Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 17 No. 18 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijim.v17i18.42121

PAPER

Performance Analysis of Sink Mobility Models for Wireless Sensor Networks: A Comparative Study

Anas Abu Taleb[1], Qasem Abu Al-Haija[2](✉), Ammar Odeh[1]

[1]Department of Computer Science, Princess Sumaya University of Technology, Amman, Jordan

[2]Cybersecurity, Princess Sumaya University of Technology, Amman, Jordan

q.abualhaija@psut.edu.jo

ABSTRACT

Wireless sensor networks (WSNs), deployed in the area of interest to gather data unattended, comprise numerous tiny, ponderous, and battery-operated sensor nodes (SNs). Numerous research publications presented strategies for extending the lifespan and performance of wireless sensor networks because SNs lifetime depends on limited battery life. One strategy for enhancing the performance of wireless sensor networks is to deploy an energy-rich sink capable of mobility to gather data sensed by stationary SNs. Therefore, several mobility models (MMs) were suggested. The primary objective of this investigation is to compare the effectiveness of wireless sensor networks using two MMs for mobile sinks (MSs): Kohonen's self-organizing map-based model and the genetic algorithm-based model, in order to find the most suitable conditions under which each one of them can be used. As a result, network performance is investigated using the NS-2 simulator under various scenarios and MS speeds. Additionally, throughput, packet delivery ratio (PDR), and end-to-end (E2E) delay are the metrics used to analyze performance. Finally, messages are forwarded from their sources to the MS using the AODV routing protocol. The results show that the Kohonen-based model is suitable for small networks with moderate speeds of the mobile sink. On the other hand, the genetic algorithm-based model is suitable to be used with medium-sized networks with low speeds of the mobile sink.

KEYWORDS

genetic algorithm (GA), mobile sink (MS), mobility model (MM), self-organizing map (SOM), sensor node (SN), wireless sensor network (WSN)

1 INTRODUCTION

Wireless sensor networks (WSNs) have become a prominent example of ubiquitous and pervasive computing, primarily due to their ability to operate in inhospitable environments for extended periods while studying specific phenomena. These networks are often deployed randomly and are expected to function autonomously without human intervention. The sensor nodes (SNs) are designed to be compact,

Taleb, A.A., Al-Haija, Q.A., Odeh, A. (2023). Performance Analysis of Sink Mobility Models for Wireless Sensor Networks: A Comparative Study. *International Journal of Interactive Mobile Technologies (iJIM)*, 17(18), pp. 129–142. https://doi.org/10.3991/ijim.v17i18.42121

Article submitted 2023-06-25. Revision uploaded 2023-07-25. Final acceptance 2023-07-25.

lightweight, and battery-operated, with limited capabilities to facilitate rapid deployment. However, these nodes have finite energy resources, necessitating careful energy management to maximize the lifespan of the WSN. For these networks to operate effectively, it is crucial to maintain fault tolerance and self-organizing capabilities [1–5].

The SN unit is composed of processing, communication, and sensory modules. The communication module is regarded as the primary power consumer since power consumption in communication is distance-dependent. For instance, the energy required to execute thousands of instructions by the processing subsystem in one SN equals the energy required to communicate a single bit [6] [7].

Consequently, it is recommended that the SN employ multi-hop routing and seek the assistance of other SNs instead of sending data to the base station in a single-hop (S-H) manner. Accordingly, a multi-hop SN will consume less energy because the required distance is shorter than with S-H routing. Conversely, the energy consumption of SNs is uneven when multi-hop routing is used instead of S-H routing, especially for SNs close to the base station, since most of the traffic generated by remote SNs would pass through these nodes. Therefore, most of these SNs' energy will be consumed to relay messages from remote nodes [6] [8].

Consequently, deploying a mobile sink (MS) or sink has been introduced. In this approach, the MS gathers data from immobile SNs. It moves randomly or by a certain mobility strategy before sending the information to the base station. Furthermore, using a MS enhances the performance of WSNs in multiple aspects. This includes reducing the reliance on intermediary nodes, amplifying the network's data transfer capacity, and extending network coverage to remote locations [1].

This paper studies the performance of two sink mobility models (MMs) and compares them based on the same scenarios and simulation environment. The compared models are similar in that each employs one MS based on a designated model, systematically gathering data from stationary nodes and transmitting it to the central base station. Therefore, the following points serve as a summary of this paper's significant contributions:

- Simulate a WSN at various scales as the MS travels at various speeds and according to various mobility patterns.
- Examine the effects of various scales, movement patterns, and speeds on the effectiveness of WSNs while utilizing the same protocol to route messages.

Following is a description of the remaining sections of this study paper. Related work is demonstrated in Section 2. The MMs under study are introduced and described in Section 3. Section 4 explains the simulation environment, scenarios, and performance metrics. Additionally, the outcomes of simulating the MMs are shown and discussed in Section 5. Section 6 sums up the conclusion of the paper.

