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The Wireless Sensor Network of an Adaptive Hybrid Swarm Optimization Technique for Location Privacy Using an Infrastructure-Centric Method

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Abstract:

The WSN has been successfully used in a variety of research topics such as network protocol selection, topology control, node deployment, location technology, and network security, among others. Data accumulation via good network organization enables nodes to be divided into small groups known as clusters. Clustering is the process of grouping sensor nodes into clusters. Cluster chiefs are the leaders of all clusters (CHs). The challenge of clustering networks in order to minimize total distance is NP-hard. For efficient clustering, the current research proposes a hybrid differential evolution with Adaptive Hybrid Bird Swarm Optimization (AHBSO). The CH selection technique is based on transmission cost as well as factors like residual energy and the resource - constrained measure. Simulation results show that the Adaptive Hybrid Bird Swarm Optimization technique outperforms CL-LEACH and Hybrid Bird Swarm Optimized in terms of packet delivery ratio, packet loss ratio and network lifetime. Finally, when compared to Partial Swarm Optimization, Hybrid Bird Swarm Optimization, and its derivatives, AHBSO performance is competitive. For various numbers of nodes, the suggested technique enhances delivery ratio by 25.34–35.50 %.

Keywords: *Wireless sensor networks, Adaptive Hybrid Bird Swarm Optimization, Cluster head, Partial Swarm Optimization, CL-LEACH*

I INTRODUCTION

Wireless sensor network (WSN) applications are quickly expanding in a variety of domains, and it has received a great deal of attention in recent years. The progress of technology in the design and kind of sensors has rekindled researchers' interest in WSN. The WSN is made up of a massive number of battery-powered sensors that collect data from the environment for various applications. The sensor nodes are linked by a wireless means and communicate with one another to carry out their respective responsibilities. The WSN has applications in a variety of disciplines, including military, weather, biomedical, environmental monitoring, industrial areas, and so on. In an energy-constrained WSN, hierarchical clustering is an efficient way to spend energy. Clusters are groups of sensors that perform similar functions. A hierarchical cluster is made up of the Cluster Head (CH), normal Nodes, and a Base

Station (BS). When CH is chosen, it collects data from each member node and aggregates it to minimize redundancies, resulting in reduced data transfer to BS. Factors to examine include Cluster Number, Intra-cluster Communication, Node and CH Mobility, Node Type and Roles, Cluster Selection, Multiple Levels Clustering, and Overlap. For efficient clustering, the current study proposes a hybrid differential evolution using Adaptive Hybrid Bird Swarm Optimization (AHBSO). The CH selection technique considers communication energy, residual energy, and the energy constraint measure. In terms of packet delivery ratio, packet loss ratio, and network lifetime, simulation findings demonstrate that the Adaptive Hybrid Bird Swarm Optimization technique beats CL-LEACH and Hybrid Bird Swarm Optimized.

II LITRATURE SURVEY

Network life time will be increased by using a robust strategy to deal with the complexity of node traffic. This paper investigates a method based on Cat Swarm Optimization (CSO) to predict potential Articulation Point network. Defining points are nodes that are vulnerable to a network that, if removed, lead to the graph being terminated. [1] Due to its high integration, the CSO-based approach is well suited to address this issue. In terms of delays and limitations, the proposed strategy improves network performance. [2] Wireless nerve networks are becoming more and more powerful technology in a variety of fields. Clustering protocols were divided into three groups in this study based on their integration process and operational capabilities: traditional merger agreements, non-compliant merger agreements, and co-operative agreements. [3] The so-called LEACH (Low-Energy Adaptive Clustering Hierarchy) method was developed, but was determined to be economical in energy management. The study examines the complexity of choosing the right path to a wireless network of network routers to extend network life. [4] In HWSN, the SOSS energy-efficient route is based on the RP and most MS. The Bald eagle search method is utilized to choose the best CHs, while multiple MS is used to collect data efficiently. The usage of numerous MSs can improve data gathering efficiency while lowering energy consumption in HWSNs.

