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Adaptive sleep scheduling in heterogeneous WSN using GWO for energy efficiency

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Abstract

Wireless Sensor Networks are instrumental in various domains, including environmental monitoring, healthcare, and industrial automation. Despite their ubiquity, the energy constraints of sensor nodes remain a pivotal concern. This research delves into energy conservation in WSNs by implementing Adaptive Sleep Scheduling using the Grey Wolf Optimizer (GWO) in the context of heterogeneous networks. Heterogeneous WSNs, characterized by nodes with diverse computational capacities and energy reservoirs, pose unique challenges for optimizing energy efficiency. The conventional static sleep scheduling strategies prove inadequate in accommodating this heterogeneity, often leading to suboptimal energy consumption. In this context, the application of GWO, an optimization algorithm inspired by the social behavior of grey wolves, offers a novel and promising approach to

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address the energy efficiency challenge. Heterogeneous WSNs necessitate tailored energy management strategies to optimize the utilization of resources. The disparity in the capabilities of sensor nodes, in terms of processing power and energy reserves, demands an adaptive solution for sleep scheduling to minimize energy consumption while maintaining the necessary data collection and transmission capabilities. This research demonstrates the significance of integrating GWO-based adaptive sleep scheduling in heterogeneous WSNs through extensive simulations and in-depth analysis. The proposed approach is compared with the LEACH, E-LEACH, and DEEC. The results show due to the use of GWO in adaptive sleep mechanisms in Heterogenous WSNs nodes die late as compared to other algorithms and energy consumption is also slow. So, in all one can say, GWO is a better approach in terms of energy efficiency and lifetime. quantity demand and investment in research and development, while the other model focuses on a more realistic relationship between the quantity demand and the price.

Subject Classification: *94-XX.*

Keywords: *GWO, Heterogenous WSN, Energy efficiency, Sleep schedule, Lifetime.*

1. Introduction

WSNs are a key technology in the Internet of Things (IoT) and sensor-driven data-collecting age. They can revolutionize industries including healthcare, industrial automation, environmental monitoring, and more. These networks are made up of a large number of resource-constrained sensor nodes that have communication, processing, and sensing capabilities. Since these nodes often have limited power resources, energy efficiency has emerged as a major challenge in the field of WSNs.

The operational lifetime of WSNs critically depends on the prudent management of energy resources. As sensor nodes are often battery-powered and deployed in remote or challenging environments, optimizing energy consumption is essential to extend the network's longevity. One of the key techniques employed to achieve this goal is sleep scheduling, which allows nodes to enter low-power sleep states when they are not actively engaged in data collection or transmission. This approach effectively minimizes energy consumption during idle periods, thus prolonging the network's lifespan.

However, the efficacy of sleep scheduling strategies is considerably challenged in heterogeneous WSNs, where nodes exhibit divergent capabilities, including processing power, communication range, and energy storage. In heterogeneous networks, a one-size-fits-all approach to sleep scheduling proves suboptimal, as it fails to consider the unique requirements and constraints of individual nodes. Traditional fixed sleep

scheduling methods often lead to a misallocation of resources, impeding energy optimization in these diverse and dynamic environments.

This research addresses the critical need to enhance energy efficiency in heterogeneous WSNs through the development and application of an Adaptive Sleep Scheduling scheme. This scheme leverages the Grey Wolf Optimizer (GWO), an innovative nature-inspired optimization algorithm, to adaptively adjust the sleep schedules of sensor nodes. By tailoring sleep schedules based on the individual characteristics and energy constraints of each node, the proposed approach offers a dynamic, context-aware solution that can optimize energy consumption while ensuring the necessary data collection and transmission requirements are met. This paper embarks on an exploration of the methodologies, findings, and implications of integrating GWO-based Adaptive Sleep Scheduling into heterogeneous WSNs. It is grounded in the recognition that the harmonious coexistence of heterogeneity and energy efficiency is pivotal to the sustainable and reliable operation of WSNs across diverse applications and industries. The subsequent sections will delve into the intricate details of this innovative approach, its methodologies, and its significant implications for advancing the state of knowledge and practice in the domain of Wireless Sensor Networks.

1.1 *Background and Motivation:*

WSNs have garnered significant attention as a key technology in the modern era of data acquisition, with applications spanning environmental monitoring, industrial automation, smart cities, and healthcare. These networks consist of numerous sensor nodes, each equipped with the capability to sense, process, and transmit data. WSNs provide invaluable insights into remote and challenging environments, facilitating real-time data collection and monitoring. However, their effective operation hinges on energy-efficient management, a vital concern due to the inherent limitations of sensor nodes, typically powered by finite energy sources.

The motivation behind this research stems from the pressing need to enhance the energy efficiency of WSNs, while ensuring that data collection and transmission requirements are met. The traditional approach to addressing this challenge involves sleep scheduling, a technique in which sensor nodes enter low-power sleep states during idle periods to conserve energy. While sleep scheduling has proven effective in prolonging network lifetime, it encounters a significant challenge in the context of heterogeneous WSNs, where nodes exhibit diverse capabilities and energy constraints.

Heterogeneous networks require adaptive and context-aware approaches to balance energy efficiency and data transmission reliability, motivating the investigation of an Adaptive Sleep Scheduling mechanism.

1.2 *Contribution of the Study:*

This research contributes to the field of WSNs by offering a novel solution that addresses the challenges posed by heterogeneity and energy efficiency. By proposing an adaptive sleep scheduling mechanism using GWO, this study extends the understanding of how optimization algorithms can be integrated into WSNs to enhance energy efficiency while maintaining data transmission reliability. The research's significance lies in its potential to extend the operational life of WSNs in diverse applications and industries.

