Sink Mobility Model for Wireless Sensor Networks using Kohonen Self-Organizing Map

Anas Abu Taleb

Department of Computer Science, King Hussein School of Computing Sciences, Princess Sumaya University for Technology, Jordan

Abstract: Wireless sensor networks are expected to operate in an unattended manner for long periods of time. As a result, different mobility models were proposed by many research papers in order to improve the performance and extend the lifetime of the network. In this paper a new sink mobility model that is based on kohonen self-organizing maps is proposed in order to provide a mobile sink node with the ability to collect data from static sensor nodes. Moreover, the performance of the proposed mobility model was studied using NS-2 simulator under different network sizes and movement speeds of the mobile sink. Finally, the performance of the proposed model was evaluated based on different performance metrics namely, end-to-end delay, packet delivery ratio and throughput.

Keywords: Wireless Sensor Networks, Mobility, Self-organizing Map, Performance

1. Introduction

Wireless sensor networks (WSNs) are distributed architectures composed of hundreds or thousands of small, lightweight and battery operated static sensor nodes. Consequently, WSNs can be randomly deployed in the area of interest in order to measure specific phenomena of parameters such as humidity, pressure and temperature and so on. Therefore, WSNs have many applications in various areas such as military, agricultural and healthcare [1][2].

In WSNs, sensor nodes are not only responsible for collect information from the environment and reporting these information to the base station but also, they are required to forward and route messages sent by other sensor nodes until these messages are delivered to the base station. This approach helps to prolong the network lifetime by reducing the amount of energy consumed in communication sine every sensor node used multihop communication. Thus, every sensor nodes is communication with its neighbors only. On the other hand, sensor nodes that are close to the base station might consume most of their energy forwarding messages send by other sensor nodes. As a result, close sensor nodes will get there battery depleted quickly.

To solve such problem, we proposed deploying an energy rich mobile sink that is responsible for collection information from static sensor nodes and report them to the base station. To achieve this goal, the mobile node will be moving within the network according to a specific mobility model and visit the static sensor nodes in order to collect data from them. In this paper, we propose a new intelligent sink mobility model, based on Kohonen self-organizing map, that assist the mobile sink visit static sensor nodes while taking the following constraints into account; first collect data from sensor nodes in a timely manner such that data gets reported to the base station before it becomes old and obsolete.

Second reduce the amount of time between two consecutive visits of the same static sensor node. As a result, a static sensor node do not need to store large amounts of data and suffer from buffer overflow.

Therefore, average end-to-end delay, packet delivery ratio and throughput are the performance parameters that will be taken into consideration to study the performance of the proposed mobility model under different scenarios using NS-2 simulator.

The rest of this paper is organized as follows; in section 2 related work is discussed and reviewed. After that, the proposed mobility model is presented in section 3. Simulation environment, metrics and scenarios are presented in section 4. In section 5 simulation results are discussed. Finally, the paper is concluded and directions of future work are provided in section 6.

2. Related Work

2.1. Kohonen Self-Organizing Map

In this section, we study Kohonen self-organizing map (SOM) that was originally introduced by Kohonen [3] and is considered as a special class of artificial neural networks known as competitive neural networks paradigm [4]. The main idea behind SOM is to establish a topological relationship of input data using a learning scheme known as competitive learning. In this scheme, the output neurons that are fully connected to input nodes compete among each other in order to get activated. Based on the input value, output neurons compete to get activated and only one output neuron, winning neuron, wins the competition and gets activated [4]. To elaborate, for each input pattern fed to the map, all neuron calculate values to determine the degree of similarity according to a discriminate function. As a result, the most similar neuron to the input value is considered the winning neuron [5].

Kohonen self-organizing map belong to the competitive neural networks paradigm and is based on a feed-forward structure consisting of single computational layer containing output neurons arranged in rows and columns. In other words, Kohonen self-organizing map can be considered as a system consisting of two layers namely; input layer and output layer. The input layer, represents the input data set that will be fed to the output neurons. The output layer consists of a set of output neurons organized in a two dimensional lattice where every output neuron is fully connected to the input nodes in the first layer. Figure 1 shows a two dimensional SOM. Worth noting, lattice with other dimensions can be used but two dimensional lattice is commonly used [4].

