Implantation modified deep echo state neural networks and improve harmony clustering algorithm for optimal and energy efficient path in mobile sink

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ABSTRACT

Wireless network sensors based on the mobile sink are regarded to be a common network and used in various fields in the last few years, they are thought to be easy to use, but contain the problem of energy loss and are affected by an energy hole problem, as it depends on batteries. This paper proposes a solution to this problem by using an innovative objective function for a consistent distributing of cluster heads, the enhanced harmony search based routing protocols based on energy equilibrated node clustering protocol. In order to route the data packet among the sink and cluster heads, an enhanced modified deep echo state neural network is suggested. The efficiency of a projected integrated clustering and routing protocol has been investigated at 500 nodes, and the 96 per cent success data for the proposed algorithm is given using the average energy consumption, send and receive packaged and optimum numbers of CH.

Keywords: WSN, Mobile sink, clustering, echo state Neural Networks, Harmony Search algorithm

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1. Introduction

Wireless sensor network (WSN) stands for widespread networks in recent times that have been employed in various industrialized systems like safety and security surveillance. It is considered a smart and low-cost network. This network generally has a huge number of sensors nodes, which are small in power and compact in size [1]. Sensor nodes are normally resource limited in WSN Energy resources, measurement and storage systems. The key concern in the field of energy efficiency and scalability Design of protocol for WSN mobile sink for extending the lifetime of the network. The classifications are the one technology that has been provided to address this problem by several researchers [2]. An amount of cluster members (CMs) and a cluster header are part of each cluster (CH). CH's key function is for coordinating data collecting with CMs. Every CH receives sensor data from its CMs through this coordination process, collects data from its CMs, and subsequently conveys the data to a mobile sink through multi-hop communication [3-4]. The solutions that have been built aren’t energy-efficient and scalable [2]. CHs close to the mobile platform deplete their power resources faster than CHs far from the energy hole issue. The network thus creates a gap area that prevents node-to-node interaction. This can be resolved Issue, an algorithm, named a modified Harmony Clustering Protocol and modified deep echo state neural network for finding optimum pathway from source to destination. This paper proposes. To minimize and balance more, the method of relocation of mobile sinks is energy consumption. Protocol efficiency review a well-known LEACH protocols energy use and number is taken into consideration. Living nodes by the number of network node sand even by separate data collection rounds Network [5]. Network.The rest of a research is structured in accordance with subsequent sections. Section 2 contains the associated brief summary works. The assumptions and system models are defined in section 3. Section 4 explains in detail a proposed clustering protocol. Section 5 offers an assessment of result and section 6 presents the concluded points of this study.

2. Related works

In this part of the paper, provide an overview of the works that are considered relevant in the field of the metaphoric-based clustering procedure and the neural networks employed for finding the best path in this type of wireless network. In [4], a method was proposed based on harmony research using central aggregation in which the objective function includes two parameters, for example the residual node energy and the distance within the block. This scheme does not ensure a consistent set of fundamental parameters and suffers from an unequal energy consumption. In [5], the target function involves three parameters, for example the node's residual energy, the overall distance amid CH and CM and a distance amid CH and a base station. A scheme is proposed in this paper. The key constraint of this system is that all CHs are situated close to a base station leaving several nodes that do not related to a cluster in a network. In [7], an enhanced harmony-based search-clustering protocol for WSNs with a mobile sink has presented. This optimizing algorithm has three components, including average residual energy, intra-cluster distance and cluster size, as an objective function. In [3], the authors suggested a separate main component analysis (PCA) and neural network approach. The gotten consequences indicate that the projected algorithm performs superior than before.The algorithm for localizing was developed using neural networks ensemble to estimate the location of the hop count for non-node knowledge.It has the effect of the various training algorithms based on particle swarm optimization [7] .