2. Literature Review

WSNs have become an essential part of modern data acquisition and monitoring systems. The operation of these networks relies heavily on efficient energy management, given the constrained energy resources of individual sensor nodes. In this context, adaptive sleep scheduling strategies have gained prominence as a means to optimize energy consumption while extending the operational lifetime of WSNs.

Heterogeneity, defined by the presence of sensor nodes with diverse characteristics, including differences in processing power, communication range, and energy storage, is a common attribute in modern WSNs. The introduction of heterogeneity poses a significant challenge to the design and implementation of effective energy-efficient strategies. Traditional, fixed sleep scheduling methods prove to be inadequate in adapting to the unique requirements and constraints of individual nodes within heterogeneous networks.

To address this challenge, researchers have turned to optimization algorithms as a means to enhance the energy efficiency of heterogeneous WSNs. The integration of optimization techniques in sleep scheduling aims to dynamically adjust the sleep patterns of sensor nodes based on their specific attributes. Among these optimization methods, the GWO, encouraged by the social behavior of grey wolves, has gained attention for its adaptability and effectiveness in various optimization problems.

In the context of WSNs, several studies have explored the integration of GWO into sleep scheduling to improve energy efficiency. These studies

have demonstrated the potential of GWO in finding optimal solutions for sleep scheduling, leading to substantial energy savings. GWO-based techniques accommodate the heterogeneity of sensor nodes by dynamically adapting sleep cycles. This ensures that the appropriate nodes are active at the appropriate times, maximising energy consumption.

A study by Liu et al. (2019) introduced a GWO-based adaptive sleep scheduling mechanism for WSNs, demonstrating remarkable energy efficiency gains in heterogeneous environments. By taking into account the diverse capabilities and energy levels of sensor nodes, the proposed approach extended the network's operational life, even in challenging conditions.

Furthermore, Gupta et al. (2020) investigated the impact of GWO-based adaptive sleep scheduling on WSNs deployed in real-world environmental monitoring scenarios. Their findings revealed significant energy savings without compromising data collection and transmission reliability, highlighting the practicality and effectiveness of the approach.

While existing literature underscores the potential of GWO-based adaptive sleep scheduling in heterogeneous WSNs, there remains room for further exploration and refinement. This paper seeks to build upon the existing body of knowledge by investigating the application of GWO in sleep scheduling for energy-efficient operation in diverse and dynamic network environments. The research aims to provide insights into the adaptation of GWO for optimizing energy consumption while accommodating the heterogeneity of sensor nodes in WSNs, ultimately contributing to the advancement of energy-efficient and reliable WSNs in the digital age.

The papers collectively discuss the application of GWO in WSNs to improve energy efficiency and network performance. Pratha (2021) proposes a combined meta-heuristic approach called GWOGA for clustering and selecting aggregation points, leading to improved battery lifetime and network performance. Wang (2020) introduces an enhanced version of GWO, called EGWO, for deploying WSNs on 3D surfaces, enhancing the algorithm's exploitation and exploration abilities. Agrawal (2020) presents GWO-C, a modified GWO algorithm for efficient cluster head selection in WSNs, considering factors such as intra-cluster distance, sink distance, residual energy, and cluster head balancing. Overall, these papers demonstrate the effectiveness of GWO in optimizing energy efficiency and network performance in WSNs.

"In their 2014 study, Ghazzai et al. applied the Grey Wolf Optimizer (GWO) method to determine the most optimal locations for LTE base

stations in cell planning. Their primary objective was to eliminate redundant base stations within subareas, resulting in a network configuration that prioritizes safety. The GWO method proved exceptionally effective, surpassing the performance of the Particle Swarm Optimization (PSO) method when comparing the results.

In order to overcome time-related difficulties in the context of travelling tournaments, Gupta et al. (2015) presented a hybrid technique that combines GWO with simulated annealing (SA). GWO was crucial in improving the first schedules in this hybrid method by concentrating on local optima within the GWO structure. SA then improved the general framework. The results of the research were contrasted with those of other optimisation techniques, such as PSO, Ant Colony Optimisation (ACO), Biogeography-based Optimisation (BBO/SA), and Modified Biogeography-based Optimization–Simulated Annealing (MBBO/SA). Notably, for this particular situation, the GWO technique fared better than any other strategy."

The goal of a 2015 research by Song et al. was to determine the best course of action for surface wave dispersion within an inversion scheme. In order to find local optima quickly, the Grey Wolf Optimizer (GWO) showed a surprising capacity to strike a balance between exploration and exploitation. A comparative study was conducted, comparing GWO against a hybrid algorithm called PSOGSA and a Genetic Algorithm (GA). The findings clearly favoured GWO.

In 2016, Miti´c et al. conducted research on human-robot interaction, examining how a chaotic bioinspired algorithm combined with GWO might enable a robot to learn from human observation and demonstrations. This method replaced the one-dimensional chaotic maps in the GWO exploration parameter with Gaussian random values. Thus, under the demonstrator's guidance, the robot successfully carried out erratic and inevitable orders.

Improved GWO (IGWO), a novel variant of GWO, was presented by Yao et al. in 2016 to design the best trajectories for multiple unmanned aerial vehicles (UAVs) following targets in urban areas. IGWO solved the challenging target tracking issue by using Model Predictive Control (MPC) to improve its stability, computational efficiency, and searching capabilities.