To construct Kohonen self-organizing map, four major processes must be applied; Initialization, Competition, Cooperation and Adaptation that can be described as follows:

a. Initialization

In this phase synaptic weight of all connections in the network is initialized. This can be achieved by assigning them small values generated by a random number generator. According to [7], there are different approaches that can be adopted to initialize the self-organizing map such as using random values or trying to reflect the input data distribution to the self-organizing map. However, the authors of [4] argue that to avoid bias and to make sure that no prior order is enforced on the feature map it is better to use random number generator.

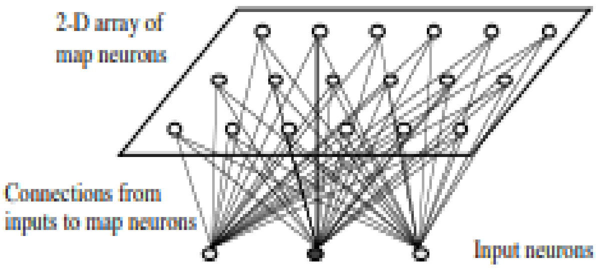

Figure 1: Two Dimensional Kohonen Self-organizing Map [6]

b. Competition

After executing the initialization process, the algorithm proceeds to the competition process. In this process, every neuron calculates its own respective value for each input pattern based on a discriminant function. Consequently, the neuron whose discriminant function value is the closest to the input pattern is the winning neuron [4][6].

To elaborate, if the input space consists of D input nodes i.e. the input space is D dimensional, the input pattern can be represented according to Eq. 1 which is adapted from [4]

$$x = [x_1, x_2, \dots, x_D]^T \qquad (1)$$

Since neurons in the output layer are fully connected to all input nodes in the input layer, the dimension of the synaptic weight vector for each neuron must be the same as that in the input space. As a result, Eq. 2 can be used to denote synaptic weight vector of neuron j [4]

$$w_j = [w_{j1}, w_{j2}, \dots, w_{jD}]^T \qquad ,j = 1, 2, \dots, N \qquad (2)$$

where N represents the number of neurons in the output layer. To find the winning neuron that provides the best match for the input patter $\boldsymbol{x}$, the inner product of $w_j^T x$ is calculated for each neuron based on the input patter. After that, the calculated values of the neurons are compared and the neuron with the largest inner product is selected as the winning neuron. This is mathematically equivalent to finding the minimum squared Euclidean distance, presented in Eq. 3, between $\boldsymbol{x}$ and $\boldsymbol{w_j}$. As a result, the neuron whose weight becomes closer to the input patter is the winning neuron because it is the most similar neuron to the input pattern [4].

$$d_j(x) = \sum_{i=1}^{D} (x_i - w_{ji})^2 \qquad (3)$$

In this way the input patterns use the squared Euclidean distance as their discriminant function to be mapped to the output neurons using the competition process between the output neurons.

c. Cooperation

The cooperation process is derived from neurobiological studies that are based on finding the lateral interaction between a set of neurons known as excited neurons. Say it in another way, when a neuron is selected to be the winning neuron, neurons that are the closest to it have a tendency to get excited more than neurons that are located far away from it. Thus, a topological neighborhood around the winning neuron can be identified and the foundation for cooperation between neighboring neurons is established through this process [4][5][6].

To define the topological neighborhood centered at the winning neuron, let $\boldsymbol{h_{ij}}$ represents the topological neighborhood centered around a winning neuron $\boldsymbol{i}$. This neighborhood consists of a set of cooperating neurons where each one of them is denoted by $\boldsymbol{j}$. Furthermore, the lateral distance between the winning neuron I and the cooperating neuron $\boldsymbol{j}$ is denoted by $\boldsymbol{d_{ij}}$. Hence, the topological neighborhood of the winning neuron I can be calculated according to Eq. 4 according to [4].

$$h_{j,i(x)} = \exp\left(-\frac{d_{j,i}^2}{2\sigma^2}\right) \qquad (4)$$

In Eq. 4, the index of the winning neuron is indicated by $\boldsymbol{i(x)}$. Also, the size of the neighborhood is denoted by $\boldsymbol{\sigma}$ calculated according to Eq. 5 where $\boldsymbol{k}$ denotes the number of iterations and $\boldsymbol{\tau_1}$ is an exponential time constant defined by the designer and $\boldsymbol{\sigma_0}$ is the initial value of $\boldsymbol{\sigma}$ [8][4].

$$\sigma_{k} = \sigma_0 \exp\left(-\frac{k}{\tau_1}\right) \qquad (5)$$

Additionally, the authors in [4] provided the following requirements that must be satisfied by the function presented in Eq. 4:

1. The maximum value is obtained at the winning neuron.
2. The topological neighborhood decreases monotonically to zero as the lateral distance goes to infinity.
3. It is independent from the location of the winning neuron.

