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The Impact of the Relation Between Movement Patterns and Nodes Distribution on the Performance of Smart Cities

Wael Hadeed

Computer Science Department, College of Computer Science and Mathematics, University of Mosul, Mosul, IRAQ

wael.hadeed@uomosul.edu.iq

Abstract. In smart cities, it is believed that there exists an impact of the relation between the movement patterns of mobile nodes from one side, and their distribution from the other side, on the overall performance of the smart city. This work tries to investigate this kind of relation using simulations. To this end, experiments were designed using a variety of parameters. Different distributions were used as well as a mobility model with a routing protocol. Four kinds of experiments were designed, each of which includes different settings. The simulations were carried out and the results were obtained and then analyzed. The performance and the stability of these experiments were investigated. The results showed interesting facts about the simulations. The results of this research can be of benefit to smart city researchers. It will also be of interest when it comes to developing optimal strategies for spreading advertising in a smart environment.

Keywords. Smart Cities, Dynamic Objects, Movement Patterns.

1. Introduction

The great revolution on the Internet and its technologies introduced the concept of Smart Cities [1]. A smart city includes many sensing objects that measure particular events in the environment (see Figure 1) [2]. These objects (or called nodes) can be sensors, mobile phones, and/or other smart devices. Some of these nodes are static, while other nodes are dynamic (mobile). Also, these nodes can be distributed within the environment of a smart city. The static nodes follow a particular topology and their positions are also static [3]. Simulating static networks have been extensively investigated in the literature and there are many approaches that offer efficient simulations.

On the other hand, when simulating mobile nodes, it is crucial to include a mobility model that governs the movements of nodes [4]. In addition, the positions of these mobile nodes should be determined before starting the simulations [5]. Hence, simulating mobile networks requires describing the movements of nodes in terms of speed and direction as well as a description of how the nodes are deployed within the simulation environment. Since the mobile nodes move, their positions are changed over time causing to break the distribution. Therefore, it is beneficial to study the relation between the mobility models and the distribution of nodes and analyze the performance of the network under this phenomenon. The performance, in this case, is affected in terms of information spreading, connectivity of nodes, or scalability of the network, which directly affects the consumption of smart city resources.

Measuring the performance of mobile networks is more challenging than static networks [6, 7]. Smart cities are considered hybrid networks due to the inclusion of static (e.g., weather sensors, road sensors, cameras, etc.) and mobile nodes (e.g., GPS of cars, smart devices, etc.). Also, monitoring the consumption of smart city network resources is considered one of the promising fields of research. The performance of smart cities can be measured in terms of power consumption, connectivity, scalability, memory consumption, etc. [8].

Figure 1: A Smart City with a variety of nodes and technologies.

The literature on mobility models is not rich due to the modernity of the topic. In fact, the research on mobility models was started in the last decade but most of the studies were related to physics. For instance, the first mobility model developed was the Brownian Motion that described the movements of particles in liquids [9]. With the advent of dynamic networks, the need to have mobility models for simulating such networks was increased [10]. Munsifa and Das (2021) [11] simulated a dynamic network using different mobility models such as Random Direction, Random Way Point, Constant Velocity, and Gauss Markov model. Their goal was to evaluate the performance under these models in terms of Quality of Service (QoS). The results showed that the Gauss Markov model reflected better performance in terms of delay. Also, their results proved that Constant Velocity and random Way Point were efficient when it comes to network throughput. Wheeb et al. (2022) [12] presented a comprehensive study that considered "Unmanned Aerial Vehicle (UAV)" networks and their performance using a variety of settings such as mobility models, topology, and routing protocols. The study showed that these terms have a direct impact on this kind of network and simulating such networks should consider these terms aiming to have real results. In the same context, a work performed by Mboup et al. (2022) [13] investigated the issue of simulating dynamic networks and how to incorporate mobility parameters. The study involved different topological characteristics observed in real-world networks in simulating temporal networks and benchmarking the performance. The results demonstrated that similarities can be observed in these networks such as the "heavy-tailed" distribution of encounters among nodes as well as the frequency of encounters. Pandey et al. (2022) [14] studied the impact of information routing during nodes movements. They suggested a technique that optimizes and maintains the routes of the data within the network. Their technique involved parameters such as delivery ratio and throughput. Other works in the literature such as [15-18] investigated issues related to mobility models and real-world applications.

