Employing nature-inspired computing techniques for energy optimization of Underwater Wireless Sensor Networks

Bhumika Khatwani, Nandini Jain, Ketaki Gharal, Preeti Gupta, Aditya Kasar
SVKM's Narsee Monjee Institute of Management Studies, Navi Mumbai
Maharashtra, India
School of Technology Management and Engineering
bhumikakhatwani03@gmail.com, jain.nandini1909@gmail.com, ketakigharal2501@gmail.com, preeti_i@rediffmail.com, kasar@gmail.com

***Abstract*— Underwater wireless Sensor Networks (UWSNs) are used for communication in underwater environment. These are also responsible for monitoring pollution levels, underwater ecosystems etc. Underwater military surveillance is a flourishing application of UWSNs where energy efficiency remains a critical challenge due to high signal attenuation, dynamic environmental conditions, and the limited power capacity of underwater sensor nodes. This research uses optimization strategies and techniques to lower energy usage while maintaining efficient data transfer to address these problems. Evolutionary Algorithmic Strategies which include Particle Swarm Optimization (PSO), Differential Evolution (DE), Artificial Bee Colony (ABC), and Glowworm Swarm Optimization (GSO) are employed in this research paper for dynamic transmission power control and optimal routing. As an alternative optimization approach, this paper also explores usage of simplex method for minimizing energy usage. It provides a mathematical framework for efficient energy resource allocation and improved network performance. A real-world sensor data (temperature, conductivity, pH, and dissolved oxygen) is used to compare these techniques so as to determine their effectiveness in optimizing transmission power and routing paths. The results of this research contributes to the development of energy-efficient UWSNs deployment strategies for underwater military applications, with potential benefits for long-term surveillance and operational sustainability.**

***Index Terms*— Underwater Wireless Sensor Networks (UWSNs), Energy Optimization, Evolutionary Algorithms, Simplex Method, Particle Swarm Optimization (PSO), Differential Evolution (DE), Artificial Bee Colony (ABC), Glowworm Swarm Optimization (GSO), Underwater Surveillance**

I. INTRODUCTION

Underwater Wireless Sensor Networks (UWSNs) are broadly used in environmental monitoring, military surveillance, and checking pollution levels in water. However, their performance is limited by energy constraints, as sensor nodes operate on batteries that are difficult to replace, especially in underwater environments. High signal attenuation, environmental variability, and inefficient routing lead to excessive power consumption, reducing the network's lifespan. Optimizing energy usage is crucial for ensuring long-term, reliable data transmission.

Sensor nodes monitor changes in salinity, temperature, and conductivity to detect unauthorized activity. However, maintaining long-term surveillance is challenging due to limited energy availability and harsh underwater conditions.

- High Signal Attenuation – Water weakens signals, requiring higher transmission power.
- Dynamic Environmental Conditions – Salinity, temperature, and pressure variations impact communication.
- Network Instability – Underwater currents make sensor nodes change location, necessitating adaptive routing.
- Limited Bandwidth & High Latency – Reduced data transmission impacts real-time monitoring.

To overcome these issues, this study utilizes evolutionary optimization algorithms for dynamic transmission power control and optimal routing:

- Particle Swarm Optimization (PSO) – Determines energy-efficient paths through bird flocking behavior simulation.
- Differential Evolution (DE) – Adjusts transmission power dynamically to minimize energy consumption.
- Artificial Bee Colony (ABC) – Explores optimal energy-efficient routing through swarm intelligence.
- Glowworm Swarm Optimization (GSO) – Balances energy consumption across nodes to extend network lifespan.

These algorithms adapt to environmental variations, minimize power usage, and prolong network lifetime, making them well suited for underwater military and environmental applications. While existing research evaluates nature-inspired techniques individually, this research provides comparative analysis of already established energy optimization techniques. It examines their effectiveness in reducing energy consumption in UWSNs to identify the most efficient approach.

