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Chain based Leader Selection using Neural Network in Wireless Sensor Networks protocols

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Abstract: The selection of a chain leader is an important issue in wireless sensor networks (WSN). In this paper, we introduce a new method to select chain leaders in chain-based routing protocol using Neural Network (NN). Our proposed method can be applied to any chain based routing protocol such as PEGASIS (Power-Efficient Gathering in Sensor Information Systems), CBERP (Cluster Based Energy Efficient Routing Protocol), CCM (Chain-Cluster Based Mixed Routing Protocol), CCBRP (Chain-Chain Based Routing Protocol), etc. To approve our claim that our idea can be applied to any chain-based routing protocol we have applied our method to two of the most known protocols, PEGASIS (original chain-based routing protocol) and CCBRP. It is very well known that energy consumption is a very important issue for all Wireless Sensors Networks (WSNs). Our proposed method is based on the Neural Networks tool to select chain leaders based on the node's residual energy. The simulation result shows that the use of our proposed method has improved the performance of both PEGASIS and CCBRP in terms of the consumed energy and the network lifetime.

Keywords: wireless sensor networks, Neural Network, chain based routing protocols, PEGASIS-NN, CCBRP-NN.

1 Introduction

Wireless Sensor Network (WSN) consists of huge numbers of tiny sensor nodes in a sensor field, which is non-deterministically installed over the region where human intervention is a bulky task. In past, the WSNs mainly are developed for military applications, especially for battlefield surveillance. Nowadays, it extends its applications to Internet of things applications (IoT) such as machine monitoring, patient monitoring, smart home, and smart traffic control [1-4]. Neural networks (NN) are used in many scientific, medical, and commercial applications such as pattern recognition problems, illness diagnoses, clustering networks, dynamic time series [5], and others. Fig. 1 shows a typical view of the WSN.

Energy conservation is a primary issue for the organization of the sensor nodes in the field because the sensor nodes have limited energy. Many routing protocols are introduced for data transmutation from the sensor nodes to the base station (BS). One of such protocols is LEACH (Low Energy Adaptive Clustering Hierarchy) [6-8] which is a cluster-based routing protocol. LEACH first forms clusters of sensor nodes then elect a Cluster Head (CH) for each cluster. For energy conservation purposes, PEGASIS (Power-Efficient Gathering in Sensor Information systems) was introduced, a near-optimal chain-based protocol [9-11]. PEGASIS starts forming a chain of sensor nodes using a greedy algorithm then selecting randomly a leader for the chain. The leader of the chain consumed more energy than the other nodes in the network as it sends the data to the BS so the selection of the chain leader is an important issue that can affect the lifetime of WSN. However, PEGASIS suffers from a large delay as the data are transmitted through the chain from one sensor node to another till reaches the leader node, many chain algorithms are proposed to solve this issue [12-16].
In this paper, we proposed a new method based on NN to select the chain leader for any chain-based routing protocol to extend the lifetime of the network.

The rest of the paper is summarized as follows. Section 2 describes related works on recently developed techniques. PEGASIS protocols are described in Section 3. In Section 4 we present Artificial Neural Networks. Our proposed algorithm is elaborated in Section 5. In Section 6 Experimental results with simulation are explained. Conclusion and future work are mentioned in Section 7.

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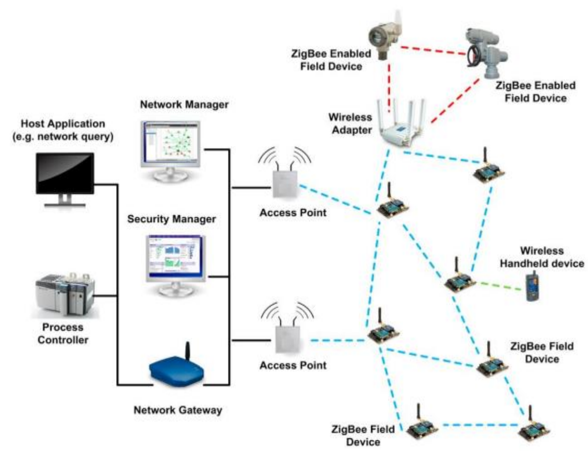


Fig. 1: A typical view of WSN with central monitoring [17].

2 Related Works

The literature is very rich with protocols for WSNs to extend their lifetimes. CBERP [17] is one such protocol. It is a hybrid protocol of LEACH and PEGASIS. CBERP combines the clustering mechanism of LEACH and the chaining mechanism of PEGASIS. More specifically, it organizes the clusters using the same mechanism of LEACH-C with the exception that each of the header nodes is not permitted to transmit data directly to BS; it sends its data through a chain to reduce the energy consumption as in PEGASIS protocol.

