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ANN based Routing for Improving Energy Efficiency in Wireless Sensor Networks

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Abstract: In Internet of Things, sensors that make up sensor network, are deployed at the remote locations and to supply energy to them is burdensome. Wireless sensor network (WSN) suffers from sensor node's energy limitations. Lifetime of each of the nodes in WSN is decided by the lifetime of the battery of the nodes. Often it is impossible to recharge or to replace the batteries. It warrants solutions and methods to save the energy of the nodes as much as possible. The important approach is to exclude those routing paths which contains the least power nodes. For this, an artificial neural network based model has been proposed for routing in WSN to improve the energy consumption in sensor network by balancing in energy consumption among the nodes in the network. Its improves the efficiency of the sensor nodes by reducing the energy consumption and thus increasing the lifetime of the sensor network. Simulation results exhibit and affirm the improvement in the lifetime of the nodes and so the lifetime of the sensor network.

Keywords: Wireless sensor networks, Internet of Things (IoT), Artificial neural network (ANN), Routing, Power consumption, Residual energy.

1 Introduction

Internet of Things are getting popular nowadays in order to make our life smarter and making most of the automated activities. IoT heavily relies on the sensor devices which are deployed in the regions to sense and actuate. To support, technical development in Nano Electronics systems has led to the appearance of small, low-cost, multifunctional sensor devices. These sensors can communicate, to themselves as well as the cloud, wirelessly deriving power from their batteries. Thus, the functionality of the WSN depends on the power of their batteries and how judicially one utilizes this power.

A wireless sensor network is the set of small sensor nodes in which each sensor has the ability to sense the environment in the surrounding medium. Main aim of such networks is to monitor the physical events and capture the data such as movement, temperature, humidity etc. [1]. The important applications of wireless sensor networks have been observed in many environmental, medical, military fields and industries. However, these networks suffer from several limitations and challenges that have become major research fields for many researchers [2]. These limitations include limited battery life, limited data processing capacity and poor storage capacity. Of these, energy is the most important requirement and is to be considered seriously as energy resources of wireless sensors are often limited and non-renewable. In many applications when nodes are deployed in hard- to-reach areas, recharging or replacing the battery is difficult or even impossible.

Many researchers have presented various approaches to solve this problem in order to extend the life of the network and to preserve the energy of the nodes for a longer time period [3]. In this research, an algorithm has been proposed to improve the energy efficiency by judicious routing mechanism in the sensor network. The proposed algorithm assigns a certain threshold value to each of the path/route in the network. The paths, that do not reach to this threshold, are excluded for communication purpose. The

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proposed algorithm chooses an alternative path which has sufficient energy to sustain and does not contain a low-energy node.

As the WSN contains a good number of nodes, a machine learning technique of ANN has been applied for this purpose. Artificial neural network has many characteristics which facilitates the addressed problem of routing in wireless sensor network. Some of these characteristics include distributed processing, learnability, predictability, flexibility, and simple calculations. This motivated us to apply ANN in this work. Prediction ability of ANN has been well utilized. In this work, a neural network has been trained on a set of paths with certain parameters. Candidate paths are the suitable paths for routing, from the target node to sink node.

It has been observed that using this strategy, routing mechanism and energy efficiency within the sensor network have been improved. Moreover, lifetime of the WSN is also extended.

The rest of this paper is organized as follows. Related works are discussed in Section 2. Section 3 presents the preliminaries: energy consumption problem in WSN, brief description of Artificial Neural Networks, the studied WSN model and the applied Neural Network. Section 4 presents the proposed model. Section 5 contains the obtained results and discussions. Conclusions and future work are included in section 6.

2 Related Works

Many studies have been conducted to address the problem of the energy limitations in wireless sensor networks. Most of them focus on reducing the energy consumption and extending the lifetime of the network.

In [2] an agent-based solution was proposed to process the sink power hole problem in flat wireless sensor network. The objective was to reduce the moved repeated data to the nodes which are close to the sink and thus reducing the overhead and saving the battery life. The authors used network levels approach. The network was divided into three levels for avoiding the redundant transmission in nodes located near the sink node. They are able to reduce the power consumption and increase the lifetime of the network.