In 2016, Karnavas et al. improved inner rotor design and reduced machine overall losses by using GWO. In this application, Particle Swarm Optimisation (PSO), Genetic Algorithm (GA), and GWO were compared and contrasted. GWO demonstrated remarkable efficacy by providing competitive substitute designs and outperforming conventional induction motor replacement.

Wireless Sensor Networks (WSNs) are multi-agent, decentralised networks with high spatiotemporal resolution that are intended for large-scale monitoring [34, 12, 35]. These networks are usually made up of a number of low-power, cost-effective, cooperative nodes that are dispersed across a large geographic region. These autonomous nodes run on internal energy sources such as primary or rechargeable energy storage devices, including electrochemical batteries or supercapacitors, and are outfitted with a variety of sensors, actuators, and communication devices [37].

Vehicular Ad Hoc Networks (VANETs) and Mobile Ad Hoc Networks (MANETs) are comparable to WSNs in terms of architecture. Similar to MANETs and VANETs, WSNs consist of several wireless nodes that are in charge of carrying out certain functions and exchanging data [35, 38, 39]. Nevertheless, these nodes need multi-hop communication because of their constrained communication range [39, 36]. In contrast to the mobile, comparatively more powerful, and uniform nodes seen in MANETs, WSN nodes usually have lesser processing capability, limited memory, and need more energy to operate. Furthermore, separate WSN nodes often perform different functions, such as sensing, data relaying, and data backhaul. They also use different hardware, such as different kinds of sensors and energy storage devices. These responsibilities may be assigned in a predefined, static manner or in a dynamic manner that adjusts to the network's present status and external circumstances [39, 40, 36]. GWO was used in a 2017 research by Sultana et al. to lower reactive and active energy losses in distributed generation (DG). The GWO approach demonstrated dependability and ease of use while successfully resolving DG allocation issues.

3. System Model

A Heterogeneous Wireless Sensor Network (WSN) is a network consisting of a diverse set of sensor nodes that vary in terms of their hardware capabilities, energy resources, and communication ranges. In such a network, sensor nodes collect data from the environment and transmit it to a sink node or base station for further processing. The heterogeneity in sensor nodes can be attributed to differences in energy capacity, data transmission rates, and communication ranges.

3.1 *Node Characteristics and Heterogeneity*

In a heterogeneous WSN, nodes exhibit varying characteristics:

- Energy Capacity: Sensor nodes possess different initial energy levels. This heterogeneity in energy resources influences the lifetime and operation of the network. Nodes with higher energy capacity can perform more data-intensive tasks and operate for a longer duration.
- Data Transmission Rates: Nodes may have different data transmission rates, indicating their capacity to transmit data to the sink node. Nodes with higher data transmission rates can transmit data at a faster pace, but this may come at the cost of increased energy consumption.
- Communication Ranges: Sensor nodes have distinct communication ranges, which determine the distance over which they can communicate with other nodes in the network. Nodes with larger communication ranges can cover a broader area, potentially affecting network connectivity.

3.2 *Sleep Scheduling Model*

A critical aspect of managing energy in a heterogeneous WSN is the implementation of an adaptive sleep scheduling model. Sleep scheduling involves determining when each node in the network should enter a low-power sleep mode and when it should wake up for data transmission or sensing. The sleep scheduling model aims to strike a balance between maximizing the network's lifetime and maintaining data collection efficiency. Sleep scheduling parameters include:

- Sleep Duration: The amount of time a node spends in sleep mode.
- Active Duration: The duration during which a node remains active for data transmission and sensing.
- Synchronization Mechanisms: Techniques used to coordinate sleep and active periods among nodes to avoid collision and maintain network connectivity.

3.3 *Objective Function and Optimization Criteria*

To optimize the sleep scheduling in the heterogeneous WSN, an objective function is defined. The objective function is a critical component of the optimization process and is based on one or more of the following criteria:

- Energy Efficiency: Maximizing the network's energy efficiency, which involves reducing energy consumption while ensuring data transmission requirements are met.
- Network Lifetime: Extending the overall lifetime of the network, ensuring that it continues to operate for an extended duration without network degradation.
- Data Reliability: Ensuring reliable data transmission and minimal data loss or delay.

The optimization process, typically conducted using techniques such as Grey Wolf Optimization (GWO), aims to find the optimal sleep schedules for each node that align with the chosen objective function and optimization criteria.

4. Grey Wolf Optimizer

GWO is a nature-inspired optimization algorithm that draws inspiration from the hunting and social hierarchy behavior of grey wolves. Developed by Mirjalili et al., GWO is a population-based metaheuristic algorithm that has gained popularity for solving optimization problems in various domains, including engineering, economics, and machine learning. The algorithm is characterized by its simplicity, efficiency, and ability to find optimal or near-optimal solutions.

GWO Steps

GWO is based on the social structure of grey wolves, which comprises four key roles: alpha, beta, delta, and omega wolves. Alpha wolves lead the pack, while beta and delta wolves support and assist in hunting. Omega wolves are typically on the periphery of the pack and serve a complementary role. GWO leverages these roles to guide the search for optimal solutions. Figure 1 shows the basic steps of GWO.