ECHERP (Equalized Cluster Head Election Routing Protocol) [18] developed double cluster heads in one chain to avoid the existing long chain they prepared a hierarchical structure in the new algorithm. Their simulation results showed that their algorithm was able to increase the productivity of energy using the load balancer, which helped to extend the lifetime of the whole network.

The CCBRP [16] however, divided a WSN into a number of chains and runs in two phases. The CCBRP utilized a Greedy algorithm to form each of the chains. In the first phase, sensor nodes in each chain transmit their data to their chain leader nodes in parallel. In the second phase, all chain leader nodes form a chain (also using a Greedy algorithm) and then all the leader nodes send their data to a randomly chosen leader node. This chosen leader node fuses its data with the received data and sends it to the BS. Experimental results demonstrated that the proposed CCBRP outperforms each of LEACH E. Eldosy et al. [19] proposed a technique to reduce battery consumption based on the Artificial Neural Network, the author train NN to made data fusion in a reliable manner by reducing the undesirable flooding of information. In [20], authors introduced an algorithm based on Neural Networks to select CH for clusters depending on the amount of remaining energy for LEACH protocol, CH selection is depending on the amount of remaining energy. Their model is composed of three layers, one input layer, one hidden layer, and an output layer.

PEGASIS, and CCM with respect to the product of the consumed energy and delay. In [21], the authors proposed a cluster-based hierarchical routing path protocol, which is a modified PEGASIS protocol based on traditional PEGASIS with the employment of Self Organizing Map (SOM) Neural Network (NN). Their protocol runs in the two-step, the first step the network is divided into clusters then **Cluster Head (CH) are selected by SOM-NN**. In the second step, every cluster forms a chain based on the greedy algorithm, and chain leaders are select randomly, after that data transmission occurs. Authors in [22] proposed a PEGASIS double cluster head with Artificial Neural Network (ANN), The proposed algorithm is composed of four phases: first clustering the network nodes using firefly algorithm [23], second cluster head (CH) selection performed using ANN, the third chain formed by **PEGASIS double cluster head (PDCH) [24]**, and fourth a secondary CH (SCH) selected using grey wolf optimizer [25].

3 Pegasis Protocol

PEGASIS [9] is a near-optimal chain-based routing protocol. The main goal of this protocol is the extension of the WSN lifetime. In PEGASIS protocol each node of the WSN intercommunicates only with its closest neighbor and the nodes continue communicating with each other in their turns until the aggregated data reaches the Base Station. This method of communication reduces the power consumption required to transmit data per round. Thus PEGASIS protocol achieves a factor of two improvements in energy consummation over the LEACH protocol [9-11]. The architecture of the PEGASIS protocol works in three steps as shown in the Fig. 2. PEGASIS protocol starts forming a chain using the Greedy algorithm then randomly selects a leader for the formed chain after that data transmutation takes place.

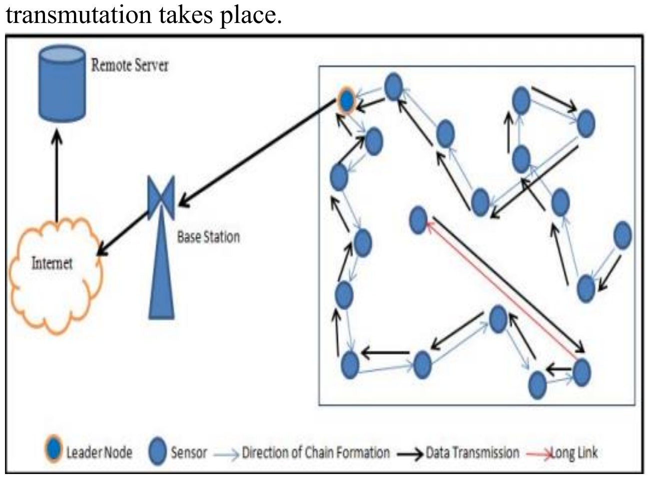


Fig.2: WSN with PEGASIS Protocol Architecture [24].

3.1 Chain Formation

To construct the chain PEGASIS protocol starts from the furthest node from the BS and uses a Greedy algorithm to form it. The main idea here is that each sensor node communicates only with its closest two neighbors to minimize the power consumption.

3.2 Leader Selection

At the beginning of each round, a chain leader is selected at random. This way of selection is easy and fast since no extra computation is performed. After the leader has been selected it passes a token message to initiate a data-gathering process. Passing a token also consumes energy, however; the cost of passing a token is very small since the size of the token message is very small. The energy consumption consistently depends on the leader nodes in the networks [9].

