of UAV-based communication solutions in disaster scenarios.

Meanwhile, there were some studies investigated various approaches to improve communication and resource allocation in disaster scenarios using MANETs. Godbole [16] analysed the performance of the AntNet-LA protocol in ad-hoc networks using a DA mobility model, observing enhanced PDR and E2E delay performance. Trono et al. [17] proposed a DA mapping method using spatially distributed computing nodes across a delay tolerant network (DTN), resulting in improved DA mapping and resource allocation. Guo and Huang [18] discussed coverage and capacity for DA wireless networks using mobile relays, leading to optimized network performance in terms of coverage and capacity. Lastly, Guo and Huang [19] proposed a mobility model and relay management for DA wireless networks, resulting in improved PDR and reduced E2E delay.

However, these studies have limitations. Godbole [16] did not consider the potential impact of network congestion on the AntNet-LA protocol, Trono et al. [17] overlooked the potential impact of network congestion on the DTN, Guo and Huang [18] did not account for environmental factors affecting mobile relay movement, and Guo and Huang [19] did not consider the impact of environmental factors on node mobility and relay management. Addressing these limitations could further enhance the effectiveness of these communication and resource allocation solutions in disaster scenarios.

Sakano et al. [20] and Shimizu et al. [21] have explored the use of a MDRU, for disaster response and communication in disaster-stricken areas. Sakano et al. [20] reported improved network connectivity and coverage, while Shimizu et al. [21] demonstrated the MDRU's effectiveness in establishing communication during disasters. However, neither study addressed the potential impact of network congestion on MDRU performance or evaluated its scalability and ability to handle large-scale disasters. Further investigation in these areas could enhance the MDRU's effectiveness in disaster response scenarios.

2.2Realistic mobility model

This section provides a summary of related works that focus on the performance of MANETs under different routing protocols and mobility models in the context of DRT’s movement. Recent research has explored the network performance of routing protocols and algorithm methods using various mobility models through simulations, where the movement traces of nodes are generated using software like Bonnmotion. Aschenbruck et al. [22] introduced BonnMotion, a tool for generating and analyzing mobility scenarios. The tool can be used to evaluate the performance of MANETs in different mobility scenarios. The results showed that BonnMotion is effective in generating and analyzing mobility scenarios. However, the tool does not consider the impact of environmental factors on node mobility.

Aschenbruck et al. [11] proposed the DA model, a mobility model for DA scenarios, aiming to imitate civil defense tactics. The researchers utilized a mobility model based on the behavior of people in disaster situations. The key finding is that this model effectively imitates civil defense tactics but lacks features like group mobility. This research is limited by its simplicity and may not accurately represent the complexity of human behavior in disaster situations.

Nelson et al. [23] presented an event and role-based mobility (ERM) model for disaster recovery networks. The authors utilized roles and events to model the movement of people and resources in a DA. The results indicate improved performance in terms of network connectivity and resource allocation. However, this research does not consider the potential impact of environmental factors on role-based mobility.

Papageorgiou et al. [24] simulated mission-critical MANETs namely, mission-critical mobility model (MCMM) to evaluate their performance in disaster scenarios. The results showed that the proposed MANET architecture is effective in maintaining network connectivity in disaster scenarios. However, the simulation did not consider the impact of node failure on network performance.

Pomportes et al. [25] proposed a composite mobility (CoM) model for ad hoc networks in DAs. The model considers the mobility of nodes and the impact of obstacles on node mobility. The results showed that the proposed model is effective in maintaining network connectivity in disaster scenarios. However, the model does not consider the impact of environmental factors on node mobility.

Conceição and Curado [26] proposed a mobility model based on obstacle-aware human behavior in DAs known as human behavior for disaster areas (HBDA). The model considers the impact of obstacles on node mobility and the behavior of nodes in disaster scenarios. The results showed that the proposed model is effective in maintaining network connectivity in disaster scenarios. However, the model does not consider the impact of environmental factors on node mobility.

Reina et al. [27] evaluated the performance of ad hoc networks in disaster scenarios. The results showed that the proposed network architecture is effective in maintaining network connectivity in disaster scenarios. However, the evaluation did not consider the impact of node failure on network performance. The study by Raffelsberger and Hellwagner [28] evaluated the performance of MANET routing protocols such as ad-hoc on-demand distance vector (AODV), optimized link state routing (OLSR), better approach to mobile ad-hoc networking (BATMAN), and dynamic manet on-demand (DYMO) in a realistic emergency response scenario. The results showed that the proposed routing protocol is effective in maintaining network connectivity in disaster scenarios. However, the evaluation did not consider the impact of environmental factors on node mobility.

Martín-campillo et al. [29] evaluated opportunistic networks in disaster scenarios. The results showed that the proposed network architecture is effective in maintaining network connectivity in disaster scenarios. However, the evaluation did not consider the impact of node failure on network performance.

Reina et al. [30] proposed an evolutionary computational approach for optimizing broadcasting in disaster response scenarios. The approach considers the mobility of nodes and the impact of environmental factors on node mobility. The results showed that the proposed approach is effective in maintaining network connectivity in disaster scenarios. However, the approach does not consider the impact of node failure on network performance.

Reina et al. [31] proposed a modeling and assessment approach for ad hoc networks in disaster scenarios. The authors used a multi-layer mobility model to simulate the movements of people and vehicles in a DA. The results showed that the proposed model can effectively predict the network performance in different disaster scenarios. However, the model does not consider the impact of environmental factors such as weather conditions on network performance.

Reina et al. [32] introduced a multi-objective optimization approach for probabilistic similarity/dissimilarity-based broadcasting schemes in MANETs for disaster response scenarios. The proposed approach uses an evolutionary algorithm to optimize the broadcasting scheme based on network connectivity, energy consumption, and message delivery ratio. The results showed that the proposed approach outperforms traditional broadcasting schemes in terms of network performance and energy efficiency. However, the approach assumes a homogeneous network, which may not be the case in real-world disaster scenarios.

Ebenezer [33] proposed a mobility model for MANETs in large-scale disaster scenarios known as large-scale disaster mobility model (LSDMM). The proposed model considers the movements of people, vehicles, and obstacles in a DA. The results showed that the proposed model can effectively predict the network performance in large-scale disaster scenarios. However, the model does not consider the impact of network topology on network performance.

Arbia et al. [34] investigated the behavior of wireless body-to-body networks routing strategies for public protection and disaster relief. The authors proposed a routing strategy based on the position and velocity of the nodes. The results showed that the proposed routing strategy can effectively reduce the E2E delay and increase the PDR in disaster scenarios. However, the strategy assumes a homogeneous network, which may not be the case in real-world disaster scenarios.

Gondaliya and Atiquzzaman [35] proposed a role-based 3-tier mobility model (RTTMM) for evaluating delay tolerant routing protocols in post-disaster situations. The proposed model considers the movements of people, vehicles, and infrastructure in a DA. The results showed that the proposed model can effectively predict the network performance in post-disaster situations. However, the model does not consider the impact of network congestion on network performance.

Stute et al. [36] reverse engineered human mobility namely, ND model in large-scale disasters using mobile network data. The ND model was based on the movement patterns of people in a DA. The results showed that the proposed model can effectively predict the network performance in different disaster scenarios. However, the model does not consider the impact of environmental factors such as weather conditions on network performance.

Sani et al. [37] evaluated the performance of transmission control protocol (TCP) under different MANET routing protocols in disaster recovery scenarios. The authors used NS2 to simulate the network performance under different routing protocols. The results showed that the proposed approach can effectively improve the network performance in disaster recovery scenarios. However, the approach assumes a homogeneous network, which may not be the case in real-world disaster scenarios.

Al-shehri et al. [38] compared the design strategies and performance evaluations of tactical and commercial MANETs in disaster scenarios. The authors used optimized network engineering tools (OPNET) to simulate the network performance under different design strategies. The results showed that the proposed approach can effectively improve the network performance in disaster scenarios. However, the approach does not consider the impact of environmental factors such as weather conditions on network performance.

Kim et al. [39] proposed a new routing protocol for UAV relayed tactical MANETs. The proposed protocol uses a hybrid routing approach based on the position and velocity of the nodes. The results showed that the proposed protocol can effectively improve the network performance in disaster scenarios. However, the protocol assumes a homogeneous network, which may not be the case in real-world disaster scenarios.