In [8], the protocol for selecting the cluster head (PSO-ECHS) was based on PSO Suggested. Intra-cluster distance parameters are used by PSO-ECHS, All CHs in their fitness function residual energy and sinking distance. Not each node for CHs selection is included in this protocol. But Select a number of nodes randomly as applicants for CH, then submit PSO-based CH Selection meta-heuristic. Because of that and Parameter such as CH and Sink distance, do the chosen CHs. Not covering the whole area equally. This results in unequaled resources Network usage. In [9], performance of the network location algorithm on the range-based neural network. Gharistan et al., in [10], developed an artificial neural network for hybrid particle swarm optimization (PSOANN) Algorithm. Algorithm. The established range-based system calculates the distance Mobile node and trainer using the neural and Leven berg feed-forward type of network ,Training algorithm for Marquardt. Three AN1, AN2 and AN3 anchor nodes have been fixed. A mobile Node tests and tracks all beacon node RSSI values Train and test the distance algorithm for the artificial neural network (ANN) amid AN1 node and a mobile node.

In [19] Rao and banka , suggested a clustering protocol based on a new procedure to optimize a chemical reaction (nCRO). The NCRO employs various limitations like the distance from CH and sink, residual power, and inner cluster distance to design the fitness functions. Nevertheless, this protocol doesn’t assure the uniform distributing for CHs, which cause the energy hole problem. With the intention of mitigating energy issues, a different clustering and routing protocol is proposed using nCRO algorithm. In connection with the remote clusters from a base station, the clusters have created nearby a base station throughout the clustering process. The choice of CH and the nCRO routing software has elaborated and tested under different network scenarios.

Head Selection Protocol (PSO-ECHS) in [8] has suggested for energizing particle swarm (PSO) optimization. PSO-ECHS uses intra-cluster time, residential energy and sink distance for each CH in fitness functions. This protocol doesn’t involve entire nodes of the CH array. Nevertheless, pick a random number of nodes and use the PSO-based CH metaheurism to choose the CH. Due to their parameters like a distance between sink and CH, the selectable CHs don’t homogeneously cover an entire field. This unbalances the grid's energy consumption.

The two-stage clustering and routing procedure using PSO was proposed in [11]. However, the fair use of energy is not taken into account and the unfair use of energy is enforced. After the review of literature, the bulk of the works are used for the clustering and routing purposes. In certain works, CHs communicate directly with the drain. CHs must, however, communicate with the sink in the WSN by means of multi-hop communication. Clustering and routing are considered as an included problem of optimization and an effectual metaheuristic solution in this work.

3. System model

After clustering CM data, every CH groups the received sensors, and the aggregated data to sink is transferred via multi-shop communication. The energy-efficient way amid the CH problem and the NP-hard thing is drain to extend the existence of the WSN network. In this article, a metaheuristic optimization algorithm (Geem) was proposed for the resolution of this problem based on the harmony research [12]. One purpose The function of optimizing the choice of track from CH to a sink is extracted containing the next hop node of residual power, distance of the sink and route length of a next hop node. Every node from the sink computes firstly a hop count Nodes in this algorithm. Knots. Knots. Knots. Knots. Then, *p(i, j)* was determined for each node selection like its subsequent hop node when the node i to a sink is routed to the next hop expression [13]:

$p(i,j) = \{\left(\frac{Ei}{\sum_{k\in Ni} Ek} + \frac{hi}{\sum_{k\in Ni} hk}\right)$ if $j \in Ni \quad else$ -------(1)

Ni: the list of adjacent nodes for node i.
hi and hk : magnitude for hop count from node i and j correspondingly.
Ei: remaining energy of node i.
The Harmony Memory (HM) has adjusted after a calculation of likelihood of *p(i, j)* . This lists each path from a source node to a sink node. CH Nodes or non-CH Nodes may be the middle node among the source nodes of a sink node. As harmony is a Vector, a direction that includes together CH and non-CH nodes in the HM signifies transmission. As shown in the Eq.2, the duration of each vector of harmony in the HM is different.

HM= $\{x_1, x_2 \ldots . xHMS\} = \{($s, x1,2,……………., d)… (s, x2.2,……….d)… (s, xHMS.2,…….d)
After the initialization stage the Harmony process is improvised. The HMCR (harmony memory tax) is the basis of X1 developed. A new harmony (i.e. path) in Harmony improvisation method. A source node is the first element of X1. The first option to pick a subsequent hop is a random P1 number between 0 and 1. If the P1 is less than HMCR, the next hop will be chosen by randomly in the next column of the selected node.
The suggested amended harmony as a five-step search-optimization algorithm:
• Initialization parameter;
• Initialization of Harmony Memory,
• Modern Harmony vector improvement, •
• Memory update Harmony and the final move,
• Cancelation criteria checking.