3.3 Data Transmission

Gathering the data each round; each node except the terminal nodes receives data from one neighbor (its predecessor in the chain), fuses its data with it, and transmits it to the other neighbor (its successor in the chain) until the whole chain data reaches the chain leader. Finally, the chain leader sends this data to the Base Station.

4 Artificial Neural Network

A Neural Network (NN) is an interconnected assembly of simple processing elements, units, or nodes. The processing ability of the network is stored in the interunit connection strengths, or weights, obtained by a process of adaptation to or learning from, a set of training patterns. The NNs are trained by a set of examples, each example with a specific input and its desired corresponding output. When the training completes, the NN will be able to make a decision for new examples and produce predicted outputs.

The Neural Networks (NNs) consists of neurons connected via weighted connections that permit to associate the input layer to the output layer, through a transfer function of the sum of the products of inputs values and their weights, see Fig. 4, and it stores the information, thus NNs don't need data storage. The four elements constituted the model that is adopted for artificial NNs.

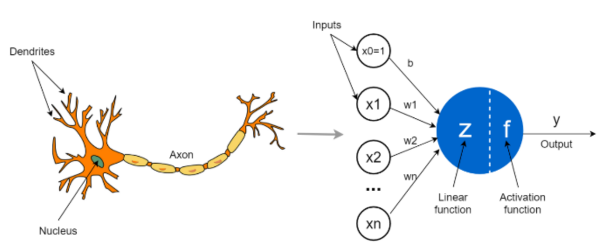


Fig. 3: the Concepts of Artificial neuron

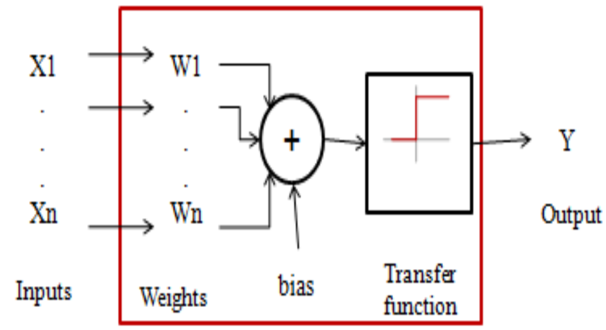


Fig. 4: Artificial neuron.

The training process is considered supervised learning because it learns from labeled examples. The model is organized in layers, offer the capability to perform nonlinear statistical training and detect complicated relation between variables without requiring formal statistical training, but like any model, it has some issues such as the greater computational burden, and the overfitting.

Backpropagation is the most powerful algorithm of Neural Networks (NNs), it computes the error between the actual output computed by using forward pass, and the desired output is given in the datasets, then a backward pass for adjusting the weights in order to minimize the error. The algorithm is repeated until some specific conditions are satisfied [26]. There are many versions of the algorithm, but the most standard steps are:

- Forward propagation
- Compute error between actual output and desired output
- Backward propagation to minimize error calculated
- Repeat iterations

5 Proposed Algorithm

The main goal of our proposed algorithm is to extend the lifetime of WSNs by improving the selection process of leader nodes for chain-based routing protocols. We have utilized NN to select leader nodes based on residual Energy for every node in the network. The node which has the highest energy will be selected as the leader node.

Thus, the energy could be more conserved and the lifetime of WSN is extended. Our proposed NN consists of four layers as shown in Fig. 5, an input layer, two hidden layers, and an output layer. The input layer is composed of two nodes one for Energy and the others for Bias. Every hidden layer contains five nodes and the sigmoid function are used as a transfer function. The output layer has one node that can take either a value of "1" for the leader node or a value of "0" for the non-leader node.

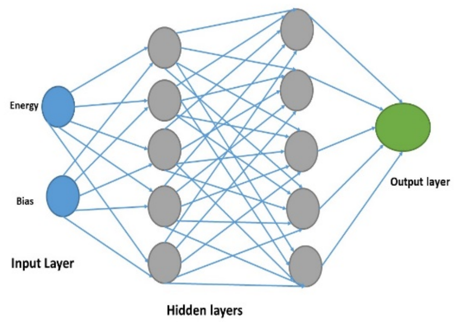


Fig. 5: The Structure of the Proposed Neural Network.

The flow chart for the proposed PEGASIS-NN protocol is shown in Fig. 6. As demonstrated in Fig. 6 we start by chain formation using a greedy algorithm as in PEGASIS protocol, then we utilize the NN to determine the leader of the chain by feeding the energies of all nodes to the input of the NN and assign the node with a value of "1" at its output as the chain leader after that data transmission takes place from the chain end to the assigned leader node.

