

Propose effective routing method for mobile sink in wireless sensor network

Raghad Mohammed Hadi¹, Najlaa Abd Hamza², Slama Hameedi Abdullah³

¹ Mustansiriyah University –Medical College

² University of Baghdad - College of Nursing

³ University of Technology – Department of Computer Engineering

ABSTRACT

Wireless sensor network is one of the popular technologies used for maximizing the lifetime of network and to enhance the data collection process and energy efficiency by mobility. So, this work was proposed and focused on sink mobility which plays a key role in data collection process. The main challenge task was to discover the route in the active network. We have proposed an opportunistic algorithm in this paper with mobile sink to discover the ideal path starting the source to destination node. The proposed system has focused on a sensor field to sense and to report on building during fires where the sensors could be destroyed. The proposed system was evaluated through simulation and compared with existing algorithms (Genetic algorithm, multilayer perceptron neural network). The performance which showed data delivery can be increased by up to 95%.

Keywords: Sensor Node (SN), Wireless Sensor Network (WSN), mobile sink node, Genetic algorithm, neural network, Cellular Neural Network (CNN)

Corresponding Author:

Raghad Mohammed Hadi
Medical college
Al Mustansiriyah University
Baghdad, Iraq.
E-mail: raghad_alrudieny@uomustansiriyah.edu.iq

1. Introduction

The use of sink mobility (SM) has been recently increased to solve problems related to energy hole in wireless sensor networks (WSN). It is important to improve network performance. However, sink mobility is often associated with delayed data collection. Such delay could be attributed to the boundary of sink haste in applications like structural health monitoring and fire monitoring. In other words, it is essential as a certain dead line, that the facts are composed by sensor nodules brought to the mobile sink. Hence, the main issue being addressed now is project to optimize the route of the mobile sink to reduce the entire network vitality ingesting and also to meet the delay requirements [1], [2]. In the sensor network, the effort of the sensor node is not simply to intelligence ecological data, then to transmit those data to the sink. WSNs are definition energy-constrained networks and balance the weight on the sensor nodes. In addition, it is almost impossible to have routing as an option in case of a scarce or a separated network. Therefore, sink mobility plays a key role [3]. Two challenges can be identified. The first is the devising of the movement pattern of the mobile sink while the second is data forwarding to the sink in specified time in a happening focused and delay sensitive network. Otherwise, there will be a problem with data relevance. Therefore, the aim is to make a demand of mobility pattern for the sink

into consideration and for the emergency data to reach the sink before its deadline is over [4], [5]. The proposal trend is to reduce the cost of communication using CNN optimization algorithm by cutting off expensive neural connection that does not affect the capability of network to retrieve stored information. In this paper, we have proposed a mobile sink networks to operate in volatile environments where the firefighters were pretend and supplied with small computers which are able to act as mobile sink points where these nodes like points themselves offer transient and shorter paths to relay data. These nodes also provide connectivity in area where networks are disconnected. Different ways were examined, so that uncontrolled mobile sinks may improve performance in addition to developing method by which the presence of the mobile sinks was advertised. Furthermore, data for forwarding were gathered and disconnected regions prioritized. The rest of paper was prepared in various sections. In section 2, we have presented a previous associated work and in section 3, the mobile sink was included and described. In section 4, GA was illustrated while in section 5, the neural network was explained in details. In section 6, the proposed cellular neural network was illustrated and its algorithm explained in details and in section 7, the experiments and results were illustrated which followed by the conclusions.

2. Related work

Fodor and Vidács et al. [6] have shown that in a classic wireless sensor network cover a huge zone the variety of the devices is in universal quite short when associated to the network scope. As of the little rate of strategies the process of the network is very vitality subtle. Ours resolution to overawed this constraint is to usage mobile sink(s) to change from exhausted areas. In this paper ours existing a simple routing protocol, which uses to deluge to inform the paths towards many mobile sinks in the network. The planned explanation attempts to discovery cooperation among the ideal routes and the amount of posts wanted to appraise these routes.

Suneet et al. [7] have shown that when the sensor nodes were susceptible to failure, a genetic algorithm-based scheme has been proposed. Two advantages of the proposed scheme were detected which firstly, it has delivered k attention to all goals and secondly, it has provided m connectivity to all sensor nodes. Regarding GA created method. It was characterized by effectual chromosome illustration as well as effectual fitness function in addition to the typical GA process.

Sharma et al. [4] have proposed dispersed tree to find data distribution protocol by mobile sink. The resulting in the minor lifetime of the system. To extend the lifetime of the system, they have used the mobile sink approach and 200 arbitrarily organized sensor nodes where the whole trial was achieved through the variable sink that hasted from 5 meter/sec to 30 meter/sec.