To conserve energy in WSNs, a multi-purpose-based clustering and Sailfish Optimizer (SFO)-guided route algorithm is used. It selects Cluster Head (CH) [5] according to the effective durability function available for several purposes. The SFO is used to determine the appropriate route to the data transfer sink after the CH selection. [6] At WSN, we have developed an energy-saving planning algorithm based on the Deep Reinforcement Learning (DRL) (E2 S-DRL) algorithm. The assembly phase, the cycling phase, and the road phase all contribute to DR2's E2 S-capabilities to extend network life and reduce network delays. [7] The particle swarm optimization (APSO) method is proposed to resolve the transmission node location of the gateway, with the length of the path between the node and the gate as intended. Advanced techniques such as random adjustment of inertia weights, flexible change in learning variables, and neighbor search are added to the APSO algorithm. [8] EALAR (local power-assisted route) is a newly developed MANET routing system that combines particle swarm optimization (PSO) with the implementation of traditional LAR law enforcement protocols. All key performance indicators, including packet delivery rate, power consumption, overhead, and end delays, are enhanced by integrating the OPSO into the LAR protocol.

III PROPOSED METHODOLOGY

A high-energy node serves as the cluster leader in the novel method, resulting in clusters that are evenly distributed over a sensor network. The new Hierarchical Clustering method selects CH which reduces the intra-cluster distance between self and cluster members while also using network power management capabilities. A hybrid differential evolution with Adaptive Hybrid Bird Swarm Optimization is presented in this paper (AHBSO). The CH selection technique takes into account communication energy as well as residual energy and the energy constraint measure.

3.1 ADAPTIVE HYBRID BIRD SWARM OPTIMIZATION (AHBSO)

CH selection is achieved using an analytic fitness function with transmission energy as a key component in the proposed Hybrid differential evolution with adaptive hybrid Bird Swarm Optimization algorithm (AHBSO) based technique. Energy is used by the distance between transmitting elements. Residual energy and the Energy Constraint (EC) measure are two further elements to consider. Other particles will migrate toward a particle that has found a current ideal position. If the position is the local optima, the algorithm will converge and cluster in the local optimal. The CH selection technique takes into account communication energy, as well as residual energy and the energy constraint measure. Clustering and overlapping at multiple levels, CH selection.

When a particle finds a current optimal position, the other particles will gravitate toward it. The algorithm will be convergent and clustered in local optima if the position is the local optima. It's possible that the premature will appear. Assume that the HPSO-DE population size is NP, that each i^{th} particle's fitness value is f_i, and that the average fitness value is f_{avg}. The degree of convergence is defined as follows:

$$d = \sqrt{\sum_{i=1}^{NP}\left(\frac{f_i - f_{avg}}{\max\{1, max_{1 \le i \le N}(f_i - f_{avg})}\right)^2} \quad (1)$$

The degree of convergence is represented by the parameter d. The algorithm is in random search when the parameter d is large. On the other hand, the algorithm may enter a local optimum, causing premature termination. The following formula is used to calculate the parameter $d, d\ c$, where p is the mutation probability.

$$P = \int \begin{matrix} K, & d < d_c \\ 0 & others \end{matrix} \quad (2)$$

The balanced parameter p is one of the most critical parameters for the proposed AHBSO. In the next subsection, we will compare the AHBSO's performance in the optimization of a number of representative functions in order to undertake an integrated analysis of the key parameter.

3.1.1 Hierarchical Clustering

CH chooses a route to transmit data based on mobility factors such as power consumption. When searching for numerous paths between CHs and sink nodes, an energy limited metric is employed. Inter-flow interference, transmission rate variation, and wireless connection loss ratios are all computed using the EC metric. Because the sensor node saves energy in order to transport data to the cluster geometric center, the mass center was employed in the CH selection. The following expression is used to select the cluster head:

where $N_i(c)$ is a set of i^th neighbors, C is channel c, and $N_i(c)$ is the total number of nodes disturbed with through the communication events between Node i and Node j via channel c. $ETT_{ij}(c)$ or anticipated transmission delay, is used to compute transmission rate disparities and link loss ratios.

$$IEC_{ij}(c) = ETT_{ij}(c) * \left|N_i(c) \cup N_j(c)\right| \quad (3)$$

The proposed Adaptive hybrid Bird Swarm Optimization algorithm (AHBSO) technique runs in rounds, with each round beginning with a setup stage in which clusters are produced, followed by a steady state stage. Cluster heads are nodes that have a higher energy level than the rest of the cluster. Later, based on the average Euclidean distance of nodes to their linked Hierarchical Clustering of CH and total beginning energy of each node, base stations utilize the (AHBSO) protocol to determine ideal K CHs that can decrease cost function. The fitness function maximizes network energy efficiency while decreasing based on inter distance between nodes and cluster heads.

