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Propose effective routing method for mobile sink in wireless sensor network

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ABSTRACT

One of the prevalent technologies that is used to extend the lifespan of networks, improve the quality of the data collection process, and increase energy efficiency through mobility is the wireless sensor network. Therefore, this work was suggested with a primary emphasis on sink mobility, as this aspect of the data collection process is critically important. Finding the route in the operational network was the primary obstacle that needed to be overcome. In this paper, we suggest an opportunistic algorithm with a mobile sink in order to find the optimal path beginning at the source node and ending at the destination node. The suggested system has centered its attention on a sensor field to sense and report on buildings even during fires, which have the potential to destroy the sensors. Simulations were run to analyze the performance of the suggested system, and the results were compared to those of other algorithms. (Genetic algorithm, multilayer perceptron neural network). The results of the performance test revealed that the delivery of data could be improved by up to 95%.

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

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1. Introduction

In recent years, there has been a rise in the utilization of sink mobility (SM) as a solution to issues in wireless sensing networks associated with energy holes. (WSN). Improving the performance of the network is very essential. On the other hand, sink mobility is frequently correlated with delayed data acquisition. In some applications, such as structural health monitoring and fire monitoring, a delay of this kind could be attributed to the threshold of the sink's haste. In other words, it is important as a certain deadline, that the facts are composed by sensor nodules that are brought to the mobile sink. Therefore, the primary problem that is being worked on right now is a project to optimize the route of the mobile sink to lower the amount of vitality that the complete network is consuming and also to satisfy the delay requirements [1, 2]. In the sensor network, the effort of the sensor node is not merely to gather ecological data and then send those data to the sink; rather, the effort of the sensor node goes beyond this. WSNs are, by definition, energy-constrained networks, and they maintain an equilibrium between the loads that are placed on the sensor nodes. In addition, if there is a limited amount of network space or the network is physically separated, it is extremely difficult to implement routing as an alternative. Therefore, the mobility of the sink serves an important role [3]. There are two obstacles that need to be overcome. The first step is to plan out the path that the mobile sink will take, and the second step is to ensure that data is sent to the sink at the appropriate moment within a network that is centered on current events and is sensitive to delays. In the event that this does not occur, there will be a problem with the relevance of the facts. As a result, the objective is to consider the sink's demand for a certain movement pattern and to ensure that the emergency data reaches the sink before the deadline passes [4, 5]. The current tendency in the proposal is to reduce the cost of communication by using a CNN optimization algorithm and severing expensive neural connections. This will not affect the ability of the network to retrieve information that has been stored. In this article, we suggest a mobile sink network that can function in unstable environments. The firefighters are pretended to be using small computers that can act as mobile sink points, and these nodes like points themselves offer transient and shorter paths to relay data. These computers were provided to the firefighters along with the pretend equipment. Connectivity can also be provided by these sites in areas where networks are not currently available. In addition to the development of a method by which the existence of the mobile sinks was advertised, various methods were investigated to determine whether or not uncontrolled mobile sinks could improve performance. In addition, statistics for forwarding have been collected, and disconnected regions have been given priority. 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 detail. 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] demonstrated that in a traditional wireless sensor network that covers a large area, the diversity of devices is, in general, quite limited when compared to the network's overall scope. Due to the low number of strategies being implemented, the process of the network is extremely vitality nuanced. The approach that we have come up with to overcome this limitation is to use mobile sinks to change from exhausted areas. In this article, we present a straightforward routing protocol that makes use of deluge to inform the paths that lead to a variety of mobile sinks located within the network. The planned explanation tries to discover whether or not the optimal routes are working together, as well as the number of posts that are required to evaluate these routes.

Suneet et al. [7] have demonstrated that in situations where the sensor nodes are prone to failure, a scheme that is based on genetic algorithms has been suggested. Two benefits of the proposed plan have been identified. The first is that it has provided k attention to all the objectives, and the second is that it has provided m connectivity to all of the sensor nodes. Both of these benefits were found. In reference to the method developed by GA. In addition to the standard GA process, it exhibited effective chromosome illustration as well as effective fitness function. These characteristics set it apart from other GA processes.