In conclusion, based on the functions defined in Eq. 4 and 5, the winning neuron is defined and its topological neighborhood is calculated. Note that the size of the topological neighborhood must be decreased with time in order to construct Kohonen SOM and find an optimal solution.

d. Adaptation

According to [4] and [6], to improve the winning neuron response in the next iteration of input patterns, the cooperate neurons adjust their discriminant function values according to the current input pattern. As a result, the cooperate neurons adjust the weight of the links associated with them using suitable adjustment values. According to [4], the adaptation process is based on Eq. 6 that is used to adjust the weight of $\boldsymbol{j}$ at time n+1 and will be applied on all neurons in the topological neighborhood of the winning neuron.

$$w_j(n+1) = w_j(n) + \eta(n) h_{j,i(x)}(n)(x(n) - w_j(n)) \qquad (6)$$

Worth noting that the learning rate in Eq. 6 is indicated by $\boldsymbol{\eta(n)}$ and is calculated according to Eq. 7. Additionally, when Eq. 6 is applied on all neurons that fall inside the topological neighborhood of the winning neuron. As a result the weight vector of the winning neuron will move towards the input vector. Consequently, the weight vector of winning neurons will follow the distribution of the input vector when this step is applied repetitively [4].

$$\eta(n) = \eta_0 \exp\left(-\frac{n}{\tau_2}\right), n = 0, 1, 2, \dots, \qquad (7)$$

From Eq. 7 it can be observed that the learning rate starts with an initial value indicated by η_0. After that the learning rate decays gradually when time, **n**, increases. Also, this equation is based on a time constant $\boldsymbol{\tau_2}$ of the self-organizing map algorithm [4].

2.2. Sink Mobility Models

To improve the performance of WSNs many research works have proposed deploying a single mobile sink that will be moving within the area of deployment of a WSN in order to collect data from static sensor nodes and relay such piece of information to the base station for further processing.

Consequently, the authors of [9] proposed a data gathering protocol that is responsible for designing a trajectory that can be used by the mobile sink in order to collect data from static sensor nodes. As a result, the proposed protocol is based on four stages namely, data sensing, rendezvous point (RP) selection, trajectory design, and data gathering. Additionally, three algorithms to construct the mobile sink movement trajectory were proposed in order to support various applications Hence, data will be collected by the mobile sink based on these trajectories.

Additionally, a sink relocation method was proposed in [10]. In this research, a clustering technique based on grouping sensor nodes that are closer to the sink node into the same cluster was proposed. In other words, the distance between the sink node and sensor nodes is taken into account in order to group intermediate sensor nodes in the same cluster. Furthermore, sink node repositioning is accomplished based on the selected cluster head according to two cases, namely cluster head with minimal distance and cluster head with long distance, that are adopted based on the distance between the sink node and the cluster head.

In order to prolong sensor networks lifetime, a mathematical model for sink node mobility was proposed in [11]. The proposed model is based on having the mobile sink to be initially deployed at the center of the area of interest. After that, a number of tentative sink sites are calculated and a asa result of this calculation the location of the sink node is selected.

The authors on [12] proposed a location based sink mobility model where the movement of the mobile node is dependent on network topology, the distance between the current and previous locations and the distance between the current location of the sink node and the and the newly selected on which the sink nodes may start moving to. Additionally, the mobile node behavior can be divided into active and inactive phases. Thus, data is transmitted during the active phase. On the other hand, mobile node movement is executed during the inactive phase.

To improve energy consumption and extend the sensor network lifetime, the authors of [13] proposed a solution for the relay selection problem. In their work, K-mean method was adopted to create clusters. After that, a cluster head selection method that employs the use of a mobile sink was developed in order to enhance energy consumption within the cluster. Furthermore, the use of a virtual cluster head was introduced which enables energy optimization because the mobile sink will act as a virtual cluster head and will move near to sensor nodes in order to collect data from them.

