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Comparison and Analysis on AI Based Data Aggregation Techniques in Wireless Networks

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Abstract

In modern era WSN, data aggregation technique is the challenging area for researchers from long time. Numbers of researchers have proposed neural network (NN) and fuzzy logic based data aggregation methods in Wireless Environment. The main objective of this paper is to analyse the existing work on artificial intelligence (AI) based data aggregation techniques in WSNs. An attempt has been made to identify the strength and weakness of AI based techniques. In addition to this, a modified protocol is designed and developed. And its implementation also compared with other existing approaches ACO and PSO. Proposed approach is better in terms of network lifetime and throughput of the networks. In future an attempt can be made to overcome the existing challenges during data aggregation in WSN using different AI and Meta heuristic based techniques.

Keywords: Data Aggregation, Particle Swarm Optimization (PSO), Wireless Sensor Networks (WSN), Ant Colony Optimization (ACO), Network Lifetime

1. Introduction

Artificial intelligence (AI) includes number of techniques like Particle Swarm Optimization (PSO), Neural Networks (NN), Genetics Algorithms (GA)Ant Colony Optimization (ACO) etc. Artificial intelligence based techniques help in improvement of network lifetime & throughput. ACO may be used for the better routing to wireless sensor networks and PSOis good solution for clustering to select the best cluster head in the network. These approaches may be used in wireless sensor networks at different stages. Basically there are four energy dissipation ways in wireless sensor networks; First one is retransmitting the data, second one is overhearing means "when a particular node catch unwanted data", third one is idle listening and fourth one is overhead of the data [14]. When data aggregation operation performed in WSN, data conflicting arises in the networks.To overcome thisissue of data conflicting in WSN environment, secure data aggregation may be considered as one of the solution. There are number of data aggregation approaches in WSNssuch as;(i) Centralized approach, (ii) In network aggregation, (iii) Cluster based approach and (iv) Tree based approach [3]. Some researcher used particle swarm optimization technique for cluster head selection. Number of cluster head in wireless sensor networks, iscalculating by equation 1[15].

$$K = \frac{S\sqrt{n}.\varepsilon_{amp}}{\sqrt{2\Pi(n.E_{start} + \varepsilon_{amp}.d_{avd}^2)}} \tag{1}$$

Where n represents nodes,ε_{amp} is enlargement factor, E_{start} is the energy cost of 1 bit data and d_{avd}^2 is optimal value of cluster head. Particle swarm optimization uses more number of iteration for the optimal solution. Position of swarm at i^{th} iteration is calculated by equation 2 [15].

$$x_{k+1}^i = x_k^i + v_{k+1}^i \tag{2}$$

Where velocity $\boldsymbol{v_{k+1}^i}$ of swarm is calculated by equation 3[15]

$$v_{k+1}^i = \omega_k v_k^i + c1r1(p_k^i - x_k^i) + c2r2(p_k^g - x_k^i) \tag{3}$$

Where p_k^i is the position of swarm corresponding to the iteration i, p_k^g is the best position of swarm at k^{th} iteration, r1 and r2 are the random number whosevalue lies between 0 and 1, c1 and c2 are the acceleration constant. Ant colony optimization may be considered as one of the best way to identify the optimal route in the networks. There are two terms which are important in ant colony optimization; first one is pheromone and second one is heuristic information [20]. PSO [17], ACO [6], Fuzzy Logic [13], NN [21], GA [16]and Cuckoo optimization [12]are the popular AI based algorithms used in WSNs. Efforts has been made to explore the merits and demerits of these existing AI based approaches in next section of this paper.

This paper is organized into five parts. Introduction is followed by the literature survey in section 2. Section 3 shows the proposed algorithm. This paper is designed with the objective to identify the AI based technique for WSN in context to data aggregation. Results are analyzed in section 4 and finaly conclusion and future work in section 5.

2. Literature Survey

This section based on the search string identified to do the analysis on data aggregation in context to AI based approaches various databases like IEEE Xplore, Google Scholar, ACM Digital Library and many more have been searched. After manual review of each paper, we have considered the most relevant papers for further analysis during the related work. We have followed the similar approaches as adopted by otherauthors [8,9].