Sharma et al. [4] have come up with the idea of using a dispersed tree to locate a data distribution strategy using mobile sink. The consequence of this was that the system had a relatively short lifespan. The mobile sink approach and 200 arbitrarily organized sensor nodes were used during the trial, and the entire thing was made possible by a variable sink whose speed ranged from 5 meters per second to 30 meters per second. This was done so that they could prolong the lifespan of the system.

During this exercise, Carolina and Carlos and Juan Arturo et al. (2020) [8] projected a Wireless Sensor Network using the power consumption of each component. These goals are connected to a vitality perspective as well as presentation measures. After that, the intended system is discarded to compute the power consumption of the routing protocol and widely recognized network sensor routing protocols. The trial was carried out on an arbitrary configuration that featured dual gatherer nodes. Reproductions were tested. When compared to the actual configuration of a network, the designed system achieves a correctness level of 97%.

In the study done by Layla and Hanane et al. [9], an extremely large number of sensors were utilized. These sensors were spread out in zone checking to collect significant signals. And it was utilized in a variety of proposals. Therefore, recovering the energy that was wasted is the most important part of planning for WSNs. The objective of the paper was to develop an efficient joint perfect as a means of facilitating the collection process. The results of the simulation demonstrated that utilizing the suggested protocol extended the system's lifetime by 35% and utilized the remaining 15% to 25% of its power.

It has been demonstrated by Kashif, Muhammad, Jaime, and Antonio Leon et al. [10] that sensor hosts are recognizing and checking the ecological situations and communicating the facts to the improper location. Due to several boundaries, the sensor hosts that are in close proximity to the incorrect position are consistently communicating. Because of this, the training recommends a Gateway Clustering Energy-Efficient Centroid-(GCEEC-) founded routing protocol in which the cluster head is designated from the centroid location and gateway hosts are designated from each cluster. The results of the study designated an enhanced presentation of the planned protocol and delivered additional possibilities for WSN founded checking for infection and moisture.

3. Mobile sink

A novel idea known as Mobile Sink (MS) was developed with the goal of either increasing energy efficiency or lowering overall energy consumption. In a sensor network that utilizes a mobile sink, the sinks are built out of drives, and the sensor nodes in the network communicate data to the mobile sinks with little to no layering of protection. It is possible for a data sink to have either controlled movement or uncontrolled movement. Controlled movement is the word used when the movement of the sink follows a predetermined trajectory; uncontrolled movement is the term used when the sink moves at random within a predetermined environment [11], [12], and [13].

4. Genetic algorithm

An approach that has been used to find solutions to issues connected to optimization is called GA. It is an approach to metaheuristics that is well recognized. The genetic algorithm begins by first arbitrarily generating a set of potential solutions before moving on to the next step. An individual solution can be represented by a straightforward sequence of chromosomes. This arrangement of genes is known as a chromosome or an individual. The evaluation of an individual's fitness function is one way to ascertain the individual's overall quality. The procedure begins with establishing the initial population of the generation, and then moves on to the three operations of selection, crossover, and mutation in that order. During the stage of selection, you will need to acquire a traditional or plausible explanation dating back to the beginning of the population. After that, children are assigned their guardians. (parents are two randomly selected chromosomes). Through the process described previously, two sets of child chromosomes are derived from each set of parental chromosomes. The transfer of genetic information from one set of parent chromosomes to another is what takes place during the crossover procedure. The final step involves subjecting the infant chromosomes to the mutation, which ultimately results in the development of an improved solution. After that, the chromosomes of the infant are analyzed in the same manner as described earlier, and then they are contrasted with the chromosomes that were produced in the generation before that. The fitness value is what establishes whether the present offspring replace the chromosomes of their parents [7], [14], [15], and [16].

5. Neural network

Examples of neural networks include the human brain and artificial neurons, which are developed using actual human neurons as a model. Neural networks are also known as neural networks. It is possible for these to take the form of a solely physical device or an entirely mathematical function. Processing happens simultaneously across multiple nodes within a neural network. It is made up of many simpler processing components that are connected to one another in a specific way in order to carry out a specific operation. The development of neural networks was motivated by the fact that they are capable of extremely powerful calculations, are noise and fault tolerant, have a high degree of parallelism, have low energy consumption, and are simple to train. Three parameters can describe the operation of a neural network. The first one is the connectivity that exists between all the different levels. The second step is the modification of the weight, and the final step is the implementation of the function that transforms input into output. In a neural network, the amount of inputs are passed through an input layer, and then, once they have been solved with weight, they are passed through to a hidden layer. The activation function operates on the input and generates the output [17], [18], [19], and [20] in this concealed layer.

