Using Genetic Algorithms to MAC Clustering in Wireless Sensor Networks through Local Search Binary Particle Swarm Optimization (LSBPSO)

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Abstract—***Abstract*** – This research explores the application of a B-MAC cluster protocol incorporating a cross-genetic algorithm (GA) and PSO methods to address the challenge of clustering in Wireless Sensor Networks (WSNs). WSNs consist of numerous small nodes with limited capabilities, and the primary concern is energy constraints. Clustering is identified as a resource-efficient solution to this issue, involving the division of networks into groups with each having a cluster head. Cluster heads are responsible for gathering and transferring data to base stations.

The study, employing simulations with OPNET, focuses on evaluating the proposed protocol's performance in terms of packet delivery rate, end-to-end delay, hop number, and jitter. Experimental testing was conducted under varying node mobility levels, revealing that the LSBPSO MAC Cluster Clustering outperformed both BMAC (with flooding) and BMAC (with cluster-based routing) in static and dynamic scenarios. Considering various MAC protocols, it can be inferred that LSBPSO's BMAC holds promise for applications requiring agility in WSNs, such as military reconnaissance maneuvers, tragedy management, safety, healthcare, industrial automation, and more.

Keywords–MEMS,Flooding,Cluster-Head(CH),Genetic Algorithm (GA), Medium Access Control (MAC), Particle Swarm Optimization (PSO), Wireless Sensor Network(WSN), wireless sensor and actuator networks (WSAN).

I. INTRODUCTION

Due to significant advancements in Micro-Electro-Mechanical Systems (MEMS) and wireless communication technologies, Wireless Sensor Networks (WSNs) have emerged as a valuable tool in various applications, including military reconnaissance, disaster management, security, environmental monitoring, healthcare systems, and industrial automation. WSNs establish crucial connections between the physical world, computing realm, and civilization.

Typically, WSNs consist of numerous small sensor nodes distributed over a large area, with one or more efficient sinks or Base Stations (BS) collecting data from these nodes. Each node operates with limited energy resources and has the capability to sense, process, and communicate wirelessly.

To manage access to shared media and address energy depletion issues, WSNs employ Medium Access Control (MAC) protocols. Energy-efficient MAC protocols optimize sensor node duty cycles based on available traffic, reducing idle listening and overall energy consumption. While most schedulers focus on sensor node traffic patterns without considering residual energy, incorporating remaining energy into node schedules is crucial for enhancing network performance.

The widespread use of sensor nodes results in significant transmission packet overhead in WSNs, leading to energy wastage. Clustering has been employed to mitigate this issue in designing Wireless Sensor Networks.

Wireless sensor networks, sometimes referred to as wireless sensor and actuator networks (WSAN), consist of spatially distributed autonomous sensors monitoring physical or environmental conditions. These sensors cooperatively transmit data to a central location, and modern networks may also allow for bidirectional communication, enabling control of sensor activity.

A typical WSN node includes a radio transceiver, a microcontroller, an electronic circuit interfacing with sensors, and an energy source. The size and cost of sensor nodes vary, ranging from shoebox-sized nodes to miniature versions, with corresponding constraints on resources such as energy, memory, computational speed, and communication bandwidth. The topology of WSNs can range from a simple star network to a more complex multi-hop wireless mesh network, with propagation techniques including routing or flooding.
Clustering reduces communication volume to Base Stations as Cluster Heads manage communications for all clusters. Clustering is renowned for its scalable nature, offering load balancing and efficient resource utilization by grouping nodes in close proximity as clusters.

Designing effective MAC protocols for Wireless Sensor Networks (WSNs) involves addressing energy efficiency, latency, and fairness. MAC sub-layer protocols aim to tackle energy-related issues such as collisions, overhead, overhearing, idle listening, and complexity. Simplicity is a major goal in WSN design, with other considerations including fairness, latency, throughput, and bandwidth.

Optimization in WSNs is a challenging task involving the balancing of lifecycle, Quality of Service (QoS) requirements, and security. Optimization procedures, including Evolutionary Algorithms (EAs) and Swarm Optimization Algorithms, draw inspiration from the natural world to navigate dynamic environments.

Several proposed MAC protocols aim to enhance efficiency. One, the Cross-Layer MAC protocol (CL-MAC), efficien rse traffic loads. Another energy-efficient MAC protocol, AS-MAC, reduces overhearing tly handles multi-packet, multi-hop, and multi-flow traffic patterns, adapting to dive and contentions through asynchronous scheduling, showing significant improvements in energy usage, packet losses, and delays compared to other protocols.

