Sistemasi: Jurnal Sistem Informasi ISSN:2302-8149
Volume 15, Nomor 8, 2026: 3368-3377 e-ISSN:2540-9719

Network Emergent Coverage Patterns from Stochastic Dynamic Models

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(***received***: 4 August 2026, ***revised***: 29 August 2026, ***accepted***: 30 August 2026)

Abstract

This work investigates the influence of the movement patterns (mobility) of network nodes on the overall performance of the network in terms of the area that can be covered by nodes' communications. This is important because, in urban areas, there are still areas that cannot be covered due to a lack of communication range of network nodes (sensors). Usually covering all areas may lead to a heavy cost due to the number of static sensors that might be implanted in particular areas. Therefore, this research comes to overcome this issue by testing a variety of mobility models and seeing which of them lead to a better performance. This work is based on simulations performed on a wide range of settings and variables such as mobility models, number of nodes within the network, network distribution of nodes, communication range of nodes, and other settings. The evaluation is based on the amount of area that is covered under particular settings. The findings show that the Exponential and Levy Flight models reflect the highest exploration efficiency (MNVL = 96.39 and 95.59 respectively). The Rayleigh Flight model show the largest average coverage area with alomost 36.3%. However, it shows high variability of CV=5.04%. The Levy with Exponential Cutoff model reflects high stability rate with CV=0.16% and moderate coverage of 31.7%.

Keywords: coverage area, dynamic networks, mobility model, network simulation, node density, stochastic mobility.

1 Introduction

1.1 Research Overview

Mobile Ad hoc Networks (MANETs) are infrastructure-less wireless systems in which mobile nodes are connected to each other via direct or multi-hop paths. Contrary to the traditional networks, MANETs do not depend on centralized management or fixed base stations. In this architecture, each node acts as a router for data transmission to other nodes and a communication terminal. This flexibility enables MANETs for fast deployment in various situations such as disaster recovery, military operations, and emergency response where traditional infrastructure is difficult to presents [1] (Sarkar & Ali, 2025).

Even with these advantages, the continuous movement of nodes leads to a dynamic and unstable network topology. The positions of nodes are changing and the distance between devices is changing. So, communication links are getting connected or disconnected. Moving out of the transmission range of its neighbors may isolate a node temporarily, while moving towards other nodes can increase communication opportunities and improve network connectivity. Furthermore, mobility has a major effect on the effective coverage area of wireless networks. Recently Sun et al. (2023) [2] study the influence of Node Speed and 3D Mobility on Coverage Probability and Handover Frequency based on UAV Networks. The experimental results the effect the speed, altitude and geographic location on the continuity and quality of wireless coverage. Consequently, during the investigation of dynamic wireless environments, mobility is considered along with transmission range and node distribution. Coverage and connectivity, while related, represent different properties of the network. Coverage means the physical coverage where wireless services are available, while connectivity refers to the ability of a node in a network receiving and sending information. Controlled mobility can help to optimize the node distribution and reduce coverage holes, but high-speed or uncontrolled movement can result in unstable links, frequent topology changes, and network fragmentation.

 ISSN:2302-8149
e-ISSN:2540-9719

Recent studies are recognizing mobility-related parameters as an important metric that determine the performance of MANETs. In particular, Eltahlawy et al.(2023) [3] published a detailed analysis about the parameters that effect the MANETs behavior's. They revealed that the communication manner is influenced by node mobility, density, transmission range, and topological dynamics. The changes induced directly with mobility have an immediate impact on the link availability and stability of nomadic networks, as shown by their detailed analysis. stressing that the integration of mobility and connectivity is to be assessed jointly in ad hoc environments.

In addition to that, the research has also been primarily directed towards modeling mobility. In [4], De Nardis and Di Benedetto also proposed a modular mobility model for next-generation wireless networks, demonstrating that various movement behaviors generate diverse topological properties and spatial correlations of nodes. They concluded that mobility models play an important role (over network structure and communication opportunities) and should therefore be taken into account in the coverage/connectivity analysis of dynamic environments. In addition, Fazio et al. (2023) [5] Research on Mobility Behavior in Wireless ad hoc Environments and found that those variations of movement behavior of nodes do exercise an impact on stability. They also corroborated that a characterization of mobility is necessary for an accurate performance assessment in dynamic scenarios. This finding is especially relevant for the study of the correlation between the mobility patterns and the effective coverage area in MANET.