In [3], the proposed routing scheme improves the network lifetime by forwarding the data packets via the optimal shortest path using A-Star algorithm. The optimal path was found with maximum residual energy of the next hop sensor node. In other words, the researcher took into account the residual energy for nodes to forward the packets. This helps in saving nodes' energy in the network.

In [4] LEACH (Low Energy Adaptive Clustering Hierarchy) routing protocol was proposed. Its aim is to improve the lifetime of the WSN by reducing the power consumption required to create and maintain the cluster heads. A node is elected as a header of a cluster and thereafter waits to become head till all other nodes once become head. This helps balance the power consumption. However, it does not consider the residual energy for each node.

In [5] the possibility of using neural network techniques within the working environment of WSN was studied. The researchers took into account the limitations of the WSN in terms of processing capacity, memory and energy source. It was found that the use of the neural network in processing the data of the WSN led to reduction in the number of packets exchanged within the network. Therefore, they were able to save the energy consumed by the exchange of the packets in the network.

Researchers in [6] presented a new method for power management based on neural networks in WSN.

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This method resulted in more efficient routing paths detection and power management. The main idea was to predict the nodes which consume more power based on the set of sensor attributes. They achieved an increase in the average lifetime of the network by 3.064%.

The authors in [7] aimed at reducing nodes' power consumption and increasing its lifetime by adding a social network to WSN. This network was mainly users with smart phones connected to the internet. The authors worked on reducing the number of nodes from source to BS. Thus data transmission was reduced. This led to reduction in the energy consumption.

In [8] Enhanced Smart Energy Efficient Routing Protocol for Internet of Things in Wireless Sensor Nodes was proposed to increase the lifetime of the WSN. It selects the Cluster Head (CH) depending on energy-efficient cluster head selection algorithm that considers variety of factors such as distance, cost, remaining energy and scope. The researchers applied Sail Fish Optimizer (SFO) to find the appropriate routing path from CH to sink node. Results showed increasing in the lifetime of the network and reducing in the energy consumption compared with other approaches.

Researchers in [9] presented Enhanced Energy Efficient Routing for Wireless Sensor Network Using Extended Power Efficient Gathering in Sensor Information Systems (E- PEGASIS) protocol which aimed to reduce energy consumption by enhancing in leader selection phase. This work took into account the average between residual energy with distance from node to the base station. The simulation results proves that E-PEGASIS is outperforming PEGASIS, and LEACH by attaining the highest energy efficiency along with the extending network lifetime

Most of the work, mentioned above, suffers from one or more limitations such as number of hops of selected routing paths with taking into account minimum node’s energy in the path, unbalance energy consumption between nodes in the network. The proposed work addresses these limitations and proposes an ANN based model for efficient energy consumption of WSN.

3 The Preliminaries

Before we present the proposed model, a preliminary will be helpful to understand it.

3.1 Energy Consumption in WSN

Energy consumption is one of the bottleneck in building a vibrant wireless sensor network. Because of the tiny size of the sensor nodes, a restriction on the size of its battery is also imposed [10]. This restriction results in the limited energy capacity of the battery. Therefore, lifetime of the wireless sensor node is related to its battery lifetime. Functions of the sensor nodes can be divided into three: sensing, processing, and finally transmitting data wirelessly. Studies have shown that 97% of the sensor node energy is consumed on transmitting and receiving [11]. Figure 1 shows the energy consumption methods used in the wireless sensor network, where sensor node can operate in four modes of operation; transmit, receive, idle, and sleep mode. It is clear that the communication process of sending and receiving data consumes most of the nodes’ energy [8] [9]. Loss of energy results in the node going out of work. Thus, the network loses an active node of sensing, processing and saving data. This issue may cause many changes in the path. Therefore, a new alternative path is needed. It has been observed that most of the WSNs use power saving algorithms in order to extend the lifetime of their node batteries [12].