Node positioning strategies using Genetic Algorithms aim to decrease energy utilization while maintaining coverage in WSNs. A clustering method based on genetic clustering path algorithms combines GA and Fuzzy C-Means (FCM) to form optimal clusters and choose Cluster Heads effectively, outperforming the Low Energy Adaptive Clustering Hierarchy (LEACH).

Linear/Nonlinear Programming (LP/NLP) formulations and PSO-based models address routing and clustering concerns, demonstrating improved performance in terms of network lifetime, energy usage, dead sensor nodes, and delivery of information packets to Base Stations.

Lastly, a multi-objective optimization problem for cluster head selection in a sensor network for UAV data acquisition is presented. The study considers realistic models and constraints, comparing with the existing LEACH-C algorithm for WSN data collection.

Design Methods: In this section, the GA-PSO BMAC clustering is introduced and explained. The BerkeleyMAC (B-MAC) protocol is discussed, emphasizing its flexibility, minimal code execution, and memory size requirements. B-MAC incorporates Clear Channel Assessment (CCA), packet back-offs, and link layer acknowledgements.

For CCA, B-MAC utilizes a weighted dynamic average of samples during idle channel periods, enhancing background noise assessment and collision detection. Configurable packet back-off times, selected from linear ranges, reduce delays and improve functionality based on common transmission patterns in Wireless Sensor Networks (WSNs). B-MAC also supports packet-by-packet link layer acknowledgements, minimizing the additional costs incurred by significant packets.

To reduce idle listening, a major source of energy wastage, B-MAC uses adaptive preambles. Nodes wait for a back-off time before checking channels when they have packets to transmit. If the channels are clear, data is sent; otherwise, another 'congestion' back-off is initiated. Low-Power Listening (LPL) periodically checks channels, and if they are idle and nodes have no data to send, they switch to sleep mode. The preamble sampling strategy aligns with frame preamble sizes, and the interval for checking channels is adjusted accordingly.

An advantage of using B-MAC in WSNs is its avoidance of Request to Send (RTS), Clear to Send (CTS), ACK, or other control frames by default, although they can be added if needed. B-MAC has been evaluated in hardware, does not require synchronization, and its performance can be fine-tuned by higher layers to meet different application requirements. The main drawback is the significant overhead caused by preambles, e.g., 271 bytes for transmitting 36 bytes of information.

The protocol involves active nodes broadcasting control messages at the end of reconfiguration, while remaining nodes flood once to connect with neighbors. Each node expends energy to transmit one 'up' message. After receiving multiple 'up' messages from other nodes, a node polls the channel and then sleeps for the remaining time. The polling interval for Low-Power Listening (LPL) during reconfiguration is denoted as Tp, with the understanding that Tp may vary from T.lpl. During flooding, nodes need to send the 'up' message only once. Assuming an average carrier sense time of tcs and a communication time for the 'up' packet as tup, the energy expended by a node in communication is calculated.

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The power expended by a node in reception can be calculated by considering the energy consumption related to overlistening to preambles. If a node receives n packets from n neighboring nodes, and on average it overlistens T2p preamble for one packet, the energy expended in reception (E_receive) can be expressed as follows:

Ereceive=n·T2p

Here: n is the number of packets received from neighboring nodes.

T2p is the average time spent overlistening to the preamble for one packet.

This formula accounts for the energy consumption associated with receiving multiple packets from neighboring nodes and the corresponding over listening time for each packet's preamble.

The proposed GA-PSO BMAC clustering method is discussed in this section. The Berkeley MAC (B-MAC) protocol is introduced, highlighting its adaptability, minimal code execution, and memory size requirements. B-MAC incorporates Clear Channel Assessment (CCA), configurable packet back-offs, and link layer acknowledgements.

B-MAC utilizes a dynamic average of samples for CCA during idle channel periods, reducing delays and improving collision detection. The packet back-off times are configurable and selected from linear ranges, enhancing functionality in Wireless Sensor Networks (WSNs). Adaptive preambles are employed to reduce idle listening, a significant source of energy wastage.

In the context of data rates, B-MAC suggests a sim method for optimizing polling periods. However, analysis is based on periodic data traffic, and closed-fc equations are not provided. During Low-Power Listen (LPL) with flooding, periodic data traffic is not generat and the flooding of 'up' messages is the primary cause of traffic.