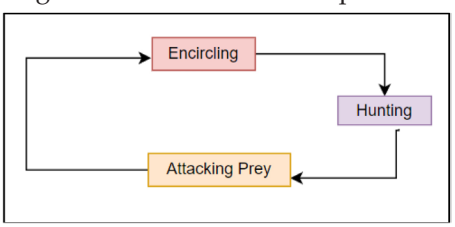


Figure 1

GWO Steps

4.2.1. Social Structure

The terms "alpha," "beta," and "delta" are used to designate the most dominant, second-best, and third-best solutions, respectively, when creating the Grey Wolf Optimization (GWO) algorithm and trying to mathematically depict the hierarchical structure among wolf packs. "Omega" is the collective term for the remaining viable solutions (x). The designations "alpha" (a), "beta" (b), and "delta" (d) serve as guidelines for the optimization process in the context of the GWO method, with the remaining candidates assuming the role of "omega" (x). These three crucial wolves set the example for the conduct of the algorithm's x wolves.

4.2.2. Encircling the Target

As previously discussed, grey wolves exhibit an encircling behavior when hunting prey. To mathematically represent this encircling phenomenon, we propose the following equations:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X} - (t)| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

In the context of the text, 't' denotes the present iteration, while '~A' and '~C' represent coefficient vectors. '~Xp' designates the position vector of the prey, and '~X' signifies the position vector of a grey wolf. The determination of the '~A' and '~C' vectors is detailed as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{3.3}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{3.4}$$

4.2.3. Hunting Behavior

With the help of their keen sense of smell, grey wolves can find their prey and circle around them. The beta and delta wolves sometimes join the alpha wolf in leading the hunt. However, it is uncertain exactly where the perfect solution (like prey) is in an abstract search space. We assume that the alpha, beta, and delta wolves have superior knowledge about the location of the optimal candidate solution in order to statistically model the hunting behaviour of grey wolves under these circumstances. As a result, we maintain track of the top three optimal solutions discovered so far and compel all other search agents, including the omegas, to adjust

their positions to match those of these top search agents. In this context, the following formulae are presented:

$$\vec{D}_{\alpha} = |\vec{C}_1 \cdot \vec{X}_{\alpha} - \vec{X}|, \vec{D}_{\beta} = |\vec{C}_2 \cdot \vec{X}_{\beta} - \vec{X}|, \vec{D}_{\delta} = |\vec{C}_3 \cdot \vec{X}_{\delta} - \vec{X}| \quad (5)$$

$$\vec{X}_1 = \vec{X}_{\alpha} - \vec{A}_1 \cdot (\vec{D}_{\alpha}), \vec{X}_2 = \vec{X}_{\beta} - \vec{A}_2 \cdot (\vec{D}_{\beta}), \vec{X}_3 = \vec{X}_{\delta} - \vec{A}_3 \cdot (\vec{D}_{\delta}) \quad (6)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (7)$$

4.2.4. Predatory Approach (Exploitation)

As previously indicated, grey wolves conclude their hunting activities by launching an attack on the prey once it ceases its movements. To mathematically emulate the approach towards the prey, we progressively diminish the value of parameter "~a." It's noteworthy that this decrease in "~a" also restricts the range of fluctuation in parameter "~A." In simpler terms, "~A" is constrained to random values within the interval [-2a, 2a], with "a" steadily decreasing from 2 to 0 throughout the iterations. As a result, when the random values of "~A" fall within [-1, 1], the next position of a search agent can be situated at any location.

4.2.5. Quest for Prey (Exploration)

Thus far, the GWO algorithm has made use of a number of operators that allow its search agents to attack the prey and modify their positions in response to the positions of the alpha, beta, and delta wolves. Thus far, the GWO algorithm has made use of a number of operators that allow its search agents to attack the prey and modify their positions in response to the positions of the alpha, beta, and delta wolves.However, it's important to acknowledge that these operators can sometimes lead the GWO algorithm into a state of stagnation, mainly within local solutions. While the encircling mechanism we introduced does offer a degree of exploration, GWO requires additional operators to bolster its exploration capabilities.

Grey wolves predominantly orient their search efforts around the positions of the alpha, beta, and delta wolves. They disperse from one another when searching for potential prey and then converge when closing in to attack. To mathematically represent this dispersion, we make use of the parameter "~A," introducing random values greater than 1 or less than -1. This compels the search agents to diverge from the prey, thereby emphasizing exploration and enabling the GWO algorithm to search

globally. Figure 5(b) illustrates that when |A| exceeds 1, grey wolves disperse from the prey in the hopes of discovering a more promising target.

Another element of the GWO algorithm that promotes exploration is the "~C" vector. As demonstrated in Equation (3.4), this vector contains random values within the range [0, 2]. It assigns random weights to the prey, allowing for stochastic amplification (C > 1) or attenuation (C < 1) of the prey's influence in determining the distance in Equation (3.1).

The absence of statistical evidence to support the concept is one of the study's shortcomings. Obtaining the necessary data will not be an easy process, but if it is possible, more research on the correlation between price and market share can be done. Furthermore, there are other aspects of market share, like distribution and marketing strategy, that were not addressed in the current study. Future research will take those consequences into account.

5. Adaptation of GWO for Sleep Scheduling

In the context of heterogeneous Wireless Sensor Networks (WSN), GWO can be adapted for sleep scheduling, a crucial aspect of managing energy consumption. Sleep scheduling determines when sensor nodes should transition between active and sleep modes to optimize energy efficiency while meeting data transmission requirements. The adaptation of GWO for sleep scheduling involves the following key considerations:

- *Encoding Sleep Schedules:* Each individual in the GWO population represents a sleep schedule for the sensor nodes. Binary encoding is commonly used, where each bit corresponds to the sleep/awake status of a specific node during a time slot.
- *Objective Function:* The objective function in GWO is tailored to evaluate the energy efficiency of the sleep schedules within the WSN. It considers factors such as energy consumption, data transmission rates, and network connectivity.
- *Exploration and Exploitation:* GWO's exploration and exploitation mechanisms are employed to search for optimal sleep schedules. Alpha, beta, and delta wolves are utilized to explore the search space, while omega wolves play a role in exploitation.