5.1. Multilayer perceptron neural network

An example of an artificial neural network is the Multilayer Perceptron Neural Network, or MLP for short. At least three levels of neurons make up this structure altogether. An input layer, where one or more concealed levels may be found, and an output layer are both included in these layers. In the input layer, there are no neurons that perform any kind of computation. Because of this, we do not consider it to be a genuine component. The only thing that neurons in the input layer are responsible for is passing along to neurons in the concealed layer the specifics of how the structure of an input vector is constructed. There are two components that are used in the distribution of exercise patterns container, either by a multi hop direction-finding arrangement or by an entryway or cluster head more that can reach all the WSN directly over the wireless station [21], [22], and [23]. [21] A multi hop direction-finding arrangement is used.

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].

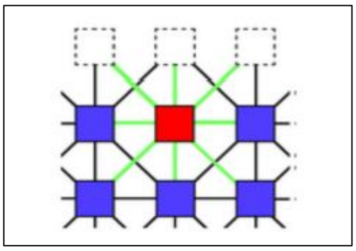

Figure 1. CNN topology

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 shown 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.

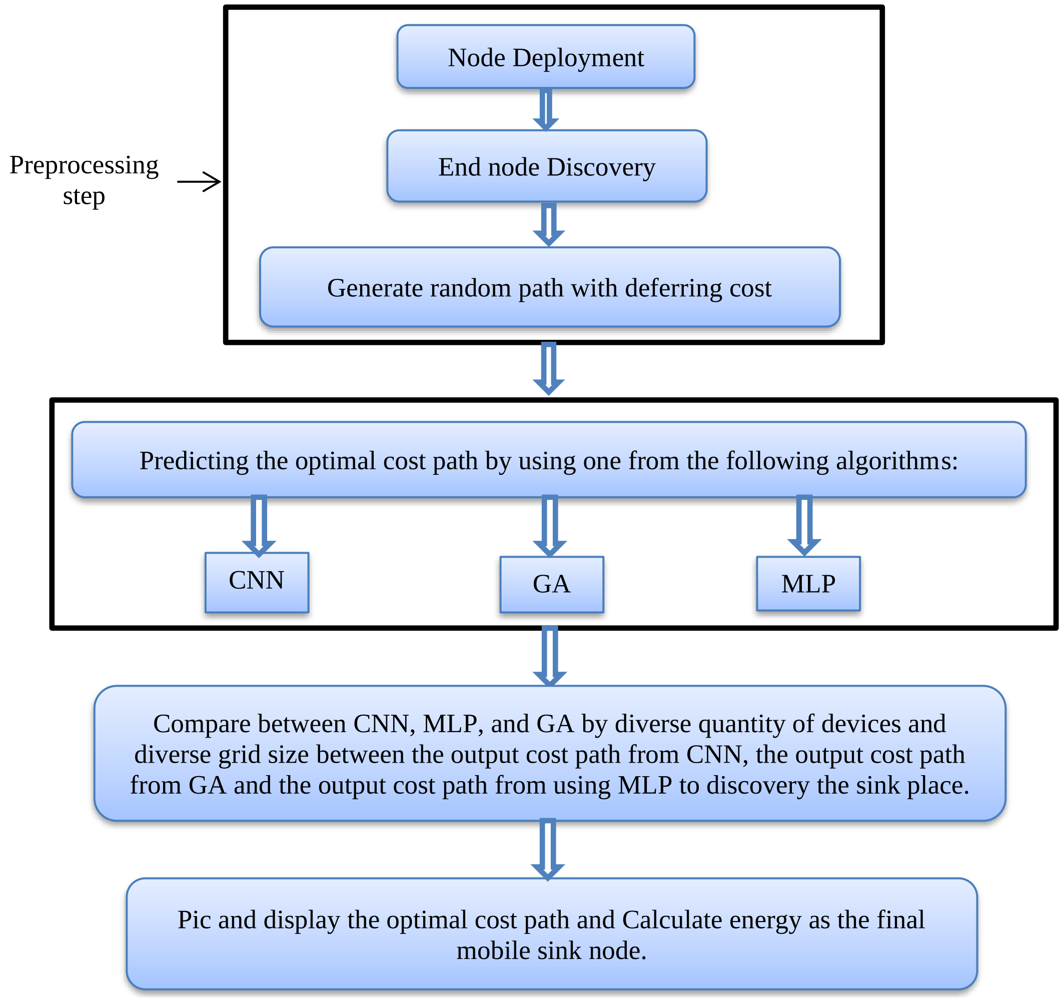

Figure 2. The proposed system.

Algorithm (1): CNN optimization algorithm
Input: *Initial array α, e, ê, and constant numbers ν, κ.* ***Output:*** : *Array A of K values for every high-cost node might be detached*
Process: **1.** R=1/2 (sign(ê − ν 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 <> 0)then **7.** while (R(i, j) <> 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) =αt(m) (∑n j=1 Ttj α(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, ν, crowded scope, (static or active), connection prices.*
Output: *Find an ideal route from first node to end node.*

Process:

1. Generate Matricese , ê.
2. At the outset, the CNN (with cells M, N = Number of rows and columns of the CNN equivalent to the number of nodes in the mobile sink) was used. Acquire the contribution specifications, initial situations, and learned templates for a wireless sensor network. Please ensure that all of the wireless network route information is loaded. Load the optimal parameters from the other wireless nodes. (crowded scope, static or active, connection prices).