Based on the previous studies, it can be seen that few works consider the impact of mobility models and nodes deployment on the performance of dynamic (mobile) networks or smart cities. Therefore, this study is conducted to investigate this issue and reveals the facts related to the integration of mobility models and nodes deployment, and how they can affect the whole performance of smart cities in terms of the consumption of resources.

The rest of this paper is divided as follows: the next section describes the details of the method followed in this work. Section 3 demonstrates the experimental results based on the simulations performed. Section 4 concludes the work and provides some recommendations and future works.

2. Methodology

The method followed in this work is based on simulating a smart city that includes dynamic nodes under different mobility models and nodes deployment strategies. The simulations were performed using Netlogo simulator, which is a "multi-agent programmable modeling environment" [19]. This simulator is widely used in the literature and several works involved it in performing multi-agent-based simulations such as [20-24]. The simulator provides a variety of abilities and secures all the requirements needed to achieve this work's goals. Designing steps of the simulations in this work can be divided into the following portions:

- Mobility Models: Two mobility models were utilized in this work. The first one is called the "Human Mobility Model (HMM)", which reflects the patterns of movements of a human. This model was suggested by Song et al. [25-26]. It is used to accurately simulate the movements of people in dynamic networks. This model is adopted in the simulations of this work. The reason for adopting this model is that in smart cities most of the mobile objects are people who carry their smart devices and drive their smart cars. Simulating the movements of people can be better described by the HMM model.
- Nodes Distribution: The distribution here reflects the way how nodes are deployed in the environment. This work uses two approaches; a) Exponential distribution [27], which means the nodes are focused in the environment's center and the density is decreased when being far away from the center, and b) Lattice distribution [28], which means the nodes are evenly distributed in the environment. The reason behind adopting these two distributions is that they are different in patterns, which is of benefit when evaluating the performance of the network.

The other simulation requirements can be summarized as below:

- Communication range: Since this work considers regular Wi-Fi technology, the communication range of nodes is 50 meters.
- Communication mode: In smart cities, it is more likely that nodes can exchange information with each other. Therefore, the model is peer-to-peer based (no servers or sinks).
- The environment is designed as a circle with a radius of (2 km).
- The routing of information is based on "Probabilistic Routing Protocol using the History of Encounters and Transitivity (PRoPHET) " [29].
- Number of Nodes: the simulations include 50 and 100 dynamic nodes.
- The event: for the purpose of spreading information in the environment and measuring the performance, in each experiment a message is randomly positioned within the simulation environment. This message will be sensed by the nodes and spread to other nodes based on the routing protocol used.
- Evaluation criteria: The message will be spread in the environment, in this case, the evaluation will be based on Spreading Percentage (SP) metric. This metric reflects the percentage of nodes that get the message even by sensing it or by receiving it from other nodes. The percentage is calculated based on the total number of nodes in the simulation environment.

The experiments performed in this work represent a combination of the mobility model used and the distribution strategies as well as performing the experiments using 50 and 100 nodes. Table 1 presents the experiments designed and their main settings. Each experiment performed is executed 10 times, which provides an accurate evaluation.

Table 1: Experiments configurations and settings

#	**Experiment Setting**
Test_0	HMM model, Exponential Distribution, 50 nodes
Test_1	HMM model, Exponential Distribution, 100 nodes
Test_2	HMM model, Lattice Distribution, 50 nodes
Test_3	HMM model, Lattice Distribution, 100 nodes

3. Experimental Results

The simulations designed in the previous section were implemented. As mentioned, each experiment was performed 10 times. The reason of this procedure is to have more accurate results and show the stability of the experiments of this work.

After executing the experiments, the results were analyzed and visualized. For Test_0 and Test_2 experiments, the number of nodes involved was 50. Figure 2 demonstrates the results of these two experiments and their performance in terms of the SP metric. As can be observed in the figure, the blue circles denote the performance of Test_0, while the orange circles denote the performance of Test_2. The line between the two circles represents the difference in the performance. For instance, in the first execution (Execution_1) of both Test_0 and Test_2, the percentages of the covered nodes by the event were 63% and 16% respectively. The figure also shows the results of 10 executions (Execution_1 to Execution_10). The average performance is also depicted in Figure 2. According to these results, it can be observed that it was reasonable to consider 10 executions instead of one. Moreover, it is clear that when using HMM mobility model and Exponential distribution of nodes, the spreading percentage outperforms the use of the Lattice distribution of nodes. The reason behind this result is that in the Exponential distribution the distances between nodes are smaller than when following the Lattice distribution. This leads the nodes to be highly overlapped in the communication range of each other, leading the nodes to exchange information. The settings of the Test_0 experiment tell us that when the goal of the applications in smart cities is to spread data to more nodes, it is more efficient to select the areas in which the nodes are exponentially distributed. Practically, this is useful when dealing with mobile advertising applications.