The CHs are chosen in this approach using the fitness function supplied by, which is derived analytically and takes into account communication energy and distance:

$$\mathrm{fitness} = \sum_{i=1}^{n} \frac{E_c^i}{E_I^i} \times D(BS_z, k_i), \quad (4)$$

$D(BS_z, k_i)$ denotes the shortest distance between the node k_j and BS_z. The k_{opt} value is calculated once more, It is derived from the CH position, which is below the Centre of the middle point in the square, corner, and Centre at this point.

IV RESULTS AND DISSCUSSIONS

Our proposed solution is implemented in Ubuntu's Network Simulator 3 (NS3) application. Because NS3 is a mysterious event simulator that can simulate several types of networks, we chose it for a hybrid differential evolution with Adaptive Hybrid Bird Swarm Optimization (AHBSO) in a WSN environment. The packet delivery ratio is the proportion of received packets to packets sent by the traffic generator. According to Fig. 2, AHBSO produces lower throughputs due to the additional overhead of the destination or path establishment, as well as for adaptively upgrading the way.

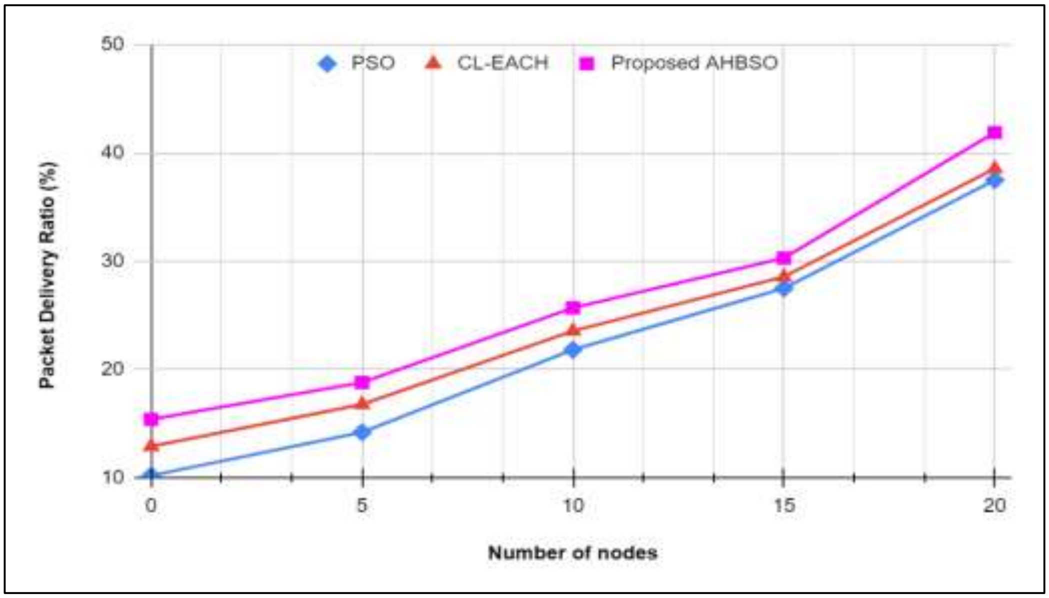

Figure 1: Average packet delivery ratio

The network lifetime statistic is used to determine how long a sensing network will last. The lifespan of a network is typically defined as the time it takes for the first node in the network to die. It's also known as the node's operating time, or the amount of time it can work on the allocated task. (Refer to Figure 2)

