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Article

YSGPO: A Hybrid Metaheuristic Framework for Energy Conservation and Lifetime Maximization in Wireless Sensor Networks

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Abstract: Wireless Sensor Networks consist of multiple sensor nodes that work together to monitor environmental and physical scenarios. These sensor nodes are typically battery-powered devices and are frequently deployed in remote locations, therefore energy efficiency becomes a major concern in determining the network lifespan and reliability. In recent years, to address these challenges, numerous metaheuristic optimization techniques have been proposed particularly for clustering and energy-efficient routing. This research presents a structured and comprehensive analysis of several evolutionary and swarm intelligence algorithms for energy-efficient WSN operations. The algorithms examined include Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Differential Evolution, Artificial Bee Colony, Firefly Algorithm, Grey Wolf Optimizer, Whale Optimization, Salp Swarm Algorithm, Yellow Saddle Goatfish Optimization (YSGO), and Pelican Optimization Algorithm (POA). Moreover, a hybrid YSGPO algorithm is proposed to maintain a balance between global exploration and local exploitation. In the proposed model, YSGO is utilized for energy-aware cluster head selection while POA is applied for finding the optimal route for data transmission between cluster heads and the base station. Experimental findings of proposed algorithm are done in MATLAB using the First order radio energy model. Simulation findings indicates that the hybrid YSGPO algorithm achieves better energy efficiency, longer network stability and enhanced convergence performance when compared with aforementioned metaheuristic techniques.

Keywords: Wireless Sensor Network, Residual Energy, Metaheuristic Algorithms, Yellow Saddle Goatfish Algorithm, Routing, ACO, PSO, Pelican Optimization, Network stability and Throughput.

1. Introduction

Wireless Sensor Networks (WSNs) is composed of numerous sensor nodes (SNs) that have the capability of sensing the environmental data, perform basic processing, and communicate the information to the base station (BS) [1]. WSNs have broad applications in diverse fields such as healthcare system, monitoring environment, industrial automation, smart agriculture and military surveillance [2]. Despite their strengths, WSN face severe constraints during data transmission due to lack of communication bandwidth, energy consumption and computing capability. Among all these issues, energy consumption by a sensor node is the most dominant aspect that affects the network lifespan [3]. Once SNs deplete their batteries, network connectivity becomes compromised which leads to a loss of data as well as low convergence. Therefore, to extend the lifespan and performance of WSN, efficient utilization of node's energy is important. One effective and suitable way to reduce the aforementioned issue is to employ a hierarchical techniques [4]. By grouping the sensor nodes into clusters, redundant data transfer can be removed which leads to efficient utilization of node energy and improved network performance. Figure 1 shows the architecture of WSN clustering.

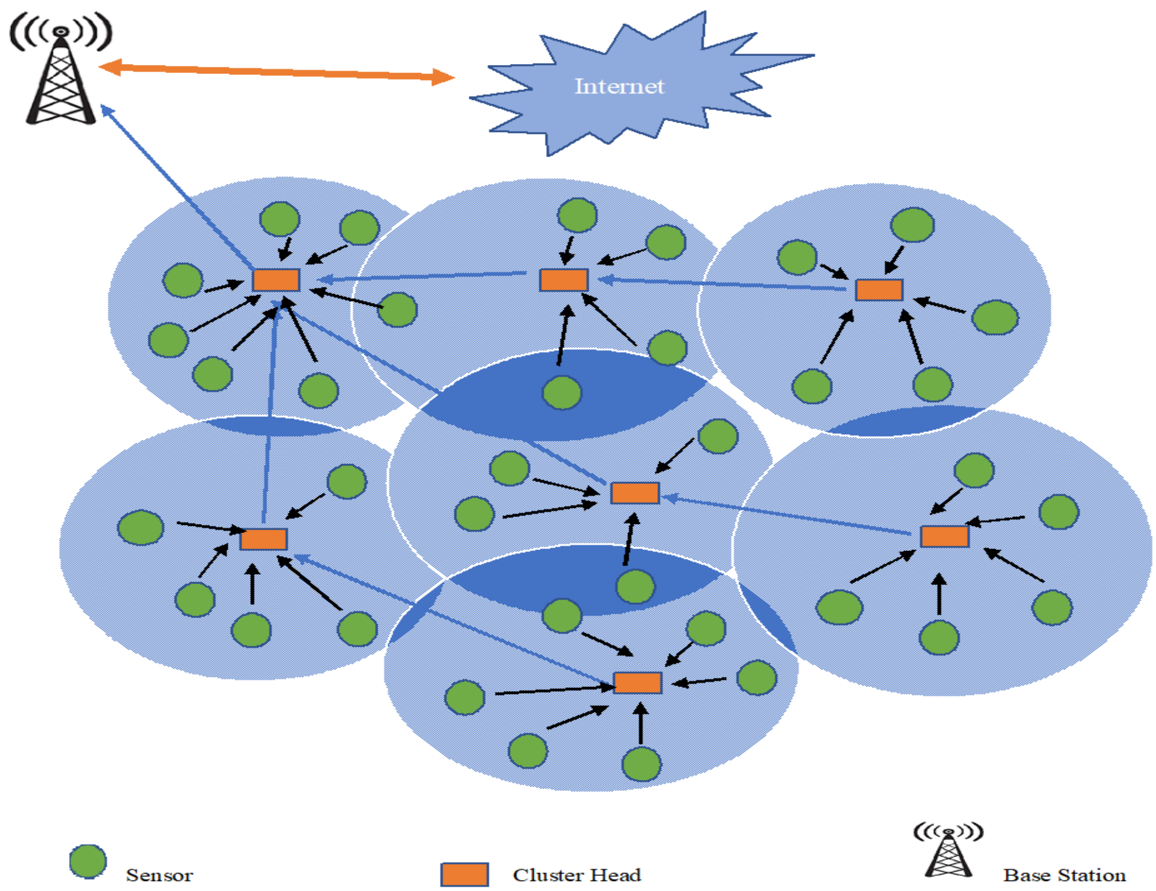

Figure 1: Structural Representation of Clustering in WSNs

Every cluster in clustering-based optimization has a designated cluster head (CH), whose task it is to manage the communication within the cluster. CH gathers the data from its SNs and then forward the aggregated data to the BS [5]. By lowering the amount of transmissions and receptions needed, this method decreases the power consumption of SNs. To ensure the balanced usage of cluster heads, the strategy of CH selection needs to receive the appropriate addressing [6]. An overload in the data collection and transmission process could cause CHs to rapidly run out of energy if they are not carefully chosen. Traditional deterministic optimization approaches are often not suitable for addressing WSN optimization problems because these issues are nonlinear, dynamic, and NP-hard in nature. As a result, to increase the enhance the nodes energy and network longevity researchers have consequently inclined towards metaheuristic algorithms such as evolutionary computation and swarm intelligence (SI) that are motivated by natural phenomena [7]. These techniques are flexible, robust, and capable to avoid local optima.

