Implementing Particle Swarm Optimization in Electronic Information Sensing Node Deployment for Smart Sensor Network Energy Optimization

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Article Info
Journal of Machine and Computing (https://anapub.co.ke/journals/jmc/jmc.html)
Doi : https://doi.org/10.53759/7669/jmc202505080
Received 02 November 2024; Revised from 12 February 2025; Accepted 04 March 2025.
Available online 05 April 2025.

Abstract – The article discusses the Relentless Particle Swarm Optimization Repeated Routing Protocol (RPSORP), a new model to find the optimal methods to set up Smart Sensor Networks (SSN) using as little energy as possible. The Discrete Particle Swarm Optimization (DPSO) picks the least EC path that meets the best routing and covering requirements. The protocol contributes to efficiency in node energy use, network coverage, and connectivity range by including a fitness metric. Results indicate that RPSORP outperforms traditional routing methods regarding network lifetime, deployment efficiency, and EC. Fields such as environmental monitoring, innovative healthcare, and security systems, where energy-efficient data communication is vital, can apply this scalable solution. The RPSORP presents a real-time and effective solution to energy management in SSN, making it more efficient and reliable.

Keywords – Smart Sensor Networks, Energy Optimization, Routing Protocol, Particle Swarm Optimization, Node Deployment, Network Efficiency.

I. INTRODUCTION

Smart Sensor Networks (SSS) have attracted many researchers in the last few years because of their great value in the environment, healthcare, industrial automation, and security. SSNs contain remote distributed Sensor Nodes (SN) that monitor specific amounts of physical or environmental phenomena such as sound, temperature, pressure, or physical motion. One of the most essential problems in solving an SSN is energy efficiency. Since SNs are primarily deployed in distant places, wired power is impossible; hence, batteries mainly draw energy. Hence, optimizing energy consumption (EC) is essential to prolonging the network's functional lifespan through uninterrupted monitoring.

Many industries, including defence, environmental safety, and security monitoring, may benefit from Wireless Sensor Networks (WSN) since they can self-organize, use little power, and are simple to expand [1-2]. By integrating physical data with theoretical physics, WSN revolutionized people's involvement in the real-time environment. Recognized as a crucial aspect of the information business's development in early 2006, WSN followed the national and medium-term scientific and technology planning and development recognized by the State Council. Massively deploying WSNs is the next big obstacle—significant transformations in human lifestyle and production methods [5]. Introducing Vehicular Sensor Networks (VSNET) stands out among these developments, offering exciting possibilities for leveraging safety-related applications. VSNETs, or WSNs, are created when mobile nodes like computers, mobile phones, or vehicles connect wirelessly to share and exchange data [6]. WSN nodes may take in their surroundings, analyze the data collected, and send it to other network nodes. In order to achieve significant improvements in areas like interaction with digital electronics and

MEMS [7], a plethora of lightweight, inexpensive, and energy-efficient sensors have been developed. The SNs operate on a battery with limited capacity. Optimizing the performance of the SN in different applications requires minimizing their EC to the greatest extent possible. The amount of time a WSN can remain operational depends on how long the batteries last. A smart city monitoring system's foundation is a WSN. Data collection and analysis are the jobs of the many SNs that make up these networks. Various WSNs are used for different types of applications since SNs are tiny and inexpensive. Real-time data is essential for making educated decisions about comfort and safety in smart cities, and this is fundamental to the development of Internet of Things (IoT) technologies. Here is a visual representation of the architecture of the SSN, as depicted in **Fig 1**.

WSNs continually introduce new applications that enhance the IoT vision. WSN nodes consume a significant amount of energy for communication, and the energy required to transmit packets disagrees based on the distance between sender and receiver nodes. As a result, multi-hop communication is recommended. The distinct difficulties brought about by acoustic signals and several communication layers render the WSN clustering and routing algorithms unsuitable to UWSNs. Consequently, researchers have shown much interest in creating clustering-based or route setup algorithms that consider the ocean properties of UWSNs [8-11].