However, very few earlier works have focused on Routing performance and mobility in UAV-assisted networks. Nevertheless, there is a lack of evidence of a direct connection between node mobility and the total effective coverage area in conventional MANETs. In this paper, we fill this void by exploring the impacts of parameters like node speed, mobility patterns, pause time, and number of nodes on coverage and connectivity.

1.2 Literature Review

The literature includes numerous studies investigating the issues of coverage area and network resource consumption. One of the earliest studies was performed by Wang et al. (2007) [6] and examined the interaction between nodal mobility, spatial density, and wireless coverage envelope. The study demonstrated that relocating a subset of sensor nodes to coverage-deficient regions in a strategic manner can improve k-coverage performance effectively. The work also demonstrated that regulated mobility can reduce the need for high nodal density compared to stationary network configurations. The authors proposed a decentralized relocation algorithm using local network state information. Thus, this study provides a theoretical foundation to explain the mechanisms of mobility to improve coverage efficiency in wireless sensor networks. Moreover, Aoueileyine et al. (2023) [7] studied the provision of wireless coverage in small-cell Unmanned Aerial Vehicle (UAV) networks for serving terrestrial Internet of Things (IoT) devices. UAVs were modeled as mobile aerial base stations, and the spatial dynamics were simulated by the Random Waypoint (RWP) mobility model. To this end, we derive analytical expressions for coverage, service, and encounter probabilities in order to shed light on the spatio-temporal frequency of communication link establishment between mobile UAVs and IoT terminals. The results show that the interaction of UAV mobility patterns and beaconing schedules fundamentally affects service availability, data transmission efficiency, and energy consumption. Thus, this research confirms that the mobility patterns of the flying nodes are a vital factor for achieving adequate wireless coverage of dynamic networks.

Khan et al. (2023) [8] provided a comprehensive technical synthesis of UAV swarm integration for network orchestration in sixth-generation (6G) wireless paradigms. The authors explain that the spatial flexibility and rapid deployment of UAVs make it possible to achieve large coverage extension, massive connectivity, and robust service delivery in emergency or highly dynamic environments. But the constant movement of aerial nodes results in frequent topological changes, which causes serious issues such as link stability, energy efficiency, cybersecurity, and network management. While the investigation does not empirically quantify coverage metrics, it provides a basic theoretical framework to characterize the effect of mobility in UAV-assisted ad hoc network architectures.

More recently, Ben Saoud and Nasraoui (2025) [9] introduced a coverage optimization framework to improve the reliability of UAV-assisted 5G and 6G communication architectures. The investigation

ISSN:2302-8149
e-ISSN:2540-9719

investigated the complex interdependencies of UAV spatial deployment, operational altitude, A2G channel characteristics, coverage radius, and system reliability. These results highlight the importance of identifying the optimal UAV coordinates and altitudes for a larger service footprint with the needed reliability. The work is found to be largely consistent with the present work, in which the spatial reconfiguration of the UAV impacts the distance of the signal propagation to the terrestrial terminals, which has a significant impact on the effective coverage envelope.

On the other hand, the authors of [10] studied the communication coverage optimization of wireless robotic networks composed of autonomous mobile agents. The authors proposed a distributed deployment algorithm that adjusts the spatial coordinates of the agents based on local network state data dynamically. The methodology was designed to achieve the largest possible aggregate communication coverage footprint while minimizing the number of active agents required. Empirical results show that regulated agent mobility improves coverage efficiency and reduces redundant coverage overlap. The study confirms that the spatial behavior of wireless nodes is an important aspect of the effective coverage envelope of a network. Almeida et al. (2021) [11] presented a traffic-adaptive topology control framework for aerial ad hoc networks. Their approach enabled the dynamic spatial reconfiguration of UAV-assisted access points as a function of the geographical distribution and heterogeneous traffic demands of terrestrial users. The study combined strategic UAV placement with predictive routing protocols to ensure link persistence during node handoffs. Empirical results show that mobility-aware spatial positioning provides better network coverage and quality of service (QoS) and reduces communication interruptions caused by topological volatility. Hence, this study highlights the critical interaction among mobility management, coverage optimization, and routing approaches in mobile wireless environments.