Hevin et *al.*discussed a new approach for secure data aggregation. Their approach considered three phases, in first phase clustering takes place, second phase calculate power consumption, trust value and distance for every node. In lastphase fuzzy logic is applied on these parameters to calculate non faulty node for performing data aggregation. Nodes classified into three category best node, worst node and normal node on the bases of signal strength. Then selection of cluster head means best node chosen from cluster. In their work, they reduced packet loss and increse the network throughput as well as packet delivery ratio. Author used following parameters for their simulation: area 500m*500 m, sensor nodes 30, cluster head 4, number of sources 4 and channel capacity 2 Mbps.

Balakrishnan et *al.* discussed an approach based on fuzzy logic, This approach used for homogenous WSNs. Approach totally based on fuzzy logic and motto of approach is reduction of energy consumption in the networks. Cluster head selection based on following parameters distance to base station, node centrality and residual energy. They compared their approach with LEACH, ECPF, MOFCA, CHEF and EAUCF.

$$NC = \frac{\sqrt{\sum_{i=1}^{ND} dist_i^2} \,/ND}{Ntk\_Dimension} \tag{4}$$

Where NC is the node centrality, ND represents node degree and $Ntk\_Dimension$ is the dimension of the area. Results verified with different number of sensor nodes 100, 200, 300 and 400.

Wang et *al.* analyzed AI based approaches for networks like fuzzy logic, NN, bio inspired techniques and genetic algorithms. There are some advanced features in self organization networks like self-configuration (SC), self-healing (SH) and self-optimization (SO). When new cells added into the network and automatically configured is known as the self-organization. When some failure occur in network is detected and recovered known as self-healing. Cellular system measures the performance parameters and optimizes them known as self-optimization.

Zhou et *al.* proposed an approach for WSNs using improved PSO. Main motto of proposed approach was to improve the network lifetime. Proposed approach based on relay nodes, transmission distance and energy efficiency used for calculating the power consumption in the networks.

$$F_{CH} = \alpha \times R_{energy}^{CH} + (1-\alpha) \times R_{location}^{CH} \tag{5}$$

$\mathrm{R}_{\mathrm{energy}}^{\mathrm{CH}}$is ratio of average residual energy. $\mathrm{R}_{\mathrm{location}}^{\mathrm{CH}}$is the location of cluster head with residual energy. Relay nodes were used for data transmission to the cluster head. Approach's complexity is order of ($N^{1.5}$) and message complexity is O(N).

Nayak et *al.* discussed a new clustering approach based on type2 fuzzy logic. Cluster head selected by using distance of node from cordinate node, remaining battery power and concentration. This algorithm focuses on efficiency of the networks.

$$\mathrm{E_{Tx}(b,s) = E_{Tx-ele}(b) + E_{Tx-amp}(b,s)} \tag{6}$$

$$E_{Tx}(b,s)=\begin{cases} b * E_{ele} + b * \varepsilon_{fs} * s^2 if s < s_0 \\ b * E_{ele} + b * \varepsilon_{mp} * s^4 if s \geq s_0 \end{cases} \tag{7}$$

Where $\mathbf{E_{Tx}}$ is energy consumption in data transmission, b is the number of bits, s is the distance, $\mathbf{E_{ele}}$ is the energy consumption in the data transmitted, $\boldsymbol{\varepsilon_{fs}}$ and $\boldsymbol{\varepsilon_{mp}}$ are the characteristics of amplifier of transmitter and$\mathbf{s_0}$is the threshold value.

Rejina et *al.* proposed an enhanced approach for routing, using PSO. There are some nodes left during clustering, so to overcome this problem authors gave an approach based on particle swarm optimization. Cluster formation done by using gravitational search algorithm. To balance the traffic on cluster head a node select for cluster head called as assistant cluster head. They have used NS-2 simulator to compare their results with existing algorithm (energy efficient routing protocol). They used following parameters nodes are 100, area of network 200*200 m, early energy of sensor node 200j, radius of cluster 30m and packet size 512 bytes. They have calculated load balancing ratio comparison, and throughput of the networketc. in their results.