Walunjkar and Rao [40] presented a study on the simulation and evaluation of different mobility models in disaster scenarios. The authors considered three mobility models, which were random waypoint (RWP), random walk (RW), and Gauss-Markov, and evaluated their performance in terms of network throughput, E2E delay, and PDR. The results showed that the RWP model performed the best in terms of network throughput and PDR, while the RW model had the lowest E2E delay. However, the study did not consider the impact of node density and mobility speed on the performance of the mobility models.

Kim et al. [41] proposed a dual-channel-based routing (DCR) technique for indoor disaster environments. The authors introduced a novel routing metric called the "disaster recovery factor" to improve the routing performance in disaster scenarios. The proposed technique was evaluated through simulations, and the results showed that it outperformed the existing routing protocols in terms of PDR, E2E delay, and throughput. However, the study did not consider the impact of node mobility and dynamic changes in the network topology on the performance of the proposed technique.

Younes and Albalawi [42] analysed the route stability in mobile multihop networks under RWP model. The authors proposed a new metric called the "route stability factor" to measure the stability of routes in MANETs. The study evaluated the performance of the proposed metric through simulations and compared it with the existing metrics. The results showed that the proposed metric outperformed the existing metrics in terms of accuracy and efficiency. However, the study did not consider the impact of node density and mobility speed on the performance of the proposed metric.

Mondal et al. [43] presented a framework for post-disaster management using device-to-device (D2D) communication with controlled mobility and opportunistic routing. The authors introduced a novel routing algorithm called the "disaster-aware opportunistic routing algorithm" to improve the routing performance in disaster scenarios. The proposed framework was evaluated through simulations, and the results showed that it outperformed the existing routing protocols in terms of PDR, E2E delay, and throughput. However, the study did not consider the impact of network scalability and dynamic changes in the network topology on the performance of the proposed framework.

Pirzadi et al. [44] proposed a novel reducted-delivery routing (RDR) protocol in hybrid DTN -MANET in critical situations. The authors introduced a new routing metric called the "disaster recovery degree" to improve the routing performance in disaster scenarios. The proposed method was evaluated through simulations, and the results showed that it outperformed the existing routing protocols in terms of PDR, E2E delay, and throughput. However, the study did not consider the impact of node mobility and dynamic changes in the network topology on the performance of the proposed method.

Reina et al. [45] presented an evolutionary computation approach for optimizing connectivity in disaster response scenarios. The authors introduced a novel optimization algorithm called the "disaster response optimization algorithm" to improve network connectivity in disaster scenarios. The proposed algorithm was evaluated through simulations, and the results showed that it outperformed the existing optimization algorithms in terms of network connectivity and resource utilization. However, the study also did not consider the impact of network scalability and dynamic changes in the network topology on the performance of the proposed algorithm.

From the studied related works, two main problems related to mobility models and node movement in post-DA have been identified. The first problem is that most existing mobility models do not adequately capture the characteristics of a DA. These models often overlook crucial factors such as the presence of obstacles and the existence of tactical areas. In reality, during SAR operations, various tactical areas are established to ensure the smooth functioning of the rescue efforts. These may include incident location (IL) areas, casual treatment areas (CTA), technical operational command (TOC), and transport zones (TZ) [11]. CTA areas consist of patient waiting for treatment (PWFT) and casual clearing station (CCS). However, previous works in this field have largely ignored or simplified the representation of these areas, limiting the realism of the mobility models [43, 44]. Additionally, the evaluation of network performance has often been conducted with small numbers of nodes and limited tactical network scales, further hindering the applicability of existing models [40].

The second problem pertains to the unrealistic node movement of rescue teams during SAR operations in post-DA. In reality, different types of rescue teams, including firefighters, police, medical teams, ambulances, and volunteers, are assigned to different tactical areas based on their roles and the nature of the catastrophe. This results in varying movement speeds of the nodes within the network. However, existing models fail to capture the diversity of movement patterns observed in real-life scenarios, where vehicles and people move at different speeds and exhibit varying node densities [45].As a result, the node movement in current mobility models lacks realism and does not accurately represent the dynamics of post-DA.

Moreover, in catastrophic areas, the mobile devices carried by rescue teams form a dynamic MANET group, where nodes may join or leave the network, leading to the loss or instability of links [5]. Maintaining stable connections between nodes is crucial for effective communication and coordination among rescue teams. Failure to do so can result in high levels of data traffic and network congestion, hampering the timely exchange of critical information.

To address these research problems, the DRT model is proposed and further described in Section 3. The DRT model intends to improve the network efficiency in the post-DA by considering the tactical areas, realistic node movement, and maintaining stable connections within the network. By addressing these research problems, the study aims to enhance the efficiency of SAR operations and communication reliability in post-DA.

3.Methods

In this section, we provide an overview of the DRT model and describe the improvements made to the previous DA model, a widely used mobility model for investigating the performance of rescue teams during post-disaster scenarios. We have implemented the DRT model using different node speeds to indicate various scenarios. The DRT mobility model modifies the IL area, dividing it based on disaster risk levels, referred to as CI, which includes zero-risk, low-risk, medium-risk, and high-risk levels. This modification aims to enhance the efficiency of SAR operations during the post-disaster phase.

Figure 1 illustrates the framework of the previous DA model, while *Figure 2* presents the framework of the DRT model. *Figures 3* and *4* describe the node movement implemented for each of the IL areas under the DRT model.

3.1Proposed DRT framework

The DRT mobility model modifies the previous DA model to improve the efficiency of SAR operations during the post-disaster phase. We implemented the model using different node speeds to indicate various scenarios. The IL area is modified and divided based on disaster risk levels or CI, which included zero-risk, low-risk, medium-risk, and high-risk levels.

Area 7, as depicted in *Figure 3*, represents the area with a high-risk level of disaster. This area is closest to the disaster, and the probability of having the next wave of disaster is high. In this area, there are only stationary nodes, and no transport nodes are involved, as we assume that this area is severely affected, and obstacles exist. Therefore, there is no movement using vehicles in this area due to the challenging terrain conditions. The stationary nodes move randomly within the area and focus on SAR operations, continuing to move until the area is declared safe, and all victims have been successfully rescued or found.

Area 6, as shown in *Figure 3*, represents the area with a medium-risk level of disaster. This area is the second closest to the disaster, and the probability of having the next wave of disaster is medium. In this area, there will be stationary nodes and transport nodes. The stationary nodes move within the area using random-based movement, while the transport nodes move back and forth from Area 6 to Area 7. The transport nodes refer to the rescue teams using vehicles to evacuate the victims in Area 7. Area 5, depicted in *Figure 3*, represents the area with a low-risk level of disaster. This area is less affected by the disaster, and the probability of having the next wave of disaster is low. In this area, there will be stationary nodes and transport nodes. The stationary nodes move within the area using random-based movement, while the transport nodes move back and forth from Area 5 to Area 0. The transport nodes refer to the rescue teams using vehicles to evacuate the victims from Area 5 to Area 0.

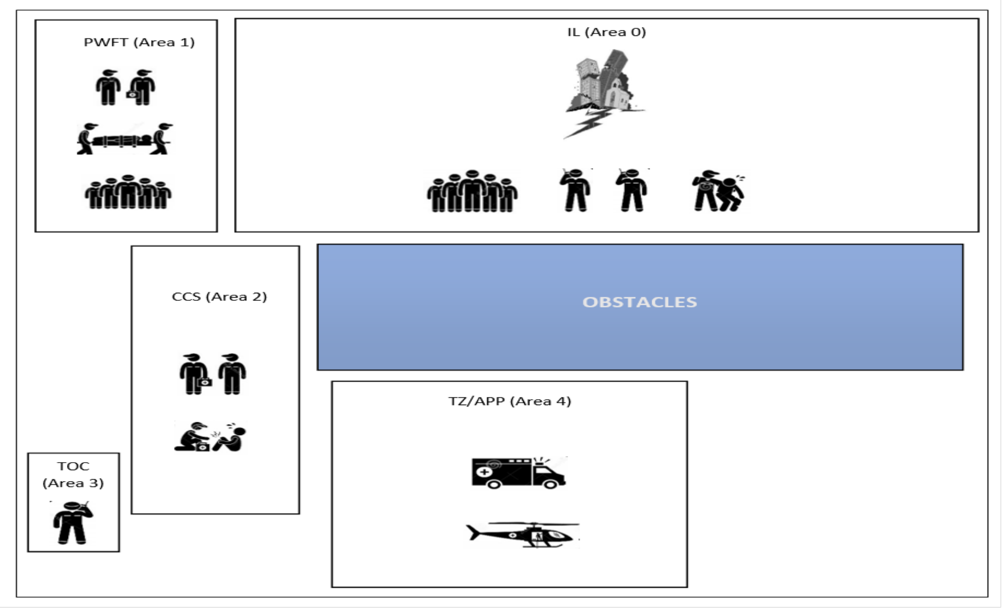

Figure 1 Previous DA model framework [11]