Carolina and Carlos and Juan Arturo et al. (2020) [8] in this training, a Wireless Sensor Network was projected by the vitality ingesting for all node. These purposes are associated to a vigour standpoint and presentation metrics. The planned system is then castoff to compute the vigour ingesting of routing protocol and extensively recognized network sensors routing protocols. Trial was test reproductions were done on a arbitrary topology with dual gatherer nodes. The planned system attains a 97% correctness associated to the real presentation of a network.

Layla and Hanane et al. [9] in this work a huge number of sensors were used, which are dispersed in zone checking to gather significant signals. And it used in numerous requests. So, the main task of scheming WSNs is redeemable the energy expended. The paper was purpose to improve the procedure of collection by an effectual joint perfect. Simulation consequences showed that proposed protocol exploited the remaining vigour by 15% and 25% and the system lifetime by 35%.

Kashif, Muhammad, Jaime and Antonio Leon et al. [10] have shown that sensor hosts are detecting and checking the ecological situations and convey the facts to the improper position. Owing several boundaries, the sensor hosts nearby the improper position are continuously communicating so this training suggests a Gateway Clustering Energy-Efficient Centroid- (GCEEC-) founded routing protocol anywhere cluster head is designated from the centroid location and gateway hosts are designated from each cluster. The trial consequences

designated the improved presentation of planned protocol and deliver additional possible WSN founded checking for infection, moisture.

3. Mobile Sink

To improve energy efficiency or decrease energy consumption, a new concept called Mobile Sink (MS) was introduced. In a sensor network with mobile sink, sinks are accomplished of drive and sensor nodes communicate data to the mobile sinks with slight or no protecting. Data sink may have controlled movement or un-controlled movement where if the MS trajectory is predefined, it is called controlled MS while if the sink moves randomly in a predetermined environment, it is called uncontrolled MS [11], [12], and [13].

4. Genetic algorithm

GA is an approach that has been used to solve problems related optimization. It is a well-known metaheuristic approach. A group of possible solutions is randomly created with which genetic algorithm can initiate. A simple string of genes represents an individual solution. This sequence of genes is titled chromosome or individual. The quality of every individual can be determined by evaluating its fitness function. The process involves determining the generation initial population followed by the three operations which are selection, crossover, and mutation. The selection stage involves obtaining a traditional of probable explanation since the early population. After that, parents are designated (parents are two randomly selected chromosomes). From parents, two child chromosomes are produced the process mentioned earlier. The crossover is a process that involves the exchange of genetic information between parent chromosomes. In the final operation, child chromosomes undergo the mutation resulting in producing a better solution. After that, the child chromosomes are evaluated as mentioned before and compared with chromosomes generated in the previous generation. The fitness value determines whether the present children replace their parent chromosome [7], [14], [15], and [16].

5. Neural network

Network of neurons is known as neural network e.g. human brain artificial neurons are developed on the basis of real human neurons. These can be either a physical device or purely a mathematical function. In a neural network, the processing is carried out in parallel. It consists of many simpler processing elements connected in a particular manner so as to perform a particular task. Neural networks were developed because of highly powerful computations, noise and fault tolerant, high degree of parallelism, low energy consumption, and easy to train. A neural network is explained by three parameters. First one is the interconnection between the different layers. Second is the updating of the weight and finally, the function which is used to convert the input into output. In a neural network, number of inputs is fed to input layer which after being solved with weight are fed to a hidden layer. In this hidden layer, the activation function acts on the input and produces the output [17], [18], [19], and [20].

5.1. Multilayer perceptron neural network

Multilayer Perceptron Neural Network (MLP) is an artificial neural network. It is composed of at least three layers of neurons. These layers include an input layer where one or more concealed layers, and an output layer. No calculation is achieved by neurons in the input layer. Therefore, it is not considered as a true layer. The only thing that neurons in the input layer do is that they allocate the workings of the pattern of an input vector to neurons in the concealed layer. Two components by which delivery of exercise patterns container performed, either by a multi hop direction-finding arrangement or by an entryway or cluster head more that can reach all the WSN straight over the wireless station [21], [22], and [23].