Algorithm 1: modified harmony as search optimization algorithm
Input: set of sensor node s=(s1----sn) N is total number of sensor node
Scale of the Harmony Memory (HMS):
Vectors for peace solution.
Output: optimal CH and place number
Phase 1: Start-up:
• The iHSC clustering process proposed is initialized:
• Number of CHs required for a network is the value of HMS.
• Important rate of harmony memory (HMCR): the HMCR value is normally from 0 to 1. The magnitude has been 0.90.
Adjustable pitch rate (PAR): PAR value typically varies from 0 to 1. We began with its value at 0.30.
Step 2: Initializing Harmony Memory (HM)
• Imaginable dimension matrix Where p is totally √N. N for the network's whole number of nodes.
• A vector line (HV) is the same length, i.e., harmony vector. Cluster heads of the specified network are encrypted by each HV.
Step3: New Harmony Vector (HV) improvisation:
• A different HV based on three variables like the random number collection, HMCR as well as PAR, will be selected in this phase. The HMCR value ranges from 0 to 1. Enable new HV
• X is depicted with its elements as Xi.
Step4: Memory Upgrade for Harmony:
• EQ assesses the health of the new HV. 2. If the current HM has a better fitness value, substitute the latest HV with the worst HV.

Step 5: calculate the energy consumptions of the new harmony vector $f_{new-path}$
Step 6: if ($f_{new-path} < f_{worse-path}$) replace the worse path with new path
Step7: Analysis of Termination Settings:

- • Repeat stage 3 and step 4 to the full value of r max. The HV is chosen from the current state of the fitness
- HM., $f = \alpha \times E\ avg + \beta \times d$ intra- cluster + $Y \times C$ size ----------(2)

Where value of α, β and γβ are 0.4, 0.3 and 0.3 respectively.
Every CH sends a linking message to its adjacent nodes after opt optimal set of CHs. The sensor node enters a closest CH with upper energy after receiving the connection post. After forming clusters, the mobile sink adapts its position to reduce the amount of distance from the sink to the CHs. This revision of the mobile sink position is accomplished with HS-based optimization as proposed.

3.2. The deep echo state network model

Deep Echo State Network (ESN) has composed by a dynamic portion of the reservoir that incorporates the background of input in a rich state representation and a feeding-forward read-out element that utilizes the state encoding, while the reservoir is employed for measuring a performance of shallow ESN model. The reservoir of a fundamental is definitely highly well-known model, with a robust hypothetical basis, and a multitude of literature implementations. Basically, ESNs are recurring random neural networks in which state dynamics have employed by a recurrently untrained hidden layer in which activation has employed for supplying the only qualified static output module in the network [14-15]. We address the ESN method extension to the deep learning system in this paper. Interestingly, this line of research can be framed within deep randomized neural networks, where the study concentrates on the performance of deep neural Architectures in which the most of links are untrained. A new topology definition was found for the Echo State Network, Figure 1. ESN's have a greatly interlinked and recurring configuration of non-linear PEs, which is a "reservoir of rich dynamics" with input and output pattern history knowledge. The outputs of these internal PEs (echo states) have been supplied with a less than adaptive (in general linear) read-out network which produces the network output. ESN's interesting aspect is that only the less readable memory has been trained, while a repetitive topology has set link weights. This decreases a complexity of RNN training into simple linear regression, whereas retaining repeated topology. However, substantial constraints have clearly not yet been thoroughly explored in the architecture as a whole [16].

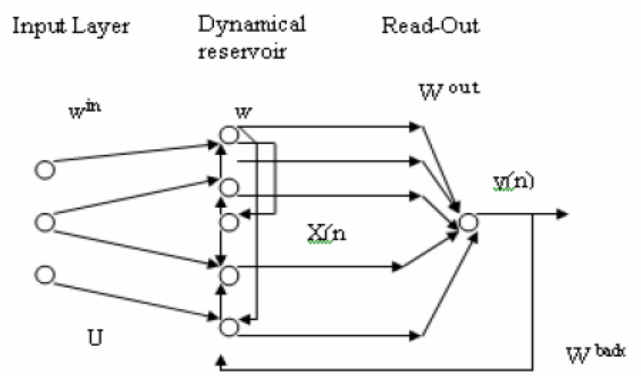

Figure 1. Stander echo state neural network

The connection weights have specified as follows:

- in an (N x M) weight matrix Wback =Wback ij designed for connections among an input and the internal PEs,
- in an N × N matrix W in W in ij regarding connections among the internal PEs
- in an L × N matrix out W Wout ij regarding connections from PEs to output units in the N × L matrix

back W, Wback ij for the connections that project back from the output to the inner PEs.
Algorithm 2: modified ESN to obtain optimal path
Input: the output from modified harmony search (number of nodes, number of cluster head, number of paths, inter cluster, intra cluster)
Output: Optimal path from source to destination

Step 1: Discover the characteristics of a node in network
Step 2: Process the target magnitudes
Step 3: Set the number of inputs, number of reservoirs, number of outputs
Step 4: Prime weight matrices, number of reservoirs set against no. of inputs, no. of outputs versus no. of reservoirs, number of reservoirs set against number of reservoirs
Step 5: Temporary matrices Initialization.
Step 6: Bargain magnitudes of matrices lower than a threshold
Step implantation heuristics by finding eigenvector of updated weight matrices.
Step 8: network training dynamics will create and then stored the final weights.
Step 9: Read the trained weights
Step 11: Process the inputs and chose the inter path, intra path
Step 12: Apply transfer function opt the optimal path
Step 13: Find the next state of the ESN.
Step 14: repeat step 6-13 until finding optimal path with crater

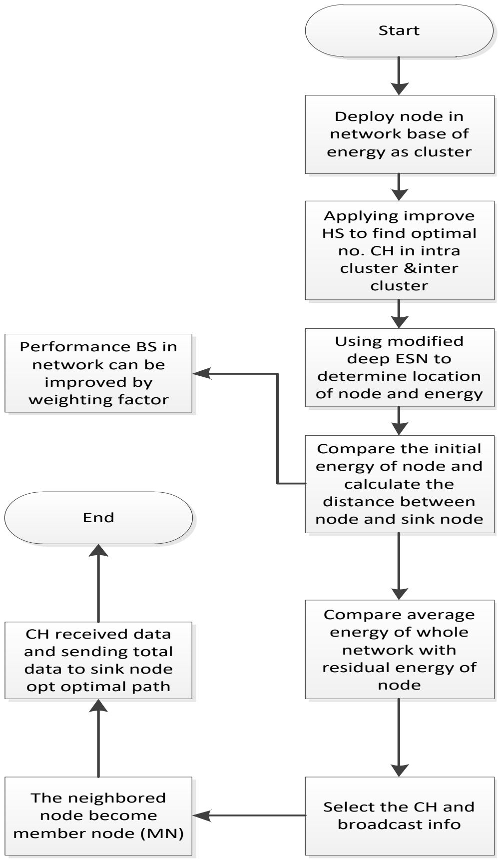

Figure 2. Proposed method

4. Performance analysis

This section gives presentation analysis and comparison of a projected clustering algorithm, modified harmony search with two well-known clustering approach, Particle Swarm Optimization PSO [18] and HS [5]. Simulation experiments of the modified harmony have prepared in MATLAB, in which all consequences are combined as a result of taking 30 independent execution of a system. Simulated parameters have been recorded in Table1. Therefore, with the intention of performing widespread performance investigation of the planned protocol and its relative study with a current state-of-art protocol, the subsequent performance metrics have employed:
Average time: It is total time that taken from node source to destination node [18].

$$\text{Average time} = \frac{\text{time taken from source node}}{\text{time taken to destnation node}} \quad \ldots\ldots\ldots(3)$$

Table 1. The different parameter used during the experimental phase have substantially different characteristics.

Parameter	Value
Network size	500x500
Initial Energy	300J
Sensor nodes	100-500
Eelec	100 pj/bit
Packet Length(l)	4000 bits
Location of the sink	100, 100), (150, 50), (200, 200)
Percentage of CHs	10%–15%

Figure 3 indicates the proposed method –PSO efficiency comparisons based on [17] and HS [5] in the total energy consumption. The monitoring area in this experiment is 200–200 and the results of different sensor nodes of 100–500 is determined. It is seen in the Fig.1.proposed method operates better than the clustering algorithm PSO and HS. This is because the uniform distribution and load balanced of the CHs selected on the. proposed method.