Lin et al. (2022) [12] developed a framework for Unmanned Aerial Vehicle (UAV) aiming to provide emergency wireless connectivity when terrestrial communication infrastructure is destroyed (or unavailable). The method optimizes the UAV three-dimensional coordinates to maximize the number of terrestrial nodes covered by the coverage footprint. The findings reveal facts related to the proposed framework such that the dynamic deploy of UAVs in space to match the distribution of terrestrial nodes can enhance the coverage of the network. Regarding this research, we state that regulated mobility is a possible way to extend the coverage of the wireless. Hu et al. (2022) [13] investigated the challenges of coverage deficits due to the stochastic mobility of terrestrial terminals in UAV-assisted network architectures. Unlike traditional models where users are static, the authors designed adaptive mobility strategies for UAV-mounted base stations to dynamically adjust their spatial configuration in accordance with the trajectories of the terminals. Simulation results show that the combination of aerial mobility and delay-tolerant service protocols substantially enhances the probability of successful communication. Our work shows that terminal mobility often leads to temporary coverage holes, whereas controlled base-station mobility is able to effectively mitigate these holes, resulting in a better overall availability of service and robustness of the network.

A similar study performed by Binh et al. (2023) [14] studied topology orchestration in 5G-enabled Mobile Ad hoc Networks (MANETs) by proposing the TFACR algorithm, which enables the dynamic adjustment of nodal communication coverage radii. The proposed algorithm adjusts the transmission ranges adaptively according to the state information of the network in real time, thus controlling the nodal degree. The results show that flexible adjustment of coverage radius significantly enhances topological stability and connectivity robustness, throughput, and energy efficiency. This study is particularly relevant for MANET architectures, since it demonstrates that the interaction between coverage radius and spatial distribution of nodes is the main factor for durability and stability of communication links.

1.3 Problem Statement and Contribution

The main limitations in the literature can be summarized as follows:

- Most of the works in the literature concentrate on the performance of routing protocols and connectivity metrics rather than coverage area.
- The literature lacks of comparative analysis of mobility models under different conditions.
- The issue of analyzing the coverage area metric under different considitions is still unexplored.

ISSN:2302-8149
e-ISSN:2540-9719

- The use of statistical analysis when validating the performance of networks is not frequently used.

Hence, this work tries to investigate this issue and test five mobility models under different settings and validate the performance using advanced statistical analysis, which is novel. This is to come up with an optimal strategy that can cover more areas within the network environment and minimize the cost. Moreover, the objectives of this research are:

- To quantify the impact of using different mobility models on network coverage area in MANET network.
- To assess the coverage area metric under a variety of nodes distributed with the simulation environment.
- To validate the performance of the experiments using advanced statistical analysis.
- To correspond the better mobility model to the best fit applications.
- To investigate the use of different node density on network performance.

2 Research Method

The approach followed in this research employs an experimental approach to analyze the impact of different mobility models on network performance in terms of coverage in mobile ad-hoc networks (MANETs). This research focuses on evaluating the Mean Number of Visited Locations (MNVL) and the Coverage Area (CA). These metrics are essential for evaluating network exploration efficiency and area coverage capability. The experimental design incorporates three primary independent variables that systematically vary across the experimental space:

- Number of Nodes (N): The number of mobile nodes deployed in the network is 100, 200, 400, 800, and 1200 nodes. This range was carefully selected to represent Small-scale networks, Medium-scale networks, and Large-scale networks.
- Nodes Distribution: In all the experiments, the nodes are distributed within the simulation environment based on a Power-Law distribution. This distribution makes all nodes follow the probability density function $P(\mathrm{k}) \propto \mathrm{k}^{\propto}$ where $P(k)$ is the probability of a node having degree k and α is the power-law exponent (typically between 2 and 3, with $\alpha \approx 2.5$ in this study). This distribution was chosen because it accurately represents real-world network topologies.
- Mobility Models: In the experiments, five mobility models are used; each of them represents different movement patterns observed in real-world scenarios (see Table 1).