5.2. Cellular neural networks (topology optimization in cellular neural networks)

A cellular neural network (CNN) can be defined as a nonlinear dynamical system that implements an associative memory and the CNN can be defined as nonlinear processing units which are often referred to as neurons or cells. The main goal behind CNN is to overcome the limited interaction between neurons (which is limited to the neighboring units only). For such aim to be applied, there should be a communication link that links a gathering of represent networks related to every other network. However, such statement approach is further exclusive than statement within each sub network. Therefore, it is an important to minimize such communication cost along with maintaining the target threshold of the network functionality and performance. As described in Figure 1 where through preparation and succeeding the placement, the output of neurons in each layer needs to be connected to the input of those neurons in other layers. The use of packet depending wireless communication that is responsible for carrying neuron production cost is performed done multi hop direction-finding. There will be delayed transfer due to several factors such as average admission. Packet mediated data processing and multi hopping (the larger the number of hops the longer the distance between the sender and receiver neurons). Although the distance is related to the real direction-finding protocol used in system. The space of the routing path can be undervalued by the number of hops, which can easily measure through various estimation schemes [24], [25], and [26].

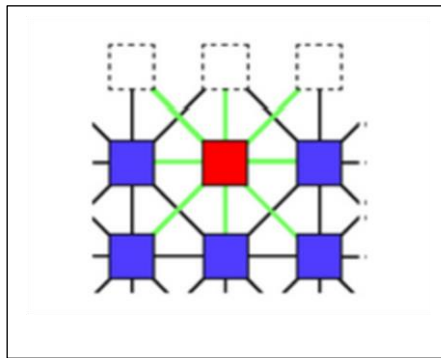


Figure 1. CNN topology

6. The Proposed system

We have proposed an effectual data distribution protocol where this technique decreases the traffic and delays the lifetime of the network. The proposed system uses four phases as show in Figure 2 where the proposed system is trained with CNN algorithm as illustrated in Algorithm 1, and in the training level is self-governing of the sink location and the CNN network acts as a group of nodes. The network parameter which was used in proposed system is given in Table 1. Two types of the nodes in CNN network were found where the first was the spread sink node and the second was non-spread node. The sink was mobile and gathered the data since the source node has finished the gateway node. The gateway node might be the spread node or non-spread node. The proposed system is illustrated in Figure 2 and Algorithm 2 shows the proposed system in details. In the following sections, we gave a brief overview of the proposed system:

6.1. Preprocessing step

In this step, we attempted to initial node deployment, end node discovering, then generated random path from initial node to another next spread node or to non-spread node without calculating the cost until reaching end node.

6.2. Extracting step

In this step, we have predicted the optimal cost path by using either CNN algorithm or GA algorithm or MLP algorithm.

6.3. Extracting the sink place

In this stage, we have discovered the sink place by diverse quantity of devices and grid size for cost path since original node to the finish node by using CNN algorithm where the value of cost path from first node to the

finish node by using GA algorithm finally value of cost path from first node to the finish node by using MLP algorithm

6.4. Display step

In this step, we pic and displayed the optimal cost path and calculated energy as the final mobile sink node.