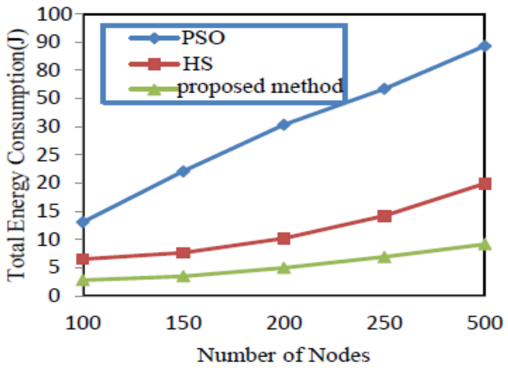

Figure 3. Performance comparison based on variable node number

Figure 4. The relation between proposed method and PSO and HS indicates a different number of rounds of full energy consumption. With a number of rounds rising from 100 to 500, the protocol also raises its overall energy consumption. In comparison with PSO and HS, the proposed method consumes less resources. This is because Proposed method ensures that the CHs are distributed equally and their charges are balanced as well.

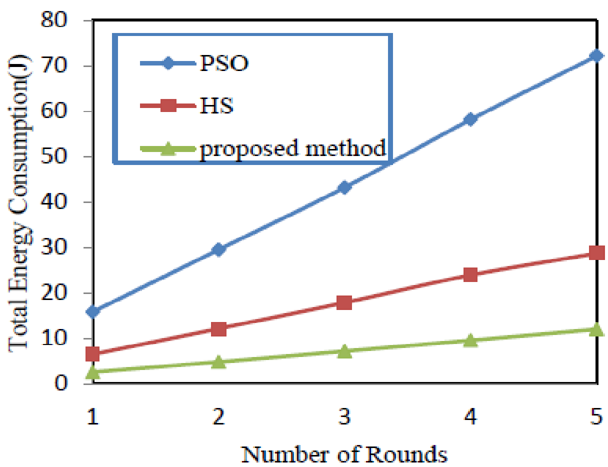

Figure 4. The relation between proposed method and PSO and HS

Figure 5. The efficiency comparison of the proposed method with PSO and HS is shown by different rounds of the total residual energy. The proposed method is more successful than PSO. Proposed method energy usage is less than PSO and HS. Energy consumption is less. Cluster Heads transfer sensed data to the mobile sink through a highly narrower communication range in the proposed process, thus reducing the energy consumption. In the two other approaches, CHs transmit sensed data through a longer route to the mobile sink requiring more energy than the protocol suggested

