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Evolutionary Optimization of Dominating Set-Based Virtual Backbone Cluster Scheduling for Enhancing Energy Efficiency in Asymmetric Radio WSNs

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Abstract: Wireless Sensor Networks (WSNs) are becoming essential for many uses, such as industrial automation and environmental monitoring. To extend the network's lifespan, energy efficiency is critical. Asymmetric radio WSNs pose a special difficulty in energy consumption optimization since nodes in these networks have different transmission capacities. This study presents a unique method for improving energy efficiency in asymmetric radio WSNs using Genetic Algorithm-based Dominating Set-Based Virtual Backbone Cluster Scheduling (GADS-VBCS). By dividing the network into clusters using the idea of virtual backbones, the proposed GADS-VBCS method efficiently lowers communication overhead. The programme considers the asymmetry in radio ranges and effectively plans the activation of clusters based on a dominating group of nodes using evolutionary algorithms. This scheduling ensures network coverage and connectivity while optimizing energy consumption. To assess GADS-VBCS's performance, comprehensive simulations across several situations are carried out and compared with current methodologies. The findings show that, especially in asymmetric radio WSNs, GADS-VBCS performs better than traditional scheduling methods regarding energy efficiency, network overhead, network lifetime, and packet delivery ratio. This work provides a useful tool for real-world deployments in resource-constrained contexts by solving energy efficiency issues in asymmetric radio WSNs.

Keywords: *Sensor node, energy consumption, routing, overhead, optimization, mutation, and backbone.*

1. Introduction

A WSN is a network formed by numerous nodes interconnected with one another. Initially, these nodes are deployed within a network range and utilized for monitoring or tracking the events or targets. These sensor nodes are very effectively used in the environmental domain to sense the data by performing simple computations. Those collected data are transmitted to the sink node known as the Base Station (BS). The sensors can detect the event and generate analogue signals. Sound, humidity, pressure, temperature, vibration, and other phenomena can be measured with different kinds of sensors available in the industry.

The analogue signals provided by the sensors are converted into digital signals by the ADCs. A CPU and built-in memory make up the processing unit. It receives digital signals from the ADCs and performs local processing based on user-defined algorithms. A radio transceiver comprises two parts: a transmitter and a receiver. It facilitates wireless communication between the sensor nodes. A tiny battery provides the necessary power for the sensor node. The battery is the primary power source and must be changed whenever its capacity has been depleted. Additional secondary power sources fueled by solar cells are sometimes included in sensor nodes.

WSN applications are divided into two groups: monitoring applications and tracking applications. In monitoring applications, the sensor nodes continuously watch the environment and regularly provide information about it to the sink or when a specified event occurs. When a sensor node's measurement exceeds a predetermined threshold value, the event is generated either as a response to the user's query or by the sensor node itself. The information regarding the measurements is updated in real-time tracking programs. WSN is widely used in

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health monitoring, environmental monitoring, military surveillance, habitat monitoring, and structural monitoring. The popular tracking applications are vehicle tracking, human tracking, enemy tracking in the military, and animal tracking.

Wireless Sensor Networks (WSNs) have become more important in many fields, such as industrial automation, healthcare, and environmental monitoring. However, the limited energy accessible to sensor nodes poses a substantial obstacle to efficiently managing energy resources in WSNs. Optimizing energy consumption becomes more difficult when WSNs comprise nodes with asymmetric radio capabilities or nodes with varying transmission and reception ranges. This is where the proposed method, known as GADS-VBCS (Genetic Algorithm-based Dominating Set-Based Virtual Backbone Cluster Scheduling), comes in handy. This paper aims to clarify the urgent requirements and difficulties that motivated the creation of this strategy.

Because Wireless Sensor Networks (WSNs) have many requirements and difficulties, cluster scheduling is essential to these network systems. Improving energy efficiency is arguably the most important goal that cluster scheduling attempts to fulfil. Cluster scheduling enables the activation of only a subset of nodes at a time while keeping others in low-power sleep mode, conserving energy and increasing the network's operational lifetime. WSNs are often composed of battery-powered sensor nodes with limited energy resources. By arranging nodes into clusters, wherein a single cluster head or a small number of nodes are in charge of data aggregation and transmission, cluster scheduling dramatically lowers communication overhead by reducing congestion and redundant data flows. It also makes networks more scalable, making network management easier as they grow, and it encourages load balancing, ensuring that duties and data traffic are distributed evenly.