2 RELATED WORK

There has been much research that has suggested methods or algorithms to support mobility in WSNs. Mobility, as defined by [9], refers to a node's ability in a WSN to change locations post-deployment. The use of MSs or sinks that can move while still receiving data from immobile SNs is the first of two major categories into which mobility algorithms for SNs can be classified. At the same time, the second category gives all SNs the ability to move, so they can move from one position to another and report data as static SNs would. Because it is more pertinent to the MMs being studied, our review will focus on studies that employed a single moving MS to gather data from immobile sensor nodes.

The research proposed in [10] provided a data-gathering approach that employs path planning to reduce the MS's traveled distances and communication ranges. An inner-center path planning algorithm reduced an MS's traveled distance. The problem of back propagation of the movement path was also considered by introducing a back-routing technique. To enable the MS to move, the proposed strategy must be able to make adaptive judgments. It is worth noting that the proposed scheme is suitable for large-size networks, and the performance decreases for small-size networks.

To further cut energy use and extend the lifespan of WSNs, the authors of [11] considered tackling the relay selection problem. As a result, the suggested study used the k-means method to create clusters within the network. A method for choosing the cluster head (CH) employing moveable sinks was proposed to maximize energy utilization inside the cluster. When the MS is near the immobile sensors, it acts as the CH to gather data and save energy on both the immobile SNs and the CH. The usage of a virtual CH to attain energy savings has been presented in the proposed work, and this is another addition to that work. However, the proposed scheme consists of several steps. Also, the MS will sometimes need to act as a cluster head, which may affect timely data collection from other sensor nodes.

A cooperative strategy was described in [12] to enhance the task of environmental monitoring and discrepancy search in WSNs. The proposed approach primarily consists of two parts. The coordinated installation of the immobile SNs is the initial area of focus, which depends on a weighted Gaussian coverage technique. On the other hand, the second component, which concentrates on scheduling a track for the MS, is built on customizing a dynamic checking and discrepancy exploration engine that uses a Markov decision process (MDP) model. Thus, the primary purpose of this system is to rapidly detect ecological abnormalities, which will allow the MS to react correctly using a cumulative reward function. Another model is suggested in [13], which zone-divides the network to improve WSN performance and lengthen their lives. Considering the load of each zone, the MS is going to get closer to the zone that is highly loaded. It is significant to notice that the heavily loaded zone uses a fuzzy logic approach to account for any potential uncertainty. This model is better suited for large networks. Also, it has been studied under 50, 100, 150, and 200 node network sizes, and the average packet delivery ratio was 90%. Furthermore, under the same circumstances, it has achieved 0.09 second average end-to-end latency results.

This protocol has been studied under 50, 100, 150, and 200 node nw sizes, and the AVG e2e delay achieved was 0.09 seconds.

The study in [14] also suggests an adaptive mobile routing technique focused on spotting a burst of traffic. The implemented network architecture depends on maintaining two MSs, and the technique depends on partitioning the network's clusters into two distinct groups. Each SN will control a particular group and interact with the CHs. Moreover, the MS would make specific visits to the group's CHs so that they could arrange themselves. If traffic increases are observed, the MS will not adhere to visiting CHs in the indicated order and will approach the heavily laden CH. This technique must incorporate the MS mobility model and cluster head selection with optimization techniques or methods to make them more efficient.

Furthermore, [15] presented an optimization-based ant colony approach employing E2E data aggregation techniques. The suggested approach creates a tree of data passing and randomly picking aggregation objects. Consequently, the path of the MS is predicted and defined. To decrease latency and power consumption, the research in [16] focuses on developing mobile paths for the sink. The algorithm's four stages are data detection, meeting location selection, trajectory design, and data transfer. Geographic navigation using portable sinks was suggested in [17]. Using two MSs, this research gathered data from SNs in cells or geographical areas. Thus, the gathered information gets delivered to the MS by each cell's SNs. It is important to remember that communication between the SNs and the MS can be done in an S-H or multi-hop fashion.

Another mobility model was proposed in [18] based on constructing a bipartite graph derived from a randomly deployed WSN. After that, the SM model is calculated based on the properties of the constructed bipartite graph. In other words, in a bipartite graph, sensor nodes will be divided into two sets, where the nodes in the first set are neighbors to the nodes in the second set. Thus, the mobility model is based on making the MS visit the nodes in the first set that are not neighbors. Then the mobile sink will visit the nodes in the other set. As a result, all the nodes in the network get visited, and the neighbors of each node have the opportunity to report data to the MS twice.

To deal with burst traffic, an adaptive mobility model based on detecting bursts of traffic was proposed in [19]. The authors suggest dividing the network into clusters and selecting a head for every cluster based on the nodes' energy levels within a cluster. Consequently, the MS sink's movement is based on detecting a burst of traffic in a cluster head and moving towards that cluster head to collect data. After that, the mobile sink stays in its location until another burst is detected.

The research proposed in [20] presented a routing algorithm based on having an MS deployed within the network. The proposed scheme is based on constructing cluster-based tree routing with an MS. First, clusters, or grids, are formed. Then, the routing tree, consisting of cluster heads only, is constructed. After that, the mobile sink selects a node within the constructed tree to be its access point or gateway. As a result, sensor nodes will send data to the cluster head, and the cluster head aggregates the data and sends it to the next node within the routing tree. Thus, the aggregated data traverses the tree until it reaches the access point selected by the MS. Consequently, the access point sends data to the MS sink, which will report it to the base station.