Kulkarni et *al.* discussed about the particle swarm optimization technique, how it is applicable for several issues (node localization, network deployment, data aggregation and clustering) in wireless sensor networks. Node localization means awareness of the position of sensor nodes. Global position system is not a better solution in wireless sensor networks cost, power constraints and size of the network. There are two major point regarding node localization first one is position of base station and second one is location of target nodes. There are two types of network deployment fixed node deployment and mobile node deployment.

Sudarmani et *al.* analyzed load balancing approach for heterogeneous wireless sensor networks using particle swarm optimization approach. They have considered energy droptrouble in homogeneous WSNs, this problem may be solved by using heterogeneous wireless sensor networks. In homogeneous network cluster heads periodically changed, but in their approach cluster heads are fixed so cluster head required more initial energy as compare to the normal nodes. They used following parameters size of area 200m*200 m, number of nodes 101, network node distribution is arbitrarydivision, packet size is 200 bytes, communication range 200m, and early energy of cluster head node & normal node 20j, 10j respectively.

Singh et *al.* discussed clustering approach for WSNs using PSO. They used nonlinear programming for clustering in their work. In their work they balanced load on the cluster head significantly by using appropriate energy consumption in the network. After that they compare their results with existing algorithms (LEACH and hybrid energy efficient distributed clustering). Their work used following parameters nodes are 100, area of network 100m*100m, early node energy 2j, packet size 500 bytes and number of cluster heads 5. In their work, they calculated following parameters end to end delay and packets reached at coordinate node.

Misra et *al.*explained a new technique for data aggregation using ACO in WSNs. Basically the finestrecords aggregation is the NP-hard problem. Their approach is depends on number of source nodes in the WSNs. Efficiency of approach vary with the presence of nodes available in the networks. According to their experiment 20% powereffectiveness improved for bigger network in terms of nodes while 45% energy efficiency improved for moderate number of nodes. They used MATLAB for their proposed work to calculate cost and other parameters.

Xie et *al.* discussed ACO for network data aggregation in WSNs. They calculated Hop-count delay, Network density and Residual energy for WSNs. Basically they have compared five algorithms sink to destination no aggregation, sink to destination with leader node, combination of sink and destination nodes, remaining energy based and sink to destination with aggregation with their results. Algorithm consists two parts, forward phase and backward phase.

Kim et *al.* suggested inter cluster ACO, basically designed for overcome the problem of transmitting the redundant data in the network. When network design very dense in nature, then such type of problem arises. Ant colony optimization used to calculate the most excellent route as of sensor knot to base station so the energy consumption could reduce.

Norouzi et *al.* explained a tree based data aggregation approach using genetic algorithm. Work based on all possible routes in the network through genetic algorithm. Genetic algorithm used to find out the best optimal solution for equalization of data and residual power in the network. Balancing the data load in the network directly increases the network lifetime.

Islam et *al.* discussed spanning tree in wireless sensor network for calculating data aggregation using genetic algorithm. In data gathering phase spanning tree consumes lowest energy but load on sensor nodes increases. Nodes those are heavily loaded depended on other nodes.

Darougaran et *al.* proposed technique for data gathering in WSNs with the help of genetic algorithm. To find out the one optimal data aggregation tree out of all possible trees in network is NP-Hard problem. One of the most important problems in data aggregation, nodes those are selected intermediate nodes to data transmission from source to destination are rapidly evacuated.

Lu et *al.* discussed a hybrid approach which is the combination of ant colony optimization and genetic algorithm. They used multi objective steiner tree (MOST) for routing in their proposed work. Routing decision dynamically updated with new value of pheromone and heuristic. Arrival of packets on intermediate nodes determined with the help of sliding window protocol.

Analysis on data aggregation techniques in WSN using AI based approaches is shown in Table 1.

Table 1 Artificial Intelligence Based Techniques used in Data Aggregation

S.No	Technique Used	Paper	Contributions
1	Fuzzy logic	Hevin et *al.*[4] Balakrishnan et *al.*[1] Nayak et *al.* [13]	Fuzzy logic suitable for calculating the fitness functions in WSNs.
2	Particle swarm optimization	Rejina et *al.* [17] Kulkarni et *al.* [7] Sudamani et *al.* [19]	PSO is better for clustering to determine the cluster head in WSNs.