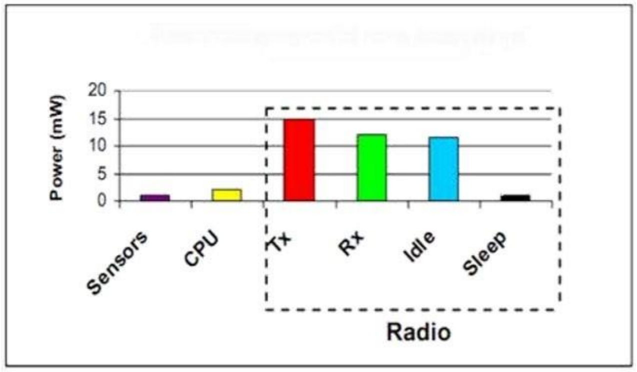

Figure 1: Energy consumption in wireless sensor [5]

The model, depicted in Figure 2, describes the consumed energy for the operations of amplification, transmission and reception within the sensors. The transmitting sensor consumes energy to operate its radio electronics and energy to amplify the signal based on the distance for the traversal of the data. The receiving sensor consumes energy to collect the data and energy to operate its radio electronics.

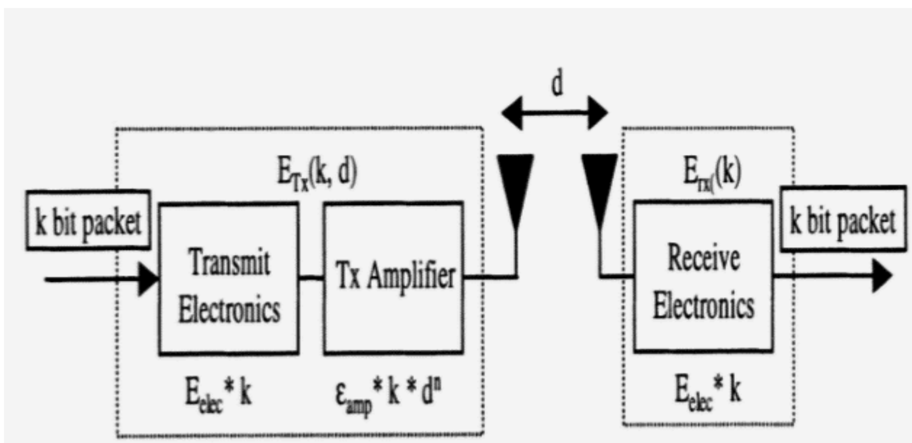

Figure 2: Sensor transmitter and receiver [13]

Sensor transmission energy is given in equation 1 [14].

$$E_{TX}(d) = \begin{cases} K * E_{elec} + K * E_{fs} * d^2, & d \le d0 \\ K * E_{elec} + K * E_{mp} * d^4, & d > d0 \end{cases} \tag{1}$$

Where k is number of bits in the message, E_{elec} is the energy dissipated to run the electronic circuits, d is the distance between the sender and the receiver, d0 is the transmission distance threshold, computed as in equation 2 [14].

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{2}$$

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E_{fs} and E_{mp} are power amplifications that depend on the distance between the sender and the receiver. Values of E_{mp} and E_{fs} are specified in [14] and [15] as 0.0013 pJ/bit/m4 and 10 pJ/bit/m2 respectively.

At reception, the sensor consumes energy to operate the electronic circuits, collect the received data, and re-transmit it. This consumed energy is calculated as in equation 3.

$$E_{RX}(d) = \begin{cases} K \, * \, (E_{elec} + E_{DA}) \, + \, K \, * \, E_{fs} \, * \, d^2, & d \leq d0 \\ K \, * \, (E_{elec} + E_{DA}) \, + \, K \, * \, E_{mp} \, * \, d^4, & d > d0 \end{cases} \tag{3}$$

Where E_{DA} is the energy consumed for the data aggregation. The energy consumed of receiving a k-bit message is given in equation 4.

$$E_{RX}(K) = K * \, E_{elec} \tag{4}$$

The energy consumed for sensing not taken into account because it is very small compared to the consumed energy for the operations of amplification, transmission and reception.

3.2 Artificial Neural Networks

Artificial neural networks (ANN) are the techniques of the machine learning which simulates the human brain. These networks acquire knowledge by training and store it based on the assigned weights. ANN consist of several layers (figure 3): input layer, processing layer, and output layer. Each layer consists of a group of units called neurons. The input layer is composed of several input units, and each network contains only one input layer. The processing layer consists of processing units in which calculations are done to adjust the weights to obtain the desired output on the output layer. The neural network may contain one or more processing layers in addition to the output layer that gives the desired output. Between each of these layers there is a layer of interfaces that connect each layer to the next layer in which the special weights of each link are set [16] [17]. An important merit of the ANN is its capability to learn by examples. To make it learn, it is trained to perform the required function by entering specific input data that leads to specific output data [18]. After training the neural network, it is able to predict the output for any new data set or classify the input data. Many researchers have explored the characteristics and the abilities of the ANN to predict and classify in the field of WSN.