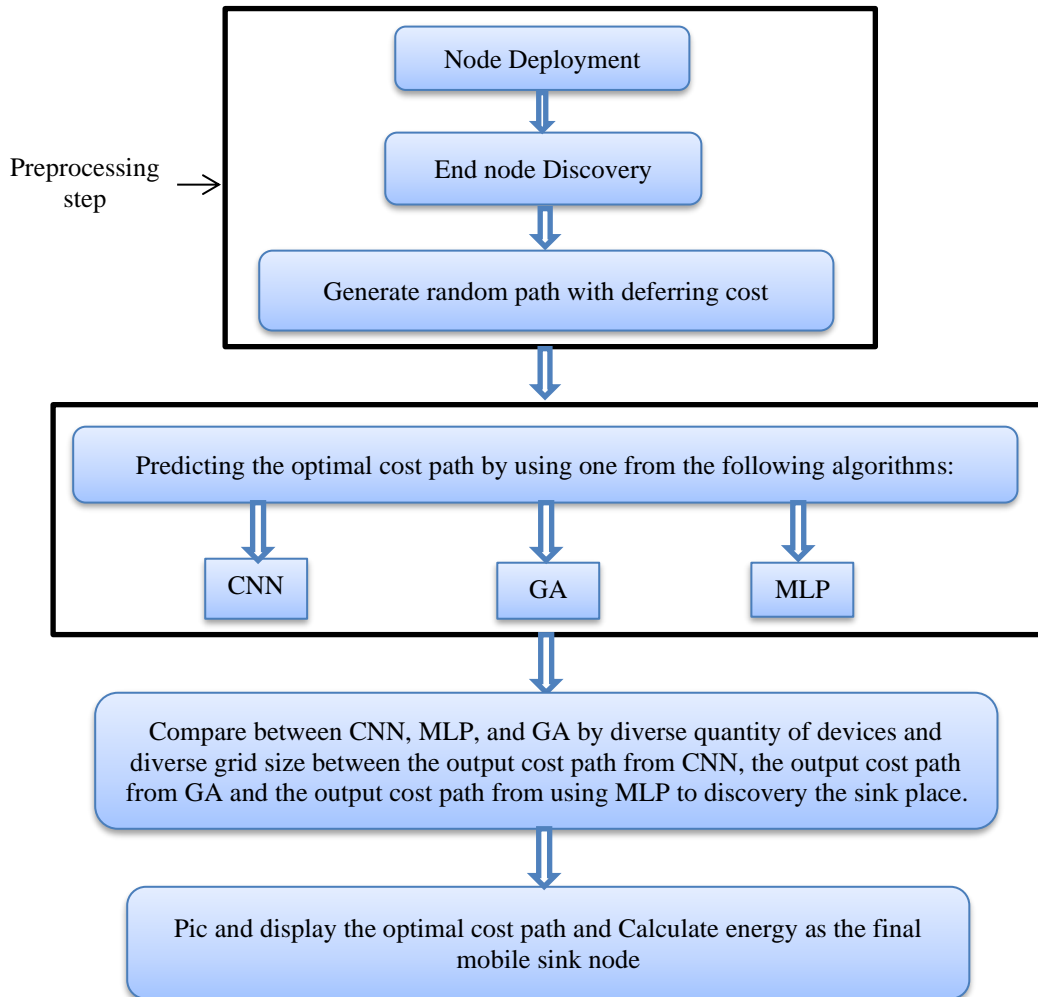


Figure 2. The proposed system.

Algorithm (1): CNN optimization algorithm
Input: Initial array α , e , \hat{e} , and constant numbers v , κ .
Output: : Array A of K values for every high cost node might be detached
Process:
<ol style="list-style-type: none"> 1. $R=1/2 (\text{sign}(\hat{e} - v e) + e)$ 2. $n=$ row length (α) 3. $MM=$ column length(α) 4. $AA = [0]N*M$ 5. $CC =[0]N*M$ 6. If (maximum R $\diamond > 0$) then 7. while (R(i, j) $\diamond > 0$) do

8. Calculate T and b
9. For m = 1 To M do
10. For tt = 1 To N do
11. $CC(tt, m) = \alpha t(m) (\sum_{j=1}^n T_{tj} \alpha(jm)) + b(tt)$
12. End
13. End
14. While (kk > κ and min CC > 1) then
15. A(i, j) = kk ; A(j, i) = kk
16. End
17. R(i, j) = 0 and R(j, i) = 0
18. End if

Algorithm (2): Topology optimization CNN to discovery ideal path algorithm

Input: Number shapes paths of signs, number of intra path pa_1 , inter path pa_2 , α , v , crowded scope, (static or active), connection prices.

Output: Find an ideal route from first node to end node.

Process:

1. Generate Matricese, \hat{e} .
2. Initially the CNN (with cells M,N = Number of rows and columns of the CNN equal to the nodes number in the mobile sink Wireless sensor network, acquire the contribution parameters, first situations and learned templates. Load the all paths information for the wireless networks. Load best other wireless nodes parameters (crowded scope, static or active, connection prices).
3. Reset a weight vector, Weight reserved as secure though the hidden to production weights are educated by smallest distance.
4. converge cells
while (converged cells < total amount of cells)
{ for ($i_1=1; i_1 \leq M_1; i_1++$)
for ($j_1=1; j_1 \leq N; j_1++$)
{if (convergences[i_1] [j_1])
continues; // the current cells was converged //
5. CNN reduction by calling algorithm 1
6. Activate the cells and get Qa from all paths results as the short path whose is minimum $E_{i_1 j_1}$ as $Qa = \min(E_{i_1 j_1})$ that enhanced through extra wireless nodules parameters (packed scope, (Active or static), connection prices).
7. Calculate a next state using stored templates for the optimal path between pa_1 and pa_2 .

$$x_{i_1j_1}(t + 1) = x_{i_1j_1}(t) + \sum_{k,l \in N_{i_1j_1}} a_{k-i_1,l-j_1} f(x_{kl}(t)) + \sum_{k,l \in N_{i_1j_1}} b_{k-i_1,l-j_1} (u_{kl}(t)) - Lc + I$$

where x_{ij} : the states of a cell at position (i_1,j_1) ,

N_{ij} : the neighbors of the cell (i,j) ,

a_{k1} : the parameters of feedback templates (Links connection weights),

b_{k1} : the feedforward template parameters,

u_{k1} : the (time-invariant) input,

I : is a bias value.

the smallest's Euclidean's distances of B_{ij} will select:

$$B_{ij} = \text{Qa} \sum_{j,i=1,2..m} \|pa_1 - pa_2\|$$

The enhanced through additional wireless nodules parameters (scope areas, crowded scope, (Active or static), connection prices).