The structure of the paper is as follows: Section II provides details on the literature review. Section III has research questions followed by Hypothesis in Section IV. Section V explains about the algorithms used for energy optimization. In Section VI the details about experimental results have been provided; followed by conclusions, abbreviations and references.

II. LITERATURE REVIEW

A. Background

Evolutionary strategies are techniques concerned with the optimization of a problem using genetic operators. Evolution strategy is based on Darwin's theory of evolution, and is also a type of Evolutionary algorithm, while the methods involved in EAs are traditional, ES on the other hand provides better solution for continuous optimization problems. Swarm intelligence algorithms like Particle Swarm Optimization, Glow-worm swarm Optimization and Artificial Bee Colony are inspired by natural swarm behavior like birds, insects etc. These algorithms are well suited for energy-efficient data transmission in UWSNs as SI algorithms optimizes routing paths and are designed for optimization in network topologies. Simplex method on the other hand is an Optimization technique used to solve linear programming problems to find the most optimal solution in the search space. Other than these the dataset addresses almost all important factors required for the research except for salinity [1]. Therefore, for this research salinity is calculated through a standard equation (1):

$$S = 0.008 \times C + 0.0005 \times T - 0.1 \tag{1}$$

where

$$S = \text{Salinity}$$
$$C = \text{Conductivity}$$
$$T = \text{Temperature}$$

This research focuses on finding the best possible algorithm that minimizes the energy utilized by Underwater wireless sensor nodes for data transmission. The algorithms mentioned above are used to optimize energy and are compared to show which algorithm out-performs others in the given scenario. To find the best solution, all possible areas are explored through this paper (e.g., Evolutionary strategies, Simplex method etc.).

B. Literature Review

Different datasets were analyzed in research papers which simulated under water military surveillance environment considering various parameters like salinity, pH, temperature and dissolved oxygen. Using this dataset, the most effective technique has been identified for minimizing the energy consumption in under water environment. The key area of research was clustering based optimization, where algorithms like Particle Swarm Optimization and Glowworm Swarm Optimization are used to increase efficiency and extend the lifetime of sensor networks. Clustering Algorithm groups various sensor nodes to increase routing and data transmission. Communication reliability is one of the factor which suffers from signal attenuation and multiple path propagation. Researches has explored various signals like RF, acoustic, optical to mitigate to the challenges of signal attenuation, propagation delay and interference. Energy consumption is major concern with strategy focusing in power adjustment with factors like salinity which directly influence the signal range and strength.

Despite this research the gaps remains in real time adaptability, hybrid communication, energy consumption and scalability .The Underwater environment requires lightweight , and scalable algorithms that make reliable communication by optimizing energy consumption. The research will integrate the comparison of different evolutionary algorithms finding the best algorithm that can be used for minimizing the energy consumption, which will further help to improves surveillance efficiency in underwater military environment.

III. RESEARCH QUESTIONS

1) How do different evolutionary algorithms (PSO, DE, ABC, GSO) compare in their effectiveness in reducing energy consumption for data transmission in UWSNs?
2) How does the Simplex optimization method impact energy consumption for data transmission in UWSNs?

IV. HYPOTHESIS

1) **Hypothesis:**
   Null Hypothesis: Nature-inspired computing techniques do not show significant improvement in energy consumption for data transmission in underwater wireless sensor nodes.
   Alternate Hypothesis: Nature-inspired computing techniques significantly improve the energy consumption for data transmission in underwater wireless sensor networks
2) **Hypothesis:**
   Null Hypothesis: Simplex method does not significantly minimizes the energy consumption for data transmission in Underwater wireless sensor networks.
   Alternate Hypothesis: Simplex method minimizes the energy consumption for data transmission in Underwater wireless sensor networks..