Table 1 Mobility models used in this work.

Mobility Model	Mathematical Description	Physical Interpretation
Exponential	$P(t) = \lambda e^{-\lambda t}$	Memoryless movement with constant probability of direction change.
Rayleigh Flight	$P(r) = \frac{r}{\sigma^2} e^{-r^2/(2\sigma^2)}$	Flight lengths with small steps are most probable, rare long jumps.
Cauchy Flight	$P(r) = \frac{1}{\pi\gamma[1 + (r/\gamma)^2]}$	Heavy-tailed distribution with occasional very long flights.
Levy Flight	$P(r) \propto r^{-(1+\beta)}, 0 < \beta < 2$	Power-law distributed flight lengths with frequent short and occasional long movements.
Levy with Exp Cutoff	$P(r) \propto r^{-\beta} e^{-\lambda r}$	Power-law with exponential truncation for realistic movement bounds.

The dependent variables and measurement used in this research are:

- Mean Number of Visited Locations (MNVL): this metric quantifies the exploration efficiency of mobile nodes and is calculated as:

$$MNVL = \frac{1}{N} \sum_{i=1}^{N} V_i \tag{1}$$

ISSN:2302-8149
e-ISSN:2540-9719

Where V_i is the number of unique locations visited by the node i during the simulation period. N is the total number of nodes in the network. Higher MNVL values indicate better network exploration and more thorough coverage of the operational area.

- Coverage Area (CA): It represents the percentage of the total operational area that has been visited by at least one node during the simulation:

$$CA = \frac{A_{covered}}{A_{to}} \text{x}100\% \tag{2}$$

Where $A_{covered}$ is the area covered by the union of all node trajectories and A_{total} is the total operational area.
On the other hand, the statistical analysis of this research includes Central Tendency Measures for each experimental configuration, we compute the Arithmetic mean that is given by:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

We also compute the Geometric mean for growth rates as follows:

$$G = \left(\prod_{i=1}^{n} x_i\right)^{1/n} \tag{4}$$

Additionally, we calculate standard deviation and coefficient of variation (CV) where applicable:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{5}$$

$$CV = \frac{\sigma}{\bar{x}} \times 100\% \tag{6}$$

Furthermore, the relationship between MNVL and the number of nodes follows a power law model:

$$MNVL = a \cdot N^b \tag{7}$$

The parameters are estimated using logarithmic transformation is given by:

$$\ln(MNVL) = \ln(a) + b \cdot \ln(N) \tag{8}$$

The growth exponent b provides crucial insights:

- If $b < 0$: Performance decreases with node count (negative scaling)
- If $b = 0$: Performance is independent of node count
- If $0 < b < 1$: Sub-linear growth (diminishing returns)
- If $b = 1$: Linear growth
- If $b > 1$: Super-linear growth (positive network effects)

We also used the 95% confidence intervals for the regression parameters. The percentage of Growth Rate increase between consecutive node counts is computed as:

$$\Delta MNVL_{i \to j} = \frac{MNVL_{N_j} - MNVL_{N_i}}{MNVL_{N_i}} \times 100\% \tag{9}$$

This metric is able to show the optimal scaling regions, the diminishing returns thresholds, and the efficiency gains from adding more nodes. The saturation level at maximum node count (N=1200) compared to the penultimate level (N=800):

$$\eta = \frac{MNVL_{1200} - MNVL_{800}}{MNVL_{800}} \times 100\% \tag{10}$$

The saturation can reveal the following:

- $\eta < 2\%$: Near-perfect saturation (little benefit from additional nodes)
- $2\% \leq \eta < 5\%$: Moderate saturation
- $5\% \leq \eta < 10\%$: Low saturation (continued benefits)
- $\eta \geq 10\%$: No saturation (still gaining from more nodes)

Finally, the efficiency metric combines MNVL with node count as follows:

$$E = \frac{MNVL}{N} \times 100 \tag{11}$$

ISSN:2302-8149
e-ISSN:2540-9719

This represents the percentage of nodes that are effectively utilized in terms of exploration. However, the complete experimental procedure follows these steps:

Step 1: Deploy N nodes in the operational area following Power-Law distribution and set initial node positions and orientations.
Step 2: Execute the specified mobility model for a fixed simulation duration.
Step 3: Calculate MNVL for each node at the end of the simulation.
Step 4: Each configuration is replicated 30 times, and statistical measures and confidence intervals are calculated.
Step 5: Perform descriptive and inferential statistical analysis.

All the simulations are conducted using NetLogo simulator that uses environment of 5x5 km^2 imitating a real life environment that includes MANET network. The communication range of the nodes of the MANET is 50m, and all the experiments are run for 30 times, where the average is considered. Also, 95% of confidence interval is used for all the experiments' ket metrics. The nodes move based on specific mobility model and no node can go out the boarder of the environment due to the restrictions involved in the settings of the mobility models and the environment used.

3 Results and Analysis

The complete MNVL results with detailed analysis are presented in Table 2 for the exponential mobility model. It can be observed that the model achieves the highest absolute MNVL values (96.39 at N=1200). Furthermore, the performance gains diminish rapidly after N=400. Near-saturation is reached at N=800 (only 1.08% improvement to N=1200). This means that this mobility model fits optimal network size of 400-800 nodes for this mobility pattern. And the marginal benefit of adding nodes beyond 800 is negligible. Table 3 shows the results of the Rayleigh Flight model. It can be shown that the highest growth rate is from N=100 to N=1200 (236.9%). The absolute MNVL values are the lowest among all models. Moreover, the best performance for small networks (N<400) is due to a high growth rate. However, it shows limited exploration capability despite high growth. The results of the Cauchy Flight model are shown in Table 4. It represents consistent improvement across all node counts with strong performance in mid-range networks (400-800 nodes). I also show that it maintains satisfactory growth even at high node densities. We also observed balanced performance between exploration and scalability. In Table 5, we present the results of the Levy Flight model. The results show that it is the second highest absolute MNVL values and reflects similar performance to the exponential model as well as better than the exponential model for N<400. It also shows near-perfect coverage stability (26.1%) and is adequate for applications requiring high exploration and stable coverage. Finally, Table 6 shows the results of the Levy flight with exp cut off. It is the most consistent growth pattern across all node counts. It also shows the lowest saturation at N=1200 (10.15% increase). Moreover, it is bounded by the cutoff mechanism, preventing explosive growth, which is good for controlled exploration.

Table 2 Results of the experiments using exponential mobility model.

Number of Nodes	MNVL	Increment	% Increase	Cumulative %
100	68.17	Baseline	-	100%
200	81.99	13.82	20.27%	120.27%
400	89.47	7.48	9.12%	131.24%
800	95.36	5.89	6.58%	139.89%
1200	96.39	1.03	1.08%	141.40%

Table 3 Results of the experiments using rayleigh mobility model.

Number of Nodes	MNVL	Increment	% Increase	Cumulative %
100	11.86	Baseline	-	100%
200	19.89	8.03	67.71%	167.71%
400	27.65	7.76	39.01%	233.14%
800	37.24	9.59	34.68%	313.99%
1200	39.96	2.72	7.30%	336.93%

ISSN:2302-8149
e-ISSN:2540-9719

Table 4 Results of the experiments using cauchy flight mobility model.

Number of Nodes	MNVL	Increment	% Increase	Cumulative %
100	41.46	Baseline	-	100%
200	51.07	9.61	23.18%	123.18%
400	67.85	16.78	32.86%	163.65%
800	80.79	12.94	19.07%	194.86%
1200	86.74	5.95	7.36%	209.21%

Table 5 Results of the experiments using levy flight mobility model.