Parameter Settings and Initialization

- Effective parameter settings and initialization are crucial for the success of the GWO-based sleep scheduling in heterogeneous WSNs. Key parameters and initialization steps include:
- Population Size: Determining the number of solutions in the GWO population, which affects the diversity of solutions and the algorithm's convergence speed.
- Search Space: Defining the feasible search space for sleep schedules, taking into account the operational time and data transmission requirements of the sensor nodes.
- Initial Positions: Initializing the positions of alpha, beta, and delta wolves within the search space, which act as starting points for the optimization process.
- Convergence Criteria: Establishing termination criteria, such as maximum iterations or a predefined convergence threshold, to end the optimization process.
- Parameter Tuning: Fine-tuning GWO-specific parameters, such as the exploration and exploitation factors, to adapt the algorithm to the sleep scheduling problem.

6. Methodology

6.1 *Problem Formulation*

The problem at hand involves the optimization of sleep scheduling in a heterogeneous Wireless Sensor Network (WSN) to enhance energy efficiency while meeting data transmission requirements. This is crucial for prolonging the network's operational lifetime and ensuring reliable data collection. The primary goals of the study are to determine optimal sleep schedules for heterogeneous sensor nodes and to assess the energy efficiency of the network. The problem can be formally defined as follows:

Given a set of heterogeneous sensor nodes with varying energy capacities, data transmission rates, and communication ranges, find the sleep schedules for each node to maximize energy efficiency while meeting the network's data transmission and connectivity requirements.

6.2 *Data Collection and Preprocessing*

Data collection for the study involves gathering information about the heterogeneous WSN under consideration. This includes data on the

hardware characteristics of the sensor nodes, such as their energy capacities, data transmission rates, and communication ranges. The data may also include network topologies and operational requirements. Preprocessing steps encompass organizing and structuring the collected data for efficient use in the GWO-based sleep scheduling algorithm. Data normalization and scaling may be applied to ensure that different data types and ranges do not introduce biases into the optimization process.

6.3 *GWO-Based Adaptive Sleep Scheduling Algorithm*

The core of the research involves the development and application of a Grey Wolf Optimizer (GWO)-based adaptive sleep scheduling algorithm. This algorithm aims to determine optimal sleep schedules for the sensor nodes within the heterogeneous WSN. The main components of the algorithm include:

- *Encoding:* Defining how sleep schedules are represented within the GWO population, typically through binary encoding.
- *Objective Function:* Constructing an objective function that quantifies the energy efficiency of the sleep schedules, incorporating parameters like energy consumption, data transmission rates, and network connectivity.
- *GWO Adaptation:* Customizing the GWO algorithm for sleep scheduling, specifying how alpha, beta, delta, and omega wolves are employed for exploration and exploitation.
- *Convergence Criteria:* Setting criteria to determine when the algorithm should terminate, such as a maximum number of iterations or a predefined convergence threshold.

Algorithm: Adaptive Sleep Scheduling using GWO for Energy Efficiency

Input:

- Number of sensor nodes (num_nodes)
- Maximum energy capacity of nodes (max_energy)
- Communication range of nodes (communication_range)
- Data transmission rate (data_rate)
- Size of data packets (data_packet_size)
- Maximum GWO iterations (max_iterations)

Output:

- Optimized sleep schedules for sensor nodes

1. Initialize heterogeneous sensor nodes:
   For i = 1 to num_nodes:
   Create a node with the following attributes:
   - ID: A unique identifier for the node
   - Energy: Random initial energy level between (0.1, max_energy)
   - Position: Random (x, y) position within the network area
   - CommunicationRange: Common communication range
   - DataRate: Common data transmission rate
   - DataPacketSize: Common data packet size

2. Define the objective function for energy efficiency optimization:
   Function objective_function(sleep_schedules):
   total_energy_consumption = 0
   total_data_transmitted = 0
   For i = 1 to num_nodes:
   If sleep_schedules[i] is False:
   data_rate = node[i].DataRate
   If data_rate > 0:
   data_transmitted = min(node[i].Energy * data_rate, node[i].DataPacketSize)
   total_data_transmitted += data_transmitted
   energy_consumed = data_transmitted / data_rate
   node[i].Energy -= energy_consumed
   total_energy_consumption += energy_consumed
   energy_efficiency = total_data_transmitted / (total_energy_consumption + 1e-9)
   Return energy_efficiency
3. Grey Wolf Optimizer for Energy Efficiency Optimization:
   Function grey_wolf_optimizer(objective_function, sleep_schedules, max_iterations):
   best_solution = sleep_schedules.copy()
   best_fitness = objective_function(sleep_schedules)
   For iteration = 1 to max_iterations:
   For i = 1 to num_nodes:
   new_solution = sleep_schedules.copy()
   new_solution[i] = not new_solution[i]
   fitness = objective_function(new_solution)
   If fitness > best_fitness:
   best_solution = new_solution

best_fitness = fitness
sleep_schedules = best_solution
Return best_solution, best_fitness