3. Reset a weight vector, with the weight reserved as safe even though the production weights that are concealed from view are educated by the shortest distance.
4. converge cells

while (converged cells < total amount of cells)
{ for (i_1=l; i_1<= M_1 ; i_1 ++)
for (j_1=l; j_1<=N; j_1++)
{if (convergences[i_1] [j_1])
continues; // the current cells was converged //

5. CNN lessening through calling algorithm 1
6. Activate the cells and obtain Qa from all of the routes, which will result in the shortest path having the lowest value.
7. $E_{i_1 j_1}$ as Qa = min($E_{i_1 j_1}$) that enhanced through extra wireless nodules parameters (packed scope, (Active or static), connection prices).
8. Compute a subsequent state by means of stored templates for the optimum path between pa_1 and pa_2.

$$\mathrm{x_{i1j1}(t+1) = x_{i1j1}(t) + \sum_{k,l\in N_{i1j1}} a_{k-i1,l-j1}\, f\big(x_{kl}\ (t)\big) + \sum_{k,l\in N_{i1j1}} b_{k-i1,l-j1}\ \big(u_{kl}\ (t)\big) - Lc + I}$$

where x_{ij}: the states of a cell at position(i1,j1),
N_{ij}: the neighbors of the cell (i,j),

a_{k1}: the factors 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:

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

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

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

If $\left(\frac{dx_{i_1 j_1}(t_n)}{dt}\right) = 0$, and $y_{lk} = \pm 1, \forall c(k,l) \in N_r(i1, j1)$
{convergences[i_1][j_1] = 1;
Converged cells++ ;}
} /* end for loops */

10. Inform the entire paths public magnitudes.

for (i_1=l; i_1 <=M_1; i_1++)
for (j_1=l; j_1 <=N1; j_1++)
{ if (convergences[i_1][j_1]) come to an end;
xij(tn) = xij(tn+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 presents the findings of a comparison carried out between the GA, MLP, and CNN algorithms with the objective of locating the drain location based on the various quantities of devices. Additionally, the table demonstrates that when compared with GA and MLP, the amount of time required to determine the optimal path from source to destination using CNN is significantly less.