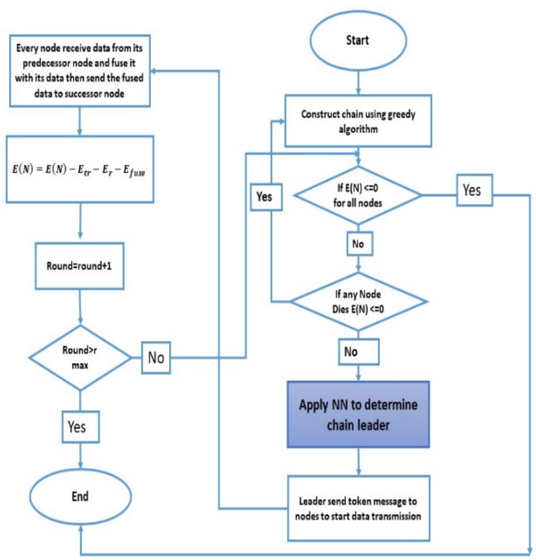
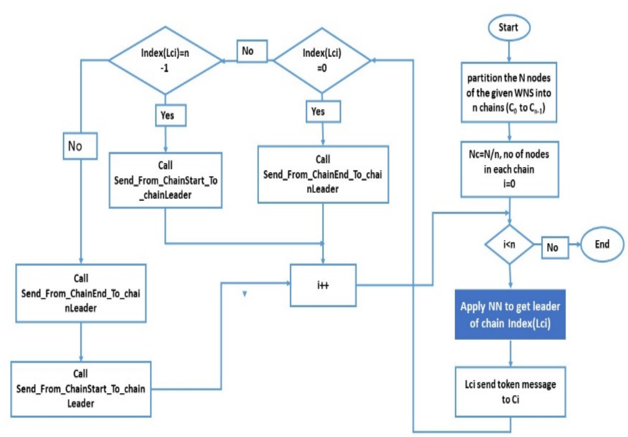
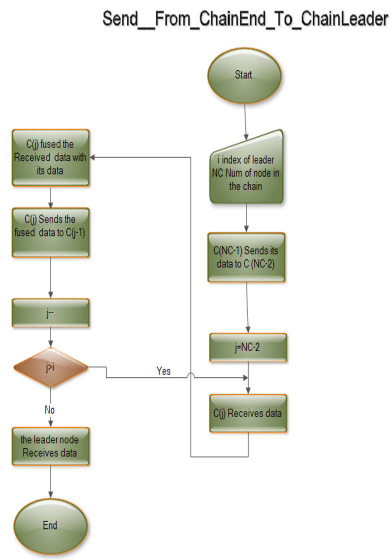


Fig. 6: the Proposed PEGASIS-NN Protocol.

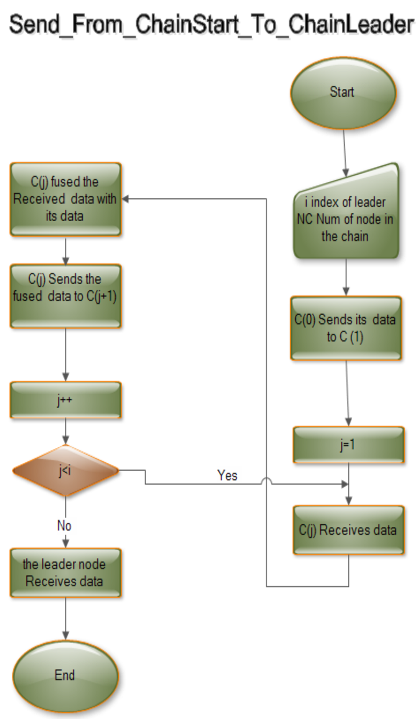
Since the CCRBRP has two phases so we have applied the proposed NN for leader selection to the two phases.
The flow chart for the first phase of the proposed CCBRP-NN protocol is shown in Fig.7. as shown in the figure, the proposed protocol starts by partitioning the WSN into "n" chains, then we apply NN to each chain to elect its chain leader, after that the chain leaders simultaneously send token messages to their chains to start data transmission. After that each of the two end nodes (first and last node of chain) of each chain starts sending its data to its closet neighbor node, the neighboring nodes receive the data and fuse its data with the received data then it sends the fused data to the next node in the chain and so on. This process is repeated till the data has reached all the chain leader nodes
The second phase of CCBRP NN starts after all the chain leader nodes have received all the data from their chain nodes. These chain leader nodes form a chain (using Greedy algorithm) and then we applied NN to select a chain leader for the newly formed chain by using the energy of the leader nodes as input to the proposed NN. Then the chosen leader sends a token message to the two ends of the newly formed chain. Thereafter, each of the two nodes at the two ends of the formed chain of leaders starts sending its data to its closest neighboring node. The neighboring nodes receive the sent data and fuse their data with the received data and send it to the next neighboring nodes and so on. This process of sending data is repeated till all the data of the WSN under consideration has reached the leader node of the chain of leader nodes. After the leader node received this data it is fused with its data and sent to the Base Station node. The flowchart of the second phase of the CCBRP-NN protocol are shown in Fig.8.



a) CCBRP- NN Phase One Flowchart



b) Sending Data from Chain End to Chain Leader.



c) Sending Data from Chain Start To Chain Leader.