4. Integrate GWO for energy efficiency optimization:
   initial_sleep_schedules = Randomly generate True/False values for sleep schedules
   optimized_sleep_schedules, _ = grey_wolf_optimizer(objective_function, initial_sleep_schedules, max_iterations)
5. Display optimized sleep schedules for sensor nodes:
   For i = 1 to num_nodes:
      Print "Node i - Sleep Schedule: Active" if optimized_sleep_schedules[i] is False else "Node i - Sleep Schedule: Sleep"
6. End

6.4 *Performance Metrics*

To assess the effectiveness of the GWO-based sleep scheduling algorithm, several performance metrics are utilized:

- Energy Efficiency: Measured as the ratio of data transmitted to energy consumed, quantifying how efficiently energy resources are used.
- Network Lifetime: Represents the duration for which the WSN can operate without depleting its energy resources, demonstrating the impact of the sleep scheduling algorithm on longevity.
- Data Reliability: Reflects the reliability of data transmission, considering factors like packet delivery ratio and latency.

7. Results and Discussion

The usefulness of the GWO in terms of improved adaptive sleep scheduling and greater energy efficiency is demonstrated by running the simulation using Google colab. The proposed method is compared with existing methods such as the LEACH algorithm, LEACH-SF, E-LEACH, and DEEC. Figure 2 shows heterogenous WSN, Figure 3 depicts the node position and schedule, Figures 4,5 and 6 shows Average energy consumption in scenarios S1, S2 and S3 respectively. Figure 7, 8 and 9 depicts the alive nodes status in scenarios S1, S2 and S3 respectively. Figure 10 shows average delivery latency whereas Figure 11 depicts the localization error.