The random waypoint model is considered a reference model in this area of research. As a result, it will be discussed in this paper to compare the obtained results. This model is based on making the mobile sink select a random location to move to. Upon arrival at the location, the MS will stay in that location for a specific period. When the time expires, a new location is randomly selected again, and the MS sink will move to it [20].

The performance of the random waypoint and mobility models proposed in [18] was studied under the same circumstances and parameters. Thus, the performance of these two mobility models is illustrated in Tables 1, 2, and 4.

Table 1. End to end latency

Model Name	Speed	Network Size			
		26 Nodes	51 Nodes	76 Nodes	101 Nodes
Ref [18]	5	192.12	31.45	19.33	78.69
	10	166.56	28.58	26.65	151.50
	15	633.29	51.74	30.60	84.37
	20	262.34	73.93	267.47	140.39
Random Waypoint Model	5	1070.78	3590.09	5344.26	7348.23
	10	1069.12	4247.96	4665.35	6904.05
	15	811.182	3507.06	5812.7	4860.76
	20	993.193	3535.66	6268.34	6077.27

Table 2. Packet delivery ratio

Model Name	Speed	Network Size			
		26 Nodes	51 Nodes	76 Nodes	101 Nodes
Ref [18]	5	95.20	98.52	99.81	95.25
	10	91.63	98.96	99.81	99.57
	15	88.70	99.24	99.02	99.25
	20	90.63	94.83	99.25	98.88
Random Waypoint Model	5	59.76	34.80	20.76	14.84
	10	53.55	31.82	19.16	13.32
	15	38.51	19.91	15.17	5.70
	20	39.72	26.49	13.85	9.47

Table 3. Throughput of the networks

Model Name	Speed	Network Size			
		26 Nodes	51 Nodes	76 Nodes	101 Nodes
Ref [18]	5	15.89	31.09	13.19	12.60
	10	14.99	32.07	13.28	13.32
	15	15.27	31.95	13.35	13.16
	20	14.35	31.94	13.20	16.20
Random Waypoint Model	5	2.44	2.85	2.55	2.43
	10	2.19	2.60	2.35	2.18
	15	1.57	1.62	1.86	1.18
	20	1.62	2.12	1.70	1.55

From Tables 1, 2, and 3, it can be concluded that the mobility model proposed in [18] is suitable to be used with medium-sized networks when the mobile sink is moving at moderate speeds. On the other hand, it can be observed that the random waypoint model did not provide good performance results in all cases because of the randomness according to which the new location of the MS was selected.

This paper examines and compares two sink MMs within the context of WSNs. The objective is to assess and contrast the performance of these models under identical scenarios and simulation environments. Both models share a common characteristic: the utilization of one MS that employs a specific mobility pattern to collect data sensed by immobile SNs and send it to the base station. The main objective of this paper is to study the performance of the Kohonen SOM-based mobility model and the genetic algorithm (GA)-based mobility model under the same simulation environments to study their behavior and decide on the best conditions under which each one can be used.

3 THE COMPARED MODELS

This section discusses the MMs employed in our comparative study, including the Kohonen self-organizing map (K-SOM) based and the genetic algorithm-based model.

3.1 Kohonen SOM-based model

Before deploying the MS, K-SOM is used to compute the movement trajectory. It is done offline to ensure the MS's movement trajectory is predetermined and fixed. Additionally, it's crucial to check that the chosen movement path includes every immobile SN that the MS will visit at this step [21].

Specifically, the network will comprise N randomly placed static SNs distributed around the study region. The MS node will also be settled randomly in the same region. The path of an MS could begin at an SN's static SN that has been arbitrarily chosen. The MS's movement is then split into sojourn and moving periods. The MS starts randomly, joins the sojourn phase, and maintains its current position for a predetermined time. The MS gathers information from the nearby stationary SN through this period. Therefore, it is evident that the suggested strategy's main purpose is to decrease the energy quantity utilized in transmission by shortening the distance connecting a stationary node and a mobile node (sink) [21].

The motion retro begins when the pause retro is over, and the MS then has to choose a new position using the K-SOM's calculations. Thus, the MS chooses a stationary SN location as its target location and moves in that direction. When the MS gets to its new location, it joins the sojourn phase again and begins gathering information from the stationary node. After visiting all stationary SNs, the sink node comes back to its initial location. The MS then embarks on a new journey in the same way until the topology of the network changes brought on by energy exhaustion are discovered. This requires the incident to be relayed to the base station, where a new course is determined [21].

3.2 Genetic algorithm-based model

The suggested work in [22] is based on a heterogeneous WSN with N stationary SNs that are randomly placed. An additional node is included to represent the MS node, in charge of gathering data from the stationary SNs. Additionally, in the described MM, the primary goal is to employ GAs to give the MS an ideal route that visits all immobile SNs and gathers data, with the movable sink's movement beginning and ending at the same node.