8. Re-check the convergence criteria after the reduction operation.

$$\text{If } \left(\frac{dx_{i_1j_1}(t_n)}{dt} \right) = 0, \text{ and } y_{lk} = \pm 1, \forall c(k,l) \in N_r(i_1,j_1)$$

{ convergences[i_1][j_1] = 1;

Converged cells++; }

} /* end for loops */

9. Inform the entire paths public values.

for ($i_1=1$; $i_1 \leq M_1$; i_1++)

for ($j_1=1$; $j_1 \leq N_1$; j_1++)

{ if (convergences[i_1][j_1]) continue;

$x_{ij}(t_n) = x_{ij}(t_n+1)$; }

iterations++; } /* end */

End

Table 1. Network parameter

parameters	scenario
network size	100 × 100 m
antenna type	all-directional
simulation time	700 seconds
number of sinks	1
position of nodes	random
number of network nodes	10,50,100,1000

7. Results and desiccation

Table 2 contains the result of the comparison between GA, MLP, CNN to discovery the sink place by diverse due to the quantity of devices. Also, the Table shows the average time that taken to find optimal path from source to destination by using CNN is fewer compare with GA and MLP.

Table 3 displays the result that shows the cost (number the hope count to reach to destination) to find the optimal path from source to destination by using CNN is fewer compare with GA and MLP with 1000m the CNN take

(0.922 s) because this algorithm takes many tamp let of wireless network and ignores the path that taken more cost so it is choosing the optimal path with low cost and low packed lose.

Table 2. Compare between GA, MLP, CNN to discovery the sink place by divers quantity of devices

Amount of devices node	Middling time by CNN	Middling time by GA	Middling time by MLP (s)	Minimum cost using CNN	Minimum cost by GA	Minimum cost by MLP
5	0.147871	0.516	1.137473	0.0	1.2848809	0.814914
10	0.145553	0.614	4.372224	0.0	1.839863	1.390808
20	0.145067	0.62	5.372224	0.0	1.30268444	1.390808
30	0.142479	1.202	6.372224	0.0	4.0151	2.390808
40	0.141248	1.946	7.372224	0.0	1.9565	3.390808
50	0.140585	3.714	8.372224	0.0	1.46182	4.390808
60	0.148472	5.518	9.372224	0.0	1.46182	5.390808
100	0.146971	11.003	10.372224	0.0	2.19553	6.390808
120	0.162272	8.225	11.372224	0.0	1.984906	7.390808
150	0.161032	20.435	12.372224	0.0	1.0403386	8.390808
180	0.161679	19.241	13.372224	0.0	1.776604	9.390808
200	0.167918	19.241	1.137473	0.0	1.776604	10.390808

Table 3. Compare between GA, MLP, CNN to discovery the sink place by diverse grid size

Grid size Using(m)	Average time using GA (s)	Average time using MLP (s)	Average time using CNN(s)	Min cost using GA	Min cost using MLP	Min cost using CNN
25	0.868	0.425827	0.142632	0.234247	0.234247	0.0
70	0.791	1.499129	0.146694	0.234247	0.234247	0.0
100	0.894	2.226887	0.146125	0.234247	0.234247	0.0
200	0.933	3.185007	0.141440	0.458735	1.234247	0.0
250	0.922	4.085537	0.144397	0.458735	2.234247	0.0
400	0.906	4.986067	0.144485	0.458735	3.234247	0.0
900	0.969	5.886597	0.146663	0.458735	4.234247	0.0
1000	0.922	6.787127	0.232139	0.458735	5.234247	0.0

In figures 3 and 4 shows comparison of average time and the cost with 200 nodes and the simulation time 7000 second CNN take lower time compare with GA and MLP. In figure 5, the result shows the total energy in joules with the simulation time 7000 second the CNN consume low power to find optimal path. In figure 6, the result shows the comparison of the number of routing packets with 100 nodes at the simulation time 7000 second CNN deliver more number of data packed so it reduce the losing packed by choosing the optimal, short reliable path from sink node to destination node (BS). So, the proposed algorithm its counterparts in terms of the rates of network to determine the number of packets sent and received in order to determine the degree of success of this protocol in transferring the generated packets to their destination in healthy conditions. In general, the closer the time intervals between the sent and received packets to one another, the more optimal the protocol procedure can be said to be. Based on the data obtained, the percentage of accurate data sent for the in proposed algorithm 95% succeed data delivered.