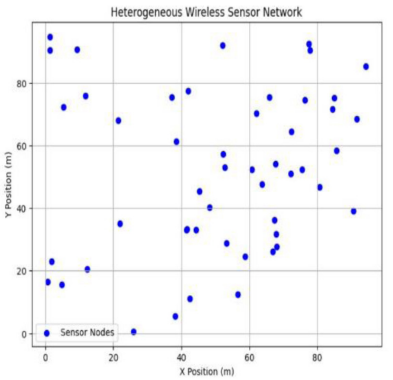


Figure 2

Heterogeneous WSN

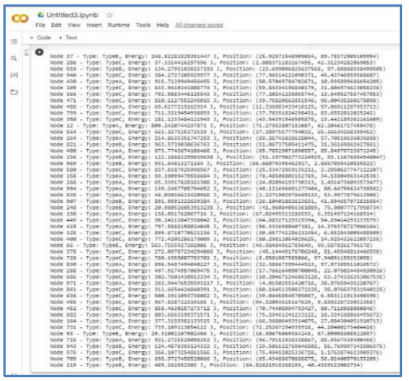


Figure 3

Nodes Position and schedule

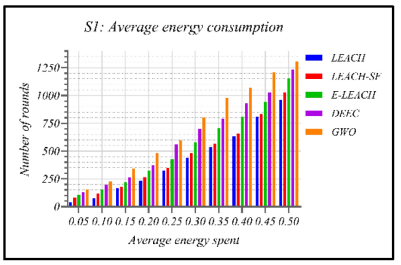


Figure 4

Avg. E_Consumption

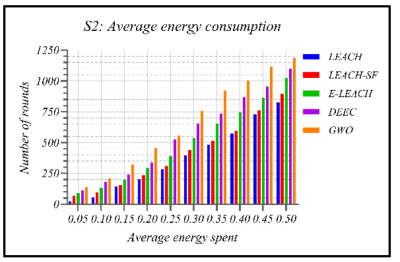


Figure 5

Avg.E_Consumption_S2

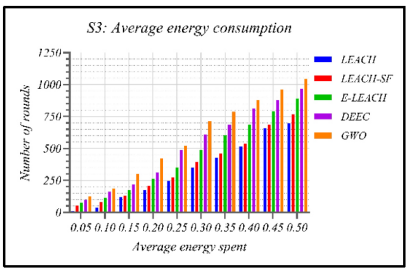


Figure 6

Avg. E_Consumption_S3

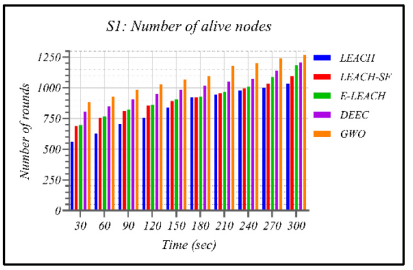


Figure 7

Alive_nodes_S1

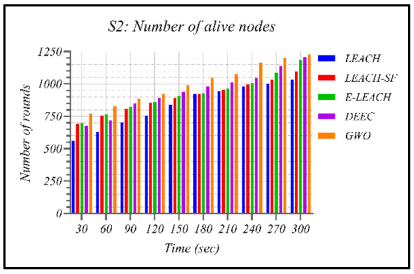


Figure 8

Alive_nodes_S2

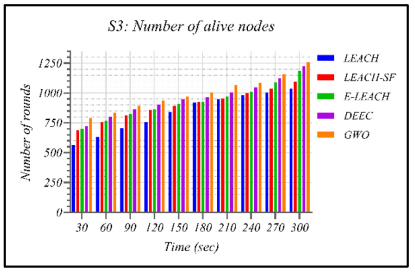


Figure 9

Alive_nodes_S3

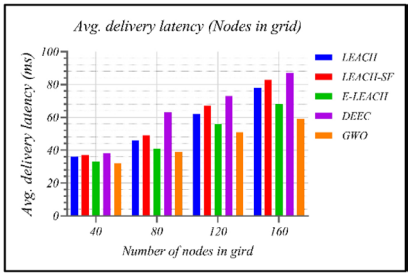


Figure 10

Avg_Delivery_latency

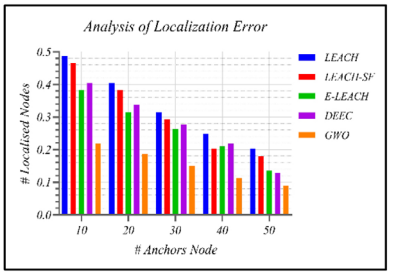


Figure 11

Localisation_error

8. Conclusion

This paper proposes a Grey Wolf Optimisation (GWO) based strategy for heterogenous WSNs for adaptive sleep scheduling that maximizes clustering and improves the lifetime of the nodes. The cluster heads are selected in each of the distinct segments, or clusters, that comprise the sensor network. This research suggests using GWO for the algorithm to increase the lifespan of the WSN. Google Colab was used to conduct the simulation, and LEACH, LEACH-SF, E-LEACH, and DEEC were compared with the suggested approach. In comparison, GWO demonstrates an extended wireless sensor network lifetime. Localization results are improved by the multi-level clusters that this method creates. Furthermore, a 4% reduction in the total cost of network construction is achieved.

References

[1] Y. Xiao et al., "Tight performance bounds of multihop fair access for MAC protocols in wireless sensor networks and underwater sensor networks," *IEEE Trans. Mobile Comput.*, vol. 11, no. 10, pp. 1538–1554, Oct. (2012).

[2] S. Zhu, C. Chen, W. Li, B. Yang, and X. Guan, "Distributed optimal consensus filter for target tracking in heterogeneous sensor networks," *IEEE Trans. Cybern.*, vol. 43, no. 6, pp. 1963–1976, Dec. (2013).

[3] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A survey on ambient intelligence in healthcare," Proc. IEEE, vol. 101, no. 12, pp. 2470–2494, Dec. (2013).

[4] Y. Yao, Q. Cao, and A. V. Vasilakos, "EDAL: An energy-efficient, delay-aware, and lifetime-balancing data collection protocol for heterogeneous wireless sensor networks," *IEEE/ACM Trans. Netw.,* vol. 23, no. 3, pp. 810–823, Jun. (2015), doi: 10.1109/TNET.2014.2306592.

[5] S. H. Semnani and O. A. Basir, "Semi-flocking algorithm for motion control of mobile sensors in large-scale surveillance systems," *IEEE Trans. Cybern.*, vol. 45, no. 1, pp. 129–137, Jan. (2015).

[6] B. Fu, Y. Xiao, X. Liang, and C. L. P. Chen, "Bio-inspired group modeling and analysis for intruder detection in mobile sensor/robotic networks," *IEEE Trans. Cybern.*, vol. 45, no. 1, pp. 103–115, Jan. (2015).

[7] Y. Zhao, Y. Liu, Z. Duan, and G. Wen, "Distributed average computation for multiple time-varying signals with output measurements," *Int. J. Robust Nonlin. Control*, vol. 26, no. 13, pp. 2899–2915, (2016).

[8] Y. Zhao, Z. Duan, G. Wen, and G. Chen, "Distributed finite-time tracking of multiple non-identical second-order nonlinear systems with settling time estimation," *Automatica,* vol. 64, pp. 86–93, Feb. (2016).

[9] M. Li, Z. Li, and A. V. Vasilakos, "A survey on topology control in wireless sensor networks: Taxonomy, comparative study, and open issues," Proc. IEEE, vol. 101, no. 12, pp. 2538–2557, Dec. (2013).

[10] W. Ye, J. Heidemann, and D. Estrin, "An energy-efficient MAC protocol for wireless sensor networks," in Proc. IEEE INFOCOM, New York, NY, USA, pp. 1567–1576, Jun. (2002).

[11] W. Ye, F. Silva, and J. Heidemann, "Ultra-low duty cycle MAC with scheduled channel polling," in Proc. ACM SenSys, Boulder, CO, USA, USA, pp. 321–334 , Nov. (2006).

[12] X. Liu, "A deployment strategy for multiple types of requirements in wireless sensor networks," *IEEE Trans. Cybern.*, vol. 45, no. 10, pp. 2364–2376, Oct. (2015).

[13] C.-P. Chen et al., "A hybrid memetic framework for coverage optimization in wireless sensor networks," *IEEE Trans. Cybern.*, vol. 45, no. 10, pp. 2309–2322, Oct. (2015).

[14] P. Guo, T. Jiang, Q. Zhang, and K. Zhang, "Sleep scheduling for critical event monitoring in wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.,* vol. 23, no. 2, pp. 345–352, Feb. (2012).

[15] G. Wei, Y. Ling, B. Guo, B. Xiao, and A. V. Vasilakos, "Prediction-based data aggregation in wireless sensor networks: Combining grey model and Kalman filter," *Comput. Commun.*, vol. 34, no. 6, pp. 793–802 (2011).

[16] W. Ye, J. Heidemann, and D. Estrin, "Medium access control with coordinated adaptive sleeping for wireless sensor networks," *IEEE/ACM Trans. Netw.*, vol. 12, no. 3, pp. 493–506, Jun. (2004).