Number of Nodes	MNVL	Increment	% Increase	Cumulative %
100	64.03	Baseline	-	100%
200	76.16	12.13	18.94%	118.94%
400	84.83	8.67	11.38%	132.49%
800	94.05	9.22	10.87%	146.89%
1200	95.59	1.54	1.64%	149.29%

Table 6 Results of the experiments using levy flight with exponential cut-off mobility model.

Number of Nodes	MNVL	Increment	% Increase	Cumulative %
100	25.16	Baseline	-	100%
200	36.93	11.77	46.78%	146.78%
400	48.72	11.79	31.92%	193.64%
800	60.99	12.27	25.19%	242.41%
1200	67.18	6.19	10.15%	267.02%

In Table 7, the performance of the mobility models used in this work is presented. The results show that Exponential models reflect perfect coverage stability that is independent of node density. The Rayleigh Flight model is considered the most variable coverage with a highest average coverage of 36.3%. However, the coverage fluctuates with node count and is the best for maximizing area coverage. The Cauchy model gains high stability of 3.08% with satisfactory coverage (31.2% on average). The Levy model gains perfect stability with moderate coverage of 26.1%. It is considered consistent across all configurations, which means it is reliable for planned deployments. Finally, Levy with Exp Cutoff model gains near-perfect stability of (CV = 0.16%) with stable coverage of 31.7% and controlled expansion, which is good for predictable operations.

Table 7 Performance of mobility models in this work in terms of coverage area.

Mobility Model	N=100	N=200	N=400	N=800	N=1200	Std Dev	CV (%)
Exponential	23.7	23.7	23.7	23.7	23.7	0.000	0.00
Rayleigh Flight	35.1	35.0	38.3	38.3	34.8	1.806	5.04
Cauchy Flight	29.2	31.7	31.6	31.7	31.6	0.973	3.08
Levy Flight	26.1	26.1	26.1	26.1	26.1	0.000	0.00
Levy with Exp Cutoff	31.7	31.7	31.6	31.6	31.7	0.052	0.16

Furthermore, Figure 1 demonstrates the impact of mobility models on network exploration efficiency, while Figure 2 shows the comparative growth rates of all the mobility models used in this work's simulations. Moreover, the coverage area heatmap of the mobility models and number of nodes involved are depicted in Figure 3. We also performed a correlation analysis of MNVL and coverage area. These figures enable us to extract many facts about the impact of mobility models used and the other settings of the network. Hence, Table 8 presents practical recommendations of the possible scenarios that network architects can consider during the design phase.

ISSN:2302-8149
e-ISSN:2540-9719

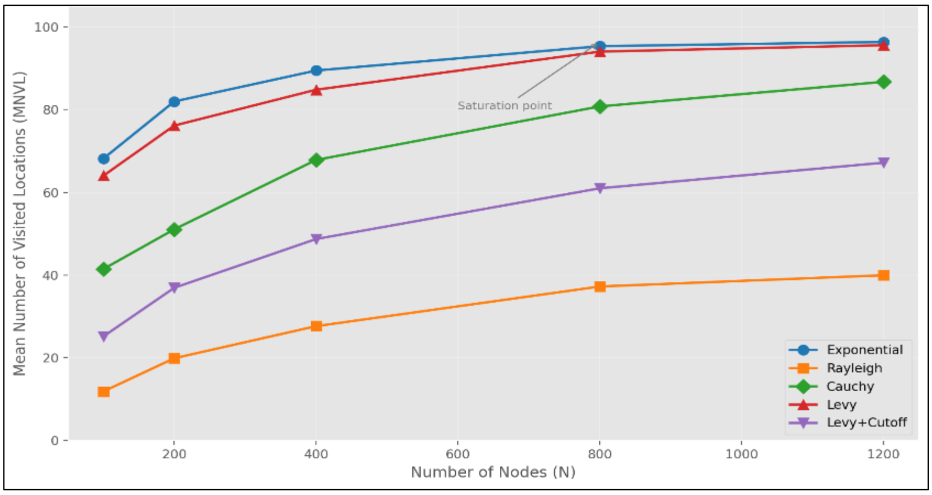

Figure 1 Impact of mobility models on network exploration efficiency.