Table 3 displays the result that shows the cost (number of the hope count to reach to destination) to find the optimal path from source to destination by using CNN is fewer in comparison 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

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
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

Figures 3 and 4 demonstrate a comparison of the average time and cost with 200 nodes and the simulation time of 7000 seconds. When compared with GA and MLP, CNN takes less time. In figure 5, the results show the total energy consumed by the CNN in joules during the simulation that lasted 7000 seconds. This indicates that the CNN used very little power in its search for the optimal route. Figure 6 presents the findings of a comparison of the amount of routing packets generated by 100 nodes over the course of 7000 seconds of simulation time. CNN sends out a greater quantity of data in a single packet, and in order to cut down on the number of packets that are lost in transit, it selects the most efficient, direct, and dependable route between the drain node and the destination node (BS). Therefore, the suggested algorithm and 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 determine the number of packets sent and received. In general, the protocol technique can be said to be more effective when the time intervals between the sent and received packets are closer to one another. This is because closer time intervals allow for more efficient data transfer. According to the information that was gathered, the percentage of correct data that was transmitted for the algorithm that was suggested had a success rate of 95%.

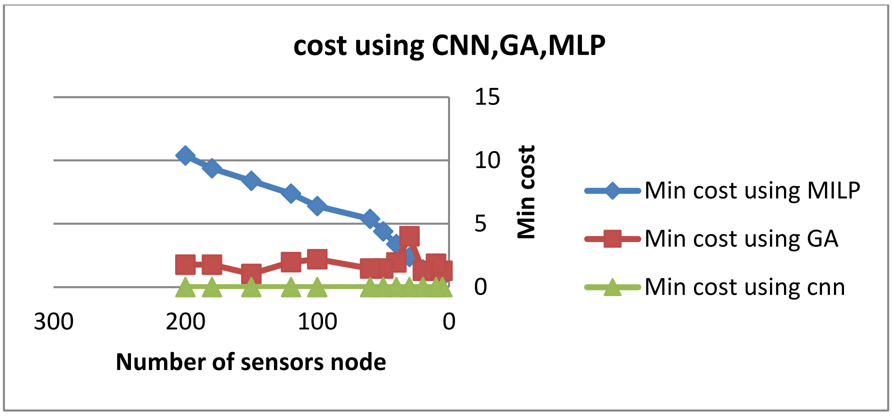

Figure 3. Comparison of average time with 200 nodes and grid 1000m size and simulation 7000 second