Algorithms like Whale Optimization Algorithm (WOA), Ant Colony Optimization, Particle Swarm Optimization and Genetic Algorithm (GA) have been proved most effective results in increasing the routing and clustering performance in WSNs. However, majority of individual metaheuristic approaches suffers from certain limitations such as premature convergence, lack of exploration and exploitation. Based on these observations, this research paper introduced a hybrid YSGPO algorithm for energy-efficient optimization in WSN. The suggested method uses YSGO algorithm for intelligent selection of CH and POA for route optimization between BS and CHs. The principal implications of this study are as follows:

- A thorough comparison of major metaheuristic algorithms used for WSN optimization.
- Design of a hybrid YSGPO algorithm that incorporates local exploitation and global exploration capabilities.

- The suggested technique is implemented in MATLAB using the first order radio energy model.
- Performance measures used for the simulation are residual energy, throughput, stability period, alive nodes and convergence speed.

2. Background

Over the years, significant research has been done for improving WSNs performance, particularly emphasis on extending the network lifespan, maximizing energy efficiency, finding optimized route for data transmission, clustering, and load balancing between nodes. In order to minimize the limitations of traditional techniques and achieve better network performance, researchers have adopted advanced methodology and hybrid optimization approaches. Heinzelman et al. [8] suggested a protocol named Low-Energy Adaptive Clustering Hierarchy (LEACH) which introduced adaptive clustering by rotating the role of CH among SNs on regular basis to balance energy usage. Rawat et al. [9] introduced a detailed survey of routing and clustering protocols and highlights that rapid consumption of energy and uneven distribution of load among nodes are major issues in WSNs. Their research emphasized the necessity of using optimization-based techniques to improve network lifetime. Metaheuristic techniques have become a popular approach for solving complex NP-hard problems in WSNs. Hartono et al. [10]conducted a systematic survey of metaheuristic optimization methods and suggest that PSO and ACO are among the most commonly used algorithms. V. Kumar *et al.*[11] introduced an optimization-based routing protocol known as AOMDV-SSPSO, which integrates PSO with multipath routing. The proposed approach improves the energy usage by SNs and maximizes the overall performance of WSN. Similarly, G. Thangarasu *et al.* [12] developed a chaotic WOA to reduces the energy requirement during data transmission. The chaotic behavior improves exploration capability and helps in identifying more efficient routing paths within the network. C. Iwendi *et al.* [13] proposed a hybrid technique that combines Simulated Annealing with WOA to determine optimal cluster heads. The findings demonstrated better efficiency in CH selection and overall network performance. M. C. M. Thein *et al.* [14] concentrated on load balancing among SNs by dynamically distributing the CH responsibilities among SNs. This method prevents premature failure of nodes because the energy usage is evenly distributed in the network. M. Praveen Kumar Reddy *et al.* [15] presented a approach that integrates Lion and Moth Flame Optimization technique for selecting optimized CHs. In another study, M. P. K. Reddy *et al.* [16] introduced a self-adaptive WOA for WSN-IoT environments. This approach considers performance measures such as delay, distribution of load, and energy usage to select efficient CHs and enhance network reliability. Z. Wang *et al.* [17] introduced a routing technique named as Artificial Bee Colony (ABC) that reduces the energy consumed during data transmission between CHs and the BS. By selecting shorter and optimized routes, the suggested method helps in maximizing the network lifetime. S. M. M. H. Daneshvar *et al.* [18] introduced a technique named as Grey Wolf Optimization (GWO) which is motivated by cooperative hunting strategy of grey wolves. The algorithm identifies suitable CHs and demonstrates improved performance in terms of energy efficiency. A hybrid method which integrates the concept of Sparrow Search Algorithm and Differential Evolution (DE) was proposed by P. Kathiroli et al. [19] to resolve energy efficiency issue in WSNs. Throughput, residual energy and alive nodes were some of the metrics that were used to assess the effectiveness of proposed technique. A. S. Shinde et al. [20] proposed an enhanced PSO based clustering technique for the selection of optimized CHs. B. Mamalis *et al.* [21] reviewed several clustering algorithms used in WSNs and analyzed their effectiveness in improving network lifetime and communication efficiency. B. M. Sahoo *et al.* [22] highlighted the potential of Swarm Intelligence (SI) techniques in achieving optimal network performance. The authors suggested a hybrid model combining GA and PSO, where GA is used to determine optimized CHs and PSO identifies the optimized route to BS. X. Zhao *et al.* [23] introduced a clustering protocol based on GWO algorithm to enhance network lifetime. The algorithm improves cluster formation by dynamically updating the locations of nodes in WSN. M. Sajwan *et al.* [24] developed the Hybrid Energy-Efficient Multipath Protocol which categorized the SN into balanced clusters and employs multi-hop communication within each cluster to reduce transmission distance and energy consumption. A. Rodríguez *et al.* [25] introduced a protocol named YSGO, which reorganizes the cluster structure of the network to ensure uniform distribution of CHs and reduce communication distances between nodes. An energy-aware CH selection algorithm based on node distance was presented by A. Panchal et al. [26]. In order to reduce energy usage, the technique considers performance metrics such residual energy, distance between nodes, and distance between CHs and BS. D. Nageswari *et al.* [27] proposed a strategy based on a queue threshold model using the N-policy M/M/1/1 queueing system. Although the approach significantly improves network lifetime, it may introduce latency in real-time applications. R. Maheswar *et al.* [28] conducted an experimental study to analyze various WSN performance metrics including synchronization delay, retransmission rate, computation time, and residual energy. Jayarajan *et al.* [29] suggested a technique which utilizes buffer-aware nodes to prevent data loss caused by buffer overflow and ensures balanced energy usage among nodes near the base station. Dr. Mukesh Kalla *et al.*[30] presented a clustering approach that divides the SNs into multiple clusters and selects optimized CHs based on metrics such as communication distance and residual energy. Ayedi et al. [30] utilizes Salp Swarm algorithm (SSA) to demonstrate the improved spectrum efficiency and minimizes energy usage under constrained communication environments. Del-Valle-Soto et al. [31] examined routing protocols and highlighted the need of protocol-level optimization in minimizing communication overhead. Their results showed significant improvements in stability period, residual energy, and network lifetime. A thorough analysis of metaheuristic approaches used in WSN optimization was provided by Houssein et al. [32] who also identified unresolved research issues in sensor network such scalability, dynamic topology adoption, and real-time adaptability.

3. Metaheuristic Techniques for WSNs Optimization

WSNs has a number of challenges that are interrelated such as CH selection, energy-efficient routing, balancing workload among nodes, and increasing overall network lifetime. These issues are caused due to the dynamically change in network topology, constrained node energy, and communication overhead. Implementation of poor optimization results in uneven energy usage by nodes, premature failures of nodes, and partitioning of network. Consequently, the implementation of an efficient optimization approach must reduce the communication cost, optimize consumption of energy among the nodes, and be able to adjust to the changing network while maintaining reliable data transmission. As a result, metaheuristic optimization algorithms have gained significant attention because they provide near-optimal solutions with reasonable computational effort [33]. These algorithms are typically population-based search techniques motivated by natural phenomena such as biological evolution, SI approach, and collective animal behavior. In WSNs, these techniques are primarily applied to optimize energy usage, maximize network lifespan, and improve routing efficiency. This section describes several widely used metaheuristic techniques in detail.