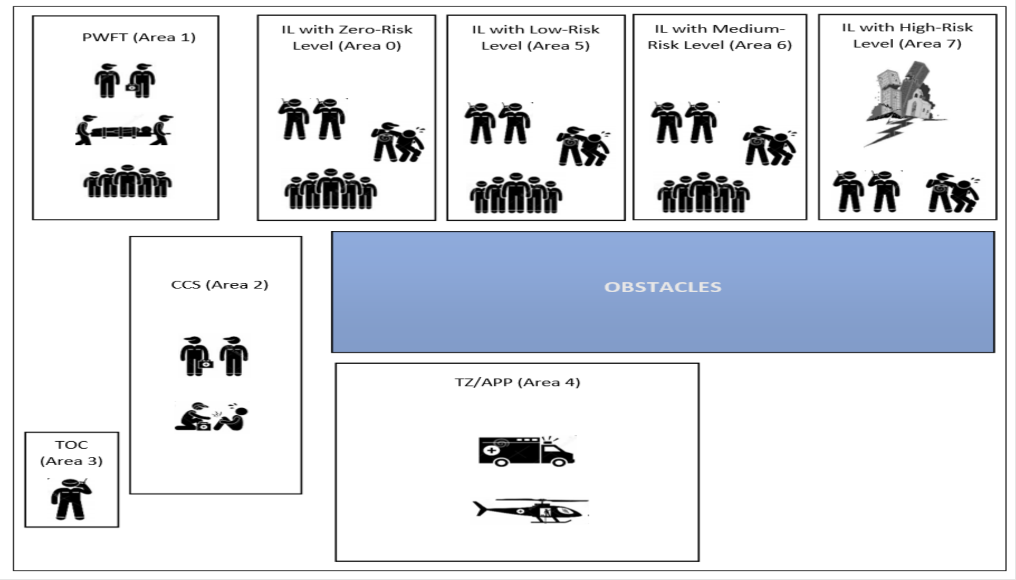

Figure 2 Proposed DRT model framework in the IL areas

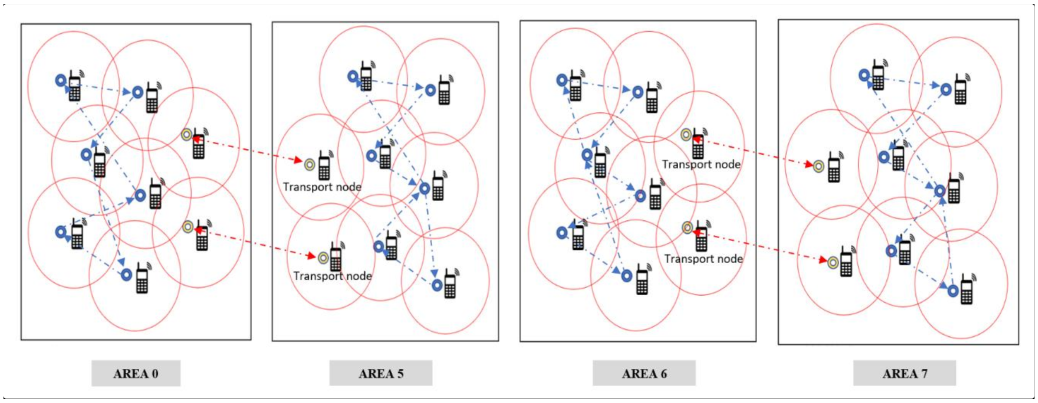

Figure 3 Movement of nodes in IL areas under DRT model

Area 0, depicted in *Figure 4*, represents the area with a zero-risk level of disaster. This area is the least affected by the disaster, and the probability of having the next wave of disaster is almost zero. In this area, there will be only transport nodes that focus on evacuating victims from Area 0 to Area 1 (PWFT).

While the DRT model is based on the DA model, there are a few differences that are highlighted as the main features. *Table 1* below shows the similarities and dissimilarities of DA and DRT models, respectively.

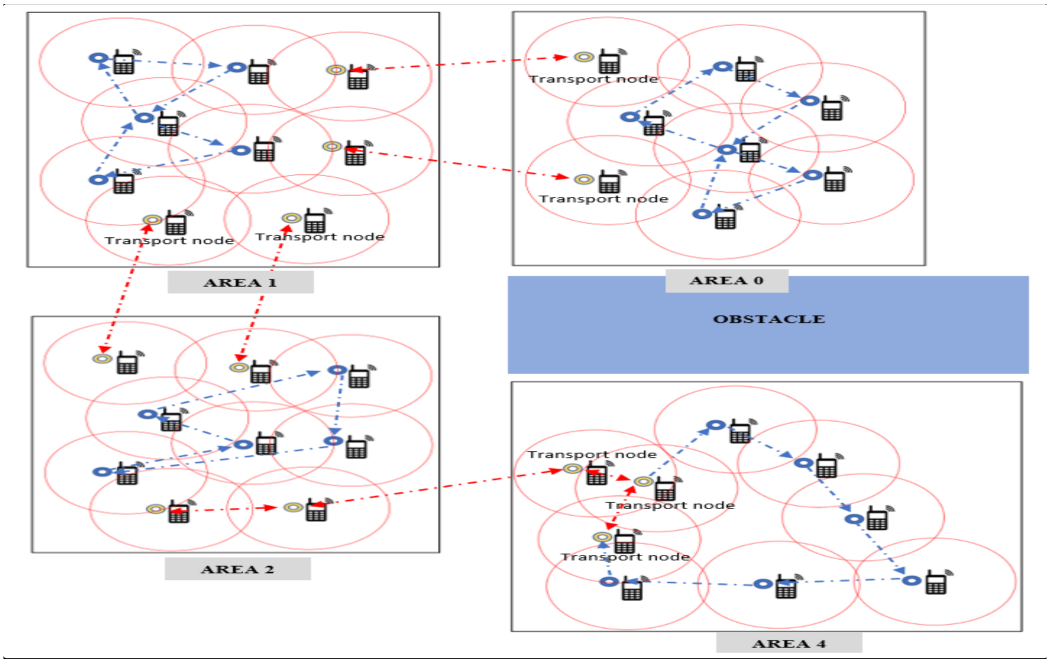

Figure 4 Movement of nodes in Area 0 under DRT model

Table 1 Similarities and dissimilarities of DA and DRT mobility models

Mobility model	**Incident Location**	**PWFT**	**CCS**	**TOC**	**Ambulance Parking Point / TZ**	**Incident Location with Zero-risk**	**Incident Location with Low-risk**	**Incident Location with Medium-risk**	**Incident Location with High-risk**	**Suit the Post-DA Scenario**	**Only Focus on the Movement of the Rescue**	**Based on Room Separation Techniques**	**Consider Different Speeds of Nodes**
DA	/	/	/	/	/					/	/	/	/
DRT		/	/	/	/	/	/	/	/	/	/	/	/

3.2 Simulation analysis

In our comparative analysis of MANET mobility models, as reported in [46], we evaluated the network performance by varying the number of nodes to 100, 120, 140, 160, 180, and 200. The node speed was configured to simulate both walking and vehicle speeds, specifically 1 to 2 m/s for walking and 5 to 12 m/s for vehicles [45]. Four sets of experiments were conducted, each consisting of six simulations. The radio transmission range for each node was set to 150 m, and the duration of each experiment was 150 seconds. The simulation area was 850 x 300 m.

We used constant bit rate (CBR) as the traffic source, which transmits data at a constant rate. The number of connections was set up to 50, indicating the maximum number of connections to a target node from a source node. The data payload size was 512 bytes, and the routing protocol used was AODV. AODV was chosen as it provides the routing table based on the shortest path, which is crucial for ensuring that messages sent by rescue team members are sent using the shortest number of hops in the routing table. This characteristic allows messages to be received successfully within a short period.