The GA's initial population is generated randomly because the suggested MM is built on a WSN deployed randomly. The nodes in this model representing the initial solution are chosen randomly. Random numbers between 0 and n are created for each generation. The system then determines whether the randomly produced number exists in the present individual. A new number is generated if it is found; it is also appended to the current individual [22][23]. The primary objective of the suggested MM is to identify an ideal path that the MS can follow to visit each static SN precisely once and gather data. To compute the distance, or cost, between immobile nodes, which may be computed using (1) [23], Euclidean distance, D, is used.

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{1}$$

In (1), the coordinates of node m's are represented by x_1 and y_1, while the coordinates of node n are represented by x_2 and y_2. It is important to note that the distance between any two nodes remains constant in both directions [23]. To determine the best course for the MS, the fitness value is derived by summing the distances. Therefore, the node with the smallest fitness function value from the MS's current location is chosen as the sink's new location. The MS will consequently travel in the direction of the new position. It is important to remember that the suggested MM is separated into rounds, each beginning at the node chosen to serve as the path's starting point. A round also ends whenever the MS finishes its cycle. To put it another way, the round ends when the MS returns to the initial location after stopping at each static SN. A new round is initiated after a previous round has concluded by following the same strategy.

4 SIMULATION ENVIRONMENT

This section describes the experimental setup used to simulate various scenarios and parameters and the evaluation metrics employed for the comparative analysis presented in this paper. The meticulous experimental setup design ensures a robust and reliable evaluation of the sink MMs. In contrast, the carefully selected evaluation metrics enable a comprehensive assessment of their performance.

4.1 Simulation scenarios and parameters

The NS-2 simulator, one of the most popular simulators for studying the performance of wired and wireless networks, was utilized in simulation experiments to evaluate the performance of the MMs. Furthermore, the messages are forwarded to the MS via the AODV routing protocol. Four different network sizes—26, 51, 76, and 101—were randomly deployed in a 1000 × 1000 flat grid to examine the effectiveness of the MMs. It is important to note that the 26-node network comprises 25 immobile SNs and an additional MS node for data collection. Furthermore, the static sensor nodes (SNs) generate consistent bit rate (CBR) traffic. In addition, we assessed the effectiveness of the MMs under various velocities of the MS, including {5 m/s, 10 m/s, 15 m/s, and 20 m/s}, while accounting for a pause duration of 5 seconds to simulate the MS's temporary stay. The efficiency of the studied MMs was inspected for every network size using the following methodology: First, immobile SNs are deployed randomly. The MS will relocate throughout the network following a certain MM. The network size is fixed in the first scenario; for example, in a network with 26 nodes, the mobile node's movement speed is adjusted following the values indicated in Table 4. We extended the network size to 51 nodes, and again, we assessed the effectiveness of the MMs at different speeds of the MS. In other words, the network size was fixed, and the MS speed was changed based on a specific MM. After that, the same approach was adopted for the same network size, but another MM was adopted, and so forth.

Table 4. Model factors

Factor Name	Factor Value
Simulation Duration	1000s
Node Count	{26 – 51 – 76 – 101} nodes
Pause Time	5s
Simulation Space	1000 × 1000
Type of Traffic	*CBR*
MS_Velocities	{5 – 10 – 15 – 20} m/s

For example, the MS moves at a 5 m/s speed, and the network initially has a size of 26 nodes for 500 seconds. An MS traveling at 10 m/s was subsequently simulated to a similar duration with the same network size using the same MM, and the same scenario was executed again at speeds of 15 and 20 m/s. Following this, we extended the size of the network to 51 nodes, and again, we assessed the effectiveness of the MMs under different speeds of the MS in the same way as for the 26-node network for the same MM. The same methodology was used for different network sizes and other MMs. Table 4 displays the simulation parameters.

4.2 Performance metrics

Three performance indicators—PDR, throughput, and mean E2E latency—were considered to examine the studied models' performance. The following is a brief description of these performance metrics:

A) The mean E2E latency is the duration a packet needs to reach its destination concerning when it originally left the source. By calculating the average time required for packet transmission between the sender and receiver nodes for every connection in the interior network, the mean E2E latency for the entire network can be determined [24]. To calculate this performance parameter, (2) is used [24].

$$T_{AVG} = \sum_{i=1}^{N} \frac{(H_r^i - H_t^i)}{N} \tag{2}$$

In (2) H_r^i and H_t^i Denote the sent and received packet copies correspondingly. Also, N represents the overall amount of received packets [24]. For a MM to perform well, low mean E2E latency values must be achieved [25].

B) According to (3) [25], the PDR is the sum of all successfully received packets divided by all transmitted packets.

$$Packet\ Delivery\ Ratio = \frac{P_{rs}}{\sum_{i=1}^{n} P_{sent_i}} \tag{3}$$

P_{rs} and P_{sent_i} represent the overall number of correctly sent and received packets.

C) Throughput, expressed in bits/sec, is computed as the total count of successfully received packets over the length of the simulation period. Consequently, a sink MM ought to attain superior outcomes for this performance metric. [24]. According to [25], (4) is used to compute throughput.

$$Throughput = \frac{Number\ of\ Packets\ Delivered * Packet\ Size * 8}{Total\ Simulation\ Time} \tag{4}$$

5 SIMULATION RESULTS

The simulation factors, along with the performance indicators, were discussed in subsections 4.1 and 4.2. This section shows and evaluates the simulation results for the MMs under investigation. Ten iterations of each scenario were done to ensure more precise results. Therefore, the simulation's results were achieved by averaging the outcomes of the 10 runs for each case.