Particle Swarm Optimization

PSO is a metaheuristic approach that was motivated by the collective behavior of fish schools and bird flocks. Each candidate solution, known as a particle in PSO, navigates the search region by adjusting its location and velocity in response to both its own and nearby particles position [34]. The movement of particles is guided by the best solution found so far by the particle itself and the optimized solution found by the entire swarm population. This collaborative behavior enables the swarm to gradually converge toward an optimal or near-optimal solution. PSO has been widely applied in WSNs for tasks such as clustering, routing optimization, and energy-efficient node selection due to its simple structure and fast convergence. However, PSO tends to converge prematurely when the search space is complex, which can lead to optimal energy distribution among SNs. The algorithm for PSO is as follows:

```
Initialize swarm particles with random position and velocity
Compute fitness function for each particle
Set personal best and global best positions
Repeat until stopping condition is not fulfilled
  For each particle do
    Update particle position and velocity based on pbest and gbest
    Compute fitness function for each particle
    Update pbest if current fitness is better
  End for
  Update gbest among all particles
End while
Return gbest solution
```

Ant Colony Optimization

ACO is based on the foraging behavior of ants in the real world in which the ants deposit pheromones to indicate the optimum paths between their nest and food sources. In the computational model, artificial ants build solutions step by step by selecting paths according to pheromone concentration and additional heuristic factors [35]. The intensity of the pheromones is updated according to the quality of the solutions, allowing better paths to become more prominent over time. ACO is especially appropriate in optimization of routing of WSNs, which can adaptively find energy efficient routes. However, in large network with dynamic topology, ACO offers slower convergence and higher computational cost. The algorithm for ACO is as follows:

Assign initial pheromone levels on all routes
Repeat While stopping condition do not satisfied
  For each ant
    Generate a solution using heuristic information and pheromone

$$\boldsymbol{P_{ij}^{k}} = \frac{(\boldsymbol{\tau_{ij}})^{\boldsymbol{\alpha}}(\boldsymbol{\eta_{ij}})^{\boldsymbol{\beta}}}{\sum \boldsymbol{l} \in \boldsymbol{allowed}(\boldsymbol{\tau_{il}})^{\boldsymbol{\alpha}}(\boldsymbol{\eta_{il}})^{\boldsymbol{\beta}}} \quad \textbf{(1)}$$

Where:

- τ_{ij}= pheromone intensity
- $\eta_{ij} = \frac{1}{d_{ij}}$ which is defined as problem specific visibility
- α= pheromone influence parameter
- β= problem specific influence parameter

    Evaluate fitness function
  End for
  Update the value of pheromone based on best solution
  Evaporate pheromone to avoid stagnation
End while
Return best solution

Genetic Algorithm

GAs are evolutionary methods of optimization that rely on the theory of natural selection and the genetics. A set of candidate solutions is developed by a series of generations with the help of selection, crossover, and mutation mechanism [36]. Each individual solution is computed using a fitness function (FF) that measures its quality. Solutions with better fitness values have a higher chance of being survived and reproduced to form the new solutions in subsequent generations. In WSN optimization, GA has been used cluster formation and routing decisions. While GA provides strong global search capability and avoids local optima, it requires to be carefully tuned and incurs high computational cost, which makes it less suitable for energy-constrained sensor nodes. The algorithm for implementing GA is as follows:

Randomly initialize the population

Calculate FF of each individual

Repeat while stopping condition is not satisfied

  choose parents according to fitness value

  For two parents, apply crossover to generate offspring

  Apply mutation to maintain diversity

  Evaluate offspring fitness

  Form new population using selection strategy

End while

Return best individual

Differential Evolution

DE is a straightforward but effective evolutionary approach which is developed for continuous optimization issues. DE creates new candidate solutions by combining the weighted difference between randomly selected population members and existing solutions. During each iteration, a mutant vector is created by adding the weighted difference between two individuals to third individual [37]. A trial solution is then obtained by performing a crossover operation of this mutant vector and the target vector. This method enhances the exploration capability of the search region. DE has been applied to WSNs for energy optimization, clustering, node deployment and optimal route selection. While DE provides strong results in exploration but its utility in dynamic WSN situations may be limited by its convergence rate and sensitivity to control parameters. The algorithm for DE is as follows:

1. Initialize the population and compute the FF for each candidate in population.
2. Repeat the following steps for each candidate until the stopping condition is not satisfied:
   - Create a mutant vector using the difference between selected members.
   - Apply a crossover operation to produce a trial vector.
   - Compare the trial vector with the target vector and retain the one with the better fitness value.

   End for

   End while

Return best solution

Artificial Bee Colony

ABC algorithm is inspired by the foraging behavior of honeybees. In this optimization technique, the bee population is categorized into three main groups: employed bees, onlooker bees, and scout bees and each of them performs certain tasks related to exploration and exploitation of food sources. The quality of food sources represents the fitness value of a candidate solution [38]. In WSNs, ABC has been applied to clustering and routing problems. While ABC demonstrates strong exploration capability, it often exhibits weak exploitation in later stages, which may result in slower convergence toward optimal solutions. The algorithm for ABC algorithm is as follows:

Initialize the food sources randomly

Calculate nectar fitness function

Repeat the steps below until the stopping condition do not met

- Employed bees explore neighboring food sources
- Onlooker bees choose the food source on probability basis
- Scout bees replace abandoned food sources

Update best food source

End while

Return best solution

Firefly Algorithm (FA)

FA technique is motivated by the flashing behavior of fireflies, where individuals are attracted to others with higher brightness. The attractiveness of a firefly is directly related to the quality of its solution and diminishes as the distance between fireflies increases. This distance-dependent mechanism allows fireflies to move toward promising area of the search region [39]. FA has been used in WSNs for conserve energy and cluster head selection. However, its performance degrades in high-dimensional optimization problems, and it may find it hard to maintain solution diversity over time. The algorithm for FF approach is as follows:

Initialize fireflies randomly

Evaluate brightness of each firefly

Repeat until stopping condition do not filled

For each firefly i and j do

If brightness(j) > brightness(i) then

Move firefly i toward firefly j

End if

End for

End for

Update brightness values

End while

Return brightest firefly

Grey Wolf Optimization

GWO is based on the hunting behavior of grey wolves and its leadership hierarchy. The population is categorized into omega, delta, beta and alpha wolves, where the alpha wolf represents the optimal solution. Other wolves change their locations based on the hierarchy of leadership. GWO has attracted attention in the area of WSN optimization due to its balanced between exploitation and exploration behavior [40]. It has been used in solving clustering and routing problems, though it might not respond in sensor networks that have been densely deployed. In such environments, the search process can sometimes stagnate or converge prematurely, limiting its ability to consistently identify the best possible solution. The algorithm for GWO technique is as follows:

Randomly initialize the wolf population

Determine the alpha, delta and beta wolves

Repeat until the stopping criteria is not satisfied

For each wolf in population

Adjust their locations based on alpha, delta and beta

End for

After updating all wolves, adjust the position of beta, delta, and alpha leaders accordingly.

End while

Return alpha wolf position as the best solution

Whale Optimization Algorithm

The WOA is motivated by the bubble-net feeding behavior of humpback whales. WOA switches between encircling prey and spiral position to update mechanisms to ensure the balance exploitation and exploration phase. The encircling behavior allows whales to move toward the optimized solution identified so far, while the spiral movement simulates the bubble-net hunting pattern used by whales [41]. A random search mechanism is also incorporated to maintain exploration capability. WOA has been used for CH selection and route optimization in WSN. Despite its strong global search capabilities, its exploitation phase may converge slowly towards optimized solution in dynamic network environments. The algorithm for WOA is as follows:

Randomly initialize the whale population

By using fitness function, choose the best whale

Repeat the steps below until the stopping condition do not satisfied

For each whale do

- Modify its position using either the encircling strategy or the spiral movement approach.
- After updating all whales, reassess their fitness and determine the current best whale.