Fig. 7: the proposed CCBRP-NN protocol

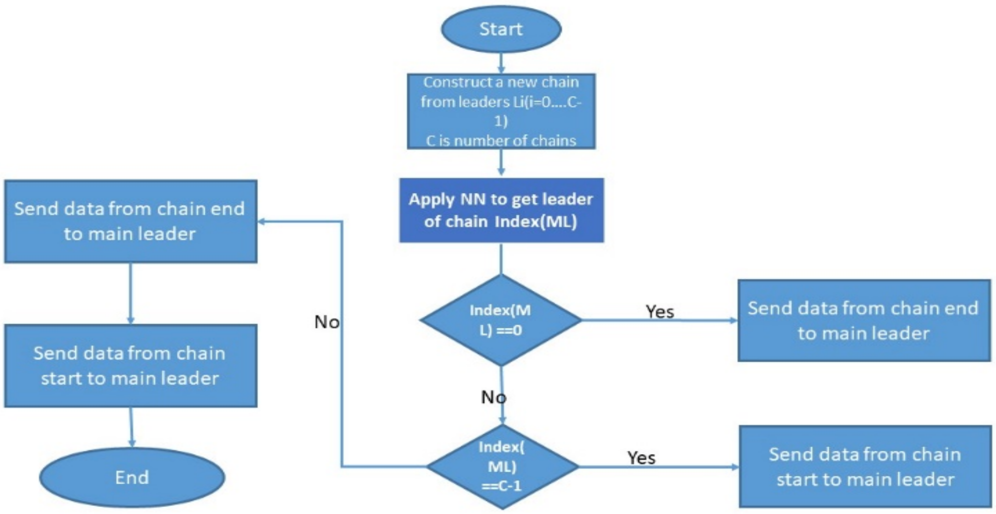


Fig. 8: CCBRP- NN Phase two Flowcharts.

6 Experimental Results and Simulations

To prove our claim that the proposed Neural Network will improve the performance of wireless sensor networks utilizing chain-based routing protocols by reducing their consumed energy and extending their lifetimes. We have built a simulator and conducted two experiments one for PEGASIS (an original chain-based routing protocol) and the other for CCBRP (Chain-Chain Based Routing Protocol) [16].

6.1 Environment Setup

we have built a simulator using java and the popular network simulation platform MATLAB to simulate our proposed protocols. Several parameters must be set for the environment of WSN such as the area, number of nodes, and initial energy of the nodes. The details of the used parameters are shown in Table I below.

Table I: The simulation parameters.

Parameter Name	**Value**
Area	100m X 100m
Number of Nodes	100
Initial Energy /Node	0.50 J, 1 J, 2 J
Relative Position of BS	(50,300)
Number of Dead Nodes at the start	0
Energy Required for Transmission	50 nJ/b
Energy Required for Receiver	50 nJ/b
Data Aggregation Energy	5nJ/message
Amplifying Energy Required by the Transmitter	100*10^ (-12) J/b/m^2
Energy required to run circuitry (both for transmitter and receiver)	50*10^ (-9); units in Joules/bit
Packet Size	2000 bits 4000 S

6.2 Energy Consumption for Data Transmutation to the Base Station

The energy required to transmit and to receive the data is given by equations (1) and (2)

$$E_{Tx}(k,d) = E_{elec} * k + Emp * k * (d)^2 \quad (1)$$

$$E_{Rx}(k) = E_{elec} * k \quad \mathbf{(2)}$$

Where,

$\boldsymbol{k}$	Size of message being transmitted and received
$\boldsymbol{E_{Tx}}$	The amount of energy required to transmit the data packets
$\boldsymbol{E_{Rx}(k)}$	The amount of energy required to receive the data packets.
$\boldsymbol{E_{elec}}$	50 nJ/bit to run the transmitter or receiver circuitry

Emp	100 pJ/bit/m2 for the transmitter amplifier

6.3 Convergence Indicator:

Convergence Indicator (CI) is used to estimate network conjunction. It is assumed that the higher value of CI is better than the fixed energy consumption of the network. The CI is given by equation. (3).

$$\boldsymbol{CI} = \frac{\boldsymbol{LND} - \boldsymbol{HND}}{\mathbf{HND} - \mathbf{FND}} \qquad (3)$$

Where FND is the number of rounds when 1% die of total nodes, HND is the numbers of rounds when 50% nodes die of total nodes and LND represents 100% die of total nodes rounds.