3	Ant colony optimization	Misra et *al*. [11] Xie et *al*. [22] Kim et *al*. [6]	ACO technique is better for routing in wireless sensor networks.
4	Genetic Algorithm	Norouzi et *al*. [16] Islam et *al*.[5] Darougaran et *al*. [2]	Genetic approach is better for tree based data aggregation in WSNs.
5	Neural network	Wang et *al*.[21]	Neural network based approach is better for heterogeneous network to determine parameter optimally.
6	Hybrid (combination of two, genetic and ant colony optimization)	Lu et *al*. [10]	This approach is better for Multi Objective Steiner Tree type data aggregation in WSNs.
7	Cuckoo optimization	Mohsenifard et *al*. [12]	Cuckoo optimization approach is better for some specific structure in wireless sensor networks, network having small distances among sensor nodes and well known residual energy.

Table 1 show the different techniques based on artificial intelligence approaches for data aggregation in WSNs along with their specific usages. All techniques have its own merits and demerits as state above table. In next section proposed approach is discussed.

3. Proposed Algorithm

Ant colony optimization is not suitable for heterogeneous wireless sensor networks. Coverage problem still exists in wireless sensor networks even after applying ACO. This problem may be solved using particle swarm optimization. But issue with particle swarm optimization is because of greedy approach to find out optimal solution. The Proposed approach is designed after modifyingthe cuckoo search optimization technique, so it may be used by dynamic approach to getthe bestway out for heterogeneous WSN. The projected algorithm outperforms the ACO and PSO algorithms and results are shown in section 4.

We have taken the same parameters for ACO, PSO and proposed approach during the simulation.

After simulation we got improvedoutcomeas measure up totothe existing approaches such as;ACO and PSO. Basically, three parameters are taken into account during the comparison in this paper with existing approaches (first node dead, packets reached to base station and all nodes dead).

Fig. 2 shows packets reached at base station, in proposed approach more packets at the cordinate node as compare to other means. Throughput of the network using proposed approach is higher as compare to the other approaches. Fig. 3 shows the all nodes dead, in proposed approach all nodes dead after long number of iterations as compare to the other approaches,which improve network lifetime as compare to the other approaches.

In general, cuckoo optimization technique optimal solution depends on the assortment of CH nodes only however in the projectedapproach optimal solution depends on assortment of CH nodes and relay nodes both.

Pseudo Code for Proposed Approach

N Sensor Nodes
M Cluster Head
MCO Modified Cuckoo Optimization
CH Cluster Head
BS Base Station
CHS Cluster Head Selection
TDMA Time Division Multiple Access

EC Energy Consumption

```
for i=1 to N
selection of cluster head with MCO
end
for i=N
if node is CH
send data to BS
end
end
creation Cluster with CHS
for i= 1to M
assignment of TDMA
end
for i=1to N
data transfer with TDMA
calculation of EC
end
for i= 1 to N
if node is CH
calculate min distance from CH to BS
end
end
```

Next section describes the experimental results with suitable parameters along with diagrams for better interpretations of findings.

4. Results Analysis

Result analysis for the proposed algorithm using different parameters is reported in Table 2. Results are implemented in Matlab 2013a using considered parameters. In this paper, the proposed work compared with existing approaches such as;PSO and ACO.

Table 2 Simulations Parameters

S.No.	Parameter	Value
1	Network Area	100M*100M
2	Number of Nodes	10,20,30,40,50
3	Sink Node Position	50,50
4	Initial Energy of Nodes	.5 Joule
5	Data Aggregation Energy	5 nJoule
6	Number of Iterations	8000