Two significant obstacles to efficient EC and network communication in target tracking with WSN exist. These challenges must be addressed to process the data effectively. Due to its exceptional features, such as adaptability, performance, robustness, and flexibility, WSNs are highly regarded in many applications [12]. Considering the limited EC of SN and the constraints of unreliable electromagnetic transmissions, delays caused by packet transfer, and shared wireless medium, it is crucial to ensure the performance and stability of the control system in a WNCS. Communication and control systems must consider many critical aspects. These aspects include the sampling period of the network's SN, the needed delay, and the probability of packet errors. Optimizing these parameters enhances the efficiency of the control system. Conversely, when the SN's transmission power and communication rate drop, so does the energy required for wireless transmission.

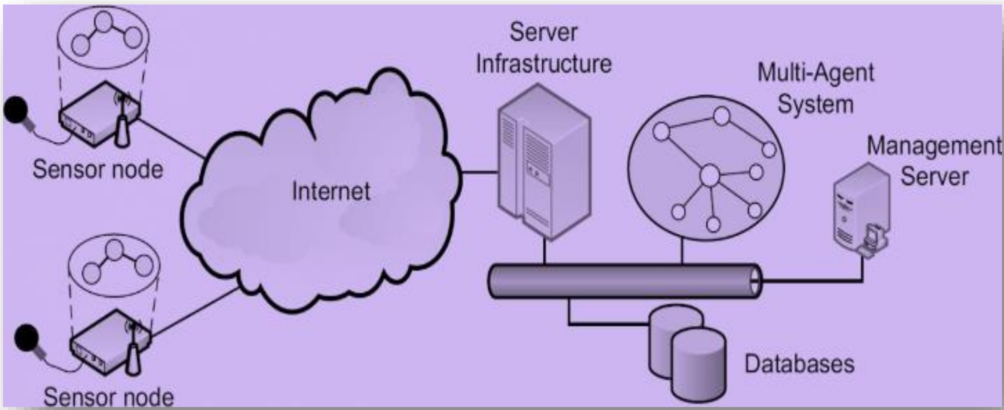

Fig 1. Architecture of the SSN.

This paper proposes a novel routing protocol to address EC concerns in SSN: The Relentless Particle Swarm Optimization-based Routing Protocol (RPSORP). RPSORP employs the Particle Swarm Optimization (PSO) algorithm in order to facilitate the selection and usage of the most minor EC routing paths. RPSORP incorporates in its design a fitness function that assesses coverage area, node energy, and communication range so that it can effectively manage and distribute EC within the area of the network. This way, the operational period of the network is extended, thereby improving reliability and efficiency.

With regards to this subject, it can be stated that the primary contributions of this research are as follows:

- Design a new routing protocol, RPSORP, that generates routing decisions with the help of PSO, aiming to achieve further EC in SSN.
- It developed a fitness function integrating node energy, coverage, and communication efficiency during network operation for the maximum network lifetime.
- Comprehensive simulations and assessment of performed RPSORP highlight significant improvement over traditional routing regarding energy efficiency, operational longevity, and network coverage.

The rest of the paper is organized into the following structures: In Section 2, the related works are defined, while Section 3 elaborates on the approach taken, including the protocol design of the RPSORP and its corresponding fitness function. The outcome of the conducted simulation and the performance analysis is described in Section 4. The summary is presented in Section 5.

II. RELATED WORKS

The Virtual Force-directed Particle Swarm Algorithm (VF-PSO) was suggested as a deployment technique [3]. Node density significantly impacts this method, which uses the link amongst nodes to compute the node mobility distance. Their distance from one another dictates the degree of mutual disagreement between nodes, and Virtual Force (VF) measures this interference. WSN comprises SSNs strategically placed and installed according to their specific applications. These sensors are accompanied by a washbasin conveniently located within or close to the radio range. When the sink needs data, it asks adjacent sensors to collect it [4]. The sensors then relay that information back to the sink. Several studies have examined the development of optimal controllers for WSN, considering factors such as delay and packet loss [13-14]. A wide range of applications has led to numerous protocols with many adjustable parameters. Nevertheless, specific parameters carry out a variety of tasks and are found in many applications, making them highly important.