Once the stopping criterion is satisfied, return the location of the optimal whale as the final optimal solution.

Salp Swarm Algorithm

The chain-like movement of salps in the ocean served as the model for the Salp Swarm Algorithm. The population categorized as followers and leaders, with followers updating their positions in response to the leaders' guidance of the search. SSA is particularly effective in maintaining exploration ability during the early stages of optimization. In WSNs, due to its simple design and low computational complexity, SSA has been applied for energy optimization and routing problems [42]. However, although SSA is easy to implement, it may experience instability and decreased performance when network circumstances change quickly. The algorithm for SSA is as follows:

1. Randomly initialize the population of salps.
2. Allot one Salp as the leader and the remaining as followers.

- Repeat until the stopping condition is satisfied:
- Update the leader's location in the direction of the food source (optimized solution).
- Adjust the followers' positions according to the chain movement mechanism.
- Re-evaluate the solutions and update the solution if an optimal candidate solution is found.Top of FormBottom of Form

End while

Yellow Saddle Goatfish Optimization (YSGO)

Yellow Saddle Goatfish Optimization is motivated by the cooperative hunting behavior of yellow saddle goatfish, where individuals take on different roles to trap prey. The algorithm dynamically assigns agents as chasers or blockers which enables effective exploration of the search area while refining the high-quality solutions. Through iterative role updates and fitness evaluation, the algorithm gradually improves the quality of solutions [43]. In WSN applications, YSGO has been successfully used for cluster head selection by dynamically adjusting clusters to balance the load and extend network lifespan and energy aware routing by choosing nodes with high residual energy and minimal distance. By incorporating residual energy and communication distance into the fitness function, YSGO ensures balanced energy usage and avoids premature node failure. The pseudocode of YSGO is as follows:

1. Randomly generate the population
2. Evaluate individuals as blockers or chasers by using the fitness function.
3. Repeat while stopping condition not met

- Chasers search widely for promising solutions, while blockers restrict movement to guide the search direction.
- Determine each goatfish's fitness value and interchange chaser and blockers roles dynamically
- Update the value of optimal solution

End while

4. **Finally, return the best solution**

YSGO has proven the promising results in resolving challenging optimization issues, particularly in network-based applications.

Pelican Optimization Algorithm

The POA is a metaheuristic approach that simulates the hunting behavior of pelicans, which involves exploration through movement toward prey and winging in water surface for exploitation. This two-stage process helps the algorithm move quickly toward high-quality solutions while searching the search region effectively [44]. In WSNs, POA has been used for routing optimization because of its fast convergence speed and strong local search ability. It can efficiently refine solutions once a promising region is found. However, POA might not provide enough exploration in large-scale networks when utilized in isolation which can limit its ability to consistently select the global optimized solution. The procedure of POA is as follows:

1. Initialize the population size and iterations count.
2. Compute the fitness value for finding route
3. Repeat the stopping condition until not fulfilled
   - Perform Exploration phase
   - Perform exploitation through surface-based refinement
   - Update the member population

   End while
4. Update the optimized candidate solution.

4. Proposed Hybrid YSGPO Model

Energy efficiency and overall network lifespan are two critical performance factors in sensor network. Although several metaheuristic techniques have been suggested in past to address cluster head selection and routing optimization but many of these approaches suffer from premature convergence, limited exploration capability, or inefficient energy balancing among sensor nodes. To minimize these limitations, this research work introduces a hybrid optimization framework that combines the advantages of YSGO and POA. The hybrid YSGPO framework, combines the strong exploration capability of YSGO with the quick exploitation ability of POA, thereby enhancing the overall network performance. In this proposed technique, the selection of optimized CHs is done by YSGO algorithm whereas the efficient routing paths between the selected CHs and the BS are chosen by POA. By utilizing the advantages of both algorithms, this hybridization increases stability, prolongs network lifetime, and improves energy efficiency. In energy-constrained WSN situations, the hybrid YSGPO approach outperforms than the individual algorithms.The Flowchart of suggested methodology is as follows:

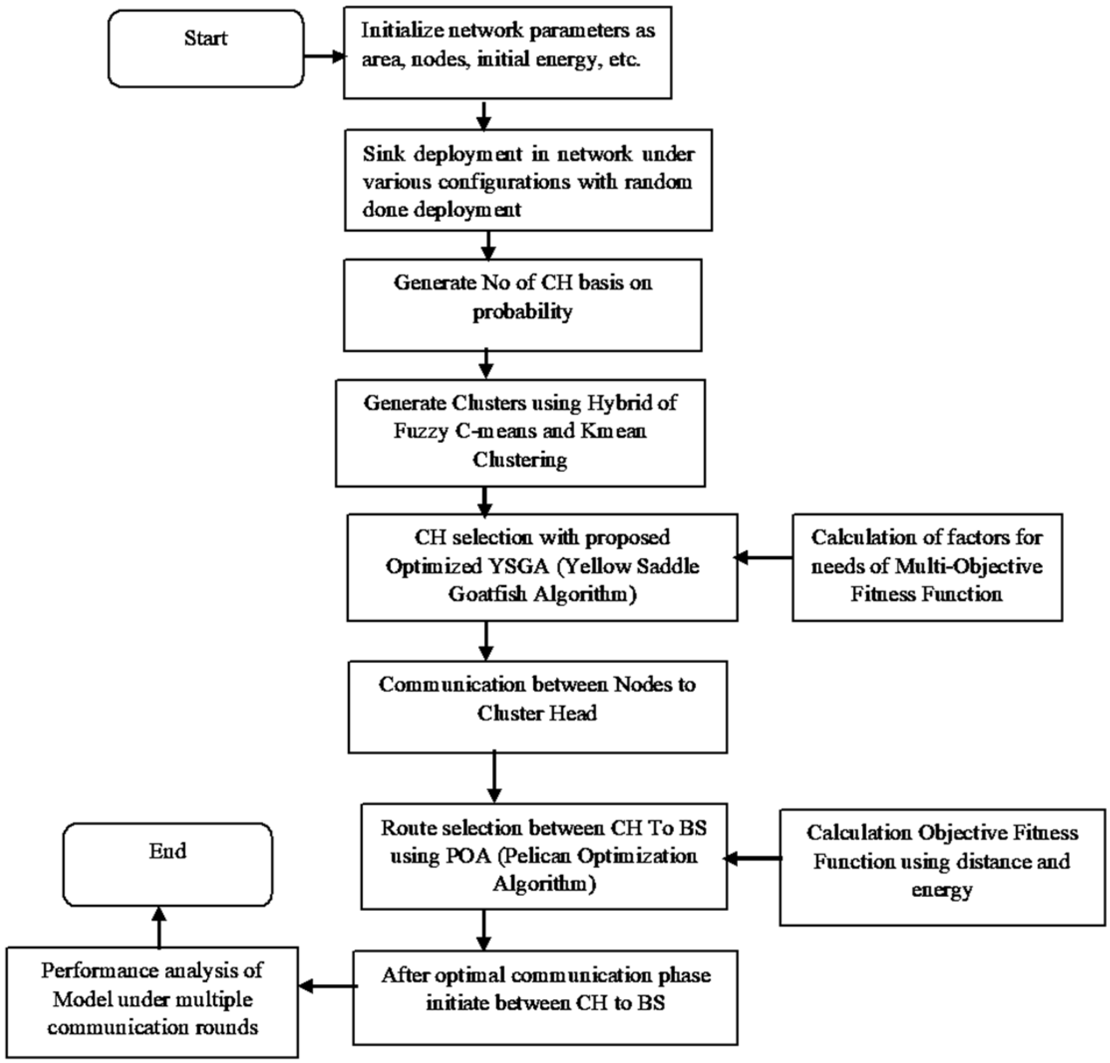

Figure 2: Flowchart of Hybrid YSGO–POA Methodology

4.1 Network Model and Assumptions

In this work, for the deployment of SNs following assumptions were considered:

1. A fixed number of SNs are randomly deployed in sensing region.
2. All SNs are stationary after deployment and have limited and identical initial energy.
3. BS is situated in the middle of the sensing area and data is send to base station through CHs.
4. Nodes communicate using a multi-hop or cluster-based communication strategy.
5. Data is aggregated at cluster heads before transmitted to base station.

4.2. Energy model

In this research work, a simplified first-order radio model is used to estimate the energy required for data transmission by the transmitter and receiver. The energy required to transmit and receive p-bit packets over a distance d1 is evaluated using equation (2) and (3).

$$E_t(i,e) = \begin{cases} pE_{elec} + pE_{fsp}d1^2, d1 < d_{t1} \\ pE_{elec} + pd1^4, d1 \geq d_{t1} \end{cases} \quad (2)$$

$$Er(l1) = pE_{elec} \quad (3)$$

Threshold distance d_{t1} is calculated by using equation 4.

$$d_{t1} = \sqrt{\frac{E_{fsp}}{E_{amp}}} \quad (4)$$

Where,

Eelec is energy consumed during data transmission.
E_{fsp} is energy required for free space.
E_{amp} is the amplification factor.
d1 is distance between source and destination.

4.3 *Fitness function for CH selection*

An effective FF is essential for identifying optimal cluster heads in WSNs. Here, the FF considers multiple parameters to maintain balanced energy usage and efficient communication between SNs.

The overall FF is defined as:

$$\boldsymbol{FF = w_1F_1 + w_2F_2 + w_3F_3} \quad \textbf{(5)}$$

Where:

- F_1= residual energy factor
- F_2= distance factor
- F_3= node density factor
- w_1, w_2, w_3= weighting coefficients

The aim of this research is to maximize residual energy and cluster stability while minimizing communication distance, thereby extending the network lifetime.

4.4 *Hybrid YSGPO Optimization Process*

The proposed hybrid framework integrates both algorithms sequentially.

1. YSGO performs global exploration to find promising regions in the search region.
2. POA performs local exploitation to refine the candidate solutions obtained from YSGO.
3. The hybrid process repeats iteratively until the stopping condition is reached.

The pseudocode of hybrid YSGPO algorithm is as follows:

1. Initialize WSN nodes and initialize population
2. Compute fitness function of each candidate.
3. Apply YSGO exploration phase

Use equation 6 for chaser fish:

$$y_{chaser} = y_{chaser} + \boldsymbol{\alpha 1} \oplus \boldsymbol{Levy}\ \boldsymbol{\lambda}(\mathbf{1}) \quad \mathbf{(6)}$$

$$Where, \boldsymbol{\lambda}1 = 0 < \boldsymbol{\lambda}1 \leq 2\ and\ \alpha 1 = 1$$

For blocker fish use equation .

$$y_{blocker} = \boldsymbol{D_g} * \boldsymbol{e^{b\rho}} * \boldsymbol{Cos2\pi\beta} + y_{chaser} \quad \mathbf{(7)}$$

$$\boldsymbol{D_g} = \boldsymbol{r} * \boldsymbol{y}_{chaser} - \boldsymbol{cy}_{blocker}$$

where r values lies between $[-1,1]$

5. Select best candidate solutions.
6. Apply POA exploitation phase using equation 8:

for j = 1 to m

$$X_{ij} = x_{ij} + R * (1 - \frac{t}{T}) * (2 * \text{rand} - 1) * x_{ij} \quad (8)$$

$$where\ R\ is\ having\ a\ constant\ value\ i.e.\ 0.2$$

End for.
Update the value of member in population using equation 9

$$X_i = \begin{cases} X_{ij}, & fitness < Cal.fitness \\ X_i, & else \end{cases} \quad (9)$$

Update position of each node
Refine cluster head configurations

7. Update global best solution.
8. Repeat until maximum iterations are reached.
9. Analyze the overall performance of network.
10. Finally, return optimized clustering and routing configuration

Below table shows the detailed comparison of various optimization algorithms that are discussed above for WSNs clustering and routing.

Table 1: Comparison of Optimization Algorithms for WSN Clustering and Routing

Algorithm	**Solution Representation**	**Main Operators Used**	**Key Control Parameters**	**Handling of Node Deployment**	**Suitability for Clustering & Routing**	**Main Advantages**	**Main Limitations**
Genetic Algorithm	Solutions are encoded as chromosomes representing node selection or routes	mutation, crossover, and Selection operators	Size of population size, crossover and mutation rate	Works best when network topology is mostly static	Applicable to both clustering and routing but computationally demanding	Best global search capability and reduces local optima	High processing cost and relatively slow convergence

Ant Colony Optimization	Routing paths represented using pheromone trails	Pheromone updating, evaporation, and probabilistic path construction	Pheromone importance, evaporation rate, number of ants	Can adapt to topology changes to some extent	Very effective for routing optimization	Finds adaptive and efficient paths	Slow convergence and communication overhead
Particle Swarm Optimization	Each particle represents a candidate clustering or routing solution	Position and velocity updating based on pbest and gbest	Inertia weight and acceleration coefficients	Suitable for randomly deployed nodes	Commonly used for cluster head selection and routing	Fast convergence and easy implementation	May converge prematurely in complex scenarios
Differential Evolution	Solutions represented as vectors	Mutation, crossover, and selection between candidate solutions	Mutation factor and crossover probability	Works well in static node placement	Suitable for clustering optimization	Good exploration ability	Sensitive to parameter settings and moderate convergence speed
Artificial Bee Colony	Food sources correspond to candidate solutions	Employed, onlooker, and scout bee search processes	Number of bees and abandonment limit	Effective in uniformly deployed networks	Applicable to clustering and routing problems	Strong exploration and simple structure	Weak exploitation in later iterations
Firefly Algorithm	Each firefly position represents a solution	Movement toward brighter fireflies	Attractiveness factor and light absorption coefficient	Works moderately well under varied deployments	Often used for clustering optimization	Flexible search mechanism	Performance degrades in high-dimensional problems
Grey Wolf Optimization	Wolf positions correspond to solutions	Position updates guided by alpha, beta, and delta wolves	Population size and control coefficients	Handles random deployments efficiently	Suitable for clustering and routing tasks	Balanced exploration and exploitation	May stagnate in dense networks
Whale Optimization Algorithm	Whale positions represent candidate solutions	Encircling and spiral position updating mechanisms	Spiral constant and coefficient parameters	Suitable for moderate deployment densities	Used in cluster head selection and routing	Good global search behavior	Slower convergence in exploitation phase
Salp Swarm Algorithm	Salp chain positions represent solutions	Leader and follower position updating	Population size and control coefficients	Works under moderate network densities	Applicable for routing and clustering	Simple implementation	Performance may fluctuate in dynamic networks