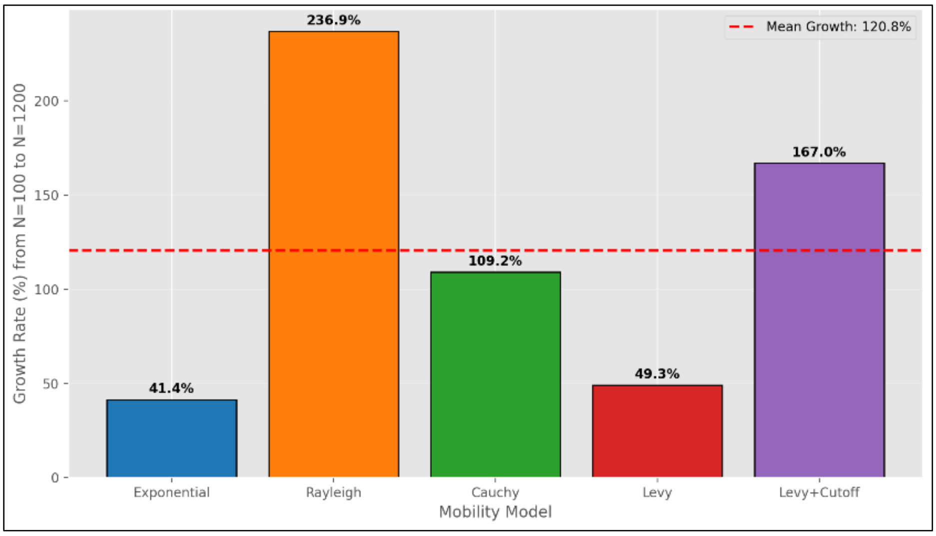

Figure 2 Comparative growth rates of the mobility models used in this work.

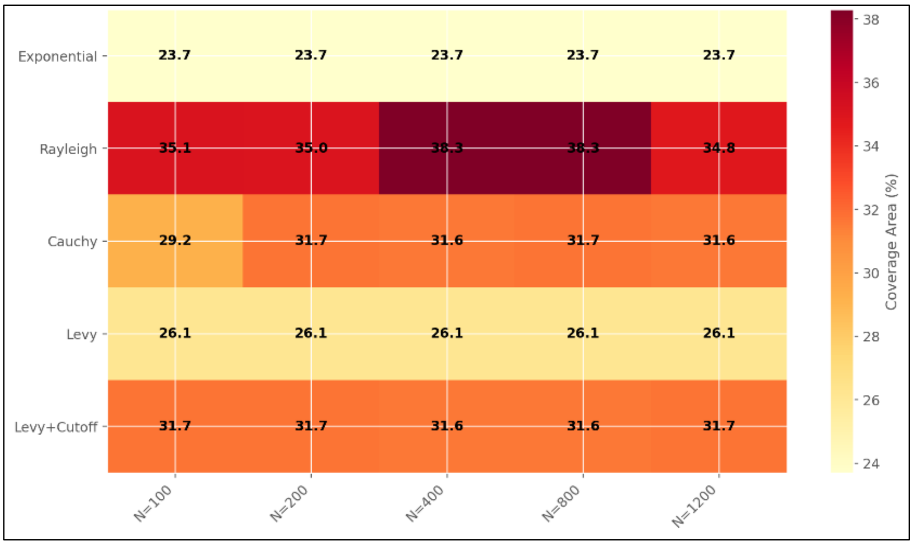

Figure 3: Coverage area heatmap by mobility models and number of nodes involved.