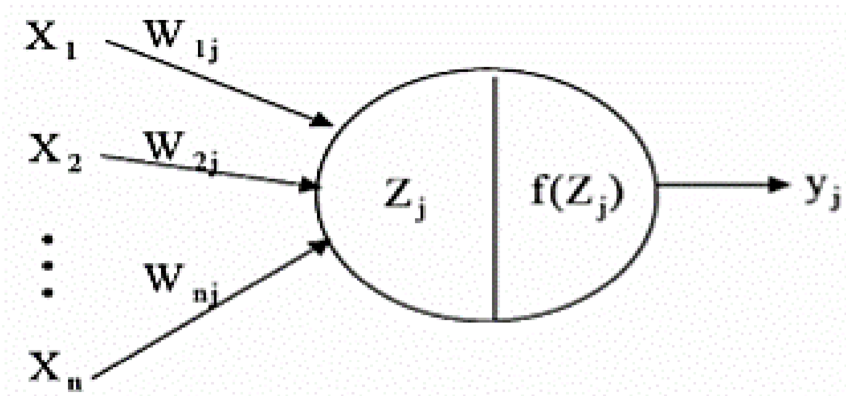

Figure 3: General artificial neural network model [19]

Where X is input, W is weight, Z is $\sum X * W$, (Z) *is activation function*, and y is output.

3.3 The Studied WSN Model

In this work, a WSN model has been simulated using python 3.9. It consists of 50 randomly distributed nodes within an area of 100 * 100 m2 as shown in Figure 4. The model contains a sink and a monitoring station.

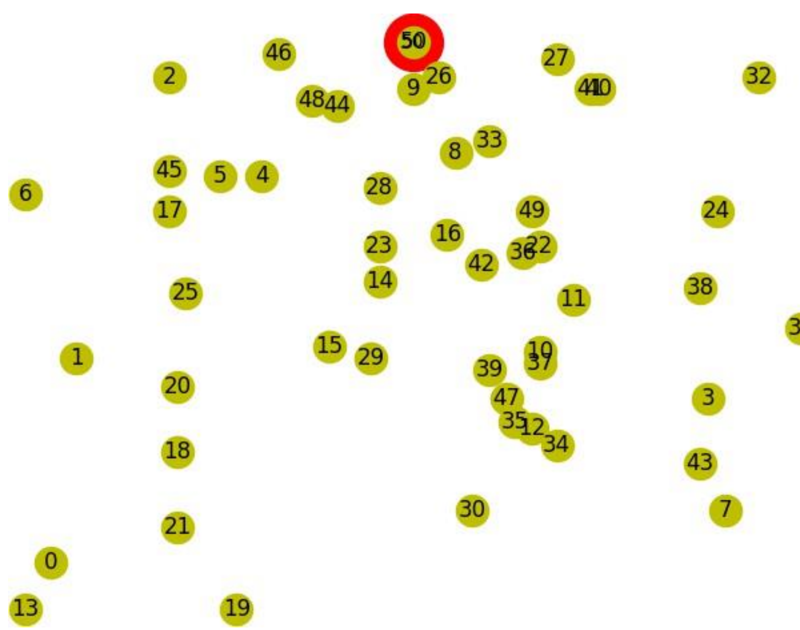

Figure 4: The studied WSN Model

After deploying the nodes, they take their positions and remain stable. The monitoring station sends a flood of messages to the network. This flood passes through different nodes. Each node delivers the flooding message to its neighbors. After that, each node receives this message. At this time, there is a reverse path to the monitoring station. After receiving the flooding message, each sensor generates a

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message. This message contains neighbor's IDs, besides the position of this sensor, and sends it back to the base station. The base station is able to create a neighborhood matrix and to form all paths from each node to the sink node. A comparison between these paths is done based on the applied algorithm.