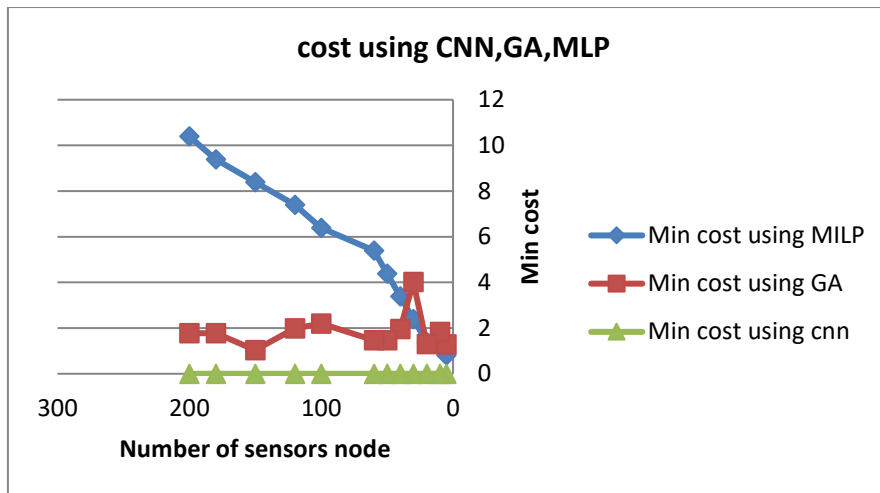


Figure 3. Comparison of average time with 200 nodes and grid 1000m size and simulation 7000 second