6.4 Simulation Results

The energy consumption and the number of dead nodes are two of the performance measures for most WSN protocols. The node is treat as a dead node if its energy less than zero [23] In our simulator, we have evaluated our proposed protocols (PEAGSIS-NN and CCBRP-NN) for initial energy 1.0J and 0.5 J and we have compared with the PEAGSIS and the CCBRP protocols without the proposed NN based on consumed energy and dead nodes. We have run our proposed protocol for one hidden layer NN and two hidden layers NN to check the effect of the number of hidden layers. The details of the reached simulation results are shown next.

6.4.1 Results for node initial Energy of 1.0 J

a) PEGASIS NN results initial Energy per Node of 1.0J

Table II shows the results of our proposed PEGASIS-NN protocol for initial energy 1.0J/node, as the table demonstrates our proposed protocol consumed less energy than the PEGASIS protocol by about 5%. However, the lifetime of WSN is improved by 900 rounds for full network dead and by 300 rounds for half network dead. Note that as the number of the hidden layers increase the consumed energy decrease and the lifetime of the network is improved. Although the consumed energy in the case of one hidden layer NN is more than PEGASIS, the lifetime of WSN with the proposed PEGASIS-NN is improved due to the selection of leader, in this case, is better than the random selection.

Figure .9 presents the number of rounds until 1%, 20%, 50%, 100% nodes die for initial energy 1J/node. When using PEGASIS, more than 20 percent of nodes have lost efficacy at the 2450th round, and this situation appeared at the 3100th round in the network by PEAGSIS-NN. Nodes lost all their energies at the 3100th round in the network of PEGASIS, but nodes lost all of their energies at the 3976th round when using our proposed PEGASIS-NN protocol. It is clear that our proposed algorithm improves the lifetime of WSN (both the time the first node dies and the last node dies). CI for PEGASIS is 0.28 while the proposed PEGASIS-NN CI is **0.32**.

Table II: Energy Consumption and Numbers of dead nodes for PEAGSIS-NN and PEAGSIS for Initial Energy 1J/node.

Rounds No	Energy PEAGSIS-NN two HLs	Dead Nodes PEAGSIS - NN two HLs	Energy PEAGSIS - NN one HL	Dead Nodes PEAGSIS - NN one HL	Energy PEAGSIS	Dead Nodes PEAGSIS
300	7.58	0	7.94	0	7.74	0
600	15.15	0	15.83	0	15.43	0
900	22.69	0	23.70	1	23.12	0
1200	30.24	0	31.59	1	30.88	0
1500	37.79	0	39.5	1	38.64	1
1800	45.37	1	47.37	2	46.45	3
2100	52.91	2	55.30	2	54.08	8
2400	60.32	2	63.17	2	61.86	19
2700	67.60	2	71.05	3	69.56	36
3000	74.89	10	78.96	11	77.34	59
3100	83.13	35	86.84	36	100	100
3500	88.16	56	92.12	60	100	100
3900	98.23	98	100	100	100	100
3976	100	100	100	100	100	100

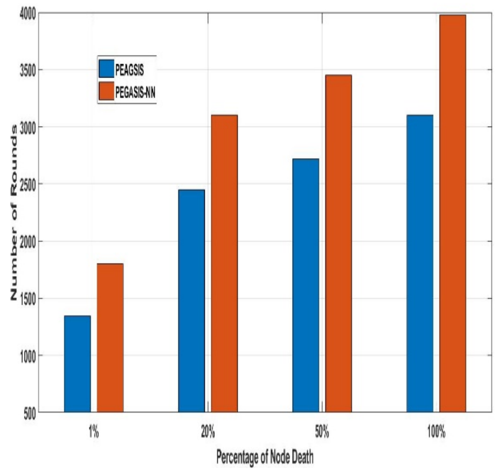


Fig. 9: The Proposed PEGASIS-NN and PEGASIS Percentage of Node Death for Initial Energy of 1.0 J/node.

b) CCBRP NN results initial Energy per Node of 1.0J

Table III demonstrates the performance of our proposed CCBRP-NN protocol (energy consumption and a number of dead nodes), as the table indicates that our proposed CCBRP-NN protocol consumed less energy than CCBRP protocol by almost 2%. While the lifetime of WSN is improved by 200 rounds for full network dead and by 125 rounds for half network dead.