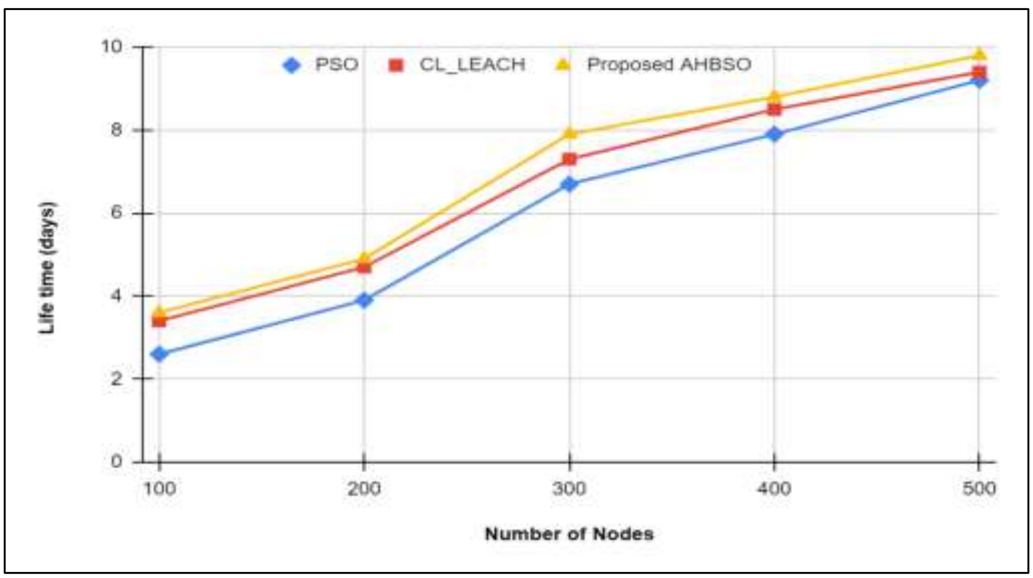

Figure 2: Lifetime computation

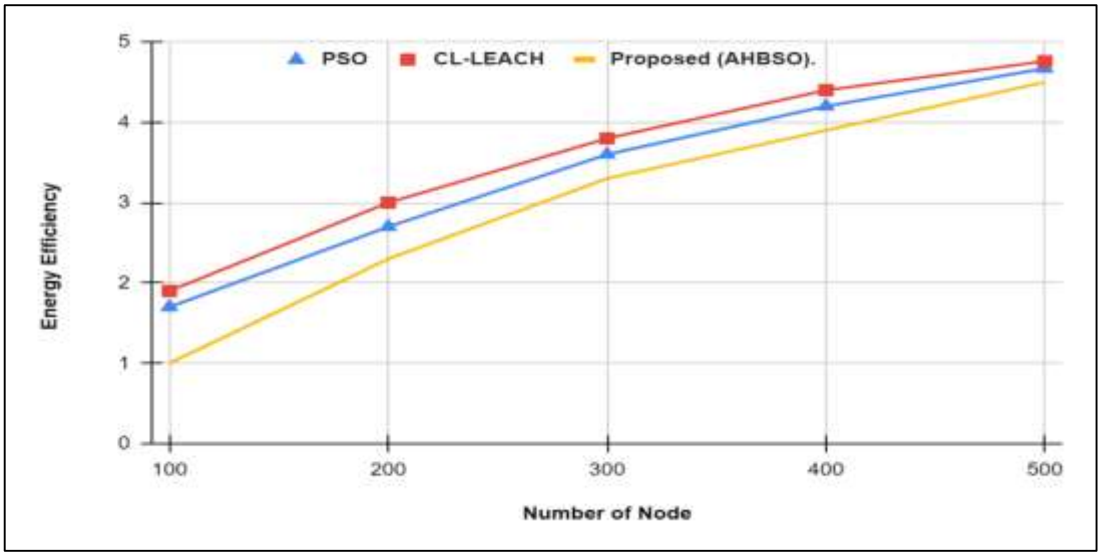

Figure 3: energy efficiency

The results of the energy consumption rate comparison between the proposed AHBSO and the existing PSO and CL LEACH are shown in Fig. 3. The study reveals that as network density increases, so does energy usage. However, the results suggest that the proposed method uses less energy than the other methods.

CONCLUSION

Clustering-based routing methods enhance the range of WSNs. A big, deployed sensor network's identity and energy efficiency are two factors that determine network operation and life. By minimizing the number of packets that must be transmitted to a sink or BS, clustering algorithms extend the life of sensor networks. Because energy efficiency is scarce, valuable, and difficult to get, it is a big challenge in WSN. Many clustering algorithms have been proposed in order to reduce energy consumption and increase the lifetime of sensor networks. Adaptive Hybrid Bird Swarm Optimization is used in conjunction with hybrid differential evolution in this study (AHBSO). The result shows that the proposed hybrid differential evolution with (AHBSO) method achieves maximum network lifetime, reduced Energy efficiency, and higher packet delivery ratio than other methods.

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