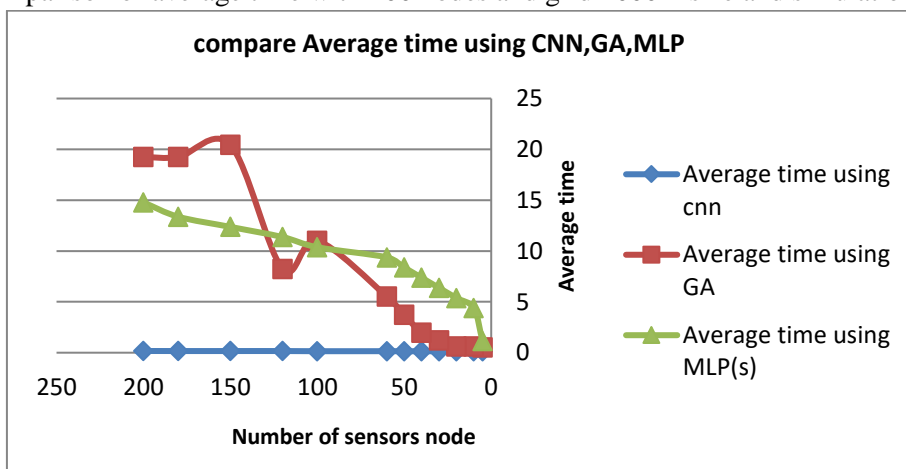


Figure 4. Comparison of cost with 200 nodes at the simulation time 7000 Second

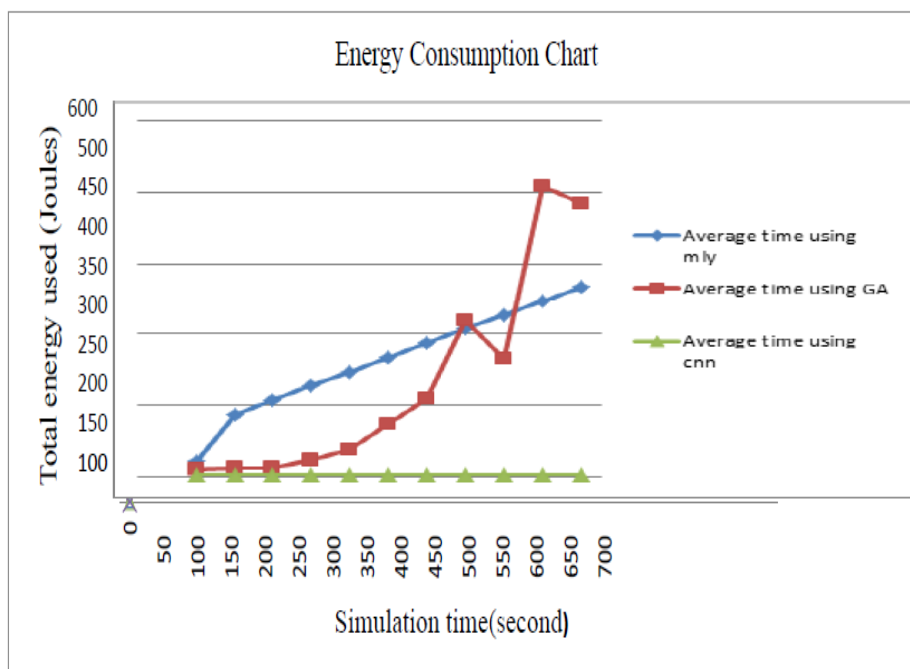


Figure 5. Comparison of total energy in joules with the simulation time 7000 sec

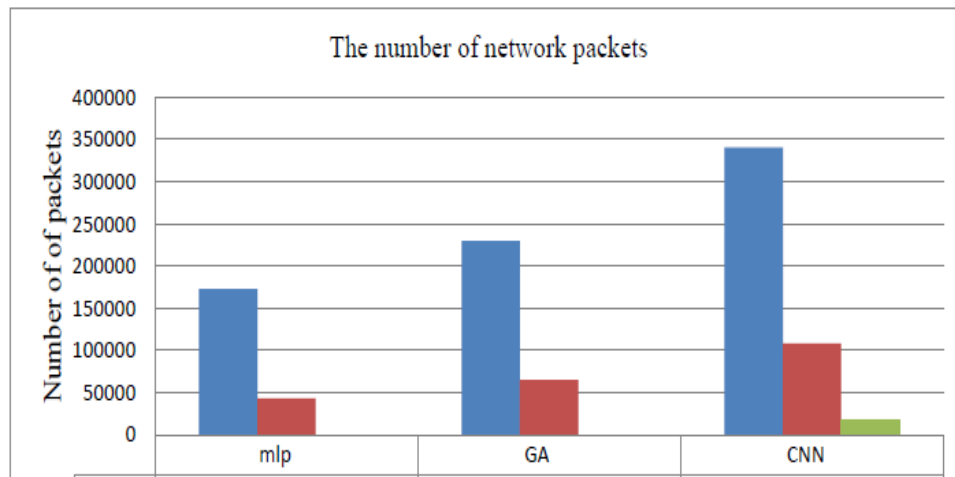


Figure 6. Comparison of the number of routing packets with 100 nodes at the simulation time 7000 second

8. Conclusions

There are many challenges are facing mobile sink wireless sensor networks where one of the major challenges in this network is the amount and quality of energy consumption in such networks. In this paper, in order to increase network lifetime, proposed topology CNN neural network and compare with different methods so the goal of this propose system was to improve network life time, reduction of network energy consumption, packed lose and to find optimal path from sink node to destination node(BS). Hence, the proposed protocol having the strategies employed in the first phase including selecting the optimal path by getting the input parameters, initial conditions and learned templates. Load the all paths information for the wireless networks. In the second phase of this protocol, a multi-step compression was performed aimed to reduce the size of data transmitted to the sink node. The Simulation results obtained from matlab2016 software showed that the proposed algorithm has displayed a greater performance in all examined parameters compared to other similar methods offered, the Genetic Algorithm and Multilayer Perceptron Neural Network

References

- [1] M. M. Hassan, R. Ramad and H. M. El-Baghdadi, "finding the best sink location in WSNs with reliability route analysis," *procedia cmputer science*, 2014.
- [2] J. Guo, "Sink Mobility Schemes in Wireless Sensor Networks for Network Lifetime Extension," *School of Computer Science. Electronic Theses*, 2012.
- [3] D. Kandris, C. Nakas, D. Vomvas and G. Koulouras, "Applications of Wireless Sensor Networks:," *www.mdpi.com/journal/asi*, 20 February 2020.
- [4] S. Sharma and S. k. Jena, "Data dissemination protocol for mobile sink in wireless sensor networks," *computational engineering journal*, no. ID 560675, 2014.
- [5] Nimisha Ghosh, Indrajit Banerjee, "Application of mobile sink in wireless sensor networks," *international conference on communication system and networks*, 10 2018.
- [6] K. Fodor and A. Vidacs, "Efficient routing to mobile sinks in wireless sensor networks," <http://www.researchgate.net/publication/228985613>, october 2007.
- [7] S. K. Gupta, P. Kuila and P. k. Jana, "Genetic algorithm approach for k-coverage and m-connected node placement in target based wireless sensor networks," *computers and electrical engineering*, 2016.
- [8] C. Del-Valle-Soto, C. Mex-perera and J. A. Nolzco-Flores, "wireless sensor network energy model and its use in the optimization of routing protocols," *www.mdpi.com/ journal/ energies*, 2020.
- [9] L. Aziz and H. Aznaoui, "efficient routing approach using a collaborative strategy," *Hindawi journal of sensors* , <http://doi.org/10.1155/2020/2547061>, no. ID 2547061, p. 17 pages, 2020.