V. TECHNIQUES AND METHODS USED TO ADDRESS THE PROBLEM

A. Artificial Bee Colony Optimization

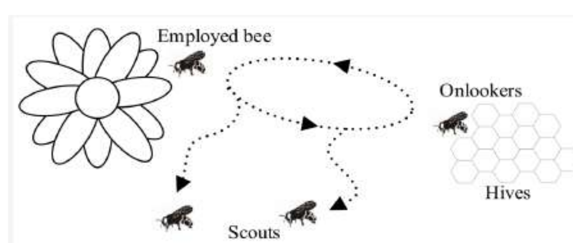

Fig. 1. Artificial Bee Colony Optimization [2]

In **Employee Bee phase** food sources are taken as a possible solution and each bee modifies an existing solution by exploring nearby sources. If new food source (solution) is better, it replaces the old one. During **Onlooker Bee phase** the bees select the most optimal solution based on its fitness and refine it. If the solution is not improving, a new random solution is introduced, during **Scout Bee phase**, and due to this phase, the algorithm does not get stuck in local minima [3]. Algorithm 1 given below shows Artificial Bee Colony algorithm used to minimize energy consumption.

Algorithm 1: ABC Algorithm

Initialization:
Initialize positions of food sources using random values.
Set Cycle = 1.
foreach *food source* i **do**
    Set C(i) = 0.
repeat
    /* Employee Phase */
    foreach *employee bee* i **do**
        Generating new solution V_{ij} in the neighborhood of X_{ij}.
        if $fit(V_{ij}) \geq fit(X_{ij})$ **then**
            Update X_{ij} with V_{ij}.
            Reset C(i) = 0.
        else
            Increment C(i).
    /* Onlooker Phase */
    Calculate probability P_i for each food source.
    foreach *food source* i **do**
        Select solution based on probability P_i.
        Generating new solution $V_{ij}^{(o)}$ in the neighborhood of $X_{ij}^{(o)}$.
        Evaluate new solution $V_{ij}^{(o)}$.
        if $fit(V_{ij}^{(o)}) \geq fit(X_{ij}^{(o)})$ **then**
            Update $X_{ij}^{(o)}$ with $V_{ij}^{(o)}$.
            Reset C(i) = 0.
        else
            Increment C(i).
    /* Scout Phase */
    foreach *food source* i **do**
        if *C(i) > limit* **then**
            Call off food source(i).
            Generating a new solution randomly.
    Store the best solution found so far.
    Cycle = Cycle + 1.
until *termination criteria met*

B. Glowworm Swarm Optimization

The Glowworm swarm optimization technique finds the most optimal solution by mimicking the behavior of Glow-worms, similar to how glow-worms communicate through luciferin, this technique uses luciferin to reach toward positions having minimum energy consumption. Algorithm 2 shows how Glow-worm optimization is used to optimize energy consumption for data transmission.

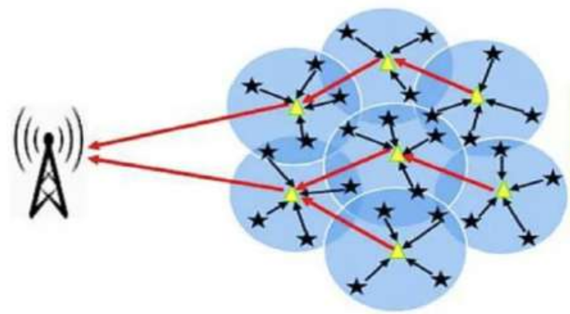

Fig. 2. Glow-worm Swarm Optimization [4]

Algorithm 2: Glowworm Swarm Optimization Algorithm

Initialization:
Initialize n glowworms with random positions in the search space.
Set initial luciferin levels l_0 for each glowworm.
Set sensor range r_s for detecting neighbors.
Set maximum iterations $max\_iterations$.
repeat
    /* Luciferin Update Phase */
    foreach *glowworm* i **do**
        Find neighbors within range r_s.
        foreach *neighbor* j **do**
            if $l_j > l_i$ **then**
                Update l_i based on l_j considering decay and enhancement.
    /* Movement Phase */
    foreach *glowworm* i **do**
        Select the best neighbor with the highest luciferin.
        Move towards the best neighbor.
until *termination criteria met*
Return the best solution found.