Figures 1 and 2 display the final results for mean E2E latency for the MMs studied in this paper. The mean E2E latency results are displayed in Figure 1, depending on different network sizes and the speed at which MSs move. As clearly seen, Kohonen-based MM has achieved lower and steady E2E latency outcomes for small networks, especially networks with 26 nodes, because the MS's movement path is shorter than that of other networks. Consequently, the MS may exchange messages with all the static nodes in its path, utilizing S-H to gather data from them. Thus, lower values for E2E latency were acquired, improving performance.

According to Figure 1, the outcomes obtained for network configurations consisting of 26 nodes exhibited higher values for speeds of 15 and 20 m/s compared to speeds of 5 and 10 m/s. When traveling at low speeds, the MS spends more time near a static SN. Thus, a stationary SN has a longer time to send data via S-H communication to the MS. On the contrary, the MS will rapidly enter and exit the neighborhood of a stationary SN with a higher velocity, such as 15 and 20 m/s. Thus, a stationary SN may need multi-hop to transfer data to the MS, raising the E2E delay values. The increased latency values obtained increased as the network size increased because of the path length the MS must travel.

Consequently, the frequency at which the MS visits immobile SNs decreases. Multi-hop routing will therefore be employed more often. Higher values for E2E latency were, as a result, gained.

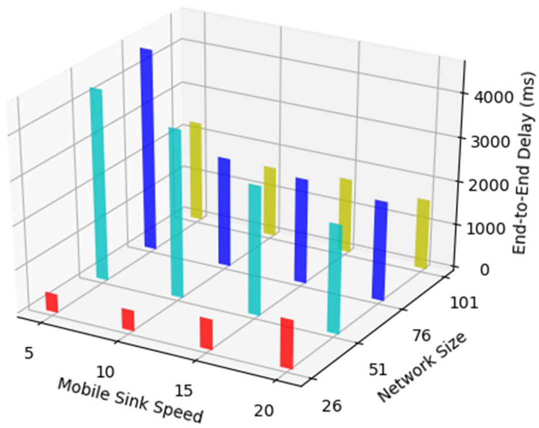

Fig. 1. Mean E2E latency for Kohonen SOM-based model

Figure 2 examines the mean E2E latency for the mobility-based GA model with various network sizes and MS velocities. As can be observed, the mobility-based GA model produced small E2E latency values at slow MS rates for all network sizes. These values augmented while increasing the speed of the MS. Additionally, the performance of the 51 and 76-node networks was nearly consistent. The rise in values was within a permissible range for various MS speeds that may be viewed in relation to the network size. On the contrary, for 26-node networks, there was a sharp rise in the E2E latency when the MS speed was equivalent to 20 m/s because sending packets from distant nodes to the MS while traveling quickly is challenging. Hence, these packets must travel long distances and may get routed through certain nodes as they follow the MS. The fact that there are many nodes and that it will take a while for the MS to visit all of the static nodes contributed to the 101-node networks' achievement of high E2E latency outcomes. Consequently, numerous data packets will be routed through many hops instead of a single hop, resulting in relatively long distances for the packets to traverse.

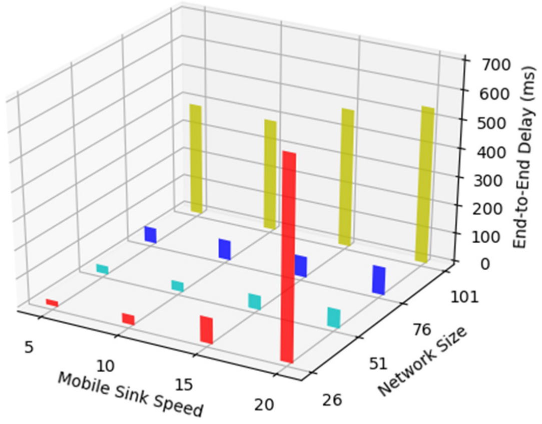

Fig. 2. Mean E2E latency for genetic algorithm-based model

Figure 3 illustrates the Kohonen-based MM results for PDR, consistent with those shown in Figure 1, since the network produced higher PDR values with minimal E2E delays. Figure 3 shows that higher ratios for small network sizes and slow MS speeds can be attained. This can be attributed to the MS's ability to visit all stationary SNs more often. Hence, S-H communication is frequently used. Moreover, the paths to perform this operation are fairly short when a stationary SN needs to employ multi-hop communication. In contrast, networks with 51, 76, and 101 nodes perform worse because stationary sensors are not visited as frequently as in networks with 26 nodes. Multi-hop routing is consequently used more frequently. However, adopting multi-hop routing could cause many nodes to become overwhelmed with messages coming from other immobile nodes, increasing the amount of dropped PDR. Additionally, the paths to transport packets are longer and could get longer if an MS relocates. As a result, dropping occurs for packets beyond the time-to-live limit (TTL).