Sensing task in WSN is usually done in cycles where each cycle consists of sensing operation and data transmission. Sensors in the network perform sensing and data transmission. Transmission is performed through the specified route from this node to the sink node and then to the monitoring station in each cycle.

3.4 The Applied Neural Network

In this work, a neural network (NN) of back propagation type has been created using python 3.9. It consists of three layers: an input layer, one hidden layer, and an output layer, as shown in Figure 5

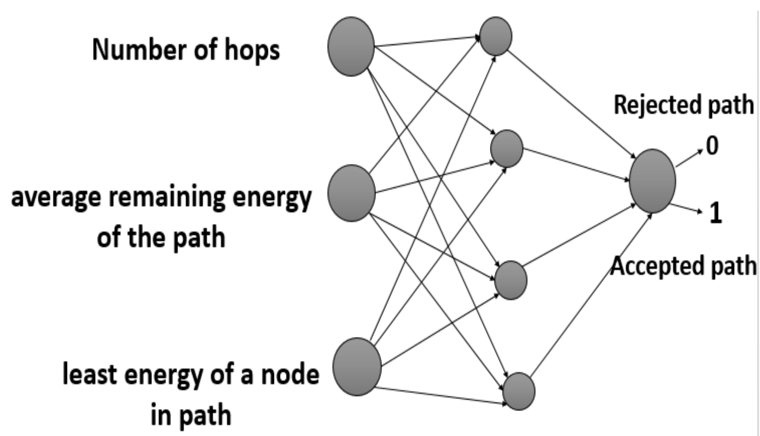

Figure 5: The Applied Neural Network

The input layer contains three neurons. Input of these neurons are routes' parameters. These parameters are: number of hops, average residual energy of the nodes which form the route, and the smallest value of the energy among the nodes which form the route. The hidden layer contains four neurons. The Sigmoid function has been used as an activation function for the neurons, because of its many types and ease of derivation. The output layer contains a single neuron. Output value is 1 if the route is accepted and 0 if rejected. The NN has been trained on training dataset, obtained from the studied WSN.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

x is sum product of input by weight $x = \sum \text{input} * \text{weight}$

Training has been done based on back propagation training algorithm. Training experiment has been repeated for 1000 rounds. Increasing number of training iterations leads to decrease in the prediction error. This in turn increases the precision of NN's prediction. Prediction error is measured by taking difference between the predicted value and the actual value. Loss value is calculated as Mean Squared

Error (MSE). With this approach, the NN reached the appropriate weights with low loss value as shown in Figure 6. Therefore, the NN is able to predict the most suitable route properly.

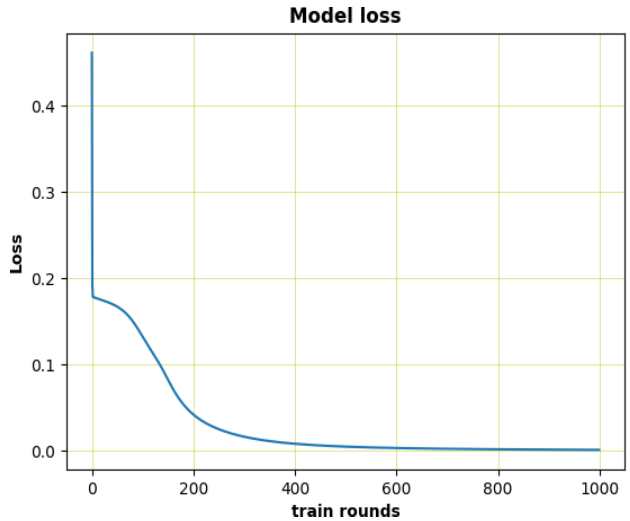

Figure 6: Loss value on training the neural network

4 The Proposed Model

An algorithm has been proposed in the model that finds the best route from the source node to destination node in a WSN. The objective is to achieve a balance in energy consumption among the nodes in the network. This helps in extending nodes lifetime by maintaining their energy level for a longer period of time and thus extending lifetime of the network. The monitoring station obtains the information from the nodes (their neighbors and their locations) and configures all available routes. After that, it computes the parameters of the routes which are required to act as input of the NN in each sensing cycle. At the end of each cycle, the nodes send a report about their residual energy to the monitoring station in order to update routes' parameters.