In **Luciferin Update Phase** Glow-worms update their luciferin by checking energy level, lower the energy higher the luciferin. The formula for updating luciferin is done by Equation (2):

$$l_i = (1-\rho)\cdot l_i + \frac{\gamma}{1+E_i} \tag{2}$$

where

$$\rho = \text{luciferin decay factor}$$
$$\gamma = \text{luciferin enhancement}$$
$$E_i = \text{energy consumption of i-th node}$$

After this comes **Movement phase**, where glow-worm identifies neighbor nodes with energy consumption within threshold and the node having minimum energy consumption is chosen and the glow-worm moves towards the selected node. Therefore, during this phase glow-worms finds the most optimal solution i.e. a path to transmit data with minimum energy consumption.

C. Particle Swarm Optimization

Algorithm 3 shows how Particle swarm optimization is used to optimize energy consumption for data transmission.

Algorithm 3: Energy Optimization using PSO

Initialization:
Set no. of particles N, iterations i_{max}, inertia weight w, and coefficients of acceleration c_1, c_2.
foreach *particle* i **do**
    Initialize random position X_i and velocity V_i.
    Set best position so far as $P_i = X_i$ and best score $f(P_i)$.
Determine global best position G as the best from all P_i.
repeat
    `/* Evaluate and update best positions */`
    foreach *particle* i **do**
        Compute fitness $f(X_i)$.
        if $f(X_i) < f(P_i)$ **then**
            Update $P_i = X_i$.
    `/* Updating global best position */`
    Set G as the best among all P_i.
    `/* Velocity and position update */`
    foreach *particle* i **do**
        Update velocity Update position
        Clip X_i within allowed limits.
until *termination criteria met*

In Particle Swarm Optimization technique, particles finds the position where minimum energy is consumed by first finding there personal best solution on a certain position, if on this new position energy consumed is less, the algorithm updates the personal best positions [5]. Updating the velocity and position using Equations (3) and (4):

$$V_i = w\cdot V_i + c_1\cdot r_1\cdot(P_i - X_i) + c_2\cdot r_2\cdot(G - X_i) \tag{3}$$

$$X_i = X_i + V_i \tag{4}$$

where

$$w = \text{inertia weight}$$
$$c_1, c_2 = \text{coefficients of acceleration}$$
$$r_1, r_2 = \text{random numbers}$$
$$X_i = \text{possible solution}$$
$$V_i = \text{velocity}$$
$$P_i = \text{best solution so far}$$
$$G = \text{global best position}$$

D. Differential Evolution

Algorithm 4: Energy Optimization using Differential Evolution (DE)

Initialization:
Set size of population N, generations G_{max}, mutation factor F, and crossover rate CR.
Randomly generate an initial population of N individuals.
Evaluate fitness for each individual in the population.
repeat
    `/* Mutation and Crossover */`
    foreach *individual* i *in population* **do**
        Select 3 random individuals X_a, X_b, X_c such that $a \neq b \neq c \neq i$.
        Generate donor vector:
$$V_i = X_a + F\cdot(X_b - X_c)$$
        Perform crossover to create trial vector U_i:
$$U_{i,j} = \begin{cases} V_{i,j}, & \text{if } rand_j \leq CR \text{ or } j = j_{rand} \\ X_{i,j}, & \text{otherwise} \end{cases}$$
    `/* Selection */`
    foreach *individual* i *in population* **do**
        Compute fitness $f(U_i)$.
        if $f(U_i) < f(X_i)$ **then**
            Replacing X_i with U_i.
    `/* Energy Calculation and Optimization */`
    Compute total minimum energy consumption.
until *termination criteria met*