Genetic Algorithms (GAs) are introduced as effective stochastic optimization search processes that mimic adaptive evolution in nature. GAs are successfully employed in addressing NP-hard issues, particularly in non-regular search spaces where global optima are required. They are less prone to premature convergence compared to gradient-based mechanisms.

GAs operate iteratively, generating populations of potential solutions, evaluating fitness functions, and evolving populations over multiple generations. The process involves selecting parent chromosomes, performing crossovers, introducing mutations, and replacing the existing population. GAs do not necessarily find the best solution but are effective in discovering very good solutions through simulated evolution.

The variables of GAs include Population, representing sets of individuals or chromosomes; Fitness, evaluating the capacity to solve an issue; Selection, performed through the Roulette-Wheel technique; Crossover, involving the combination of genetic material from parent chromosomes; and Mutation, introducing random changes to overcome the limitations of crossovers.

Population generation in the context of Wireless Sensor Networks involves representing nodes as bits of chromosomes, with Cluster Heads and individual nodes denoted as 1s and 0s, respectively. Fitness values are defined by variables such as node density and power utilization. Populations undergo transformations based on survival fitness to generate subsequent generations.
Particle Swarm Optimization (PSO) is widely used in Wireless Sensor Networks (WSN) for making clusters of nodes and optimizing various aspects. The inspiration behind PSO is derived from the social behavior of bird flocks and fish schools. It is a computational method that iteratively attempts to improve a swarm of candidate solutions or particles, following a set of basic rules.

The PSO algorithm involves the following key concepts:

1. **Swarm:** The swarm refers to a group of particles, each representing a potential solution to the optimization problem. In the context of WSN, these particles can represent individual sensor nodes.
2. **Particle:** Each particle within the swarm represents a candidate solution. In the context of WSN, a particle can be associated with a specific configuration or state of a sensor node.
3. **Fitness Function:** There is a fitness function that evaluates the quality of a solution or particle. In WSN, this function may consider parameters such as energy consumption, coverage, or other relevant metrics.
4. **Velocity:** Each particle has a velocity that determines how it moves within the solution space. Velocity is adjusted based on the particle's previous best-known position and the best-known position within the entire swarm.
5. **Position:** The position of a particle represents its current solution or configuration. The position is updated based on the particle's velocity.

The basic rules of the PSO algorithm involve the particles adjusting their velocities and positions in such a way that the entire swarm converges toward an optimal solution. The algorithm promotes exploration and exploitation of the solution space, simulating the cooperative behavior observed in natural swarms.

In the context of WSN applications, PSO can be employed for tasks such as optimizing cluster formation, improving network coverage, minimizing energy consumption, or enhancing overall network performance. The ability of PSO to efficiently explore solution spaces makes it a valuable tool for tackling optimization challenges in WSNs.
The proposed hybrid technique is named Local Search Binary PSO (LSBPSO) MAC Clustering, which integrates both Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) as a local search mechanism for enhanced performance. This hybrid approach aims to leverage the strengths of both PSO and GA to navigate the search space more effectively, reducing the likelihood of errors.

In the LSBPSO algorithm, each node in Wireless Sensor Networks (WSNs) is initially flooded with local temporal standards containing Hybrid Coefficient (HC) factors. The driving limit of the LSBPSO algorithm is defined by HC, which represents the percentage of the population that evolves using Genetic Algorithm in each iteration. Therefore, when HC is set to 0, the process is solely based on PSO, meaning the entire population evolves according to Particle Swarm Optimization. Conversely, when HC is set to 1, the process relies solely on Genetic Algorithm. If $0 < HC < 1$, it implies that a specific percentage of the population is updated using Genetic Algorithm, while the remaining portion is updated using Particle Swarm Optimization. This parameter allows for a flexible adjustment of the algorithm's behavior based on the desired balance between the two optimization techniques.

II. IMPLEMENTATIONS

In this section, the LSBPSO Cluster BMAC, BMAC with flooding and BMAC with cluster based routing methods are used. The Average Packet Delivery Ratios, Average End to End Delays in seconds, Average Number of hops to sink and Jitter are evaluated Figure 1 to 4 as shown as follows:

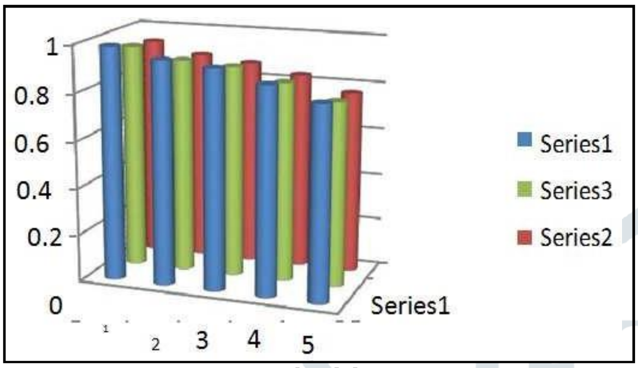

Fig.1.Averagepacketdeliveryratio

In the above chart the value 1 represents static, 2 represents 10KMPH,3 represents 20KMPH,4 represents30KMPH and 40KMPH standards.