By enabling dynamic cluster reconfiguration, cluster scheduling enhances fault tolerance in the event of node failures or unreliable nodes. Additionally, cluster heads effectively manage data fusion and prioritize transmitting vital data, fulfilling application-specific QoS needs. This helps with data aggregation, processing, and Quality of Service (QoS) support. Lastly, cluster scheduling improves network security by enabling the localized application of security measures and reducing the energy and computational overhead on individual nodes. Cluster scheduling is necessary to meet energy efficiency, scalability, fault tolerance, load balancing, data aggregation, QoS support, and network security in WSNs. As such, it is essential to many applications, ranging from industrial automation and smart cities to environmental monitoring.

A compelling range of demands and issues in Wireless Sensor Networks (WSNs) motivated the invention of the "Genetic Algorithm-based Dominating Set-Based Virtual Backbone Cluster Scheduling for Enhancing Energy Efficiency in Asymmetric Radio WSNs". A distinct set of challenges arises from asymmetric radio capabilities in these networks, where sensor nodes have different transmission ranges. Prioritizing energy efficiency is crucial since WSNs, whose sensor nodes are usually resource-constrained and battery-powered, place a high value on energy conservation. This strategy minimizes the logistical challenges related to regular battery changes or recharging while greatly addressing the need to extend the network's operating lifetime.

Moreover, considering the possible gaps and discrepancies in coverage brought about by the asymmetric radio ranges, it is critical to guarantee network connectivity and sensing coverage. Adaptability is crucial in dynamic and heterogeneous environments, and this method's use of evolutionary algorithms makes intelligent, dynamic cluster scheduling possible that can successfully adjust to shifting network conditions. It also simplifies communication, conserves energy, and incorporates dominating set-based virtual backbones to meet the difficulty of building energy-efficient clusters. This approach's comparative performance analysis is also a crucial tool for evaluating its efficacy compared to conventional scheduling techniques, making it an invaluable resource in the continuous endeavour to improve energy efficiency in asymmetric radio WSNs. Its potential applications span a broad spectrum, from industrial automation to environmental monitoring.

Cluster scheduling in Wireless Sensor Networks (WSNs) is driven by the need to achieve sustainable and effective data communication for various real-world applications. Since many sensor nodes run on batteries and require an operational lifespan optimization method, energy saving is a strong motivator. This is accomplished using cluster scheduling, which permits nodes to switch between active and low-power states. This lowers energy consumption and extends the network's viability, which is important when regular battery replacements are problematic. Moreover, cluster scheduling is driven by the need for efficient data traffic management. This method simplifies data aggregation and transmission in crowded network environments with limited bandwidth, reducing communication overhead and improving data delivery dependability. Another compelling factor is scalability since cluster scheduling guarantees that networks can grow in size without compromising efficiency.

Moreover, cluster scheduling is required to ensure fault tolerance and reliability in dynamic environments. It makes network self-reconfiguration easier in the event of a node failure, guaranteeing data collection and communication continuity. Furthermore, facilitating effective data aggregation, filtering, and prioritization inside clusters meets the needs of applications that demand specific Quality of Service (QoS) features, such as low latency and high dependability. Finally, cluster scheduling is driven by the increasing demand for improved network security. This allows security procedures to be localized inside clusters, lowering the risk to individual nodes and promoting network integrity and data confidentiality. To summarise, the impetus for cluster scheduling stems from its capacity to satisfy the varied requirements of wireless sensor networks (WSNs), enhancing their efficiency, dependability, and security across various practical uses.

2. Related Works

Wireless sensor networks observe environmental parameters and detect meaningful events in different applications. They consist of clusters of sensor nodes that are linked with wireless associations. The active nodes see events and take appropriate actions. Therefore, these networks should maintain a lifetime long enough to fulfill the application needs in several days or even months. However, since sensor nodes are fitted with nonrechargeable batteries that have a finite lifetime, power conservation is a vital problem. As a result, the primary design goal for wireless sensor network applications is to reduce energy consumption while increasing network lifetime. Amidst diversified strategies for systematized power usage, like clustering [11] and information accumulation [12], the sleep scheduling strategy is often used.