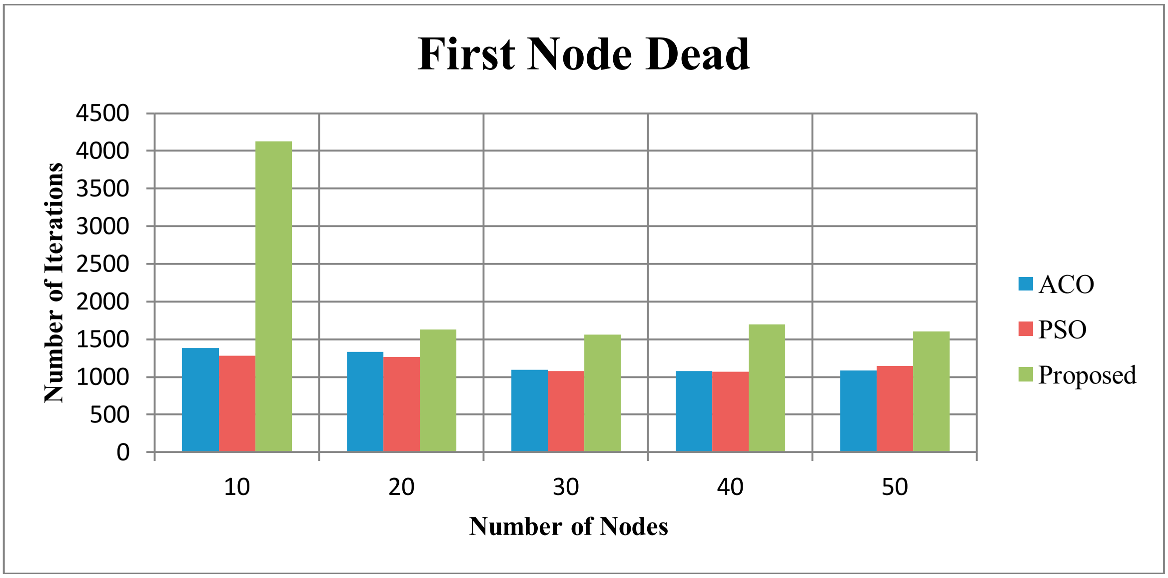

Fig. 1 First Node Dead

Fig. 1 shows the earliest node dead in the networks with different number of nodes taking into consideration during simulation. X axis represents nodes in the networks. Y axis represents iterations. As increase the nodes into the network, then first node dead earlier as compare to the lesser number nodes in the networks. If first node dead earlier means link breakage in the network, so overall network performance will be degraded.

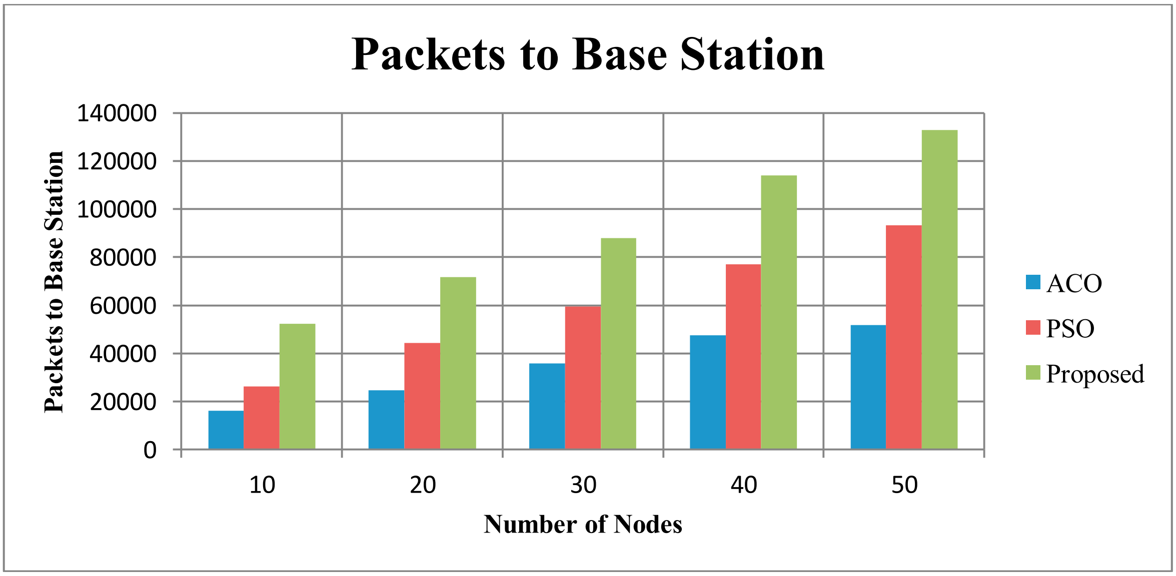

Fig. 2 Number of Packets to Base Station

Fig. 2 shows the number of packets reached at the base station. X axis represents nodes in the networks. Y axis represents packets reached to the base station. As we raisethe add up to nodes in the system, thepackets reached to the cordinator node also increases. Packets reached to cordinator node will improve the overall throughput of the network. So it is concluded that proposed approach may improve the throughput as compare to ACO and PSO.