For the first two sets of experiments, referred to as Scenario I, the parameter settings were configured to use 1-2 m/s for the node speed at the IL under the DA and DRT models to mimic the movement of rescue teams at walking speed. For the parameter settings in the next two sets of experiments, referred to as Scenario II, the node speed of 1 to 2 m/s and 5 to 12 m/s were set at the IL using the DA and DRT models, respectively, to depict the movement of rescue teams that involved both walking and vehicle speeds.

The parameters of the proposed work are presented in *Table 2*, while the list of hardware and software used is shown in *Table 3*. The experimentation was conducted using NS2, and the simulation results will be discussed in the following section, along with a discussion of the findings.

Table 2 Simulation parameters [46]

Parameter	Specification
Mobility model	DRT and DA mobility model
Speed	1-2 m/s (walking speed) 5-12 m/s (vehicle's speed)
Number of nodes	100, 120, 140, 160, 180, 200
Simulation area	850×300 (m)
Simulation time	150 (sec)
Propagation model	Two-ray ground model
Transmission range	150 (m)
Packet size	512 (bytes)
Traffic type	CBR
Number of connections	50
Routing protocol	AODV

Table 3 Hardware and software requirements

Hardware Requirements	Software Requirements
Minimum 20 GB ROM or above (memory storage)	Linux (Ubuntu 16.04) or Windows 7
Minimum 2 GB RAM or above	GCC & G++
Laptop	Bonnmotion 3.0.1
Mouse	NS2.35 & Ns2 GUI Trace File Analyzer (NsGTFA) 4.0
	Java JDK 1.8

3.3 Performance network metrics

3.3.1Throughput

Throughput is the number of packets successfully delivered per unit time [47]. It refers to the total amount of received packet size at the destination node in a simulated amount of time. Equation 1 denote the calculation for the throughput:

$$\text{Throughput} = \left(\frac{Pr\ X\ SP}{T}\right) X \left(\frac{8}{1000}\right) \qquad (1)$$

where the throughput is determined in kbps, Pr is the packet number received by the destination node, SP size packet (SP) and T is the simulation time. T is referred to the difference value between Stop Time and Start Time. The throughput is a key metric in determining the efficiency and performance of a network, as it reflects the amount of data that can be transmitted over the network in a given time. Thus, the best performance is achieved if this metric is maximum[48].

3.3.2PDR

PDR is the ratio of the total number of data packets received by the destination node and the total number of data packets sent by the source node [47]. Hence, the PDR can be formulated as Equation 2:

$$\text{PDR} = \left(\frac{Pr}{Ps}\right) X\ 100\% \qquad (2)$$

where Pr is the number of packets received by the destination node and Ps is the number of packets sent by the source node. It specifies the packet loss rate, which limits the maximum throughput of the network. A high PDR value indicates a reliable network, while a low PDR value may indicate issues with the network's performance or stability. Hence, PDR is an important metric in the evaluation of network performance, as it provides information about the reliability and efficiency of data transmission over the network.

3.3.3Overhead

Overhead is the total number of packets to be transferred from one node to another. It includes the overhead of the routing process, routing table and packet preparation in a sensor node. Overhead can be denoted as Equation 3:

$$\text{Overhead} = \left(\frac{Rp}{Dp}\right) \qquad (3)$$

where Rp is the total of routing packets and Dp is the total of data packets.

3.3.4Packet loss rate

Packet loss rate expresses the reliability of a communication network path. The packet loss rate can be explained as the difference between a total number of data packets unreceived divided by the total number of packets sent and can be denoted as Equation 4:

$$\text{Packet loss rate} = \left(\frac{Px}{Ps}\right) X\ 100\% \qquad (4)$$

where Px is the number of data packets unreceived at the destination and Ps is the number of data packets sent by the source nodes during transmission.

3.3.5E2E Delay

E2E delay is the difference time of receiving packets at the destination. The packets may experience delays due to queueing process on interface, route discovery process or retransmission process [49]. In other papers [50, 51], E2E delay is defined as the total delay or time taken by a packet to successfully reach the sink node. Equation 4 denote the calculation for the E2E delay:

$$\text{E2E delay} = N\ x\ (dproc + dtrans + dprop) \quad (5)$$

where N is the number of links between routers, *dproc* is the average processing delay incurred by a router, *dtrans* is the average transmission delay and *dprop* is the average propagation delay. The E2E delay returns the time in miliseconds (ms). This metric should be minimized to get better performance [48].

4.Results

We analysed the DRT and DA models, by measuring their performances according to the following metrics: throughput, PDR, overhead, packet loss rate, and E2E delay. *Figure 5* to *Figure 9* interpret the simulation results with the involvement of walking speed only. Meanwhile, *Figure 10* to *Figure 14* present the simulation results with the involvement of the additional vehicle’s speed.

4.1Network performance of the rescue teams using walking speed

4.1.1Throughput

Figure 5 illustrates the throughput performance of the DA and DRT models as the number of nodes varied from 100 to 200. The DRT model demonstrated a marginally better performance compared to the DA model, with an overall increase in throughput of approximately 2.5%. This result suggests that employing the DRT mobility model can improve network performance in terms of throughput, thereby enhancing communication between DRT in a post-DA. This improvement can contribute to more effective disaster response efforts by facilitating better communication among rescue teams.

4.1.2PDR

Figure 6 displays the PDR performance of the DA and DRT models as the number of nodes increased. While both models showed comparable efficacy, the DRT model performed slightly better, with an improvement of 5.4% in PDR. This result indicates that employing the DRT mobility model can enhance the network performance of PDR in IL areas, as shown in the graph. This improvement is particularly important in post-disaster scenarios, where reliable communication between rescue teams is crucial for effective disaster response efforts. The DRT model's superior PDR performance highlights its potential to improve communication reliability and support more successful SAR operations in the aftermath of disasters.