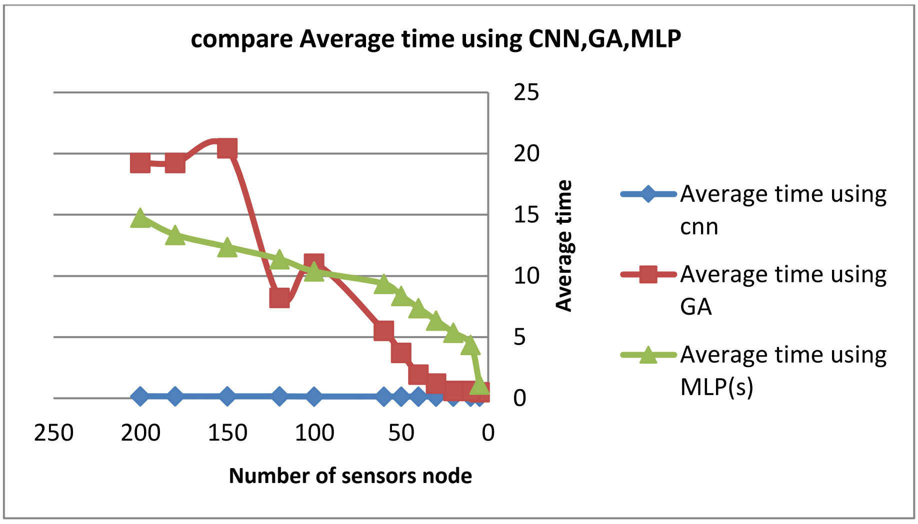

Figure 4. Comparison of cost with 200 nodes at the simulation time 7000 seconds

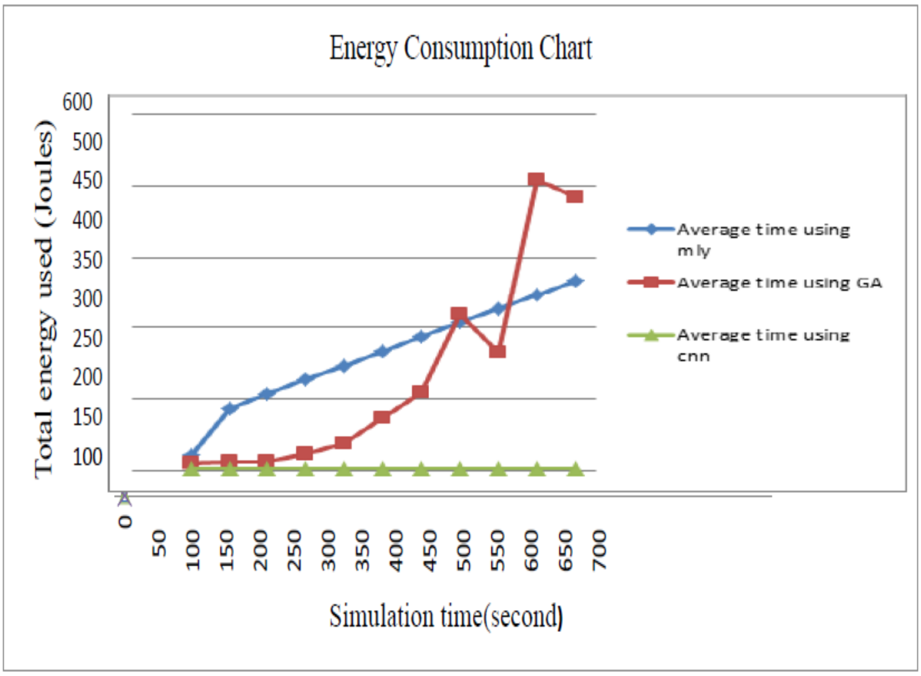

Figure 5. Comparison of total energy in joules with the simulation time 7000 sec

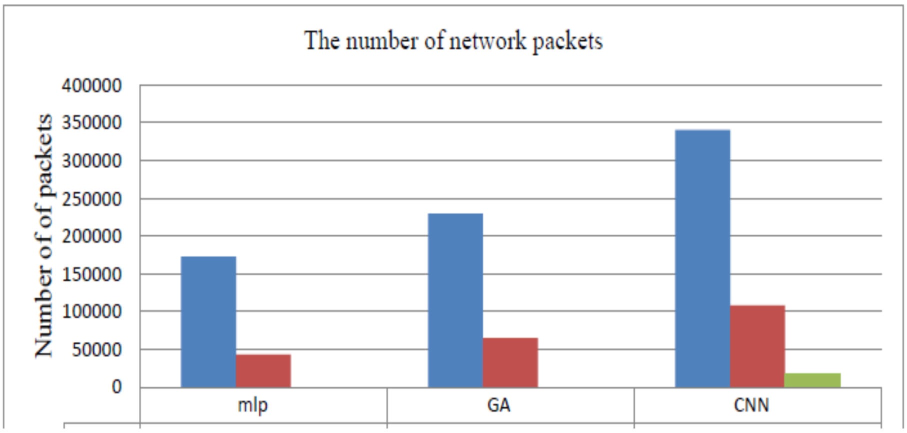

Figure 6. Comparison of the number of routing packets with 100 nodes at the simulation time 7000 second

8. Conclusions

Mobile sink wireless sensor networks are confronting many challenges, one of the most significant of which is the quantity and quality of energy consumption in such networks. Mobile sink wireless sensor networks also face several other challenges. In this paper, to extend the lifetime of the network, a topology CNN neural network was proposed, and it was compared with various other methods. As a result, the purpose of this proposed system was to improve network lifetime, reduce the amount of energy the network consumed, minimize packed loss, and locate the most efficient route from the sink node to the destination node. As a result, the suggested protocol includes the strategies that were used in the first phase, such as choosing the best route by obtaining the input parameters, initial conditions, and learned templates. Please ensure that all the wireless network route information is loaded. In the second portion of this protocol, a multi-step compression procedure was carried out with the purpose of reducing the amount of data that was sent to the sink node. The simulation results obtained from the matlab2016 software showed that the proposed algorithm has exhibited a greater performance in all investigated parameters in comparison to other similar methods that are provided, including the Genetic Algorithm and the Multilayer Perceptron Neural Network.

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