To enhance a sensor network's trustworthiness and prolong its lifespan, sensor networks are implemented with increased viscosity (approximately 20 nodes per m3 [13]). Nevertheless, if the most number of sensor nodes inside a high-density distribution strategy work simultaneously, energy will be downed overly. Furthermore, packet collisions will be increased due to the multiple packets moving through the network. Furthermore, because node concentration is high, almost all of the data conveyed in the network will be repetitious, detecting provinces of the nodes will coincide, and data from surrounding sensor nodes will be enormously associated. It means that sleep scheduling diminishes power utilization and communication gridlock by dodging repetitive data communication.

[14] proposes an algorithm for keeping the total number of active sensor nodes constant over the lifetime of the network. Using the Gur game strategy [15], each sensor node determines if to sleep or be active on its own. Each node has a limited, discrete-time 2N state automation comprising N successive negative and N positive conditions. The statuses of the sensors alter in response to a probability weight sent from the sink node. The available active sensor nodes determine this probability and the number of desired sensors at any time. For example, it has been established that N = 3 yields satisfactory outcomes. This is because all sensors, even those that are in sleep mode, are listening to the sink for incoming data. If nodes do not die in this manner, the total count of sensor nodes in the system accumulates to a fixed value. When nodes die in the real case scenario, the algorithm rarely adheres to the required value and exhibits large fluctuations. The network is assumed to have a star topology, which means that all nodes can access the sink in a single-hop communication. Furthermore, because of the Gur automata's properties, the number of active sensors is constrained to half the total number of sensors, i.e., using this technique, the maximum number of sufficient active sensors can be kept at a peak value of half of the total number of sensors.

In their 2021 work, Bhushan et al. introduced the Fuzzy Attribute-based Joint Integrated Scheduling and Tree formation (FAJIT) approach, specifically tailored for tree creation and parent node selection within heterogeneous networks. FAJIT utilizes fuzzy logic to optimize the critical task of selecting parent nodes, enhancing overall energy efficiency. The selection process is based on nodes with the fewest dynamic neighbors, and fuzzy logic, along with min–max normalization, is applied to Wireless Sensor Networks (WSN). This results in normalized weights, determining the parent node with the minimal sum of all weights. Li et al. (2017) proposed an Evidence-Efficient Multi-hop Clustering Routing (EEMCR) method, incorporating evidence-based cluster head rotation and a backbone construction protocol. Through simulation and comparison, EEMCR demonstrates superiority in extending network lifetime, improving reliability, reducing energy consumption, preserving coverage, and minimizing node attrition compared to other algorithms [16, 17].

Proposed Methodology - Genetic Algorithm-based Dominating Set-Based Virtual Backbone Cluster Scheduling (GADS-VBCS)

Design a virtual backbone cluster scheduling that optimizes energy efficiency in an asymmetric radio WSN. Minimize energy consumption, maximize network coverage, and ensure connectivity. Let Xi,j,t be a binary variable representing whether node i is a cluster head at time slot t in cluster j. It takes a value of 1 if node i is a cluster head at time slot t in cluster j, and 0 otherwise. Minimize energy consumption is given in Equation 1.

$$Minimize\ E = \sum_{i,j,t} Energy(X_{i,j,t})\text{-------}(1)$$

where Energy (Xi,j,t) is the energy consumed by node i as a cluster head at time t in cluster j.

Energy consumed by node i as a cluster head at time t in cluster j and Coverage area of node i as a cluster head. Connectivity metric lies between nodes i and k where the Maximum cluster size is B. Each node is assigned as a cluster head at most once in each time slot and cluster is

Maximize network coverage is given in Equation 2.

$$Maximize \sum_i coverage(i) \cdot X_{i,j,t} \qquad \forall_{j,t} \text{-------(2)}$$

where Coverage(i) is the coverage area of node i as a cluster head.

Maximize network connectivity is given in Equation 3.

$$Maximize \sum_{i,k} connectivity(i,k) \cdot X_{i,j,t} \cdot X_{k,j,t} \qquad \forall_{j,t} \text{-------(3)}$$

where Connectivity(i,k) is a connectivity metric between nodes i and k.