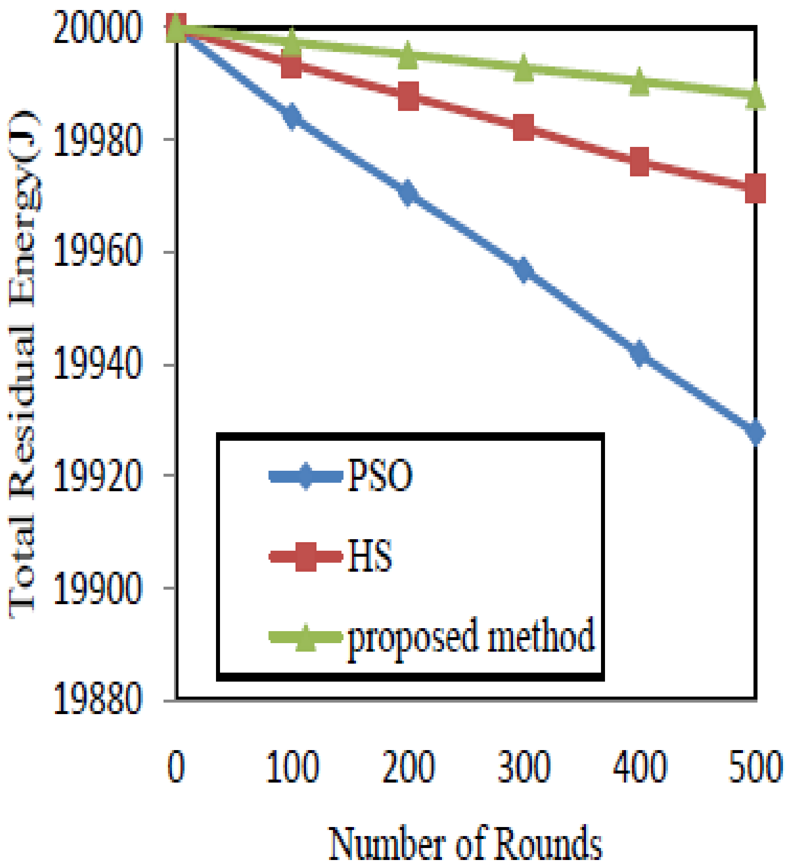

Figure 5. Performance comparison based on variable amount of rounds

Table 2. The average time that taken for finding optimum path from source to destination

Min cost using proposed method	Min cost using PSO	Min cost using HS	Average time using proposed method	Average time using HS (s)	Average time using PSO (s)	Grid size Using(m)
0	0.234247	0.458735	0.043394	1.499129	0.868	10
0	4.234247	0.458735	0.054236	2.226887	0.933	70
0	8.234247	0.458735	0.065078	2.954645	0.998	100
0	12.234247	0.458735	0.07592	3.682403	1.063	200
0	16.234247	0.458735	0.086762	4.410161	1.128	250
0	20.234247	0.458735	0.097604	5.137919	1.193	300
0	24.234247	0.458735	0.108446	5.865677	1.258	400
0	28.234247	0.458735	0.119288	6.593435	1.323	500

The result shows the average time that taken for finding out optimum path from source to destination by using proposed method is fewer compare with HS and PSO.
In Figures 6-7, the result shows comparison of average time and the cost with 200 nodes and the simulation time 1000 second proposed method take lower time compare with PSO and HS.

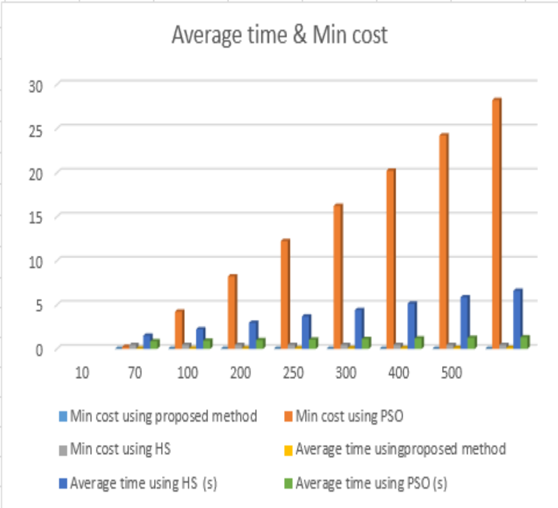

Figure 6. Average time & minimum cost with different methods

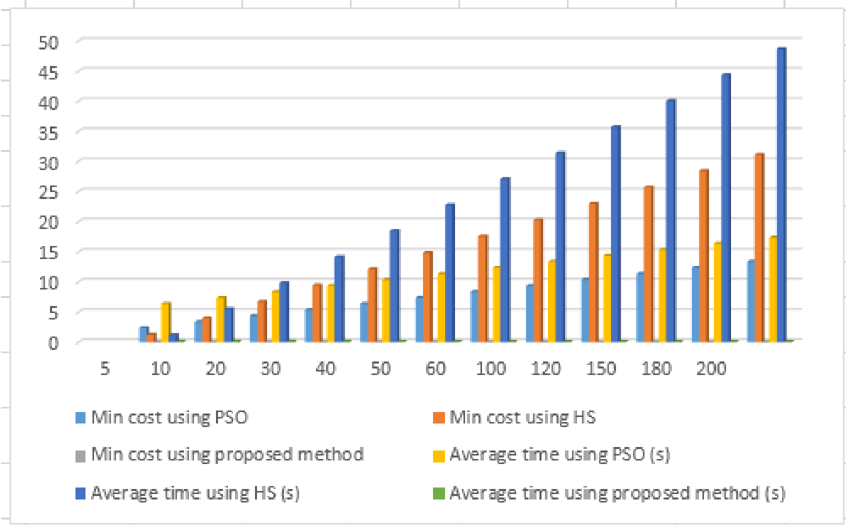

Figure 7. Minimum cost and average with 500 nodes

In Table 3, the result shows the cost (number the hope counts to reach to destination) by using proposed method is fewer compare with HS and PSO with 500 node the proposed method takes (0.128557 s) because this algorithm takes many tamp let of wireless network and ignore the path that taken more cost so it choosing the optimal path with low cost and low packed lose.