In Test_1 and Test_3 experiments, the performance is shown in Figure 3. As can be observed, similar behavior is obtained when involving 100 nodes within the simulation environment. More percentages were obtained in each execution (Execution_1 to Execution_10). This is due to the number of nodes involved that is double compared to Test_0 and Test_2. The average performance of Test_1 and Test_3 is also depicted in Figure 3.

The average performance of the experiments is shown in Figure 6. According to the figure, the performance when using the Exponential distribution is better in terms of spreading the event within the environment.

Furthermore, it was decided to perform more analysis of the results and explore more facts about the performance. To this end, the stability of the experiments was tested using the 10 executions. Figures 5 and 6 demonstrate the stability of the experiments (Test_0 and Test_2 for 50 nodes) and (Test_1 and Test_3 for 100 nodes) respectively. Interestingly, the figures showed similar behavior of the exponential distribution of nodes, which was as stable as the lattice distribution. The reason behind this result is that the distances between nodes are approximately fixed even with the mobility nature of the nodes.

All the described results and analysis provided us with facts about simulating smart cities. One of the important facts is that smart city developers should pay enough attention to the design of their networks and the goal of their applications. This is important since a trade-off may happen between the performance and the stability of this kind of network. Here, developers should be aware of such issues.

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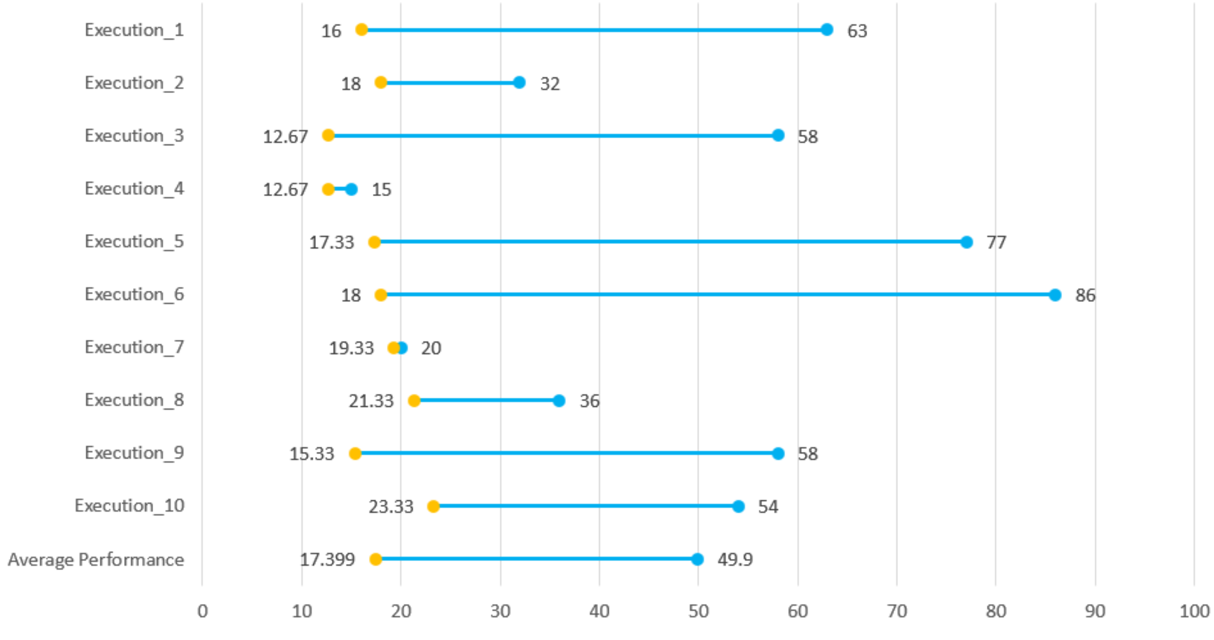

Figure 2: Performance evaluation of experiments (Test_0 and Test_2) for 50 nodes.