The mechanism of selecting the optimal route, which helps in nodes' energy preserving, is as follows:

1. In the first cycle, each node transmits its data on the shortest route that's the one with the least number of hops, Because In the first cycle all nodes have the same energy level.
2. In the following cycles, routes' parameters are entered into the NN for predicting the accepted routes. After that, a comparison is made between the accepted routes. Routing is done on the route which fulfills the following conditions:
   a. The highest average residual energy of the nodes on the selected route.
   b. Number of hops in the route is less than a threshold. Value of the threshold is decided experimentally (10 hops in this case). This value has been chosen as an average of many values of number of hops per route. It should be noticed that threshold value differs according to the studied network.
   c. The selected route does not contain a node with residual energy which is less than a threshold (Tp=0.15 Jouls). This threshold is calculated empirically with a good number of experiments. It has been found that this value is the most suitable for conducting the experiments.

3. After certain number of cycles, most of the nodes reach this threshold. Therefore, threshold value is modified to become 0.1 Jouls. This value of energy is insufficient for the node to be functional. In this work, a node is considered to be inactive (dead) when its energy drops 50% from its initial

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energy (its energy is 0.1 Jouls).

4. The following cases must be taken into account:

- If several routes meet the previous conditions, the shortest route is chosen.
- If all the routes are similar, one route is randomly selected.
- If no path fulfills the conditions, the sent data packet is dropped.

The residual energy, of each node per sensing cycle, is calculated as in equation 6.

$$E^{jj}{}_{residual} = E^{jj-1}{}_{residual} - E^{jj}{}_{consumption} \qquad (6)$$

Where E^{jj} residual is the remaining energy of the node in the current cycle. E^{jj-1} residual is the remaining energy of the node in the previous cycle. Ejj is the consumed energy by the node in the current session. Consumed energy by each node has three parts:

1. The consumed energy in receiving data calculated as in equation 4.
2. The consumed energy in collecting data EDA.
3. The consumed energy in sending data to the next node or to the sink. This is calculated according to equation 1.

The average residual energy, for all the nodes on the route, are calculated using equation (7).

$$E_{path} = \frac{\sum_{i=1}^{N} E^{i}{}_{residual}}{N} \qquad (7)$$

E^{i} residual is the remaining energy of node i. N is number of nodes in the route.

Algorithm 1: The optimal route selection algorithm

Input: all routes from source node to sink and its parameters.

Output: optimal route.

If (cycle_nb=0) **Then** optimal route = The shortest route

Else input routes' parameters to NN and the output of NN is accepted routes.

For each route in accepted routes do

If (avg_energy (route) = max_avg_energy and number_of_hops (route) < 10

and min_energy_node (route)>0.15)

Then optimal route=route

If The optimal route =several routes:

Then optimal route= The shortest route

If all shortest routes are similar

Then optimal route=random one

End if

End if

If optimal route=null:

Data packet is dropped

End if

End if

5 Results and Discussions

The experimental study in this work has been conducted on WSN and ANN. The sensor network and the ANN have been simulated using Python 3.9. Table 1 shows the simulation parameters, used in this work, for the experimentation purpose which conforms to [15].

Table 1: The Simulation parameters [15]

Parameter	Value
NB_Nodes	50
Network_area	100*100 m^2
Initial_energy	0.2J
E_{elec}	50nJ/bit/m^2
E_{fs}	10pJ/bit/m^2
E_{mp}	0.0013pJ/bit/m^4
E_{DA}	5nJ/bit
Packet_Size	4000 bits
NB_Rounds	200

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5.1 Alive Nodes

Effect of the proposed algorithm on network lifetime has been studied through two scenarios for 200 work cycles. Results obtained in both the scenarios have been compared. In the first scenario, the proposed algorithm has been applied. In the second scenario, the shortest path algorithm has been applied in each cycle. It must be recalled that each cycle begins by sensing and ends by delivering data to the monitoring station.
Figure 8 shows how the number of alive nodes changes in each scenario.