Yellow Saddle Goatfish Optimization	Agents represent candidate cluster configurations	Role switching between chasers and blockers	Population size and role switching strategy	Effective in dense network deployments	Highly suitable for cluster head selection	Good balance between exploration and exploitation, improves energy distribution	Convergence speed is moderate
Pelican Optimization Algorithm	Pelican positions denote candidate routing solutions	Exploration dives and exploitation refinements	Population size and exploitation parameters	Suitable for static or moderately dynamic deployments	Very effective for routing optimization	Fast convergence and strong local search	Limited exploration when used alone
Hybrid YSGPO	Combined solution representation for clustering and routing	YSGO-based exploration combined with POA exploitation	Parameters inherited from both algorithms	Suitable for both static and dynamic deployments	Optimizes clustering and routing simultaneously	Provides best energy efficiency, stability, and lifetime performance	Slightly higher computational complexity

5. Simulation Setup

For performance analysis, a simulation environment with 100 SNs is distributed randomly in a 100 × 100 m² sensing region. Each SN was initialized with same energy, and the BS was situated in the middle of the sensing region to ensure balanced communication distance across the network. This model predicts the energy required for communication based on message size and transmission distance. The simulation was executed over multiple rounds to guarantee a reliable assessment of overall performance of network in terms of network lifetime, throughput, residual energy, stability period and convergence speed. The parameters taken into consideration for simulation are listed in Table 3:

Table 2: Simulation setup and parameter values

Parameter	Value
Network Area	100 × 100 m²
Count of SNs	100
Initial Energy	1 Joule
Base Station Location	Center of the field
Radio Model	First Order Energy Model
Packet Size	4000 bits
Simulation Rounds	2000

5.1 Simulation Findings

Residual Energy

This metrics indicate the average energy remaining after fixed cycles. Figure 2 illustrates the comparison of average residual energy of network under various optimization techniques. Traditional techniques like GA and ACO are faster to reduce the energy usage since the amount of energy required by the SNs is unevenly distributed. Energy consumption is somewhat improved by PSO, DE, ABC, and FA; nonetheless, energy still depletes more quickly in nodes that are used extensively utilized. Other algorithms such as GWO and WOA are more energy efficient because of the enhanced search property in the process of forming the clusters and routing. By dynamically modifying node roles, YSGO improves performance and contributes to a more even distribution of energy usage. POA chooses more dependable and shorter routes, it also efficiently conserves energy. Throughout the simulation, the suggested Hybrid YSGPO algorithm has the maximum residual energy. This enhancement results from the combined optimization of clustering and routing decisions, which minimizes the amount of redundant transmissions and balances energy consumption among nodes.Bottom of Form

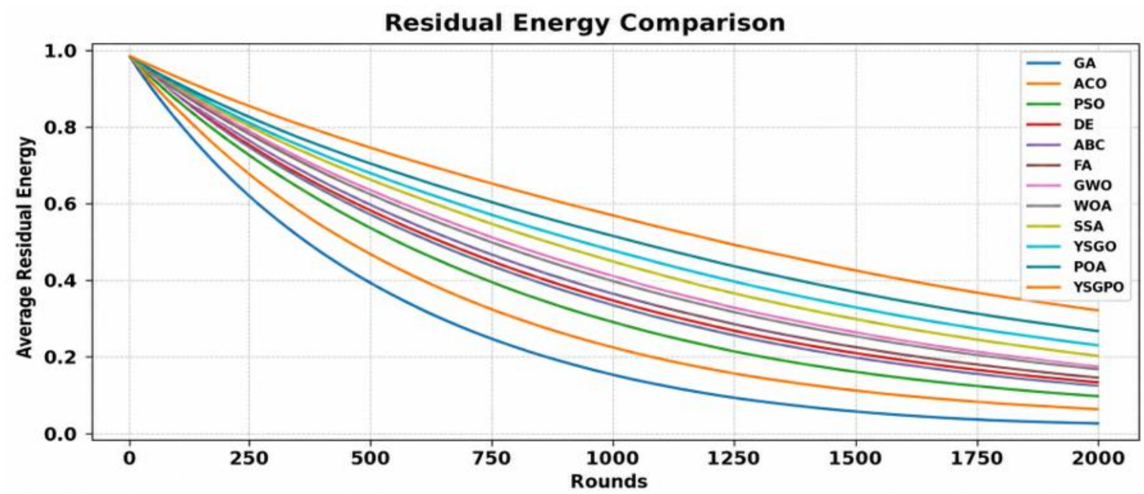

Fig. 2: Average residual energy comparison of optimization algorithms in WSN.

Alive Node Analysis

Figure 3 depicts the number of alive nodes with time, which directly measures network lifetime. This metric is commonly used to evaluate network lifetime and fault tolerance. Due to unequal load distribution, GA and ACO exhibit early node death. Although PSO and DE have networks with a moderate lifespan, they experience early convergence in subsequent rounds. ABC and FA provide slightly improved stability, but node mortality increases faster at mid-simulation. GWO, WOA, and SSA have longer stability duration due to improved exploitation mechanisms. Their adaptive search mechanisms prevent excessive burden on individual nodes. YSGO and POA further reduces node death and maintain a higher number of alive nodes compared with conventional algorithms due to their better energy-aware routing. The Hybrid YSGPO algorithm ensures the highest number of alive nodes and maintains the largest number of operational nodes throughout the simulation, significantly extending network lifetime. This indicates superior cluster balancing and less transmission burden on individual nodes.

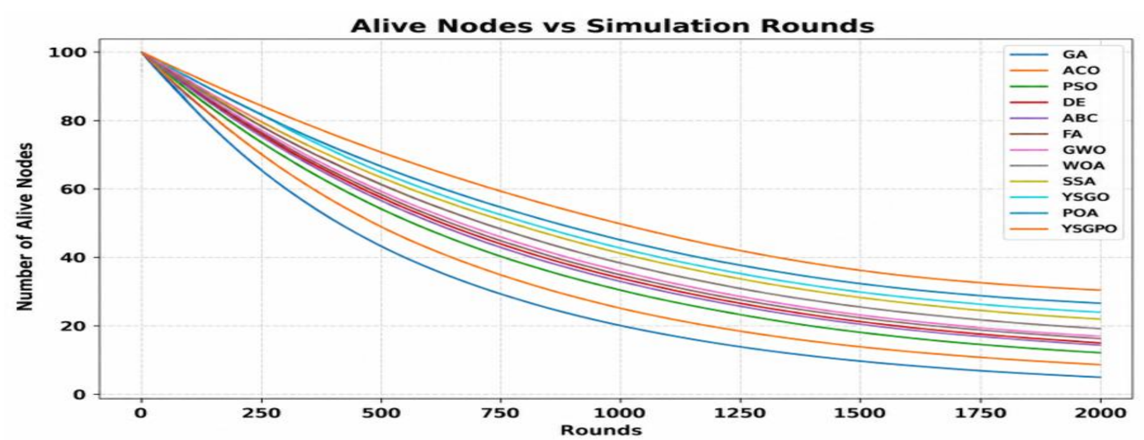

Fig. 3: Alive node analysis comparison of optimization algorithms in WSN.