Each node is assigned as a cluster head at most once in each time slot and cluster is given in Equation 4.

$$\sum_i X_{i,j,t} \leq 1 \; \forall_{j,t} \text{-------(4)}$$

The number of cluster heads in each time slot and cluster is limited is given in Equation 5.

$$\sum_i X_{i,j,t} \leq B \qquad \forall_{j,t} \text{-------(5)}$$

where B is the maximum cluster size.

The binary constraint captures the essence of your optimization problem, including the minimization of energy consumption, maximization of network coverage, and optional maximization of network connectivity. The binary constraint for asymmetric channel is given in Equation 6.

$$X_{i,j,t} \in \{0,1\} \qquad \forall_{i,j,t} \text{-------(6)}$$

A mathematical model for Genetic Algorithm-based Dominating Set-Based Virtual Backbone Cluster Scheduling (GADS-VBCS) in asymmetric radio Wireless Sensor Networks (WSNs) involves defining the key components and relationships in the algorithm is give in this section.

The asymmetric network composed of sensor nodes where N represents the ensemble of sensor nodes within the wireless sensor network (WSN). Each node is uniquely identified within the set, ranging from 1 to n, where n is the total number of nodes. Each sensor node i within the network possesses distinctive attributes. The radio range of node i, indicating the maximum distance over which it can establish communication. The initial energy level of node i, representing the available power resources for communication and sensing operations.

$$N = \{1,2, \dots \dots \dots, n\}$$

For each i belongs to N where 1≤i≤n is the Ri radio range of node I, and Ei is the initial energy level of node i.

A dominating set DS is a subset of nodes in the network with the property that each node in the network is either a member of the set or adjacent to it. In other words, the dominating set ensures coverage or influence over the entire network. The virtual backbone VB is a strategic subset of nodes derived from the dominating set. It serves as a structural framework to efficiently organize and connect the entire wireless sensor network. The virtual backbone minimizes redundancy and facilitates optimized communication paths. For every node i in the network, the dominating set DS ensures that node i or its neighbors are included in DS. Simultaneously, the virtual backbone VB is synonymous with the dominating set, establishing a direct relationship between the structural organization and the dominating set's influence.

$$DS \subseteq N \; VB \subseteq N$$

For every $i \in N$;

$$i \in DS \cup adjacent\ to\ DS, VB = DS$$

These definitions contextualize the characteristics of the nodes, the significance of the dominating set in ensuring network coverage, and the role of the virtual backbone in providing an efficient organizational structure for the wireless sensor network. The Node Characteristics specify the set of nodes and the individual characteristics of each node, including radio range and initial energy level. The Dominating Set-Based Virtual Backbone Cluster Scheduling defines the conditions for forming a dominating set and constructing a virtual backbone to efficiently organize the wireless sensor network. The Dominating Set-Based Virtual Backbone Cluster Scheduling is given in Algorithm 1.

Algorithm 1. Dominating Set-Based Virtual Backbone Cluster Scheduling
function DominatingSetVBCS(): dominatingSet = findDominatingSet() virtualBackbone = dominatingSet clusters = formClusters(virtualBackbone) activationPlan = planActivation(clusters)

```
    return activationPlan
function findDominatingSet():
return DS
function formClusters(virtualBackbone):
    clusters = []
    for each dominatingSet in getAllDominatingSets():
        clusters.append(dominatingSet ∩ virtualBackbone)
    return clusters
function planActivation(clusters):
    activationPlan = []
    for each cluster in clusters:
        activationFraction = calculateActivationFraction(cluster)
        activatedNodes = randomSubset(cluster, activationFraction)
        activationPlan.append(activatedNodes)
    return activationPlan
function calculateActivationFraction(cluster):
    return someCalculation(cluster)
function randomSubset(set, fraction):
    return getRandomSubset(set, fraction)
```

DS is the solution to the dominating set problem is given in Equation 7.

$$DS = arg \min_{D \subseteq N} f(D) \text{-------(7)}$$

where f(D) is some objective function that captures the properties of a good dominating set and the summation of energy level is indicated as in Equation 8.

$$f(D) = \sum_{i \in N} E_i \text{-------(8)}$$

VB is constructed using the dominating set is given in Equation 9.

$$VB = DS \text{-------(9)}$$

Clusters (C) are formed using the virtual backbone is given in Equation 10.