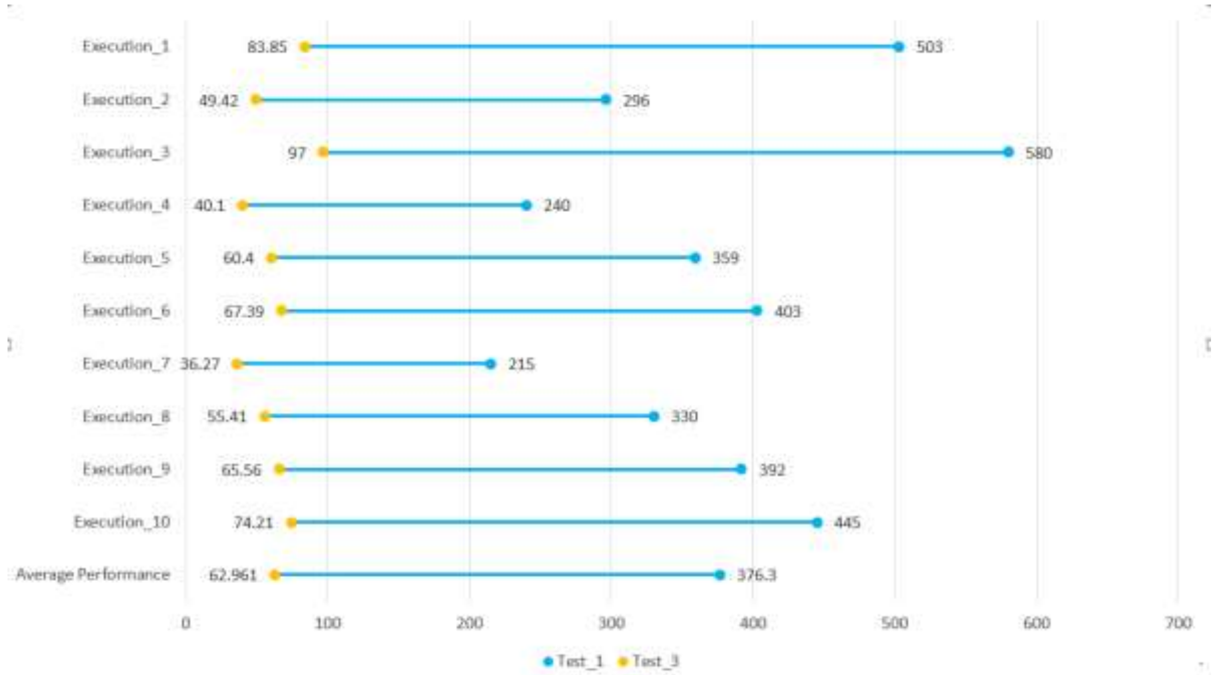

Figure 3: Performance evaluation of experiments (Test_1 and Test_3) for 100 nodes.

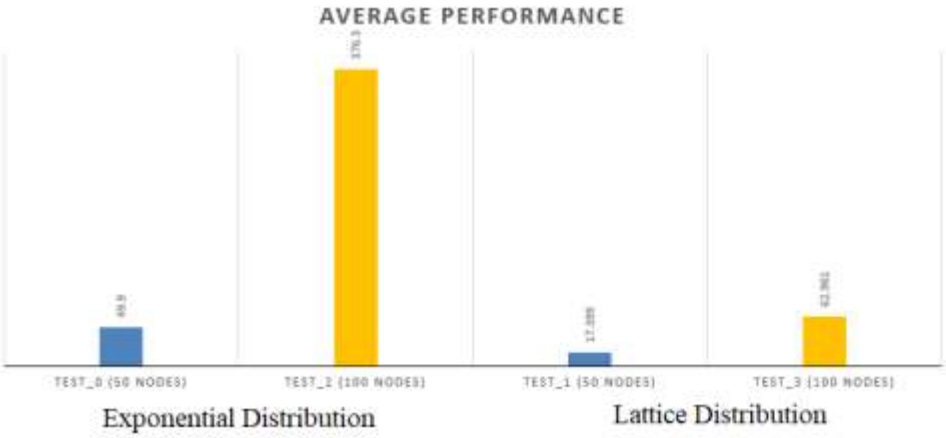

Figure 4: Average performance of the experiments (Test_0 (50 nodes) and Test_2 (100 nodes) using Exponential distribution) and (Test_1 (50 nodes) and Test_3 (100 nodes) using Lattice distribution).