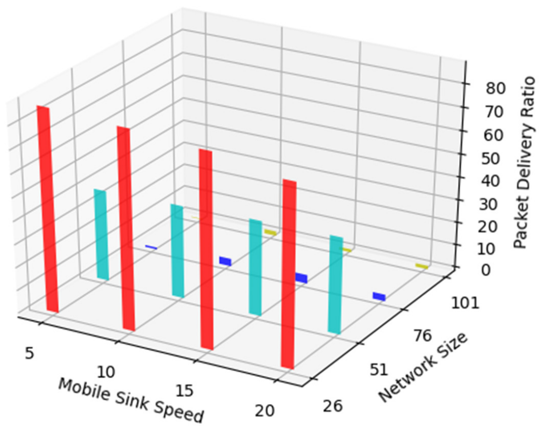

Fig. 3. PDR for Kohonen SOM-based model

The results from investigating the GA-based MM's performance based on PDR are shown in Figure 4. Network sizes 51 and 76 achieved higher and more consistent PDR results than others. The network size and the frequency with which the MS visits stationary SNs might be viewed as the causes of such behavior. Alternatively, the MS can collect data more quickly and visit the fixed SNs more frequently. On the other hand, in a network of 26 nodes, the MS may visit a stationary SN when it has no information to report. Multi-hop routing is therefore utilized when data from an SN needs to be sent to the MS. Due to the mobility of the sink node, routing becomes more difficult since packets continue to circulate the network till their TTL limit reaches zero, and they are dropped. Low PDR values are thus achieved. Furthermore, because there are so many nodes in the 101-node network, it took much longer for the MS to reach some static SNs, yielding lower results than the 51 and 76-node networks. Consequently, multi-hop routing is utilized when some stationary SNs get congested, and some packets could be dropped, impacting the network's packet delivery ratio.

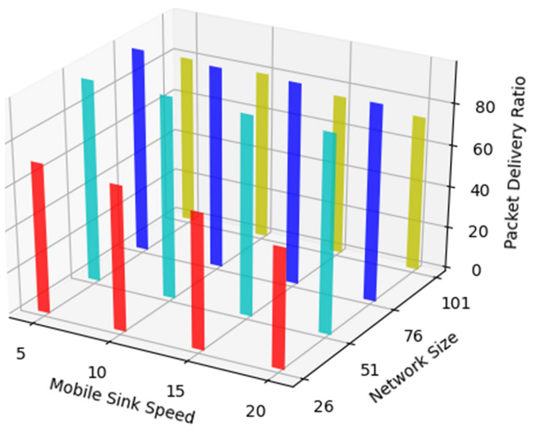

Fig. 4. PDR for genetic algorithm-based model

Figure 5 illustrates network throughput performance across a range of network sizes. It is clear that smaller networks, such as the 26-node network, had greater throughput when compared to all other network sizes, consistent with the findings from Figures 1 and 3. E2E latency and the PDR have performed better on smaller networks. As these two metrics are related, they will also deliver better throughput. Therefore, decreased E2E latency yields better throughput and PDR figures. The identical argument used to justify the behavior and output in the previous two cases can be applied to this kind of performance. Put another way, the total length of the routing pathways and increased movement speed immediately impact the use of S-H and multi-hop communication, affecting E2E latency, throughput, and PDR. It is important to note that larger networks perform better when the MS velocity increases since immobile SNs can be visited frequently. Nonetheless, the number of visits needs to be higher to have a significant effect on performance.

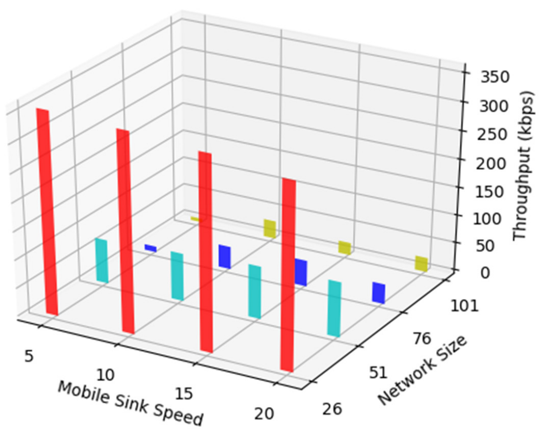

Fig. 5. Network throughput for Kohonen SOM-based model

Figure 6 displays the results from analyzing the throughput-based performance of the GA-based MM. As can be seen, network sizes 51 and 76 consistently outperformed other network sizes in terms of throughput. One could hypothesize that the causes of this behavior are the size of the network and the frequency with which the MS accesses immobile SNs. Put another way, the MS may travel more frequently to the stationary SNs and quickly gather data. In a network of 26 nodes, on the contrary, the MS might go to a static SN even if it has no data to report. Multi-hop routing sends data from an SN to an MS. However, because the sink node is moving, routing becomes more challenging because packets continue to travel through the network until their TTL parameter expires, so they are dropped. Thus, low throughput values are attained. The 101-node network also produced lower performance results than the 51 and 76-node networks because of the large number of nodes, which made it take much longer for the MS to reach some stationary SNs. Therefore, multi-hop routing is used when some stationary SNs get overloaded and some packets may be dropped, which would affect the network's performance.