Another technique to prolong network lifetime using clustering and mobile sink nodes was proposed in [14]. In this technique a mobile sink is allowed to move with a cluster and between clusters in order to collect information from static sensor nodes. As a result, when arriving to a new cluster the mobile sink will move between sensor nodes, instead of being idle, to collect information and reduce the distance required for communication.

A breadth first sink mobility model was proposed in [15] where the mobile sink movement is controlled and accomplished based on a path that is calculated according to the breadth first graph traversal algorithm. In the research proposed in [15], the mobility of the sink is divided into mobility periods and pause periods. In the first the mobile sink moves a new location while in the second on the mobile sink stay still in its new location for a period of time in order to collect data from nearby sensor nodes.

The research proposed in [16] aims to decrease the delay and increase the throughput using opportunistic method to collect data from static sensor nodes. Hence, if a sensor node is within the range of the mobile sink data is forwarded directly otherwise, a sensor node stores the data it has collected until the mobile sink moves to its vicinity so that data can be communicated via single hop communication.

3. Proposed mobility Model

The mobility model proposed on this paper is based on Kohonen self-organizing map explained in section 2.1. We will assume having a wireless sensor network consisting of N static sensor nodes with an additional mobile and energy rich sink node. The mobile sink node is responsible for collecting data from static sensor nodes by visiting these node according to Kohonen self-organizing map.

The calculation of the movement path is executed offline before deploying the mobile sink so that the movement path of the mobile sink is predefined and fixed. Also, this stage is important to make sure that the movement path adopted will include all the static sensor nodes all nodes are visited by the mobile sink.

To elaborate, the network will consist of **N** static sensor nodes that are randomly deployed in the area of interest. Furthermore, a mobile sink nodes will be deployed randomly in the same area. In other words, the journey of the mobile sink can start at a randomly selected position of a static sensor node. After that, the movement of the mobile sink is divided into movement periods and sojourn periods. Starting at a randomly selected position, the mobile sink enters the sojourn period and stays in its current location for a specific period of time. During this period of time, the mobile sink collects data from the static sensor node in this location. Thus it can be observed that the proposed model aims to reduce the amount of energy consumed in communication by reducing the distance between a static sensor node and the mobile sink.

When the pause period is over, the motion period is initiated and the mobile sink must select a new location that is selected based on the calculation of Kohonen self-organizing map. Consequently, a location of a static sensor node is selected as a target location and the mobile sink will start moving towards it. Upon arrival to its new location, the mobile sink enters the sojourn period again and starts collecting data form the static sensor node in that location. This process continues until all static sensor nodes are visited and the sink node returns to the starting location. After that, a new journey for the mobile sink is started in the same manner until changes in the network topology due to energy depletion are detected. As a result, this event must be reported to the base station and a new path must be calculated. Algorithm 1 shows the proposed mobility model for the sink node.

Algorithm 1: Proposed Mobility Model

1. **Start**
2. **Initialize a group of nodes: N = {n_0, n_1, n_2, … n_{n-1}}**
3. **Initialize a mobile sink node: SN = {n_n}**
4. **Let Q be queue**
5. **Enqueue N to Q**
6. **Dequeue the first node in the queue and store it in v**
7. **Select a starting point node S for the mobile sink where S ∈ N and S = n_0**
8. **Enqueue S to Q**
9. **While Q is not empty**
   - **9.1. Dequeue the first node in the queue and store it in v.**
   - **9.2. Get x and y coordinates of v**
   - **9.3. Let n_n move to x and y coordinates of v**
   - **9.4. Pause in new position for time t**
   - **9.5. Collect data**
10. **End While**
11. **Stop**

To avoid buffer overflow and reduce the delay at static sensor nodes, AODV routing protocol has been adopted and adjusted. Hence, if a static sensor node must report data to the mobile sink without having it in its vicinity, AODV routing protocol will be used to route messages via multihop routing to the mobile sink. On the other hand, if the mobile sink exists in the static node's vicinity data will be transmitted directly to the mobile sink via singlehop communication. Note that AODV routing protocol was adopted due to its reactive nature and ability to establish routes in a quick manner [17][18].