Differential Evolution is population based algorithm to solve optimization problems. It randomly generates the population of a solution and creates new trial solution through weighted difference of the individual which are selected randomly. For mutation, donor vector is calculated from randomly selected individuals using mutation equation (5):

$$V_i = X_a + F \cdot (X_b - X_c) \tag{5}$$

where,

$$\begin{aligned} V_i &= \text{New candidate solution for node } i \\ X_a, X_b, X_c &= \text{Random individuals} \\ F &= \text{Mutation factor} \\ X_b - X_c &= \text{Difference vector, to introduce variation} \end{aligned}$$

The crossover enhances diversity and selection ensures the most efficient solution is returned . For crossover, trial vector is generated using the equation (6):

$$U_{i,j} = \begin{cases} V_{i,j}, & \text{if } rand_j \leq CR \text{ or } j = j_{rand} \\ X_{i,j}, & \text{otherwise} \end{cases} \tag{6}$$

The fitness of this trial vector is evaluated, and if it is lesser than the fitness of target vector then it is replaced with the trial vector. After each iteration the total energy consumed is calculated. DE dynamically helps to adjust the power level and select routing path optimally based on the environmental factors. Over multiple iteration with network configuration DE finds the balance between the communication reliability and energy efficiency.

E. Simplex Method

The simplex method is an optimization algorithm that is used to solve linear programming problems by maximizing or minimizing the function satisfying some constraints. To find optimal solution it moves through the edges of feasible solution (convex polyhedron) iteratively and repeatedly evaluating the other neighboring solution until it gets to the best optimal solution.

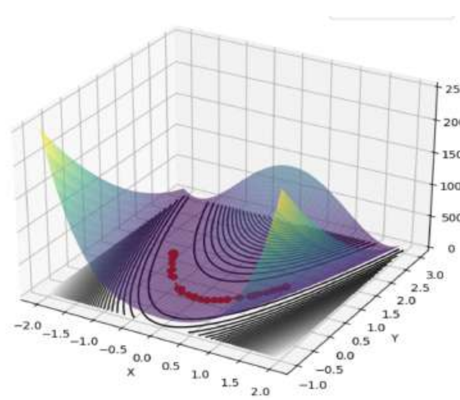

Fig. 3. 3-D visualization of Simplex Optimization

This paper uses simplex method for energy optimization in Underwater Wireless Sensor Networks (UWSNs). The main aim is to minimize energy consumption by considering the objective function that represents energy usage and constraints based on environmental factors like salinity, pH, temperature. This method helps to find optimal transmission strategy and also ensures that power is used efficiently reducing the transmission losses and prolonged network lifetime useful approach for optimizing energy in underwater communication systems .Using this method a set of equation is represented in simplex tableau and use different pivoting operations to get the solutions. Iteration is continued until the best optimal solution with best possible resource allocation is found maintaining the feasibility [6].

To reduce energy loss simplex-based optimization is applied on energy consumption function with its parameters to adjust the transmission of power dynamically. This algorithm explores different energy allocation while considering the network constraints such as to minimize the power requirements and stability of connection .This demonstrate the minimization of energy consumption underwater sensor network hence extending operational life by improving the network connectivity efficiently .

VI. IMPLEMENTATION AND RESULT ANALYSIS

The dataset of 700 nodes contains fields pH, temperature, conductivity and Dissolved Oxygen. Derivation of salinity is done using standard Equation (1) using which energy consumption is derived from the parameters available in the dataset. A new dataset is obtained along with the energy and salinity. Then, the techniques are implemented and minimized energy is calculated for each node. After implementing these techniques parameter tuning is performed in order to achieve minimum possible energy consumption. Average of the energy consumption is calculated before and after the implementation. Then, that average is used to calculate the improvement percentage of the energy consumption.