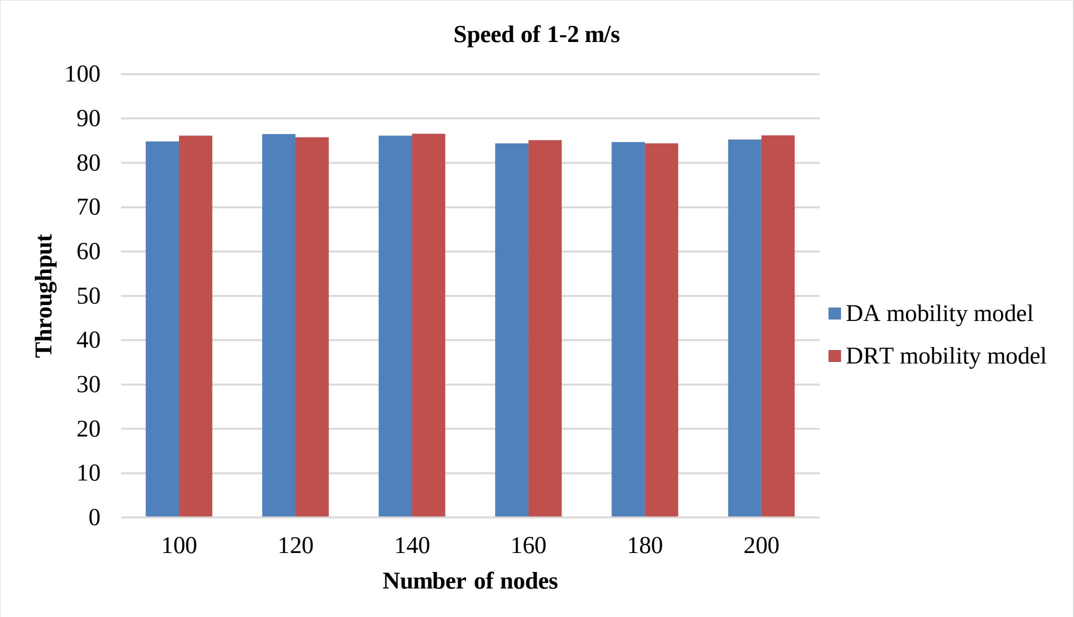

Figure 5 Throughput vs the number of nodes

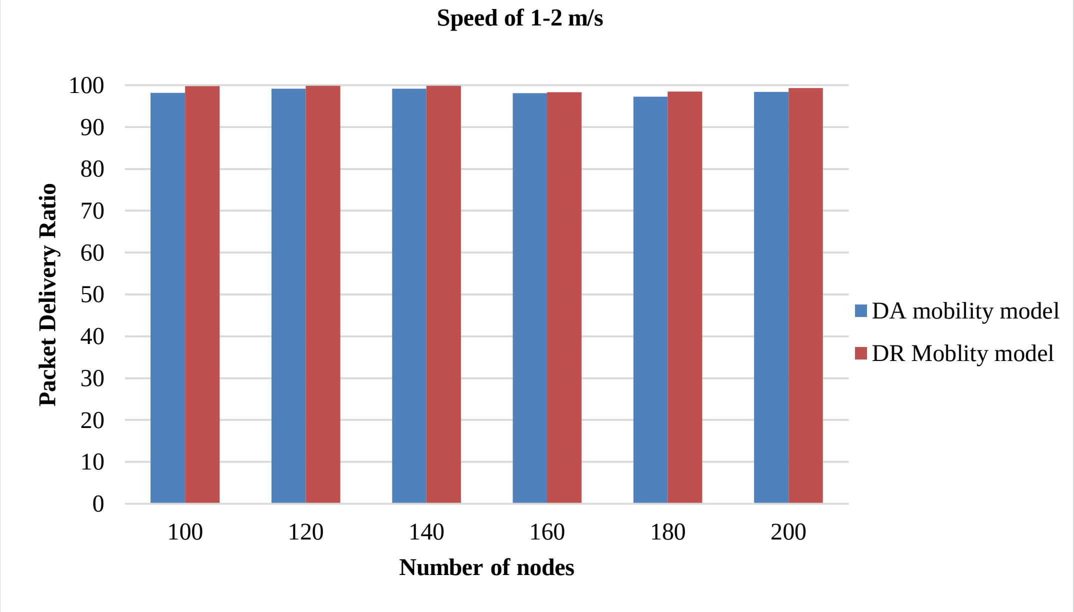

Figure 6 PDR vs the number of nodes

4.1.3Overhead

Figure 7 presents the overhead results for the DRT and DA models as the number of nodes ranges from 100 to 200. The overhead of the DRT model was significantly lower than that of the DA model throughout the experiment. Both models maintained nearly constant overhead when the number of nodes was less than 120. However, when the number of nodes exceeded 140, the overhead of both models increased linearly. When the number of nodes reached 180, both models showed a slight decrease in overhead. Despite having the same number of nodes as the DA model, the DRT model maintained a lower overhead value, indicating reduced energy consumption for each device in the IL areas. This reduction in overhead can contribute to an extended network lifespan for members of the DRT, making the DRT mobility model a more efficient choice for post-disaster communication.

4.1.4Packet loss rate

In addition, Figure 8 illustrates the packet loss rate for the DRT and DA models as the number of nodes ranges from 100 to 200. The DRT model demonstrated a slightly lower packet loss rate compared to the DA model, with differences of approximately 2% when there were 100 nodes, and nearly 1% when the number of nodes was 120 versus 140. However, when the number of nodes reached 160, both models exhibited a 1% increase in packet loss rate. When the number of nodes reached 180, the DA model demonstrated a 1% increase, while the DRT model maintained its results. Finally, when the number of nodes reached 200, both models experienced a roughly 1% decline. These results indicate that implementing the DRT model can improve communication reliability between DRT members in IL areas, as shown by the lower packet loss rate compared to the DA model. This improvement can contribute to increased effectiveness of SAR operations in disaster-affected areas, making the DRT mobility model a more reliable choice for post-disaster communication.

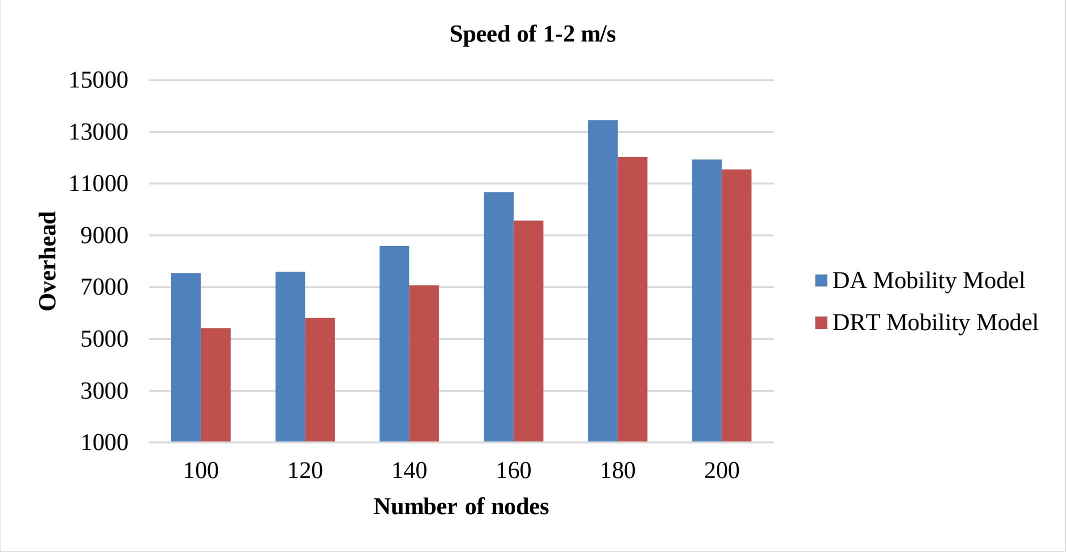

Figure 7 Overhead vs the number of nodes

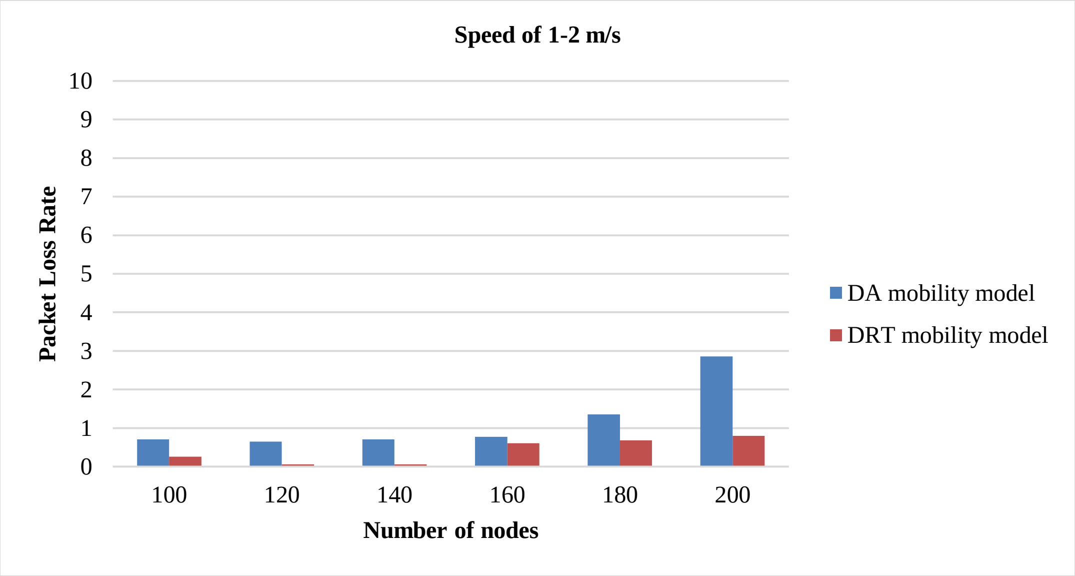

Figure 8 Packet loss rate vs the number of nodes

4.1.5E2E delay

In terms of E2E delay, *Figure 9* shows that the DRT model consistently outperforms the DA model. When the number of nodes is less than 160, both models have comparable E2E delay performance. However, as the number of nodes exceeds 160, a modest increase in E2E delay is observed in the DRT model, although it remains within an acceptable range. In contrast, the DA model exhibits greater and less stable E2E delay values than the DRT model, with a maximum E2E delay value at 180 nodes, which is higher than the DRT model's E2E delay value at 200 nodes. The DRT model consistently obtains a lower E2E delay, approximately 0.21% less than the DA model, even as the number of nodes increases. Minimizing communication delays is crucial for rescue teams to quickly adapt their strategies, allocate resources efficiently, and prioritize areas requiring immediate attention. The correlation between the movement of the DRT, E2E delay, and SAR operations highlights the importance of effective and expeditious communication in post-disaster situations. The DRT model's capacity to reduce E2E latency expedites the dissemination of vital information to DRT members, resulting in enhanced coordination, shortened response times, and improved effectiveness of SAR operations.