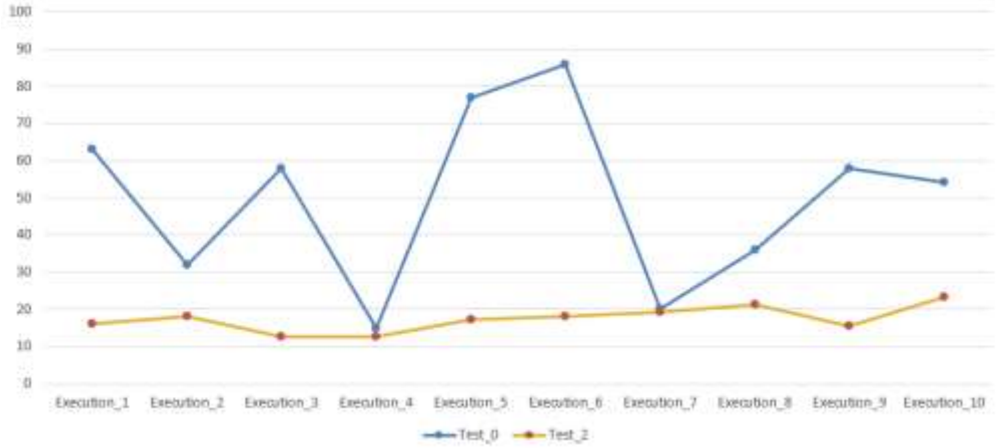

Figure 5: Performance of the stability of Test_0 and Test_2 experiments for 50 nodes.

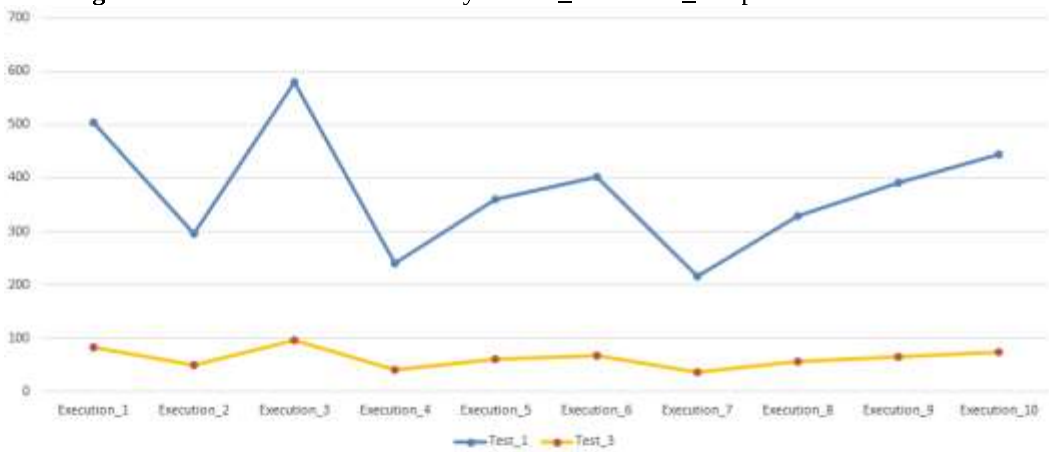

Figure 6: Performance of the stability of Test_1 and Test_3experiments for 100 nodes.

4. Conclusions

This work tried to investigate the relation between the movement patterns (mobility models) and the distribution of nodes in smart cities. The work also investigated the impact of this relation on the general performance of the network. The distribution used in this work were Exponential and Lattice distribution for deploying nodes within the simulation environment. The work also utilized the HMM model to describe the movements of mobile objects in the environment, which are most people. The routing protocol used in the experiments was the PRoPHET routing protocol. The experiments involved 50 and 100 nodes that were deployed in the environment. The designed experiments combined the aforementioned parameters and came up with four main tests (experiments). The results showed that when using Exponential distribution for deploying nodes, the percentage of the information diffusion was significantly increased. However, the results also showed that there was a trade-off between the information diffusion levels and the stability of the experiments. The Lattice distribution reflected a stable performance compared to the Exponential distribution. Based on the obtained results, special attention should be given to the design of their networks and the goal of their applications. The results of this research can be of benefit to smart city researchers. It will also be of interest when it comes to developing optimal strategies for spreading advertising in a smart environment. As future works, it is planned to include more distributions and routing protocols aiming to have a better view of the performance of smart cities and how the performance is affected.

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