From the Figure 2, it can be observed that the BMAC with cluster based routing increased Average Packet Delivery Ratio by 3.78%, 4.21%, 3.71%, 3.96% and4.79% compared for LSBPSO Cluster BMAC and by 1.57%, 1.77%, 2.59%, 1.12% and 1.34% compared for BMAC with flooding when compared with various number of node mobility.

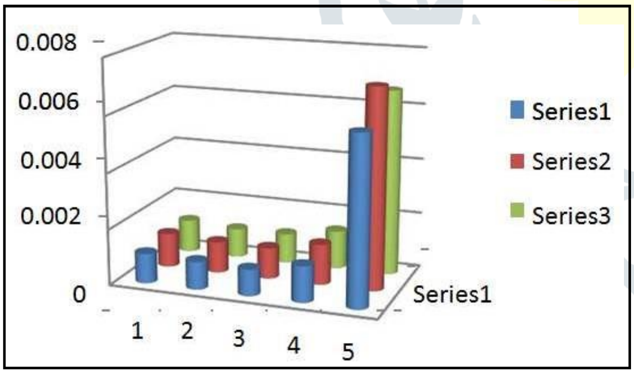

Fig.2.Averageendtoenddelaysinsecond

In the above chart the value 1 represents static, 2 represents 10KMPH,3 represents 20KMPH,4 represents 30KMPH and 40KMPH standards.

LSBPSOClusterBMACandby3.49%,6.54%,4.78%, 5.88%and7.3%comparedforBMACwithfloodingwhen compared with various number of node mobility.

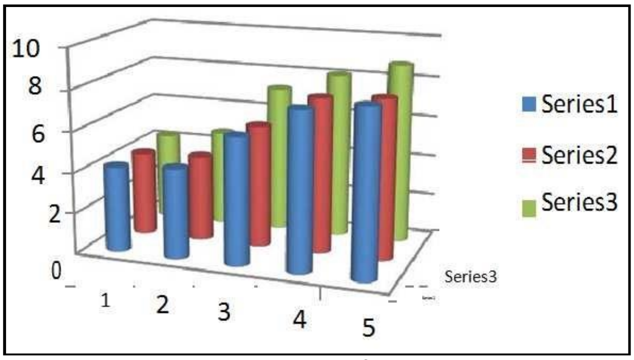

Fig.3.Averagenumberofhopsto sink

In the above chart the value 1 represents static, 2 represents 10KMPH,3 represents 20KMPH,4 represents 30KMPH and 40KMPH standards.

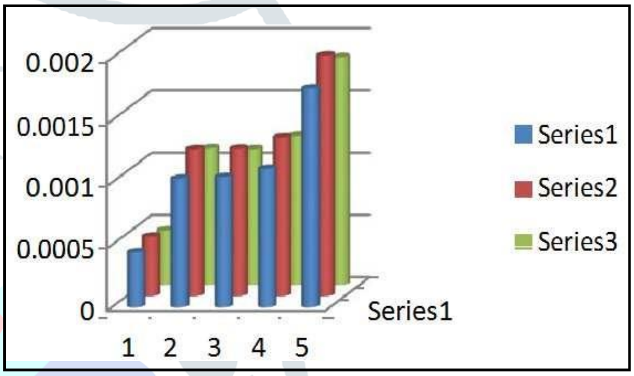

Fig.5.Jitter

In the above chart the value 1 represents static, 2 represents 10KMPH,3 represents 20KMPH,4 represents 30KMPH and 40KMPH standards.

CONCLUSION

Clustering of the network relies on the Cluster Heads to send information to Base Stations. This reduces energy expended by sensor nodes to transmit information from other nodes to a Base Station, which potentially leads to improved network life as well as larger amount of data delivery during network life. In the current work, hybrid GA-PSO based clustering method which enhanced lifecycle of Wireless Sensor Networks efficiently was presented. Genetic Algorithm was used to select CHs and their quantity while Particle Swarm Optimization method was used for choosing cluster member nodes.

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