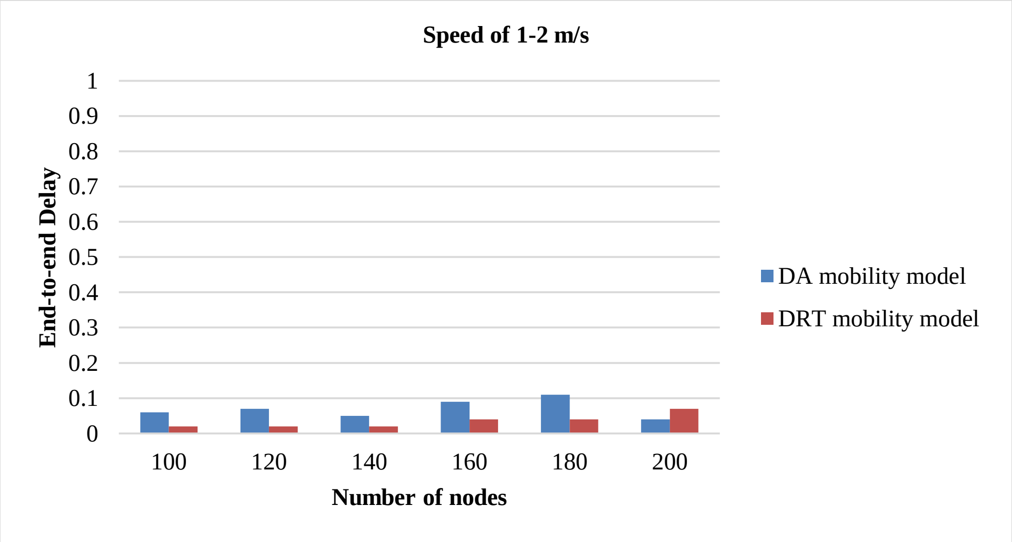

Figure 9 E2E delay vs the number of nodes

4.2Network performance of the rescue teams with additional vehicle's speed

4.2.1 Throughput

According to *Figure 10*, the two models had similar performance as the number of nodes increased. However, the DRT model demonstrated a slight performance improvement, with a rise of 4.54% in total throughput. This result indicates that network communication for transport nodes in areas 0, 5, and 6 can be enhanced by using the DRT model. The improved throughput can contribute to more efficient communication among rescue teams, allowing for better coordination and resource allocation during disaster response efforts.

4.2.2 PDR

In addition, according to *Figure 11*, both models maintained a nearly constant PDR value as the number of nodes increased from 100 to 200. The DRT model had a slight increase over the DA model, with an increase of 4.58% in overall PDR, even when vehicle speed was considered. This result confirms that the network performance of PDR in areas 0, 5, and 6 can be enhanced by implementing the DRT model. The improved PDR indicates a more reliable communication network for rescue teams, which can contribute to more successful SAR operations in disaster-affected areas.

4.2.3 Overhead

Figure 12 illustrates the fluctuation of overhead as the number of nodes increased. According to the results presented in the table below, the DRT model's overhead increased consistently when the number of nodes reached 100 and remained nearly constant until the number of nodes exceeded 160. The DRT model was still applicable for networks with more than 180 nodes, despite a slight increase in overhead.

On the other hand, when there were fewer than 160 nodes in the network, the value of the DA model's overhead rose more rapidly than that of the DRT model. When there were 160 nodes, the DA model's overhead was roughly equivalent to the DRT model's overhead. However, when the number of nodes reached 200, the DA model's overhead increased significantly and attained its maximum level, which was approximately 16,000. In contrast, the DRT model attained a maximum overhead level of 11,600. This result demonstrates that, by employing the DRT mobility model, the energy consumption of each device in zones 0, 5, and 6 can be reduced in proportion to the vehicle's speed. Therefore, the network communication between the DRT in the post-DA can be prolonged, allowing for more efficient communication and resource allocation during disaster response efforts.

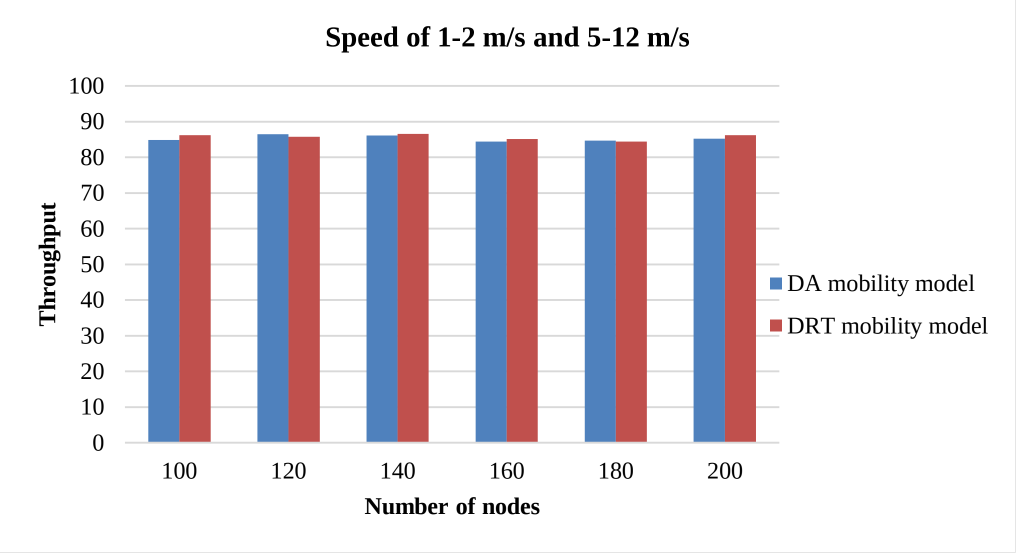

Figure 10 Throughput vs the number of nodes

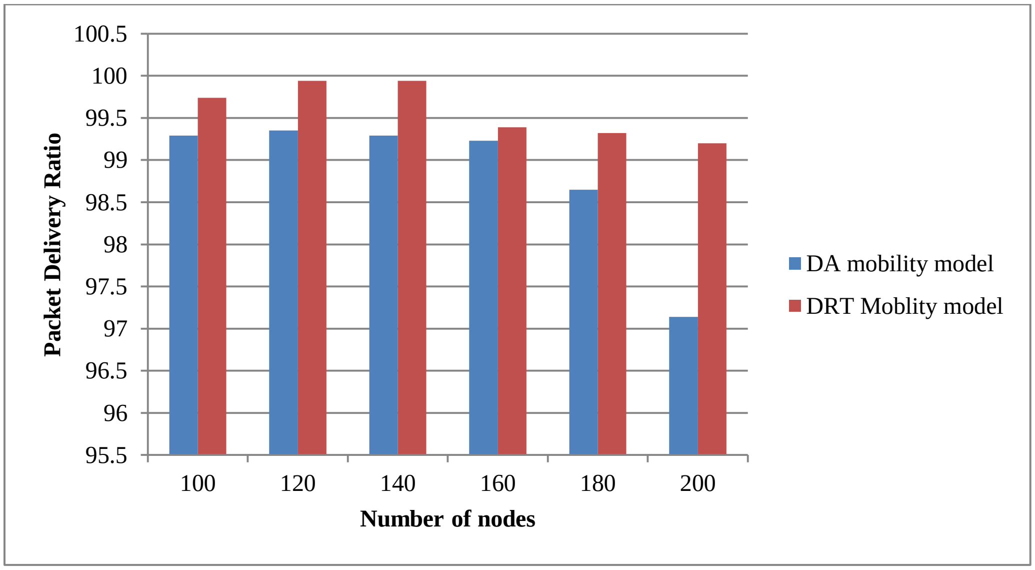

Figure 11 PDR vs the number of nodes

4.2.4 Packet loss rate

Figure 13 illustrates the packet loss rate for both the DRT and DA models as the number of nodes increased. When the number of nodes was less than 180, the efficacy of both models was nearly identical. However, when the number of nodes exceeded 180, the DA model's packet loss rate increased by approximately 2%, whereas the DRT model's performance remained virtually unchanged.

In conclusion, the DRT model was able to achieve a significantly lower packet loss rate than the DA model, even as the number of nodes increased. This improvement in packet loss rate demonstrates that the communication reliability between DRT members in zones 0, 5, and 6 can be enhanced through the implementation of the DRT model. This improvement can contribute to increased effectiveness of SAR operations between DRT in post-DAs, as reliable communication is crucial for coordinating rescue efforts and ensuring the safety of all team members.