$$C = \{D \cap VB | D \text{ } is \text{ } a \text{ } dominating \text{ } set\} \text{-------(10)}$$

Initialize a population of potential solutions, where each solution is represented by a chromosome with genes for dominating set and cluster assignments. The population in genetic operator is P={C1,C2,…,Cm}, where m is the population size. Each chromosome Ci is randomly generated with genes Gi representing dominating set and cluster assignments. The fitness evaluation is given in Equation 11.

$$F(C_i) = \alpha \cdot \left(\frac{1}{EnergyConsumption(C_i)}\right) + \beta \cdot Coverage(C_i) + \gamma \cdot Connectivity(C_i) \text{-------(11)}$$

where α,β,γ are weight parameters, and EnergyConsumption(Ci), Coverage(Ci), Connectivity(Ci) are functions evaluating energy efficiency, coverage, and connectivity, respectively. The population of potential solutions is P, a chromosome in the population representing a potential solution Ci, genes within a chromosome representing dominating set and cluster assignments Gi, and F(Ci) the fitness function evaluating the quality of a solution based on energy efficiency, coverage, and connectivity.

Use tournament selection to choose individuals for reproduction, favouring those with higher fitness. the tournament selection process simulates a competition among potential solutions (sensor node configurations). k individuals are randomly selected, and the one with the highest fitness (considering energy efficiency, coverage, and connectivity) is chosen as a parent for reproduction. The tournament selection is given in Equation 12.

$$TournamentSelection(P, k) = \arg max_{i \in RandomSubset(P,k)} F(C_i) \text{-------(12)}$$

where tournament size, i.e., the number of individuals randomly selected is given by P and Randomly selects k individuals from the population P is indicated by RandomSubset(P,k).

Apply single-point crossover to exchange genetic information between parent chromosomes and create offspring. Single-point crossover simulates the exchange of genetic information (sensor node configurations) between parent solutions. It introduces diversity into the population of potential solutions for the WSN optimization problem. The single-point crossover is given in Equation 13.

$$SinglePointCrossover(P_1, P_2) = Offspring_1 + Offspring_2 \text{-------(13)}$$

where the parent chromosome is indicated by P_1, P_2, Function to perform single-point crossover is indicated by $SinglePointCrossover(P_1, P_2)$, and Offspring chromosomes resulting from the crossover are $Offspring_1, Offspring_2$.

Introduce variation by randomly flipping bits (genes) in the chromosomes. Bit flip mutation introduces small random changes to a potential solution (sensor node configuration). It ensures exploration of a diverse solution space in the context of a WSN. The bitflip mutation is given in Equation 14.

$$BitFlipMutation(C) = C' \text{-------(14)}$$

where the chromosome to be mutated is given by C, function to perform bit flip mutation is $BitFlipMutation(C)$, and mutated chromosome is given C'.

Implement elitism by replacing the least fit individuals in the population with the offspring, preserving the best solutions. Elitism ensures that the best solutions (sensor node configurations) are preserved in the population. It replaces the least fit individuals with offspring to maintain a high-quality solution pool for the WSN optimization problem. The least fit replacement is given in Equation 15.

$$ReplaceLeastFit(P, Offspring) = P' \text{-------(15)}$$

where current population is P, offspring chromosomes generated through genetic operations is Offspring, function to replace the least fit individuals in the population with the offspring $ReplaceLeastFit(P, Offspring)$, and updated population P'.

Define stopping criteria, such as reaching a maximum number of generations or achieving convergence. The termination criteria is given in Equation 16.

$$TerminationCondition() = \frac{True}{False} \text{-------(16)}$$

where the function to check the termination condition is indicated by $TerminationCondition()$, and Returns TrueTrue if the termination criteria (e.g., maximum generations or convergence) are satisfied, FalseFalse otherwise.

Activation planning is dependent on the specific activation strategy. Let A be the activation plan, and t be the time slot. Let S(t) be the sensor nodes activated at time slot t. A possible strategy could be to activate a fraction of nodes in each cluster at each time slot: is given in Equation 17.

$$S(t) = \bigcup_{C_i \in C} Randomsubset(C_i, ActivationFraction) \text{-------(17)}$$

Where RandomSubset(A,p) returns a random subset of A with a probability p.