Figure .10 presents the number of rounds until 1%, 20%, 50%, 100% nodes die for initial energy 1J/node for CCBRP and our proposed CCBRP-NN. It's worth note that for CCBRP, more than 20 percent of nodes have lost efficacy at the 3300th round, while this situation occurred at the 3400th round for the proposed CCBRP-NN. Nodes lost all of their energies at the 4700th round in the network of CCBRP, while nodes lost all of their energies at the 4900th round in the proposed CCBRP-NN protocol. It is clear that our proposed algorithm improves the lifetime of WSN (both the time half nodes die and the last node dies). Also, note that CI for CCBRP is 0.82 while for our proposed CCBRP-NN CI is 0.83.

Table III: Energy Consumption and Numbers of dead nodes for CCBRP-NN and CCBRP for Initial Energy of 1J/node.

Rounds No	Energy CCBRP-NN	Energy CCBRP	Dead Nodes CCBRP-NN	Dead Nodes CCBRP
300	8.07	8.23	0	0
600	16.20	16.43	0	0
900	24.27	24.62	0	0
1200	32.28	32.81	0	0
1500	40.35	40.97	0	0
1800	48.35	49.16	0	0
2100	55.44	57.29	0	0
2400	62.49	65.44	**1**	1
2700	70.29	73.61	4	1
3000	79.8	81.63	10	11
3300	86.81	88.93	17	20
3600	92.99	94.66	35	46
3900	96.20	97.89	60	75
4200	97.92	99.46	77	91
4500	98.71	99.89	90	98
4700	99.50	100	95	100
4900	100	100	**100**	100

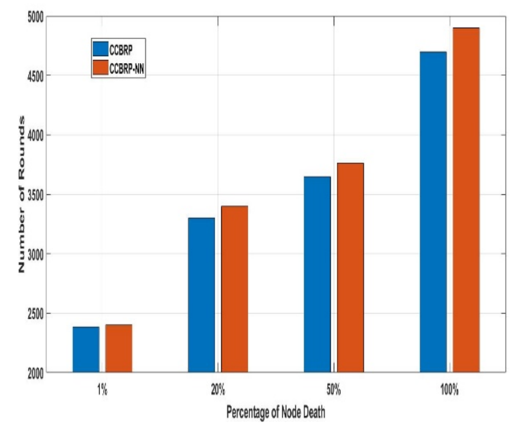


Fig. 10: the proposed CCBRP-NN and CCBRP Percentage of Node Death for Initial Energy of 1.0 J/node.

Table V: Node Death Percentage for PEGASIS-NN, PEGASIS, CCBRP-NN and CCBRP for Initial Energy of 1.0 J/node.

Node Dying	PEAGSIS-NN	PEAGSIS	CCBRP-NN	CCBRP
First Node dies	1800	1346	2399	2381
20% Node dies	3100	**2450**	3400	3300
Half Network dies	3450	**2720**	3765	3650
Full Network dies	3976	**3100**	4900	4700

6.4.2 Results for node initial Energy of 0.5 J/node

a. PEGASIS NN Results Initial Energy per Node of 0.5 J/node

The results of our proposed PEGASIS-NN protocol for initial energy 0.5J/node are presented in Table V, as the table demonstrates the Energy consumption is improved when we use our proposed protocol by about 8%. However, the lifetime of WSN is improved by 200 rounds for full network dead and by 220 rounds for half network dead.

Figure .11 presents the number of rounds until 1%, 20%, 50%, 100% nodes die for initial energy 0.5J/node. When using PEGASIS, more than 20 percent of nodes have lost efficacy at the 1250**th** round, and this situation appeared at the 1500th round in the network by PEAGSIS-NN. Nodes lost all their energies at the 1600th round in the network of PEGASIS, but nodes lost all of their energies at the 1800th round when using our proposed PEGASIS-NN protocol. It is clear that our proposed algorithm improves the lifetime of WSN (both the time the first node dies and the last node dies). CI for PEGASIS is 0.33 while the proposed PEGASIS-NN CI is **0.36**.

Table VI: Energy Consumption and Numbers of Dead Nodes for PEAGSIS -NN and PEAGSIS for Initial Energy of 0.5J/node.