-
- [10] K. N. Qureshi, M. U. Bashir, J. Lloret and A. Leon, "optimized cluster based dynamic energy aware routing protocol for wireless sensor networks in agriculture precision," *Hindawi journal of sensor*, <http://doi.org/10.1155/2020/9040395>, p. 19, 2020.
- [11] L. B. and D. C., "An Energy efficient secure routing (EESR) using Elliptic curve cryptography for wireless sensor networks," *second international conference on inventive communication and computational technologies (ICICCT)*, 2018.
- [12] L. L. J. P. Michal Piorkowski, M. Grossglauser and J. P. Hubaux, "mobiRoute :Routing towards a mobile sink for improving lifetime in sensor networks," *conference paper*, <http://www.researchgate.net/publication/225714285>, June 2006.
- [13] M. Chen, X. Xu, S. Zhang and G. Feng, "Energy efficient Routing protocol in mobile sink wireless sensors networks," *TELKOMNIKA*, pp. pp. 2056-2062, December 2012.
- [14] H. Zhang, Z. Li, W. Shu and J. Chou, "Ant colony optimization algorithm based on mobile sink data collection in industrial wireless sensor networks," *EURASIP journal on wireless communications and networking*, <http://doi.org/10.1186/s13638-019-1472-7>, 2019.
- [15] K. Praveena and T. Sripriya, "Genetic algorithm based data aggregation using mobile sink in wireless sensor networks," *international journal of engineering research and technology (IJERT)*, vol. 2, no. Issue 2, pp. ISSN 2278-0181, february 2013.
- [16] G. Rivera, L. Cisneros, P. S. Solis, N. r. Valdez and j. r. osollo, "Genetic algorithm for scheduling optimization considering heterogeneous containers: a real word case study," www.mdpi.com/journal/axioms, 4 March 2020.
- [17] s. Gursel and z. gao, "complexity analysis of multilayer perceptron neural network embedded into a wireless sensor network," *Procedia computer science*, 2014.
- [18] R. M. Hadi, S. j. Al-khalisy and n. a. Hamza, "prediction model for financial distress using proposed data mining approach," *journal of Al-Qadisiyah for computer science and mathematics*, pp. 37-44, 2019.
- [19] A. Akbas, h. u. yildiz, a. m. ozbayoglu and b. tavil, "neural network based instant parameter prediction for wireless sensor network optimization models," *article in wireless networks*, <https://www.researchgate.net/publication/326831419>, August 2019.
- [20] S. kumar, R. sharma and e. R. Vans, "Localization for wireless sensor networks: A neural network Approach," *International journal of computer networks and communication (IJCNC)*, vol. 8 No.1, January 2016.
- [21] b. Varsha and h. G. Tanner, "Topology optimization in cellular neural networks," *49th IEEE conference on Decision and control (CDC)*, 2010.
- [22] G. Astray, F. J. Rodriguez-rajo, b. J. A. ferreiro-lage and J. C. Mejuto, "The use of artificial neural networks to forecast biological atmospheric allergens or pathogens only as Alternaria spores," *journal of environmental monitoring*, August 2010.
- [23] L. Zhu, l. Huang, l. fan, j. Huang, f. huang, J. chen, z. zhang and y. wang, "Landslide susceptibility prediction modeling based on remote sensing and a novel deep learning algorithm of a cascade parallel recurrent neural network," www.mdpi.com/journal/sensors, 6 March 2020.
- [24] y. yinggao, L. jianqing, f. hehong and q. Qin, "Optimization based extreme learning machine for data fusion in mobile wireless sensor network," *International journal of innovative computing information and control*, vol. 12 number 5, october 2016.
- [25] S. ayub and m. babak, "An energy efficient clustering algorithm using fuzzy c mean and genetic fuzzy system for wireless sensor network," *journal of circuits system and computers*, vol. 26 number 1, 2017.
- [26] W. Gilpin, "Cellular automata as convolutional neural networks," *Quantitative biology initiative*, wgilpin@stanford, 20 January 2020.