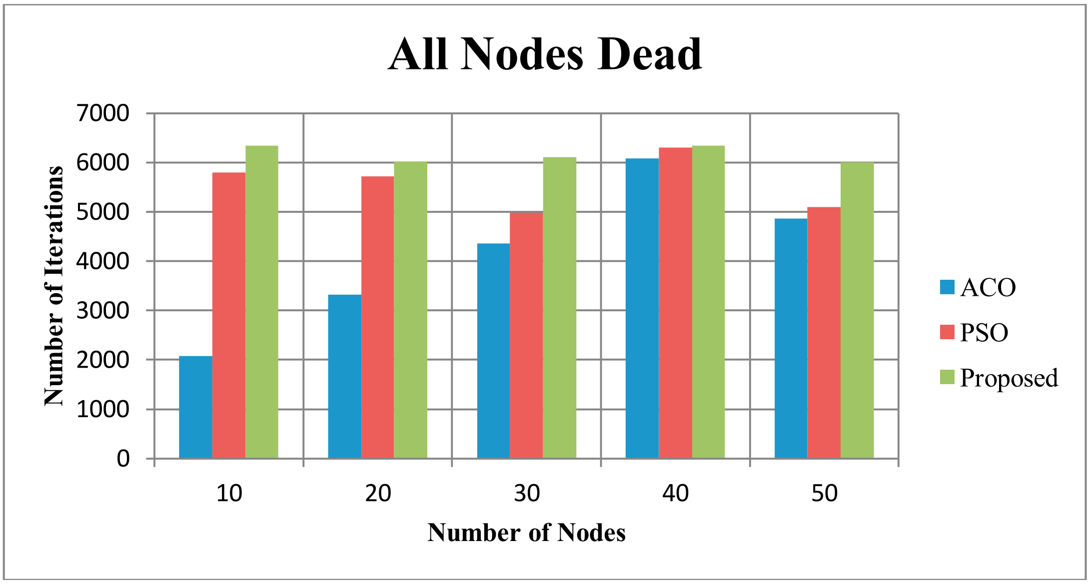

Fig. 3 All Node Dead

Fig. 3 shows the all node dead in the network. X axis represents nodes in the network. Y axis represents iterations. If all nodes dead earlier means completely network will dead earlier. As we increases the numbers of nodes in the network, all nodes dead improve slightly for ACO up to 40 nodes and start reducing further after deployment of 40 nodes in the system. In case of PSO, dead nodes slightly decreases while rising the quantity of nodes in the system from 10 to 30 nodes and an improvement is shown in case of 40 numbers of nodes. However proposed approach, shown all nodes dead at later stages as compared to ACO and PSO. Perhaps there is a need to explore the algorithm in terms of all node dead to conclude a better decision. It is experiential that while increasing the add up to nodes, it alsoenhance the network lifetime up to a certain stage and thereafter due to more number of nodes deployment and other computational effects performance start degrading.

5. Conclusions and Future Work

In this paper, projected work is compared with existing approaches PSO and ACO. Proposed approach is better in terms of first node dead, packets reached to the base station and all nodes dead in the network as compare to the PSO and ACO. Energy consumption is one of the most prominent research areas in WSNs. If network has less energy consumption then network lives longer. Artificial intelligence based techniques may further help in improving the network lifetime and throughput. Ant colony optimization may used for the better routing in WSNs and PSO isgood solution for clustering based data aggregation to select the cluster head in network. Fuzzy logic based approaches may be used for calculating the fitness function in the network. In future, combination of these approaches may be tried to check the suitability of these approaches for WSNs.

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