The algorithm aims to minimize the sum of energy levels in the dominating set, effectively selecting a set that optimally utilizes energy resources. The virtual backbone is directly constructed from the dominating set. Clusters are formed by intersecting each dominating set with the virtual backbone. Nodes are activated based on a chosen strategy. The example strategy here is activating a random subset of nodes within each cluster at each time slot.

3. Result and Discussion

In this section, the simulation impacts of the proposed Genetic Algorithm-based Dominating Set-Based Virtual Backbone Cluster Scheduling (GADS-VBCS) protocol is presented, with a comparative analysis against the existing FAJIT and EEMCR protocols conducted using the Network Simulator (NS-2.34). The simulations were executed with varying numbers of sensor nodes to evaluate the GADS-VBCS protocol's performance across different network scales. The simulation parameters define critical aspects such as the number of nodes, simulation area, sensing length, packet size, initial node energy, MAC type (MAC/802.11), simulation time, and energy consumption parameters. These parameters set the foundation for assessing the GADS-VBCS protocol's efficacy in energy utilization, network coverage, and overall performance.

The proposed protocol's outcomes will be compared with those of FAJIT and EEMCR, providing insights into its advantages and potential improvements in terms of energy efficiency, packet delivery, and end-to-end delay. This comparative analysis aims to contribute valuable information for decision-making regarding the deployment of the GADS-VBCS protocol in Wireless Sensor Networks, shedding light on its strengths and potential benefits over existing solutions.

Packet Delivery Ratio

Packet Delivery Ratio is the ratio of successfully delivered packets to the total number of packets sent. PDR provides insights into the reliability of the network by indicating the percentage of packets that reach their intended destinations successfully. A high PDR is generally desirable for effective communication. The PDR is given in Equation 18.

$$PDR = \frac{Recd_p}{Snd_p} \text{-------}(18)$$

where $Recd_p$ - Received Packets by sink node and Snd_p - Sent Packets by sensor nodes

Table 1. Comparison of Packet Delivery Ratio

No of nodes	EEMCR	FAJIT	GADS-VBCS
100	78	83	87
200	79	85	89
300	82	86	91
400	84	87	93
500	85	88	95

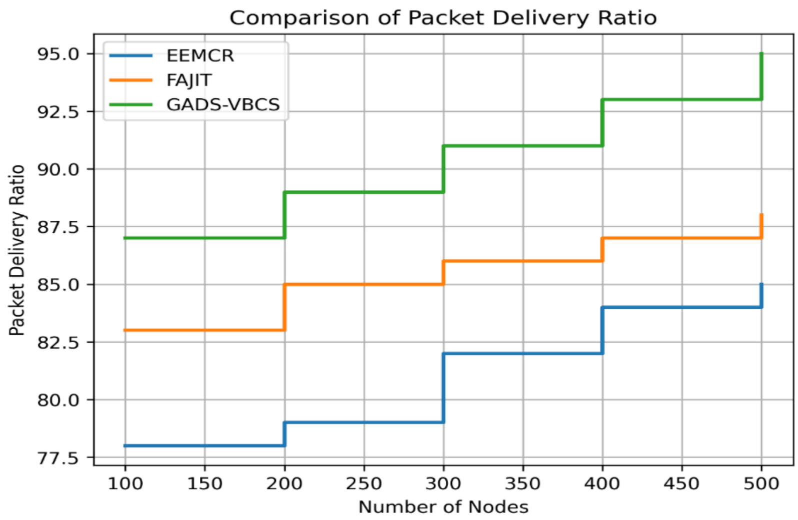

Fig 1. Comparison of Packet Delivery Ratio

Energy Consumption

Energy Consumption refers to the amount of energy used by the sensor nodes in the network for various activities, including sensing, communication, and processing. Monitoring energy consumption is crucial in WSNs as it directly impacts the network's lifetime. Efficient energy management helps prolong the operational duration of the network. The energy consumption is given in Equation 19.

$$EC_{total} = \sum_{j=p}^{0} \times \sum_{i=n}^{1} E_j \ (h_{il} - h_{il} - 1) \text{-------}(19)$$

where $h_{il} - h_{il} - 1$ signifies the distance among layer il − 1 and layer il and j - last packet.