Performance of nature-inspired techniques depends on the scenario, which is why it wouldn't be appropriate to say one technique is better than the other, rather than that stating, one technique performs better than the other in the scenario provided would be appropriate. Hence, after performing all the algorithms it was found that Artificial Bee colony out-performs the other three taken into consideration. Below is the table showing the percentage of improvement in each technique considered for this research.

Nature-inspired techniques	**Percentage of Improvement (%)**
Artificial Bee Colony	67.86
Differential Evolution	30
Glow-worm Swarm Optimisation	62.92
Particle Swarm Optimisation	15.96

TABLE I

IMPROVEMENT PERCENTAGES OF THE APPLIED TECHNIQUES

A. Result and Analysis of All optimization techniques

As seen in Table 1 percentage of improvement of the applied techniques, it can be interpreted that there is significant improvement in the energy consumption from all of these techniques, and from them Artificial Bee Colony Optimization out-performs the other techniques taken into consideration. In Fig.4,5,6 and 7, the red line shows energy usage before applying any technique and Green line shows energy usage after applying the technique. Wilcoxon Signed-RankTest was performed to find if the energy is optimized significantly or not. The test yielded a p-value< 0.05 (rejecting null hypothesis) indicating significant reduction in energy usage [7].

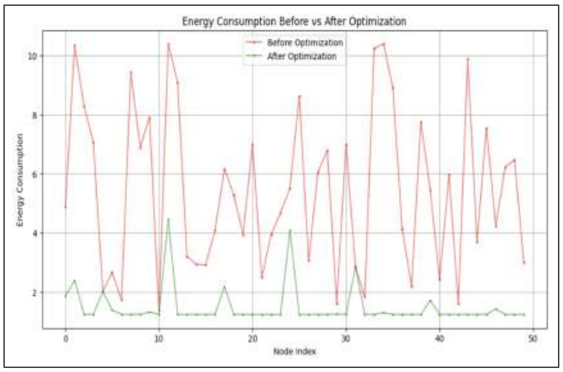

Fig. 4. Artificial Bee Colony

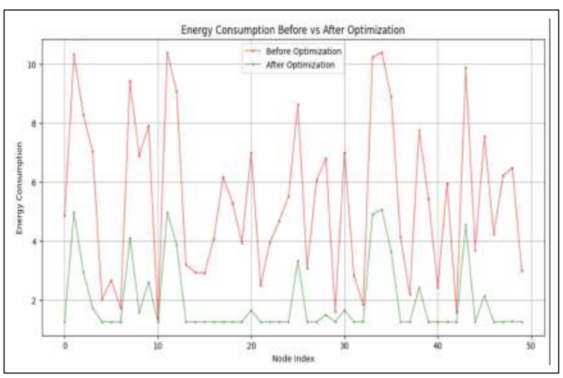

Fig. 5. Glow-worm Swarm Optimization

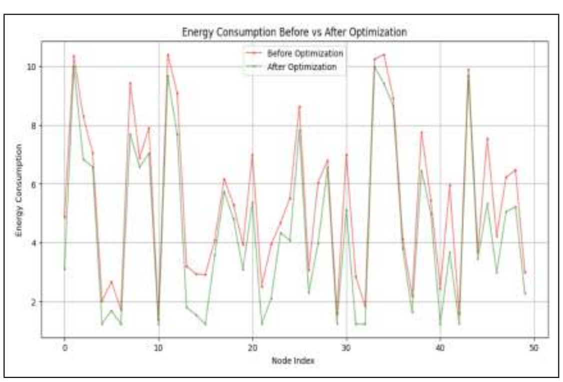

Fig. 6. Particle Swarm Optimization

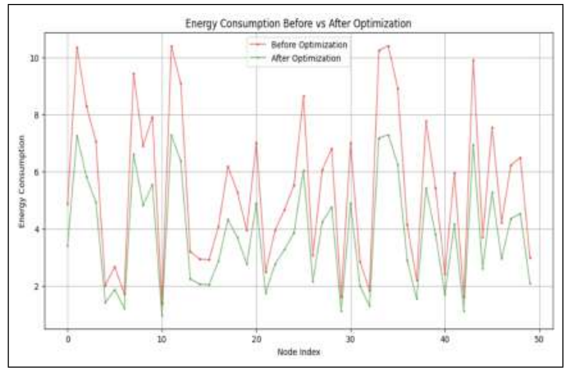

Fig. 7. Differential Evolution

B. Result and Analysis of Simplex Method

After implementing Simplex Method on the same dataset it was found that energy is significantly improved. To visualize the improvement 2-D and 3-D graphs were plotted where, in Fig.8 the red points shows energy consumption of each node and Green points shows energy consumption after simplex method was applied. In Fig.9 we can see a Line Graph showing the difference. For testing the Hypothesis Wilcoxon Signed-RankTest was performed and found that there is a significant difference hence, Null Hypothesis is rejected.