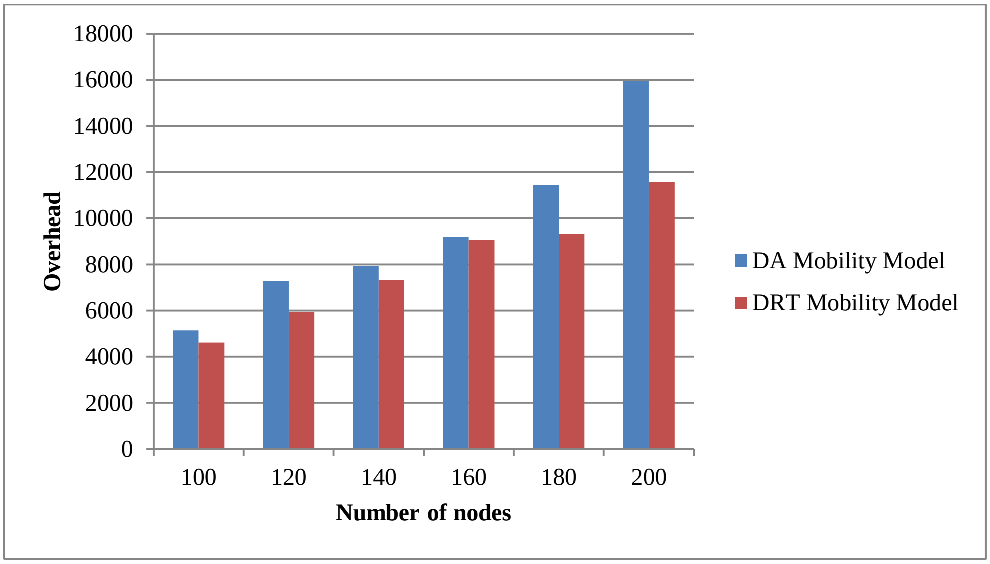

Figure 12 Overhead vs the number of nodes

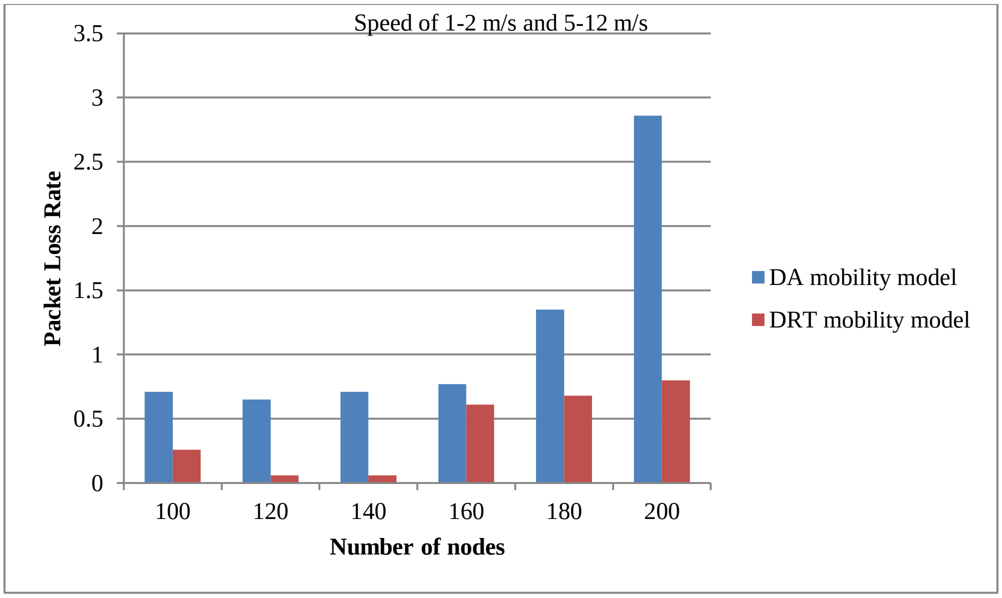

Figure 13 Packet loss rate vs the number of nodes

4.2.5 E2E delay

Lastly, *Figure 14* illustrates the E2E delay for both the DRT and DA models as the number of nodes increased. The DRT model consistently reduces the E2E delay in comparison to the DA model, even as the number of nodes increases. The highest E2E delay value for the DRT model is observed at 160 nodes, whereas the highest value for the DA model is observed beyond 160 nodes and remains constant thereafter. However, the highest value of the DRT model is regarded as acceptable because it is lower than that of the DA model.

In terms of overall efficacy, the DRT model reduces the E2E delay by approximately 0.3%, even with an increasing number of nodes. This reduction in communication delays enables the DRT to rapidly adapt its strategies, effectively allocate its resources, and prioritize areas requiring immediate attention. The correlation between the movement of the DRT, E2E delay, and SAR operations highlights the importance of effective and expeditious communication in post-disaster situations. In conclusion, the DRT mobility model demonstrated superior performance in terms of E2E delay compared to the DA model. This improvement can contribute to more effective disaster response efforts by facilitating faster communication among rescue teams, improving coordination, and shortening response times. The DRT mobility model's potential to reduce E2E delay highlights its potential to significantly enhance communication among rescue teams and improve the overall efficiency of disaster response efforts. Future research can focus on implementing and testing the DRT mobility model in real-world disaster scenarios to further evaluate its effectiveness and potential for improving disaster response efforts.

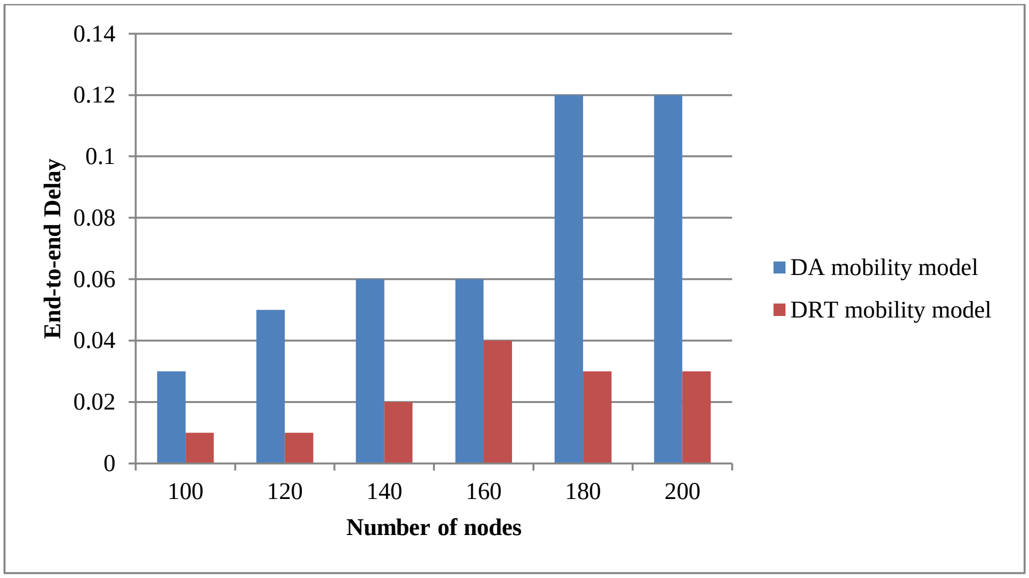

Figure 14 E2E delay vs the number of nodes

5.Discussion

This section explores into the profound implications of our research, focusing on the DRT mobility model's impact on SAR operations in disaster-affected areas. Our findings are pivotal, not only in enhancing the effectiveness of SAR operations but also in contributing to the broader discourse on disaster management and technology integration. *Table 4* and *Table 5* below offer a comprehensive performance assessment for both models, DA and DRT, in the SAR operations within IL areas, considering varying node speeds representative of walking rescue teams (1-2 m/s for walking speed) and transportation teams (1-2 m/s, 5-12 m/s for vehicle speed).

Our study introduced the DRT mobility model, a novel approach designed to realistically simulate the dynamic movements of SAR teams and improve communication in disaster-stricken environments. Key findings indicate that Under walking speed conditions (*Table 4*), the DRT model significantly outperforms existing DA models by improving network throughput, and PDR, and reducing E2E delay and network overhead. Specifically, we observed a 2.5% increase in throughput and a 5.4% improvement in PDR when compared to the DA model.