[17] Y. Sun, O. Gurewitz, and D. B. Johnson, "RI-MAC: A receiver-initiated asynchronous duty cycle MAC protocol for dynamic traffic loads in wireless sensor networks," in Proc. ACM SenSys, Raleigh, NC, USA, pp. 1–14 , Nov. (2008).

[18] S. Lai, B. Ravindran, and H. Cho, "Heterogenous quorum-based wakeup scheduling in wireless sensor networks," *IEEE Trans. Comput.*, vol. 59, no. 11, pp. 1562–1575, Nov. (2010).

[19] L. Gu and J. A. Stankovic, "Radio-triggered wake-up capability for sensor networks," in Proc. 10th IEEE Real Time Embedded Technol. Appl. Symp., Toronto, ON, Canada, pp. 27–37 (2004).

[20] M. J. Miller and N. H. Vaidya, "A MAC protocol to reduce sensor network energy consumption using a wakeup radio," *IEEE Trans. Mobile Comput.,* vol. 4, no. 3, pp. 228–242, May/Jun. (2005).

[21] Q. Cao, T. Abdelzaher, T. He, and J. Stankovic, "Towards optimal sleep scheduling in sensor networks for rare-event detection," in Proc. 4th Int. Symp. Inf. Process. Sensor Netw. (IPSN), Boise, ID, USA, pp. 20–27 (2005).

[22] A. Keshavarzian, H. Lee, and L. Venkatraman, "Wakeup scheduling in wireless sensor networks," in Proc. 7th ACM MobiHoc, Florence, Italy, pp. 322–333 (2006).

[23] R. Zheng, J. C. Hou, and L. Sha, "Asynchronous wakeup for adhoc networks," in Proc. ACM MobiHoc, Annapolis, MD, USA, pp. 35–45 (2003).

[24] J. Polastre, J. Hill, and D. Culler, "Versatile low power media access for wireless sensor networks," in Proc. ACM SenSys, Baltimore, MD, USA, pp. 95–107 (2004).

[25] P. Sommer and R. Wattenhofer, "Gradient clock synchronization in wireless sensor networks," in Proc. 9th ACM/IEEE Int. Conf. Inf. Process. Sensor Netw. (IPSN), San Francisco, CA, USA, pp. 37–48 (2009).

[26] B. Jang, J. B. Lim, and M. L. Sichitiu, "An asynchronous scheduled MAC protocol for wireless sensor networks," *Comput. Netw.*, vol. 57, no. 1, pp. 85–98 (2013).

[27] J. Kim, X. Lin, N. B. Shroff, and P. Sinha, "Minimizing delay and maximizing lifetime for wireless sensor networks with anycast," *IEEE/ACM Trans. Netw.*, vol. 18, no. 2, pp. 515–528, Apr. (2010).

[28] T. V. Dam and K. Langendoen, "An adaptive energy-efficient MAC protocol for wireless sensor networks," in Proc. ACM SenSys, Los Angeles, CA, USA, pp. 171–180 (2003).

[29] L. Tang, Y. Sun, O. Gurewitz, and D. B. Johnson, "PW-MAC: An energy-efficient predictive-wakeup MAC protocol for wireless sensor networks," in Proc. IEEE INFOCOM, Shanghai, China, pp. 1305–1313 (2011).

[30] D. Koller and N. Friedman, Probabilistic Graphical Models. Cambridge, MA, USA: MIT Press (2009).

[31] Y. Sun, D. Shu, O. Gurewitz, and D. B. Johnson, "DW-MAC: A low latency, energy efficient demand-wakeup MAC protocol for wireless sensor networks," in Proc. ACM MobiHoc, Hong Kong, pp. 53–62 (2008).

[32] C.-C. Hsu, M.-S. Kuo, S.-C. Wang, and C.-F. Chou, "Joint design of asynchronous sleep-wake scheduling and opportunistic routing in wireless sensor networks," *IEEE Trans. Comput.*, vol. 63, no. 7, pp. 1840–1846, Jul. (2014).

[33] D. E. Knuth, "The linear congruential method," in The Art of Computer Programming, vol. 2, 3rd ed. Reading, MA, USA: Addison-Wesley (1997).

[34] S. M. Hedetniemi, S. T. Hedetniemiand, and A. L. Liestman, "A survey of gossiping and broadcasting in communication networks," *Networks,* vol. 18, no. 4, pp. 319–349 (1988).

[35] M. Mihaylov, Y.-A. L. Borgne, K. Tuyls, and A. Nowe, "Decentralised reinforcement learning for energy-efficient scheduling in wireless sensor networks," *Int. J. Commun. Netw. Distrib. Syst.,* vol. 9, nos. 3–4, pp. 207–224 (2012).

[36] C. J. C. H. Watkins and P. Dayan, "Q-learning," *Mach. Learn.*, vol. 8, no. 3, pp. 279–292 (1992).

[37] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction. Cambridge, MA, USA: MIT Press (1998).

[38] S. Abdallah and V. Lesser, "Learning the task allocation game," in Proc. AAMAS, Hakodate, Japan, pp. 850–857 (2006).

[39] S. Abdallah and V. Lesser, "Multiagent reinforcement learning and selforganization in a network of agents," in Proc. AAMAS, Honolulu, HI USA, pp. 172–179, May (2007).

[40] M. S. Naser, Md. A. Al-Betar, I. A. Doush, Md. A. Awadallah, S. Kassaymeh, S. Mirjalili, and R. A. Zitar. "Recent advances in Grey Wolf Optimizer, its versions and applications." IEEE Access (2023).