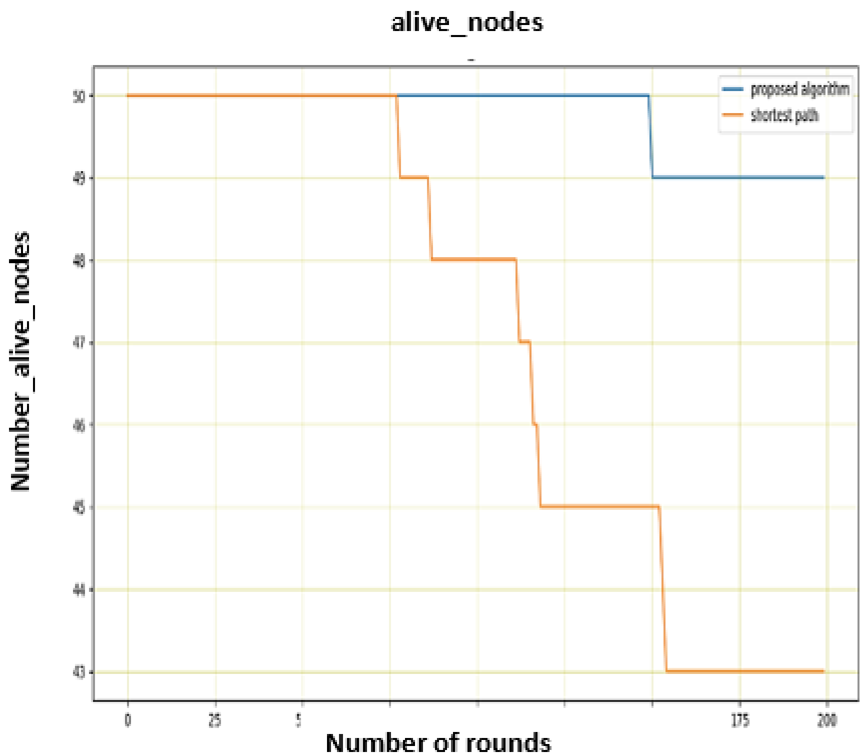

Figure 7: Number of alive nodes with various rounds

It is clear from figure 7 that at round 78, number of alive nodes starts to decrease while choosing the shortest path. Number of alive nodes at round 78 decreases to 49 nodes. On the other hand, with the proposed algorithm, number of alive nodes doesn't decrease until round number 150. Though, number of alive nodes at this round also decreases to 49 nodes. This means that after applying the proposed algorithm, the network continues to work for longer period of time. The reason for this early decline, with the shortest path, is that one of the nodes may be present in different paths when choosing the shortest path. This causes more energy consumption. Therefore, this node will stop functioning (die). With the proposed algorithm, the path of low energy nodes is excluded. Therefore, lives of the nodes will be extended. As a result, life of the network will be extended. It is clear from figure 8 that number of alive nodes after applying the proposed algorithm remains 49 nodes till round number 200. It is noticeable that number of alive nodes decreases till 43 nodes when applying the shortest path algorithm at round number 200. Hence, the sharp difference between the two cases is quite clear.

5.2 Dropped Packets

Number of dropped packets for the two previously algorithms (the shortest path and the proposed one) has been observed. Figure 9 shows a comparison between the number of the dropped packets during each work cycle.

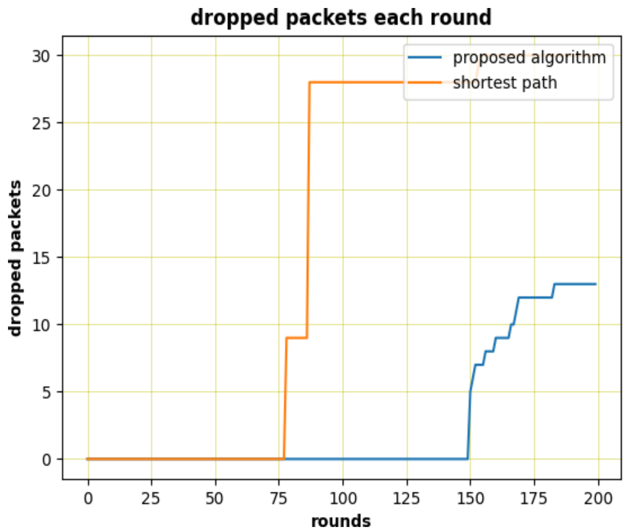

Figure 8: Number of dropped packets after various rounds

When some connected nodes in a network run out of energy, the network goes down and the transmitted packets will be dropped. This is the case of sensor network under study. It is clear from figure 8 that number of the dropped packets is higher before applying the proposed algorithm. The reason is that the proposed algorithm helps in preserving nodes energy and extending the lifetime of the network. This reduces the number of the dropped packets.