Table 3. Comparing between PSO, HS and proposed method for finding minimum cost and average time with different number of sensors

Min cost using PSO	Min cost using HS	Min cost using proposed method	Average time using PSO (s)	Average time using HS (s)	Average time using proposed method (s)	Number of sensors node
2.390808	1.302684 4	0	6.372224	1.202	0.135553	5
3.390808	4.0151	0	7.372224	5.518	0.134917	10
4.390808	6.727515 6	0	8.372224	9.834	0.134281	20
5.390808	9.439931 1	0	9.372224	14.15	0.133645	30

6.390808	12.152347	0	10.372224	18.466	0.133009	40
7.390808	14.864762	0	11.372224	22.782	0.132373	50
8.390808	17.577178	0	12.372224	27.098	0.131737	60
9.390808	20.289593	0	13.372224	31.414	0.131101	100
10.390808	23.002009	0	14.372224	35.73	0.130465	120
11.390808	25.714424	0	15.372224	40.046	0.129829	150
12.390808	28.42684	0	16.372224	44.362	0.129193	180
13.390808	31.139256	0	17.372224	48.678	0.128557	200

In Figure 8 and Table 3, the result depicts the comparison based on a number of routing packets with 500 nodes at the simulation time1000 second prosed method deliver a greater number of data packed so it reduces the losing packed by choosing the optimal, short reliable path from sink node to destination node (BS).
Therefore, the projected procedure its counterparts based on the rates of network to determine the number of packets sent and received for determining a 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 protocol procedure can be based on the data obtained, the percentage of accurate data sent for in proposed algorithm has been 96% from data delivered.

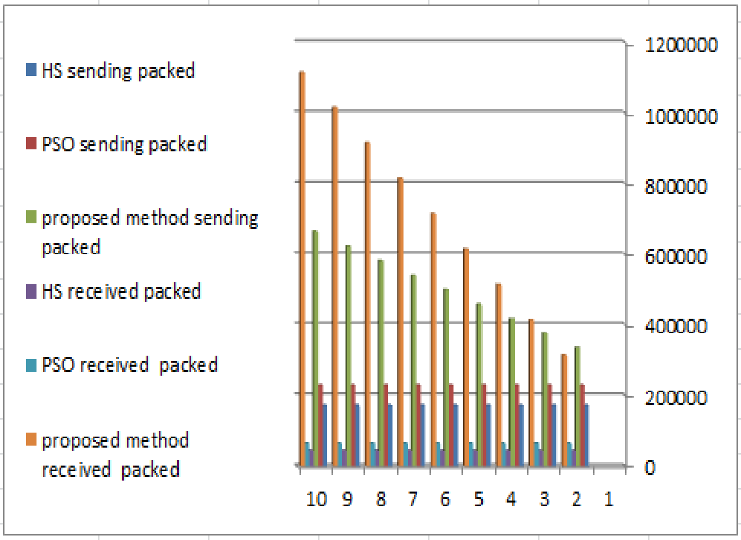

Figure 8. Sent and received packed in different methods

5. Conclusions and future trends

In this study, there are dual familiar optimizing problems: the selecting and routing of CHs between CHs and the sink with an optimized harmonic search algorithm and an updated deep ESN for mobile sink based WSN. This optimizing algorithm has three mechanisms, including average residual energy, intra-cluster duration and cluster size. The objective function is used. The optimum position of mobile sink is correspondingly assessed with updated deep ESN. In comparison to the PSO and HS protocols, the performance evaluation of the protocol method proposed. The consequences explain that the enhanced HS-algorithm exceeds the existing protocols with the enhanced objective characteristic. This is because CHs send detected data to a mobile sink through the shortest way in the process suggested, thus making a moderately low energy consumption. In both other techniques, CHs transfer sensed data to a mobile sink through a lengthier pathway that increases energy consumption. In future, the projected algorithm can be improved by adding void, obstacle network and sensitivity to communication issues.

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