ISSN:2302-8149
e-ISSN:2540-9719

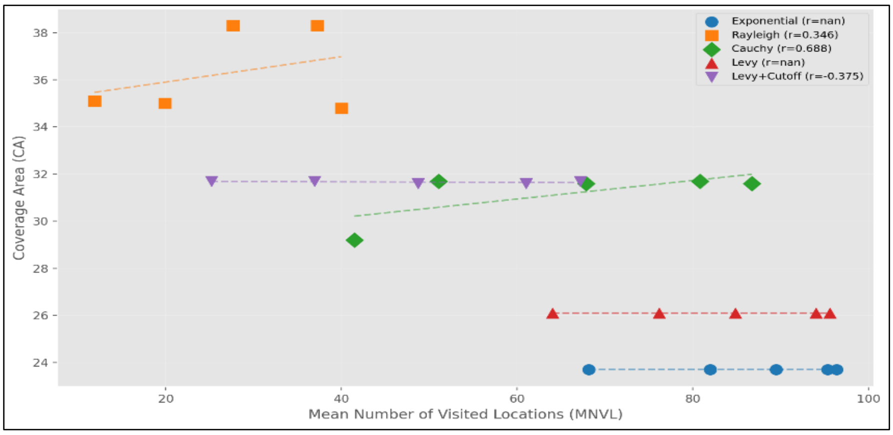

Figure 4 Correlation analysis of MNVL and coverage area.

To discuss the abovementioned results, the obtained findings are in agrement with thw rok of Wang et al. (2007) when controling the mobility for the sake of performance in terms of coverage areas. This means mobility models can play a crucial role on the performanc of the whole network. However, this work is considered an extension their work by quantifying the relative performance of different mobility patterns. On the other hand, the work of De Nardis and Di Benedetto (2022) focused mainly on topological properties, but in this work the focus was on measures coverage area. Also, the Rayleigh Flight model gained high performance when it comes to coverage area of 36.3%). This is also in agrement with the work of Fazio et al. (2023) when it comes to the impact of mobility on the stability of network. The high stability of Exponential and Levy models with the CV of 0% was not in agrement with the variability shown by the work of Sun et al. (2023).

Table 8 Practical recommendations based on the experiments implemented in this work.

Application Scenario	Recommended Model	Reason
Urban Monitoring	Levy Flight	High exploration + stable coverage
Wildlife Tracking	Rayleigh Flight	Large area coverage despite variation
Industrial IoT	Exponential	Maximum exploration in dense networks
Emergency Response	Cauchy Flight	Balanced performance across conditions
Controlled Experiments	Levy+Cutoff	Predictable, bounded behavior

4 Conclusion

This work analyses the role of mobility models on network performance in terms of coverage. The experiments used colorful settings in terms of the mobility models used and the parameters of the simulations. Different number of nodes were also used to reflect small-scale, medium-scale, and large-scale networks. The findings led to an important fact, which is there is no particular mobility model is optimal for all networks and scenarios, but rather each model presents distinct trade-offs that must be carefully weighed against deployment requirements. The results of this work can be summarized as follows:

- The Exponential and Levy Flight models consistently delivered the highest exploration efficiency. They achieve MNVL values above 95% with near-perfect coverage stability. Furthermore, their rapid saturation beyond 800 nodes suggests diminishing returns in dense deployments.
- The Rayleigh Flight model shows significant growth and the largest coverage areas.
- The Cauchy and Levy-with-Cutoff models occupied a pragmatic middle ground. They show balanced performance and predictable scaling behavior that could appeal to practitioners seeking reliable outcomes across varying network densities.
- The use of ANOVA proved that the obtained results were statistically significant and there exists differences among mobility models ($p < 0.05$).

This work is limited in the folloiwng aspects:

- The power-law ditribution used in the simulations may not reflect all the environments in the real-life.

ISSN:2302-8149
e-ISSN:2540-9719

- The duration of the simulation may need to be extended aiming to have a wider window that may show behaviours that couldn't be observed in the time considered of the simulations of this work.
- More mobility models can be involved to extend the experiments and extract more facts about MANET performance.

The future direction of this research may extend to inclue 3D environments for UAV and include the power consumption as a metric for this kind of environments. Also, Machine learning and deep learning may also be used to explore the performance or make predictions on the patterns of the mobility models used in this work.

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