Rounds No	Energy PEAGSIS-NN	Energy PEAGSIS	Dead Nodes PEAGSIS-NN	Dead Nodes PEAGSIS
300	7.52	7.96	0	0
600	14.98	15.69	0	0
900	22.46	23.40	0	3
1200	29.94	31.80	1	4
1300	32.52	33.86	4	22
1400	35.03	36.52	14	**51**
1500	37.51	39.17	24	70
1600	42.51	50	**50**	100
1700	45.02	50	75	100
1800	50	50	**100**	100

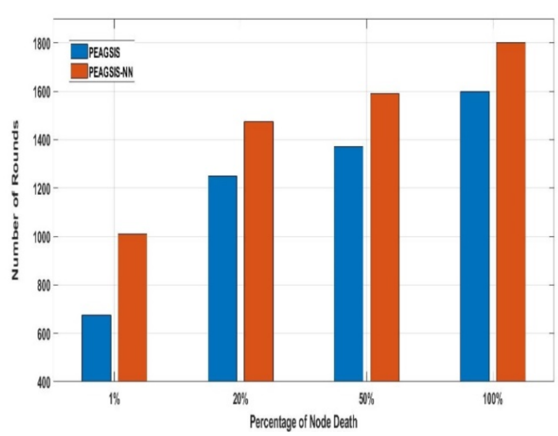


Fig. 11: The Proposed PEGASIS-NN and PEGASIS Percentage of Node Death for Initial Energy of 0.5 J/node.

b. CCBRP NN results initial Energy per Node = 0.5J/node

Table.VI shows the performance of the proposed CCBRP-NN protocol for initial energy 0.5J/node, as the table demonstrates the Energy consumption and the network life time are improved when we use our proposed CCBRP-NN.

Figure .12 presents the number of rounds until 1%, 20%, 50%, 100% nodes die for initial energy 0.5J/node for CCBRP and our proposed CCBRP-NN protocols. When using CCBRP, more than 20 percent of nodes have lost efficacy at the 1300**th** round, and this situation appeared at the 1400th round in the network by CCBRP-NN. Nodes lost all their energies at the 1900th round in the network of CCBRP, but nodes lost all of their energies at the 2000th round when using our proposed CCBRP -NN protocol. It is clear that our proposed algorithm improves the lifetime of WSN (both the time the first node dies and the last node dies). CI for CCBRP is 0.33 while the proposed PEGASIS-NN CI is **0.36**.

Table IV: Energy Consumption and Numbers of Dead Nodes for CCBRP-NN and CCBRP for Initial Energy of 0.5J/node.

Rounds No	Energy CCBRP-NN	Energy CCBRP	Dead Nodes CCBRP-NN	Dead Nodes CCBRP
300	8.16	8.18	0	0
600	16.3	16.41	0	0
900	24.46	24.62	1	1
1200	32.10	32.57	1	10
1500	39.77	40.42	34	47
1800	47.95	48.55	79	89
1900	**49.50**	50	95	100
2000	**50**	50	**100**	100

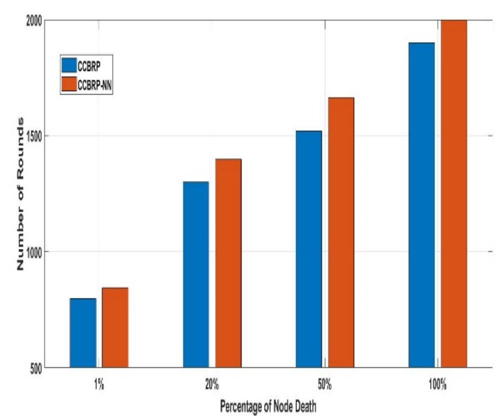


Fig. 12: the proposed CCBRP-NN and CCBRP Percentage of Node Death for Initial Energy of 0.5 J/node.

Table VII: Node Death Percentage for PEGASIS-NN, PEGASIS, CCBRP-NN and CCBRP for Initial energy 0.5J/node.

Node Dying	PEAGSIS-NN	PEAGSIS	CCBRP-NN	CCBRP
First Node dies	1011	675	844	800
20% Node dies	1475	1250	1400	1300
Half Network dies	1590	1370	1665	1520
Full Network dies	1800	1600	2000	1900

5 Conclusions

Energy consumption and the lifetime are the most important performance factors in WSNs. In this paper, we proposed a new method for leader selection in chain-based routing protocols for WSNs. In our method, we have utilized an ANN to select the leader of the chain in a single-chain protocol (PEGASIS-NN) and multi-chains protocols (CCBRP-NN). The used ANN is consisting of four layers, an input layer, two hidden layers, and an output layer. The inputs to NN are the energies the WSN, therefore, the node with the most residual energy is selected as the leader node this extends the network lifetime as the simulation results in the previous section indicated. We have applied our method to PEGASIS and CCBRP, the simulation results showed that our proposal have improved the performance of WSN in terms of consumed energy and network lifetime. In the future work we will use different input to the neural network such as distance to base station to improve the performance of WSN.

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