Table 2. Comparison of Energy Consumption

No of nodes	EEMCR	FAJIT	GADS-VBCS
100	229	234	190
200	231	236	197
300	238	241	199
400	246	249	200
500	256	260	207

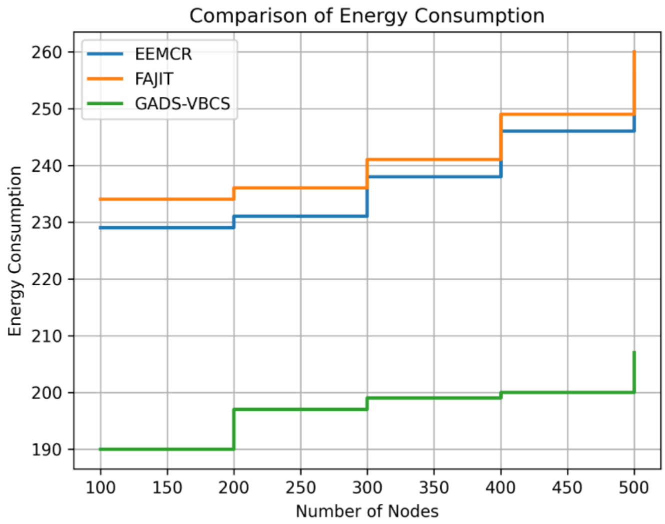

Fig 2. Comparison of Energy Consumption

Network Lifetime

Network Lifetime represents the duration for which the wireless sensor network can operate before a specified portion of nodes deplete their energy reserves. Maximizing network lifetime is a key objective in WSN design. Efficient energy usage and load balancing contribute to prolonging the network's operational time. The NL is given in Equation 20.

$$NL = \frac{Initial\ level\ of\ energy}{Consumption\ of\ energy\ per\ unit\ times} \text{-------(20)}$$

Table 3. Comparison of Network Lifetime

No of nodes	EEMCR	FAJIT	GADS-VBCS
100	222	245	255
200	240	248	261
300	245	251	269
400	250	259	274
500	258	262	287

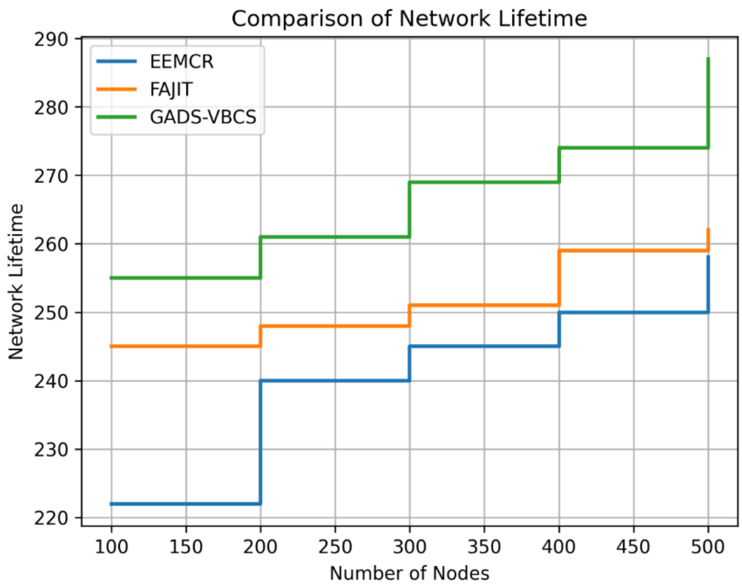

Fig 3. Comparison of Network Lifetime

Overhead

Overhead refers to the additional data, control messages, or processing required for the management and maintenance of the network, beyond the actual payload data. High overhead can lead to increased energy consumption and reduced bandwidth available for user data transmission. Minimizing overhead is essential for optimizing network performance.