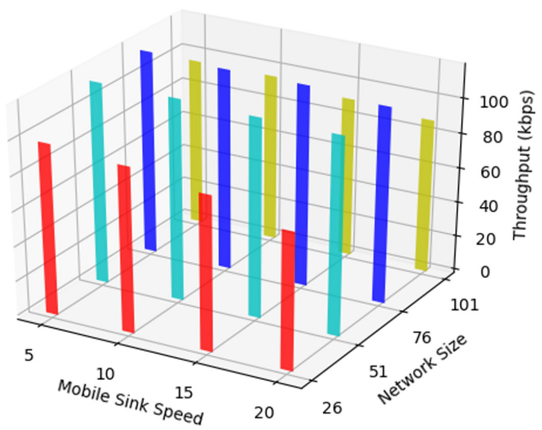

Fig 6. Network throughput for genetic algorithm-based model

6 CONCLUSIONS AND FUTURE WORK

Using the NS-2 simulator and various simulation scenarios, the effectiveness of two WSN MMs was evaluated in this study. Additionally, various measures, including E2E latency, throughput, and packet delivery rate, have been utilized to examine how these MMs operate using various network sizes and speeds of the MS. Our results show that the Kohonen-based MM suits small networks with an MS node moving at high speeds. However, the GA-based MM is better suited for small or medium-sized networks when an MS moves at moderate speeds. In our upcoming research, we intend to examine the performance of the studied models regarding energy consumption. In other words, consideration will be given to how these MMs affect the energy used by MSs and static SNs. The behaviors of the studied MMs under various packet sizes are another research direction to be considered. Along with AODV, we also intend to investigate how the MMs examined in this paper will function under other routing protocols. These limitations of this research can be addressed in future work.

7 REFERENCES

[1] A. Srinivasan and J. Wu, "TRACK: A novel connected dominating set based sink mobility model for WSNs," in *Proceedings of 17th International Conference on Computer Communications and Networks*, pp. 1–8 , 2008. https://doi.org/10.1109/ICCCN.2008.ECP.127

[2] X. Sun, Y. Yang, and M. Ma, "Minimum connected dominating set algorithms for ad hoc sensor networks," *Sensors,* vol. 19, p. 1919, 2019. https://doi.org/10.3390/s19081919

[3] A. Sikora and E. Niewiadomska-Szynkiewicz, "Mobility model for self-configuring mobile sensor network," in *The Fifth International Conference on Sensor Technologies and Applications, SENSORCOMM*, pp. 97–102, 2011.

[4] A. Sardouk, R. Rahim-Amoud, L. Merghem-Boulahia, and D. Gaïti, "Data aggregation scheme for a multi-application WSN," In *Wired-Wireless Multimedia Networks and Services Management: 12th IFIP/IEEE International Conference on Management of Multimedia and Mobile Networks and Services, MMNS 2009,* Venice, Italy, pp. 183–188, 2009. https://doi.org/10.1007/978-3-642-04994-1_16

[5] A. S, K. Makkithaya and H. Hebbar N, "Quality of service-based cross-layer protocol for wireless sensor networks," *International Journal of Interactive Mobile Technology*, vol. 16, no. 20, pp. 34–58, 2022. https://doi.org/10.3991/ijim.v16i20.31111

[6] A. A. Taleb, "A comparative study of mobility models for wireless sensor networks," *J. Comput. Sci.,* vol. 14, pp. 1279–1292, 2018. https://doi.org/10.3844/jcssp.2018.1279.1292

[7] S. Aslam, F. Farooq, and S. Sarwar, "Power consumption in wireless sensor networks," in *Proceedings of the 7th International Conference on Frontiers of Information Technology*, pp. 1–9, 2009. https://doi.org/10.1145/1838002.1838017

[8] M. Al-Razgan and T. Alfakih, "Wireless sensor network architecture based on mobile edge computing," *Security and Communication Networks,* vol. 2022, 2022. https://doi.org/10.1155/2022/9073220

[9] N. Temene, C. Sergiou, C. Georgiou, and V. Vassiliou, "A survey on mobility in Wireless Sensor Networks," *Ad Hoc Networks,* vol. 125, p. 102726, 2022. https://doi.org/10.1016/j.adhoc.2021.102726

[10] J.-Y. Chang, J.-T. Jeng, Y.-H. Sheu, Z.-J. Jian, and W.-Y. Chang, "An efficient data collection path planning scheme for wireless sensor networks with mobile sinks," *EURASIP Journal on Wireless Communications and Networking,* vol. 2020, pp. 1–23, 2020. https://doi.org/10.1186/s13638-020-01873-4

[11] J. Zhang, J. Tang, and F. Wang, "Cooperative relay selection for load balancing with mobility in hierarchical WSNs: A multi-armed bandit approach," *IEEE Access,* vol. 8, pp. 18110–18122, 2020. https://doi.org/10.1109/ACCESS.2020.2968562

[12] Y. Guo, Z. Xu, and J. Saleh, "Collaborative allocation and optimization of path planning for static and mobile sensors in hybrid sensor networks for environment monitoring and anomaly search," *Sensors,* vol. 21, p. 7867, 2021. https://doi.org/10.3390/s21237867