The implications of these findings extend beyond the immediate context of SAR operations, impacting disaster management policies, technological advancements, and community resilience strategies. By proving the efficacy of the DRT model, our research indicates the necessity for adopting advanced simulation models in planning and executing disaster response strategies. This can inform policy-making, with an emphasis on investing in technologies that support the DRT model's implementation and operationalization. Transitioning to vehicle speed conditions (*Table 5*), the DRT model continues to outperform the DA model, showing incremental improvements in throughput and PDR by 4.54% and 4.58%, respectively. Notably, the DRT model demonstrates a remarkable reduction in packet loss rates and E2E delays under vehicle speed conditions, indicating its suitability for scenarios involving faster transport.

From the comparative analysis shown by *Tables 4* and *5*, the DRT model meaningfully outperforms the previous DA model in terms of overall network performance. The DRT model shows a slight increment in throughput and PDR compared to the DA model, but it still achieves a good agreement in terms of overhead, packet loss rate, and E2E delay. The packet loss rate has been reduced as we achieved a higher throughput and PDR. When the packet loss rate is reduced, the delay in communication is also reduced. A lower value of E2E delay decreases the overhead of the network, thereby increasing the communication lifetime.

Tables 4 and *5* comparatively analyzing the DRT and DA models highlights the former's superior performance in key operational metrics crucial for effective SAR operations. This comparative study not only validates the DRT model's effectiveness but also positions it as a viable tool for enhancing disaster response strategies. Our analysis indicates the importance of adopting comprehensive and realistic simulation models in improving the overall effectiveness of disaster management efforts.

Table 4 Comparison of performance evaluation of previous DA model and DRT model with speed of 1-2 m/s (walking speed)

Num. of nodes	**Throughput (%)**		**PDR (%)**		**Overhead**		**Packet loss rate (%)**		**E2E delay**	
	DA	**DRT**	**DA**	**DRT**	**DA**	**DRT**	**DA**	**DRT**	**DA**	**DRT**
100	84.82	86.17	98.14	99.81	7545	5418	1.86	0.19	0.06	0.02
120	86.51	85.75	99.20	99.87	7599	5815	0.80	0.13	0.07	0.02
140	86.15	86.55	99.17	99.84	8599	7080	0.83	0.16	0.05	0.02
160	84.37	85.13	98.09	98.36	10668	9572	1.91	1.6	0.09	0.04
180	84.72	84.43	97.29	98.45	13448	12031	2.71	1.6	0.11	0.04
200	85.24	86.23	98.40	99.36	11932	11548	1.60	0.64	0.04	0.07
Increment (%) of DRT over DA model	**2.5**		**5.4**		**-83.27**		**-5.39**		**-0.21**	

Table 5 Comparison of performance evaluation of previous DA model and DRT model with speed of 1-2 m/s and 5-12 m/s (vehicles speed)

Num. of nodes	**Throughput (%)**		**PDR (%)**		**Overhead**		**Packet loss rate (%)**		**E2E delay**	
	DA	**DRT**	**DA**	**DRT**	**DA**	**DRT**	**DA**	**DRT**	**DA**	**DRT**
100	86.04	86.30	99.29	99.74	5145	4609	0.71	0.26	0.03	0.01
120	85.47	86.16	99.35	99.94	7269	5945	0.65	0.06	0.05	0.01
140	85.62	86.70	99.29	99.94	7938	7334	0.71	0.06	0.06	0.02
160	86.22	86.02	99.23	99.39	9188	9059	0.77	0.61	0.06	0.04
180	85.17	85.79	98.65	99.32	11446	9309	1.35	0.68	0.12	0.03
200	83.84	85.93	97.14	99.20	15945	11556	2.86	0.80	0.12	0.03
Increment (%) of DRT over DA model	**4.54**		**4.58**		**-91.99**		**-2.00**		**-0.3**	

5.1Limitations and recommendations

While our study marks a significant advancement in disaster response simulation, it is not without limitations. The model's reliance on accurate and timely data presents a challenge, especially in chaotic post-disaster environments where data collection can be hindered. Furthermore, the current implementation of the DRT model does not fully account for the unpredictable nature of human behavior in disaster situations, an aspect that future research could aim to integrate.

To address these limitations and further enhance the model's applicability, we recommend further development of the DRT model to incorporate real-time data analytics and machine learning for dynamic scenario adaptation.

Moreover, extensive field-testing of the model in varied disaster scenarios to validate and refine its predictive accuracy and operational reliability. It is recommended to establish a collaboration between disaster management agencies, technology developers, and academic researchers to ensure the model's practical implementation aligns with on-ground needs. A complete list of abbreviations is summarized in *Appendix I.*

6.Conclusion

In this work, we present significant advancements in disaster management and technology, particularly in the context of post-disaster communication networks. The DRT model demonstrates improved network performance, resulting in enhanced communication capabilities for DRT. This improvement is crucial for effective SAR operations, as quick response times, better situational awareness, and increased likelihood of successful actions can significantly save lives and resources during disaster recovery efforts.

Beyond internal team communication, the DRT model's potential to reduce network congestion enables seamless coordination with external stakeholders, such as support personnel, medical facilities, and the general public. This expanded coordination capability is essential for large-scale disasters, where collaboration between multiple organizations and the public is necessary for efficient and timely recovery efforts.

In terms of environmental and societal impacts, implementing the DRT model can contribute to sustainability and community resilience. By improving communication efficiency, the DRT model can help reduce energy consumption and resource waste associated with network congestion and ineffective communication. Moreover, the enhanced SAR operations resulting from the DRT model's implementation can minimize the environmental impact of disasters by facilitating faster recovery efforts and reducing the time required for cleanup and rebuilding.

From a societal perspective, the DRT model can strengthen community resilience by improving disaster response capabilities. Effective communication networks during disasters can empower communities to respond more quickly and effectively to emergencies, fostering a greater sense of self-reliance and preparedness. Furthermore, the DRT model's potential to coordinate with external stakeholders can facilitate better resource allocation and support from local authorities, ultimately contributing to more robust and resilient communities.

The DRT mobility model represents a significant leap forward in the realm of disaster management and SAR operations. By providing a more realistic simulation of SAR team movements and improving communication efficiency, the model sets a new benchmark for disaster response strategies. Embracing these advancements will not only improve immediate SAR efforts but also contribute to building more resilient and prepared communities.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

None.

Author’s contribution statement

Fatin Fazain Mohd Affandi: Conceptualization, writing-original draft preparation, methodology, software, visualization formal analysis, writing-reviewing-editing and validation. **Nor Aida Mahiddin:** Supervision, validation, writing-reviewing-editing and funding acquisition. **Zarina Mohamad:** Supervision, validation, writing-reviewing-editing and funding acquisition.

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Appendix I

S. No.	Abbreviation	Description
1	3D	Three-Dimensional
2	AODV	Ad-hoc On-Demand Distance Vector
3	BATMAN	Better Approach to Mobile Ad-hoc Networking
4	CBR	Constant Bit Rate
5	CCS	Casual Clearing Station
6	CI	Catastrophic Intensity
7	CoM	Composite Mobility
8	CTA	Casual Treatment Area
9	D2D	Device-to-Device
10	DA	Disaster Area
11	DCR	Dual-Channel-Based Routing
12	DRT	Disaster Rescue Team
13	DSR	Dynamic Source Routing
14	DTN	Delay Tolerant Network
15	DYMO	Dynamic MANET On-Demand
16	E2E	End-to-End
17	ERM	Event and Role-Based Mobility
18	FANETs	Flying Ad hoc Networks
19	HBDA	Human Behavior for Disaster Areas
20	IL	Incident Location
21	LSDMM	Large-Scale Disaster Mobility Model
22	MANETs	Mobile Ad hoc Networks
23	MDRUs	Movable and Deployable Resource Units
24	MCMM	Mission-Critical Mobility Model
25	ND	Natural Disaster
26	NS2	Network Simulator2
27	NsGTFA	Ns2 GUI Trace File Analyzer
28	OLSR	Optimized Link State Routing
29	OPNET	Optimized Network Engineering Tools
30	PDR	Packet Delivery Ratio
31	PWFT	Patient Waiting for Treatment
32	RDR	Reducted-delivery Routing (RDR)
33	RTTMM	Role-based 3-Tier Mobility Model
34	RW	Random Walk
35	RWP	Random Waypoint
36	SAR	Search and Rescue
37	SP	Size Packet
38	TCP	Transmission Control Protocol
39	TOC	Technical Operational Command
40	TZ	Transport Zone
41	UAVs	Unmanned Aerial Vehicles