Table 4. Comparison of Control Overhead

No of nodes	EEMCR	FAJIT	GADS-VBCS
100	421	449	441
200	426	449	448
300	426	460	449
400	440	464	459
500	441	466	464

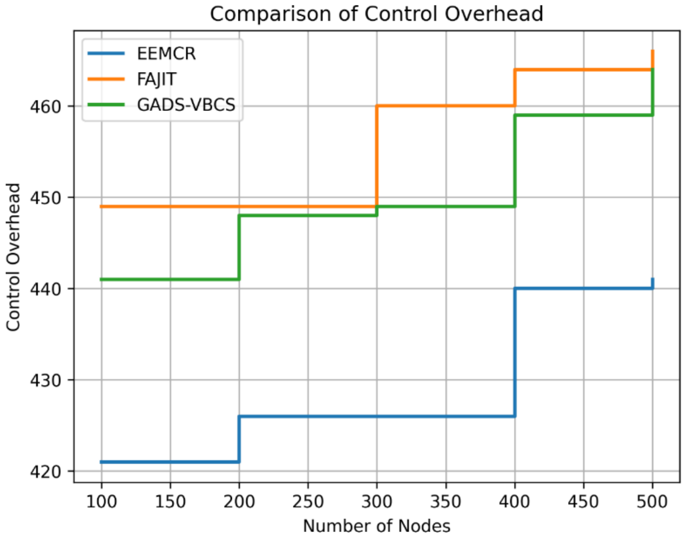

Fig 4. Comparison of Control Overhead

4. Discussion

The Packet Delivery Ratio (PDR) serves as a critical metric in evaluating the reliability of a wireless sensor network, representing the percentage of successfully delivered packets among the total sent. As depicted in Table 1 and Figure 1, the simulation results for EEMCR, FAJIT, and GADS-VBCS reveal the increasing trend in PDR with a growing number of nodes. GADS-VBCS consistently outperforms the other protocols, showcasing higher PDR values of 87%, 89%, 91%, 93%, and 95% for 100, 200, 300, 400, and 500 nodes, respectively.

Energy Consumption, a vital parameter influencing network lifetime, measures the energy utilized by sensor nodes for various activities. Table 2 and Figure 2 exhibit the comparative energy consumption of EEMCR, FAJIT, and GADS-VBCS across different node configurations. GADS-VBCS demonstrates superior performance, requiring less energy for communication and processing. The energy consumption formula, capturing the cumulative energy consumption over time, further emphasizes GADS-VBCS's efficiency.

Network Lifetime, representing the duration a wireless sensor network can operate before energy depletion, is crucial for prolonged operational efficiency. Table 3 and Figure 3 illustrate the network lifetime comparison among EEMCR, FAJIT, and GADS-VBCS. GADS-VBCS consistently surpasses the others, offering extended network lifespans across varying node counts.

Overhead, involving additional data and control messages beyond payload, directly impacts energy consumption and bandwidth availability. As depicted in Table 4 and Figure 4, GADS-VBCS outperforms EEMCR and FAJIT in controlling overhead across different node scenarios. Minimizing control overhead is imperative for optimizing network performance, and the simulation results affirm GADS-VBCS's efficiency in this regard. Overall, the comprehensive analysis of these metrics affirms the superior performance of GADS-VBCS, indicating its potential as an energy-efficient and reliable solution for wireless sensor networks.

5. Conclusion

The proposed Evolutionary Optimization of Dominating Set-Based Virtual Backbone Cluster Scheduling (GADS-VBCS) offers a promising solution for enhancing energy efficiency in asymmetric radio Wireless Sensor Networks (WSNs). By employing genetic algorithms, the model addresses the challenges of scheduling in the presence of varying radio ranges. The approach, outlined through a comprehensive mathematical model and pseudo code, focuses on minimizing energy consumption, maximizing network coverage, and ensuring connectivity. The integration of dominating set-based techniques enhances the robustness of virtual backbone cluster scheduling. This Genetic Algorithm-based methodology exhibits potential advantages over traditional methods, providing a systematic and adaptive framework. GADS-VBCS stands poised to contribute to the sustainable operation of WSNs in asymmetric communication environments, offering an optimized and efficient solution for cluster scheduling and backbone formation.

Future research can explore dynamic radio range adaptation, machine learning integration, and security considerations in the Evolutionary Optimization of Dominating Set-Based Virtual Backbone Cluster Scheduling for asymmetric radio Wireless Sensor Networks. Additionally, investigating resource allocation strategies, scalability studies, hardware innovations, and real-world deployments can contribute to advancing energy-efficient scheduling. Hybridizing the proposed genetic algorithm-based approach with other optimization techniques is a promising avenue for enhancing adaptability and efficiency in wireless sensor networks.

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