4. Simulation

4.1. Simulation Environment and Parameters

To study the performance of the proposed mobility model, simulation experiments were conducted using NS-2 simulator which is one of the mostly used simulators to study the performance of wired and wireless networks. Furthermore, AODV routing protocol is used to deliver messages to the mobile sink in the same manner explained in section 3.

Table 1. Simulation Parameters

Parameter	Value
Simulation Time	1000 seconds
Number of Nodes	26, 51, 76, 101
Pause Time	5 Seconds
Simulation Area	1000*1000
Traffic Type	CBR
Mobile Sink Speed	5, 10, 15, 20 m/s

The performance of the proposed mobility model was studied using different network sizes namely 26, 51, 76 and 101 that were randomly deployed in 1000*1000 flat grid. Note that 26 node network consisted of 25 static sensor nodes plus and extra mobile sink node to collect data and so on for all other network sizes. Also, static sensor nodes are generating traffic according to a constant bit rate (CBR). Additionally, the performance of the proposed model was studied under different speeds of the mobile sink namely, 5, 10, 15 and 20 m/s and a 5 seconds pause time to simulate the sojourn period of the mobile sink. Table I summarizes the simulation parameters that were used in order to obtain results.

For every network size the performance of the mobility model was studied in the following manner; first the static sensor nodes are randomly deployed. After that a mobile sink node will start moving within the network according to the proposed mobility model. In the first scenario, the network size is fixed e.g. 26 nodes network is used and the movement speed of the mobile node was varied according to the values shown in table I. After that, the network size is increased to 51 nodes and the performance is studied according to different speeds of the mobile sink.

To elaborate, at the beginning we start with a 26 node network size while having the mobile sink moving with 5m/s speed. This scenario was simulated for 1000 seconds. After that, the same network size was simulated for the same period of time while having the mobile sink moving with 10 m/s speed and the same scenario was repeated for 15 and 20 m/s mobile sink speed. Next, the network size was changed to 51 nodes and the performance was studied under the four different speeds of the mobile sink in the same manner adopted for 26 nodes network. Subsequently, the same approach was followed for other network sizes.

4.2. Performance Metrics

In order to study the performance of the proposed mobility model three performance metrics were taken into consideration namely average end-to-end delay, packet delivery ratio and throughput. These performance metrics can be described as follows:

A. Average End-to-End Delay can be calculated as the time required for a packet to be delivered to its destination according to the time it first left the source. The average end-to-end delay for the whole network is calculated for the whole network by averaging the time required for all packets sent between all sources and all destinations in the network [19]. This performance metric is calculated according to Eq. 8 [19].

$$T_{AVG} = \sum_{i=1}^{N} \frac{(H_r^i - H_t^i)}{N} \quad (8)$$

where H_r^i is the received copy of a packet while H_t^i represents the transmitted instance of the packet. Additionally, N denotes the total number of packets received [19]. According to [20], the proposed mobility model must achieve low average end-to-end delay in order to provide a good performance.

B. Packet Delivery Ratio can be defined as the total number of successfully received packets divided by the overall number of transmitted packets and is calculated according to Eq. 9 [20][21].

$$Packet\ Delivery\ Ratio = \frac{P_{rs}}{\sum_{i=1}^{n} P_{sent_i}} \quad (9)$$

In equation 9 P_{rs} and P_{sent_i} denote the total number of successfully received packets and the overall number of transmitted packets respectively.

C. Throughput can be calculated by dividing the total number of packets received successfully to the total simulation time and is measured in bits/sec. As a result, the proposed sink mobility model must aim to achieve high values for this performance metric in order to provide high performance levels [19]. According to [20] throughput is calculated according to Eq. 10.

$$Throughput = \frac{Number\ of\ Packets\ Delivered * Packet\ Size * 8}{Total\ Simulation\ Time} \quad (10)$$

5. Results

In this section results obtained from simulating the proposed mobility model, according to the simulation scenarios and performance metrics in section 4.1 and section 4.2, are presented and discussed. In order to achieve more accurate results each scenario was run 10 times. Thus, the simulation results were obtained from averaging the result of the 10 run for each case.