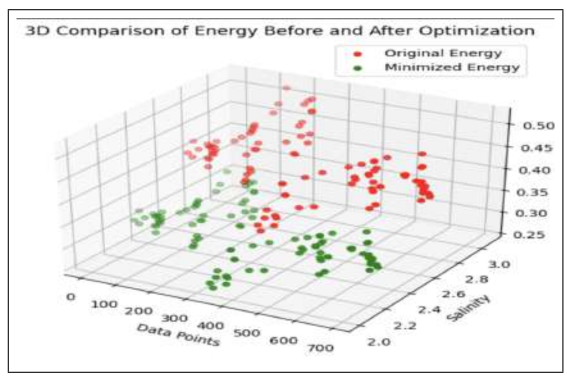

Fig. 8. 3-D comparison for Simplex Method

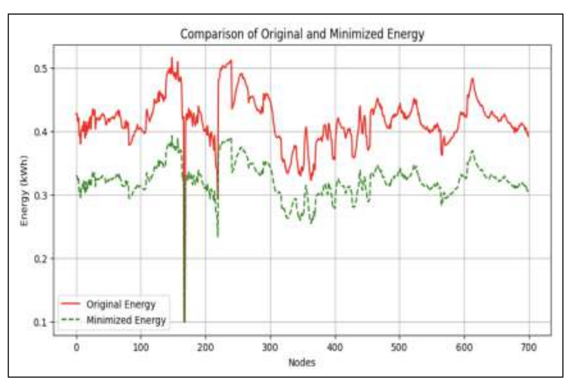

Fig. 9. Simplex Method

VII. CONCLUSION

This methodological research analyzed multiple algorithms used for Optimization and compared their efficiency in the given scenario. After the comparative analysis of the algorithms, it was found that Artificial Bee Colony Optimization out-performs all the other techniques analyzed in this paper. Alternate approach through Simplex Method also shows significant reduction in the energy consumed. The dataset used for this research contains sensor data related to factors such as pH, temperature and salinity in water which affects the rate and energy at which the data is transmitted from one node to another .The data was pre-processed in order to ensure no null values are there in the dataset. Since the data was found in a controlled environment, real-world factors such as network congestion, hardware limitations might introduce differences [8].

All the results as well as the performance comparison in this study, were obtained through coding based implementations of the optimization algorithms. Future research could explore hybrid optimization techniques, and adaptive algorithms that dynamically adjust according to the environment conditions. While this research evaluates on a dataset consisting of 700 nodes, a larger and more complex underwater network would provide deeper insights into the scalability and reliability of these optimization strategies.

VIII. ABBREVIATIONS

1) UWSNs: Underwater Wireless Sensor Networks
2) ABC optimization: Artificial Bee Colony optimization
3) GSO: Glowworm Swarm Optimization
4) PSO: Particle Swarm Optimization
5) DE: Differential Evolution
6) ES: Evolutionary Strategies
7) EA: Evolutionary Algorithm

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