5.3 Consumed and Residual Energy

Amount of the consumed energy in the whole network has been computed and compared in the two studied cases. Figure 10 shows a comparison between the consumed energy for both the studied algorithms. Figure 11 also shows a comparison between the residual energies in the network, in the two cases.

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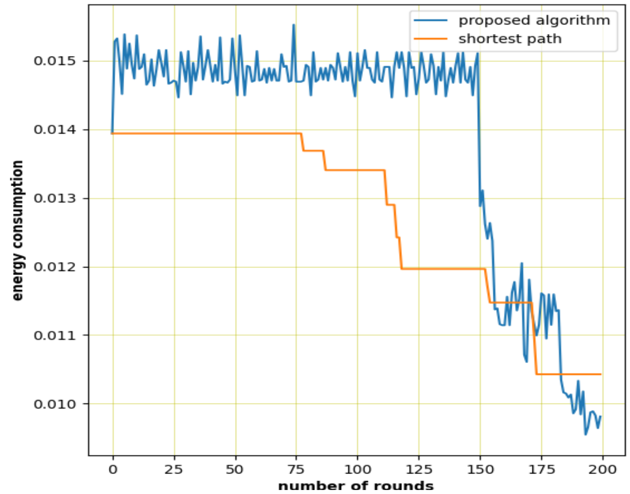

Figure 9: Consumed energy in the network

It is clear from Figure 9 that the total consumed energy with the proposed algorithm is higher than shortest path algorithm. This can be explained as follows. The objective of the proposed algorithm is to extend the lifetime of the network for the longest possible period. Therefore, number of the selected nodes in each route is not that important and is not given a heed. On the other hand, the objective of the shortest path algorithm is to find the shortest path. Therefore, number of nodes which consume more energy may be present in the route chosen by the proposed algorithm. Hence, total amount of the consumed energy is bigger. As a result, the amount of the residual energy in each node is bigger in case of applying shortest path algorithm as clear from Figure 10. Although the proposed algorithm consumes more energy, this is balanced between the nodes. Therefore, this reduces the possibility of nodes running out of energy in the early work cycles.

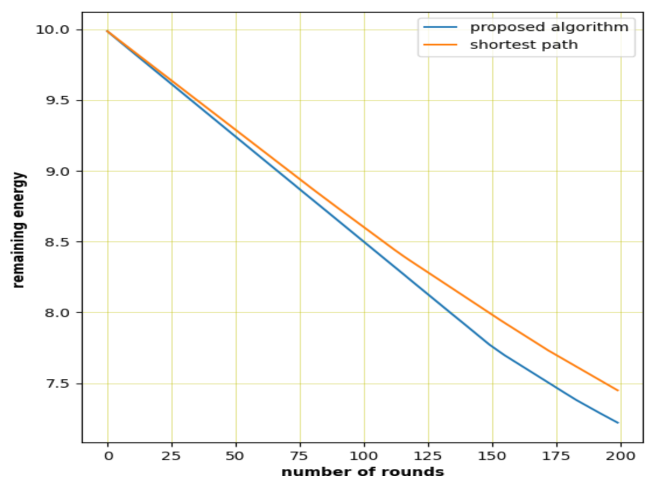

Figure 10: Residual energy in the network

6 Conclusions and Future Work

In this research, a neural network-based algorithm has been proposed for obtaining an energy-efficient routing paths. For this an ANN based model has been proposed. For the performance study, simulation experiments have been carried out. The obtained results show significant improvement in the lifetime of the network in comparison with the shortest path algorithm. Although the proposed algorithm consumes more energy than shortest path algorithm, it achieves a balance between the nodes so that the lifetime of the network is increased.

In future, the proposed work can be further extended by training the ANN to be able to predict the consumed energy for each node. Therefore, the residual energy of each node would be known. Based on this knowledge, nodes don't need to send their remaining energy to the monitoring station at the end of each cycle. This may help in saving nodes' energy. In another work, to prove the scalability of the proposed algorithm, experimental comparisons are needed on several network scales.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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