Figure 2 shows average end-to-end delay results for different network sizes and for different movement speeds of the mobile sink. It can be observed that the proposed mobility model obtain lower and stable end-to-end delay results for small network size i.e. 26 nodes networks because the movement path adopted by the mobile sink is smaller than other network sizes. As a result, the mobile sink has the ability to visit all the static sensor nodes it its path at descent frequency in order to collect data from them using singlehop communication. Thus, lower end-to end delay values were obtained and a better performance is achieved.

Furthermore, figure 2 shows that the values obtained for 15 and 20 m/s speeds for 26 nodes network were higher than those of 5 and 10 m/s because when the mobile sink is moving at low speeds, more time is spent in a static sensor node vicinity. As a result, a static sensor node has more time to transmit its data to the mobile sink using singlhop communication. On the other hand, for higher movement speeds namely 15 and 20 m/s, the mobile sink will enter and leave the vicinity of a static sensor node quickly. As a result, a static sensor node might need to use multihop communication or routing to transmit its data to the mobile sink which increases the values obtained for end-to-end delay.

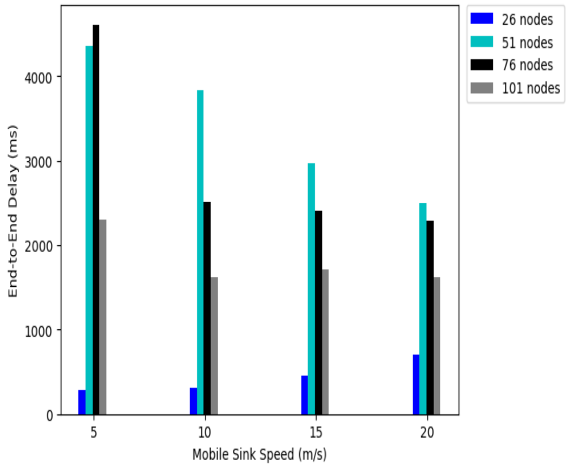

Figure 2: Average End-to-End Delay

Additionally, when increasing the network size the values of obtained for end-to-end delay were increased. This can be regarded to the length of the path that has to be followed by the mobile sink. As a result, the frequency according to which static sensor nodes are visited via the mobile sink is lower. Consequently, multihop routing will be used more frequently. Thus, higher end-to-end delay values were achieved. Also, figure 2 shows that networks consisting of 76 and 101 nodes obtained better results than 51 nodes network which can be regarded to the network node density. To elaborate, 76 and 101 nodes network have more node density than 51 nodes networks. Thus, static sensor nodes have higher number of neighbors. As a result, when the mobile sink move to the vicinity of a static sensor node to collect data, the neighbors of that static node can also communicate with the mobile sink using short paths. Hence, achieving lower end-to-end delay values.

Results regarding packet delivery ratio are presented in figure 3 which are compatible with the results obtained in figure 2 since the network that achieved low values of end-to-end delay have obtained higher values of packet delivery ratio. From figure 3 it can be observed that better ratios can be obtained for small network sizes under low movement speeds of the mobile sink. This can be regarded to the ability of the mobile sink to visit all static sensor nodes more frequently. Thus, singlehop communication is used regularly. Additionally, when a static sensor node need to use multihop communication, the paths to accomplish this task are relatively short. On the other hand, networks consisting of 51, 76 and 101 nodes obtained lower results because static sensor nodes will not be visited in the same frequency as 26 nodes network. As a result, multihop routing is used more regularly. However, when using multihop routing a lot of nodes might get overloaded with packets originating from other sensor nodes which increases the number of dropped packets and decreased the packet delivery ratio. Furthermore, the paths used to deliver packets are longer and when the mobile sink movement to another location might cause the path to be even longer. As a result, packets get dropped because of exceeding the time to live parameter.