[13] A. Prasanth and S. Pavalarajan, "Zone-based sink mobility in wireless sensor networks," *Sensor Review,* vol. 39, pp. 874–880, 2019. https://doi.org/10.1108/SR-11-2018-0310

[14] S. Yalçin and E. Erdem, "Performance analysis of burst traffic awareness based mobile sink routing technique for wireless sensor networks," *Gazi University Journal of Science,* vol. 35, pp. 506–522, 2022. https://doi.org/10.35378/gujs.863598

[15] X. Wu, Z. Chen, Y. Zhong, H. Zhu, and P. Zhang, "End-to-end data collection strategy using the mobile sink in wireless sensor networks," *International Journal of Distributed Sensor Networks,* vol. 18, p. 15501329221077932, 2022. https://doi.org/10.1177/15501329221077932

[16] A. Alsaafin, A. M. Khedr, and Z. Al Aghbari, "Distributed trajectory design for data gathering using the mobile sink in wireless sensor networks," *AEU-International Journal of Electronics and Communications,* vol. 96, pp. 1–12, 2018. https://doi.org/10.1016/j.aeue.2018.09.005

[17] M. Naghibi and H. Barati, "EGRPM: Energy efficient geographic routing protocol based on the mobile sink in wireless sensor networks," *Sustainable Computing: Informatics and Systems,* vol. 25, p. 100377, 2020. https://doi.org/10.1016/j.suscom.2020.100377

[18] Abu Taleb, Anas, Qasem Abu Al-Haija, and Ammar Odeh, "Efficient mobile sink routing in wireless sensor networks using bipartite graphs," *Future Internet*, vol. 15, no. 5, p. 182, 2023. https://doi.org/10.3390/fi15050182

[19] Yalçın, Sercan, and Ebubekir Erdem, "BTA-MM: Burst traffic awareness-based adaptive mobility model with mobile sinks for heterogeneous wireless sensor networks." *ISA Transactions*, vol. 125, pp. 338–359, 2022. https://doi.org/10.1016/j.isatra.2021.06.027

[20] Jolan Baccay Sy and Jake Dayag La Madrid, "Energy efficient routing protocol for wireless sensor network with mobile sink," *International Journal of Scientific and Research Publications (IJSRP)*, vol. 12, no. 10, pp. 67–81, 2022. https://doi.org/10.29322/IJSRP.12.10.2022.p13009

[21] A. A. Taleb, "Sink mobility model for wireless sensor networks using Kohonen self-organizing map," *International Journal of Communication Networks and Information Security,* vol. 13, pp. 62–67, 2021. https://doi.org/10.17762/ijcnis.v13i1.4813

[22] A. Abu Taleb, "Sink mobility model for wireless sensor networks using genetic algorithm," *Journal of Theoretical and Applied Information Technology,* vol. 99, pp. 540–551, 2021.

[23] A. B. Hassanat, V. S. Prasath, M. A. Abbadi, S. A. Abu-Qdari, and H. Faris, "An improved genetic algorithm with a new initialization mechanism based on regression techniques," *information,* vol. 9, p. 167, 2018. https://doi.org/10.3390/info9070167

[24] M. Amnai, Y. Fakhri, and J. Abouchabaka, "Impact of mobility on delay-throughput performance in multi-service mobile ad-hoc networks," *Int'l. J. of Communications, Network and System Sciences,* vol. 4, p. 395, 2011. https://doi.org/10.4236/ijcns.2011.46047

[25] M. Karyakarte, A. Tavildar, and R. Khanna, "Effect of mobility models on performance of mobile wireless sensor networks," *International Journal of Computer Networking, Wireless and Mobile Communication (IJCNWMC),* 2013.

8 AUTHORS

Dr. Anas Abu Taleb received a Ph.D. from the University of Bristol, UK, in 2010, an MSc. from the University of the West of England, UK, in 2007, and a BSc. Degree from Princess Sumaya University for Technology, Jordan, in 2004. In addition to wireless sensor networks, he is interested in network fault tolerance, routing algorithms, and cloud computing. He is an associate professor in computer science at Princess Sumaya University for Technology (E-mail: a.abutaleb@psut.edu.jo).

Dr. Qasem Abu Al-Haija received his Ph.D. in Computer Engineering from Tennessee State University (TSU), USA, in 2020 and his M.Sc. in Computer Engineering from Jordan University of Science and Technology, Jordan, in 2010. His research interests include Artificial Intelligence (AI), Cybersecurity and Cryptography, the Internet of Things (IoT), Cyber-Physical Systems (CPS), Time Series Analysis (TSA), and Computer Arithmetic. He is an assistant cybersecurity professor at Princess Sumaya University for Technology (E-mail: q.abualhaija@psut.edu.jo).

Dr. Ammar Odeh earned his Ph.D. in Computer Science and Engineering from the University of Bridgeport in 2015 and his M.Sc. in Computer Science from Jordan University in 2006. His research interests include Computer Security and Software Engineering, and he teaches Programming Languages, Information Security, and Software Engineering. He is an associate professor in computer science at Princess Sumaya University for Technology (E-mail: a.odeh@psut.edu.jo).