Stability Period

A longer stability period improves the reliability of sensor network. Figure 4 illustrates the stability period which defines the time from the beginning of network operation until the initial node dies. Early node failure in GA and ACO is caused by the uneven distribution of load on the chosen cluster heads. PSO, DE, ABC and FA provide a moderate survival of the node and reduces communication cost, whereas GWO, SSA and WOA prolong node failure through better selection of cluster heads and provides balance between exploration and exploitation during optimization. YSGO enhances the stability period through rotating the cluster head responsibilities, depending on energy levels. POA achieve longer stability periods because of their adaptive search strategies and improved energy management.The Hybrid approach shows the longest stability period among all techniques because by combining efficient cluster head selection with optimized routing, energy usage is better balanced which allows nodes to remain active for a long duration and preventing nodes with low energy from being overloaded. This indicates that the network remains fully operational for a longer period.

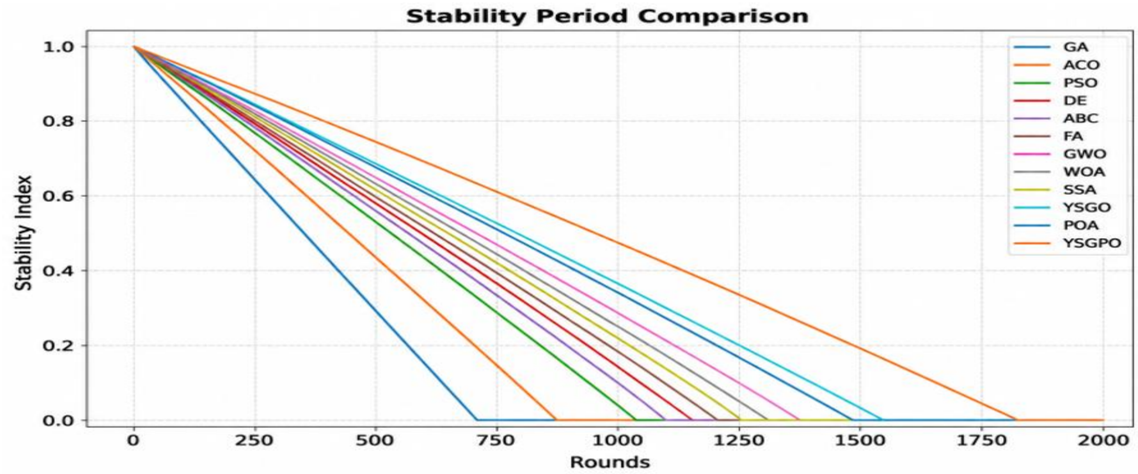

Fig. 4: Stability period comparison of optimization algorithms in WSN.

Throughput

One of the most important measures of communication reliability is throughput. It defines the rate at which data is correctly received at the receiver over the network during a specific time interval. Figure 5 shows that higher throughput means better network performance. The hybrid YSGPO algorithm achieves the highest throughput due to reduced packet loss and stable routing paths whereas, traditional algorithms experience frequent link failures caused by uneven energy depletion. Some methods that suffer from early node failures or unstable routing paths show lower throughput over time. Algorithms such as FA, PSO, DE, and GWO provide moderate improvements in packet delivery due to more stable communication paths. The swarm-based algorithms like WOA, and SSA further enhance packet delivery by maintaining stable communication paths and balanced energy utilization.YSGO and POA achieves higher throughput because their optimization strategies effectively reduce packet loss and transmission delays.. The Hybrid YSGPO algorithm delivers the highest throughput since optimized routing and stable clustering reduce packet loss and maintain communication efficiency throughout network operation. Top of Form**Bottom of Form**

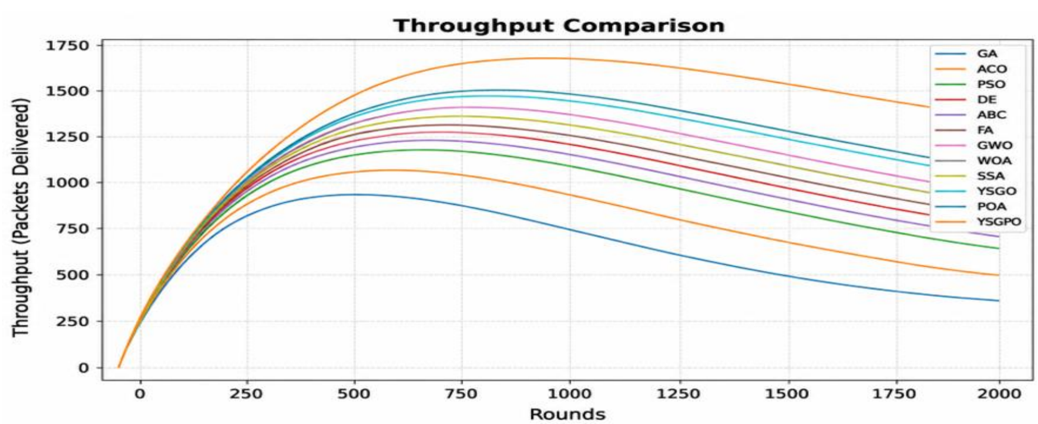

Fig. 5: Throughput comparison of optimization algorithms in WSN.

Convergence Speed

Convergence speed indicates the number of iterations required to reach nearly optimized solutions and its analysis in figure 6 demonstrates that PSO converges faster than GA and ACO because particles continuously update their positions using individual and global best experiences. However, PSO may suffer from premature convergence when particles become concentrated around local optima. The GA demonstrates the slowest convergence because its evolutionary operators require several generations to refine candidate solutions. Similarly, ACO shows gradual improvement since pheromone updates require multiple iterations before high-quality paths are reinforced. Algorithms such as DE, ABC, and FA exhibit more stable convergence patterns due to their ability to maintain population diversity while progressively improving solution quality. GWO, WOA, and SSA achieve faster convergence as these algorithms effectively balance exploration and exploitation through adaptive position-update mechanisms, allowing them to reach high-quality solutions with fewer iterations. YSGO and POA outperform most conventional approaches. YSGO provides strong global exploration capabilities, enabling the algorithm to avoid local optima, whereas POA offers efficient local exploitation, resulting in accelerated fitness improvement. The proposed YSGPO algorithm achieves the highest fitness values throughout the optimization process and demonstrates the fastest convergence rate. The superior performance is attributed to the integration of YSGO's exploration mechanism with POA's exploitation strategy. During the early stages of optimization, YSGO explores diverse regions of the search space, while POA intensifies the search around promising solutions in later iterations. This optimized behavior reduces the probability of premature convergence and enhances the ability to identify globally optimal solutions.