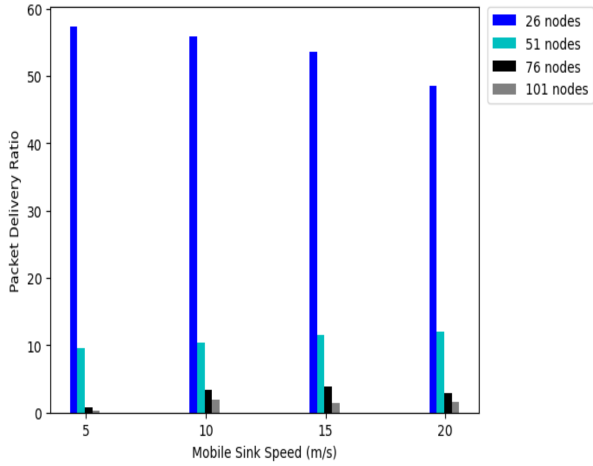

Figure 3: Packet Delivery Ratio

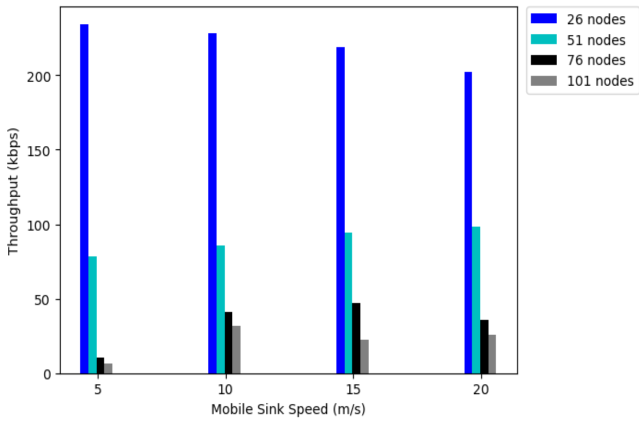

Figure 4: Network Throughput

The performance of different network sizes according to network throughput is shown in figure 4. It can be observed the networks with small sizes namely 26 nodes network obtained higher throughput than all other network sizes which complies with the results obtained from figures 2 and 3. Since small network sizes obtained better performance results regarding end-to-end-delay and packet delivery ratio, they will obtain higher performance results regarding throughput since these parameters are linked to each other. Thus, lower end-to-end delay results in higher values and results in terms of packet delivery ratio and throughput. This kind of performance can be regarded to the same reason that justified the behavior and performance in the previous two cases. In other words, the length of the routing paths and the increase of the movement speed has direct impact of the use of single hop and multi-hop communication which in term affect the end-to-end delay, packet delivery ratio and throughput. It is worth noting that the performance of larger networks has increased when increasing the mobile sink speed because static senor nodes can be visited regularly. However, the frequency of visits is not in a good level to have a direct impact on the performance.

6. Conclusion

A new sink mobility model that is based on kohonen self-organizing map was proposed in this paper. After that, the performance of the mobility model was studied under different network sizes and mobile sink speeds. Also, different performance parameters were adopted to evaluate the proposed mobility model. The results obtained show that the mobility model proposed in this paper is suitable to be used with small network sizes and moderate speed of the mobile sink.

The work proposed in this paper can be further extended to study the energy consumption of sensor network when such mobility model is used. Furthermore, other routing protocol can be used in order to study their effect on the proposed mobility model and try to enhance the performance. In addition, the performance of the mobility model proposed in this paper can be compared with other well-known mobility models using the same scenarios and performance parameter.

References

[1] Sikora, A.; Niewiadomska-Szynkiewicz, E.: “Mobility model for self-configuring mobile sensor network.” The Fifth International Conference on Sensor Technologies and applications, SENSORCOMM’11, pp. 97–102, August 2011.

[2] Sardouk A., Rahim-Amoud R., Merghem-Boulahia L., Gaïti D. (2009) Data Aggregation Scheme for a Multi-Application WSN. In: Pfeifer T., Bellavista P. (eds) Wired-Wireless Multimedia Networks and Services Management. MMNS 2009. Lecture Notes in Computer Science, vol 5842. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-04994-1_16

[3] T. Kohonen, "The self-organizing map," in *Proceedings of the IEEE*, vol. 78, no. 9, pp. 1464-1480, Sept. 1990, doi: 10.1109/5.58325.

[4] S. S. Haykin, Neural networks and learning machines/Simon Haykin, New York:Prentice Hall, 2009.

[5] D. Miljković, "Brief review of self-organizing maps," *2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 2017, pp. 1061-1066. doi: 10.23919/MIPRO.2017.7973581

[6] Bill Wilson, Self-organisation Notes, 2019, www.cse.unsw.edu.au/~billw/cs9444/selforganising-10-4up.pdf

[7] A. A. Akinduko and E. M. Mirkes, “Initialization of self-organizing maps: principal components versus random initialization. A case study”, Information Sciences, Vol. 364, no. C, pp. 213-221, Oct. 2016.

[8] Y. Bai, W. Zhang, Zh. Jin, "An new self-organizing maps strategy for solving the traveling salesman problem", *Chaos Solitons& Fractals*, Elsevier, vol. 28, no. 4, pp. 1082-1089, 2006.

[9] Areej Alsaafin, Ahmed M. Khedr and Zaher Al Aghbari, “Distributed trajectory design for data gathering using mobile sink in wireless sensor networks,” *AEU - International Journal of Electronics andCommunications*, vol. **96**, pp. 1-12, 2018.

[10] Pushpalatha, A., Kousalya, G. “A prolonged network life time and reliable data transmission aware optimal sink relocation mechanism.” *Cluster Comput* **22,** 12049–12058 (2019). https://doi.org/10.1007/s10586-017-1551-7

[11] Kumar M., Kumar D., Akhtar M.A.K. (2019) “ Mathematical Model for Sink Mobility (MMSM) in Wireless Sensor Networks to Improve Network Lifetime.” In: Verma S., Tomar R., Chaurasia B., Singh V., Abawajy J. (eds) Communication, Networks and Computing. CNC 2018. Communications in Computer and Information Science, vol 839. Springer, Singapore, 2019.

[12] Al-Rahayfeh, A.; Razaque, A.; Jararweh, Y.; Almiani, M. “Location-Based Lattice Mobility Model for Wireless Sensor Networks.” *Sensors (Basel, Switzerland)* vol. 18,12 4096. 22 Nov. 2018, doi:10.3390/s18124096

[13] J. Zhang, J. Tang and F. Wang, "Cooperative Relay Selection for Load Balancing with Mobility in Hierarchical WSNs: A Multi-Armed Bandit Approach," in IEEE Access, vol. 8, pp. 18110-18122, 2020, doi: 10.1109/ACCESS.2020.2968562.

[14] N. Gharaei, K. Abu Bakar, S. Z. M. Hashim, and A. H. Pourasl, ‘‘Inter- and intra-cluster movement of mobile sink algorithms for cluster-based networks to enhance the network lifetime,’’ Ad Hoc Networks., vol. 85, pp. 60–70, Mar. 2019.

[15] Anas AbuTaleb, “Breadth First Based Sink Mobility Model for Wireless Sensor Networks”, Journal of Theoretical and Applied Information Technology, Vol. 97, No. 8, pp. 2217-2228, April 2019.

[16] S. Yang, U. Adeel, Y. Tahir, and J. A. McCann, ‘‘Practical opportunistic data collection in wireless sensor networks with mobile sinks,’’ IEEE Transaction on Mobile Computing., vol. 16, no. 5, pp. 1420–1433, May 2017.

[17] Amine, D., Nassreddine, B., Abdennacer, H., Abdelhamid, L. and Bouabdellah, K.,” Routing in Wireless Sensor Networks a Comparative Study: Between AODV and DSDV,” International Conference on Embedded Systems in Telecommunications and Instrumentation (ICEST’14), Annaba, Algeria, Oct. 27-29, 2014.

[18] Ullah, M., and Ahmad, W., "Evaluation of Routing Protocols in Wireless Sensor Networks." Computer Science Master’s Thesis, Department of School of Computing, Blekinge Institute of Technology, Soft Center, Ronneby, Sweden 2009.

[19] Amnai, M., Fakhri, Y., and Abouchabaka, J., “Impact of Mobility on Delay- Throughput Performance in Multi-Service Mobile Ad-Hoc Networks.” International Journal of Communications, Network & System Sciences, vol. 4, no. 6, pp. 395-402, 2011.

[20] Kartakarte, M., Tavildar, A., Khanna, R.,"Effect of Mobility Models on Performance of Mobile Wireless Sensor Networks", *International Journal of Computer Networking Wireless and Mobile Communication (IJCNWMC)*, Vol. 3, no. 1, pp 137-148, March 2013.

[21] L. Guezouli, K. Barka, S. Bouam and A. Zidani, "Implementation and optimization of RWP mobility model in WSNs under TOSSIM simulator", *International Journal of. Communication Networks and Information Security,* vol. 9, no. 1, pp. 1-11, April 2017.