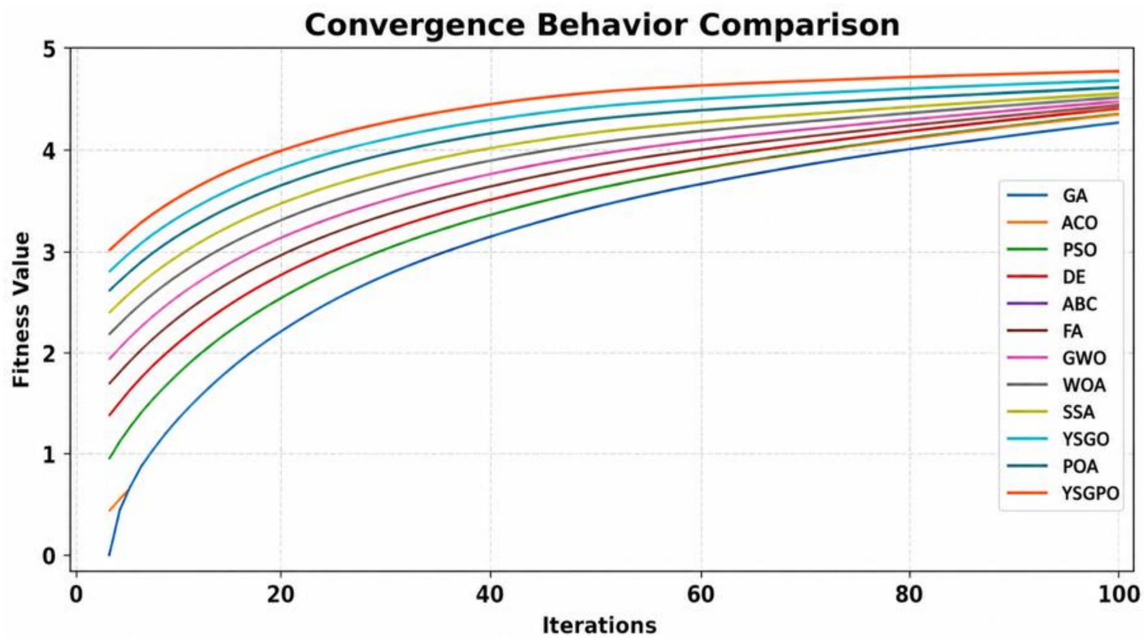

Fig. 6: Convergence speed analysis of optimization algorithms in WSN.

5.3 Result and Discussion

The Hybrid YSGPO approach consistently performs better than the individual algorithms across all performance measures. The findings show that the residual energy of SNs increases by about 28%**,** which implies more efficient energy usage during cluster head selection and network communication. Furthermore, the average life of the network increases by almost 32%, which indicates that the suggested approach successfully postpones node failures and sustains network functionality for an extended period of time. The stability period is increased by approximately 26%, which implies that the time until the first node dies is increased, which improves the reliability of sensing operations. Additionally, the proposed technique increases throughput by approximately 21%, which indicates the successful delivery of more data packets to the base station. Lastly, the rate at which the optimization process converges is also enhanced by approximately 18 percent which allows the algorithm to find optimal or near-optimal solutions at a faster rate as compared to the traditional methods. All these enhancements prove that the suggested hybrid approach is effective in energy efficiency and overall WSN performance. Thus, the suggested hybrid algorithm is appropriate for large-scale and long-lasting deployment scenarios since it offers a reliable and energy-efficient solution for WSN optimization. Below table shows the detailed analysis of all the optimization techniques on the basis of performance metrices:

Table 3: Evaluation of Various Optimization Techniques Based on Performance Measures

Algorithm	**Algorithm Type / Key Characteristic**	**Energy Efficiency**	**Stability Period**	**Network Lifetime**	**Throughput**	**Convergence Speed**	**Computational Complexity**	**Remarks**
GA	Evolutionary search using genetic operators	Moderate	Low	Low	Low	Medium	High	Good global search but computationally expensive for WSN nodes
ACO	Swarm intelligence using pheromone-based routing	Moderate	Moderate	Moderate	Moderate	Slow	High	Strong routing adaptability but slow convergence
PSO	Swarm intelligence using velocity-position updates	Moderate	Moderate	Moderate	Moderate	Fast	Low	Simple and fast but may converge prematurely
DE	Evolutionary optimization using vector differences	Good	Moderate	Moderate	Moderate	Medium	Medium	Good exploration ability but parameter sensitive
ABC	Bee foraging behavior-based optimization	Moderate	Moderate	Moderate	Moderate	Slow	Medium	Strong exploration but weaker exploitation
FA	Attraction-based swarm movement	Moderate	Moderate	Moderate	Moderate	Medium	Medium	Simple structure but struggles in complex spaces
GWO	Leadership-based swarm hunting behavior	Good	Good	Good	Good	Medium	Low	Balanced search capability and stable performance
WOA	Whale bubble-net feeding behavior	Good	Moderate	Moderate	Moderate	Slow	Low	Good exploration but slower exploitation phase
SSA	Chain movement-based swarm optimization	Moderate	Low–Moderate	Moderate	Moderate	Medium	Low	Simple model but sensitive to dynamic changes
YSGO	Role-switching cooperative hunting strategy	High	High	High	High	Medium	Medium	Excellent cluster head selection and energy balance
POA	Pelican hunting behavior with strong exploitation	High	Moderate	Moderate–High	High	Very Fast	Low	Very fast convergence but limited exploration

Hybrid YSGPO	Combined clustering (YSGO) and routing (POA) optimization	Very High	Very High	Very High	Very High	Fast & Stable	Medium	Best overall performance due to balanced exploration and exploitation

6. Conclusion and Future Work

A thorough and organized comparison of metaheuristic optimization methods for energy-efficient WSNs is offered in this research work. According to simulation findings, classical optimization approaches like PSO and ACO can enhance the overall performance of the network over baseline protocols but are unstable and have uneven energy distribution among nodes. Both YSGO and POA will outperform classical methods in terms of better exploration and convergence characteristics. In terms of energy efficiency, network lifespan, and stability, the hybrid YSGPO framework performs better than classical and swarm-based algorithms, which only offer partial solutions. The Hybrid YSGPO algorithm consistently outperforms individual optimization techniques across all investigated metrics. The suggested algorithm, as opposed to PSO, WHO, ACO, GA, YSGO and POA, offers a longer network lifetime, which is a range of 20-35 percentage, and an increased throughput as well as stability. Adaptive role switching and exploitation of routes have been linked to these improvements. Through the use of POA exploitation power and YSGO exploration capacity, the hybrid algorithm produces better outcomes on all metrics. Higher throughput, maximum network lifetime, increased energy efficiency, and greater network stability are the results of its integrated clustering and routing optimization. This comparative analysis shows that modern algorithms that are motivated by nature are able to enhance WSN optimization. Specifically:

- YSGO effective exploration prevents premature convergence.
- POA strong exploitation enhances solution refinement.
- Hybrid YSGPO improves both stability and convergence.
- Hybrid approach ensure balanced energy distribution and extended network lifetime.

Future research may extend the YSGPO framework to Internet of Things (IOT) enabled applications, where SNs and sink nodes can dynamically change their positions. In addition to minimizing energy consumption, future versions of YSGPO may simultaneously consider latency, packet delivery ratio, reliability, coverage, and Quality of Service (QoS) requirements.

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