Due to technological constraints, WSN relies on mobile energy sources and rechargeable batteries with a limited energy supply. Consequently, ensuring these networks utilize energy efficiently is vital [15]. In a study conducted by researchers [16], they introduced a routing approach called Clustering-Based Energy-Efficient Routing (CBEER), intending to prolong the lifespan of Underwater Wireless Sensor Networks (UWSNs). Performance was assessed through thorough simulations. In a different study, a technique for routing in UWSNs was introduced. This technique, known as EERBLC, focuses on energy efficiency and is based on layers and unequal clusters [17]. EERBLC was developed in three stages: the creation of layers and clusters with varying sizes, the routing of transmissions, and the ongoing maintenance and updating of clusters. In order to maximize the simultaneous deployment of gauges, the sensing field is partitioned. Energy metrics and radio range are considered during cluster formation. Parameters about coverage are handled by the grid exclusion method, whereas energy optimization is handled by the Dijkstra algorithm [18]. The use of D-S evidence theory in installing nodes for WSNs has garnered much attention and research.

When evaluating a distribution system's dependability, [19] sought to reduce the influence of subjective or incomplete parameters. Due to the nature of WSNs, SNs are vulnerable to attacks. This susceptibility is exacerbated by factors such as interference between wireless links, applications used in warfare, and nodes that are not physically protected from the surroundings. A new algorithm, NBBTE, has been created to improve network security. This algorithm combines node behavioural approaches with evidence theory [20]. The sensors in the sensing region are used for sensing, processing, and communication purposes. The overall network lifetime depends on the factors mentioned above. One method to enhance the network lifetime is by preventing the sensor from transmitting raw data. This can be accomplished by consolidating the sensed data to remove unnecessary repetitions, reducing the number of control messages, and minimizing long-distance transmission. Considering the factors mentioned above can lead to an improvement in the overall network lifetime.

Forests, rivers, and significant buildings are examples of demanding environments where WNS are frequently used, according to [21] and other researchers. In order to keep tabs on the physical world around them, SNs are frequently used as monitoring nodes. This involves taking readings of things like heat, sound, velocity, and the trajectory of objects in motion. Thanks to wireless self-organization, nodes can maintain labels on their environment without human intervention. WSNs have many uses [22], including data collecting, surveillance from afar, tracking targets, and continuous evaluation. They also noted that these networks are unusual because they span multiple disciplines. When determining the power transmission level for each SN, we considered various factors such as energy efficiency, PDR, distance, link quality, and neighborhood density. All nodes in the neighborhood are taken into account when forwarding the packets. The proposed results demonstrated superior performance in data delivery while effectively managing energy costs across all system levels. An algorithm called "FPT-Approximation Algorithm" was created to address the load balancing problem.

Using the PSO technique in WSN has effectively addressed the clustering problem. The PSO-based algorithm aims to achieve energy balance in clustering by dividing the sensor field into clusters of varying sizes. As they approach the sink node, these clusters shrink in size. One thing to maintain in attention with inter-cluster relay communication is that the Cluster Heads (CH) energy level will be more significant. The cluster head SN'-EC is minimized by inter-cluster interaction employing a multi-hop energy-aware routing mechanism.

Authors have created a new and improved clustering algorithm that considers energy economy and telecommunication distance when selecting SN to function as cluster heads. In order to reduce the CH-SN's power usage, relay SNs are selected from the pool of SN. To improve the sensing coverage, longevity, and implementation cost of WSN in practical buildings, [23] put up a theoretical framework. Using the sensor values as input data, the researchers employed a Building Information Modelling (BIM) database, which provides all the relevant building information. They used a Genetic Algorithm (GA), an evolutionary method, to resolve the optimization issue. Then, after incorporating all of the necessary sensors and barriers into a 3D building model, the enhanced solution will be shown using the BIM plugin tool. The determination variable vector in the optimization problem depicts the smart building's SN locations. The primary limitation is ensuring that every SN can communicate with the sink node. An adaptive multipath routing method is presented in the study [24] to minimize routing inefficiency and maximize EC. To improve the network's performance and increase the residual capacity in SN, the Competitive Clustering (CC) technique with sink mobility. The remaining energy and range of the competition radio are used to select the final head from among the competing contenders. The technique moves the head node closer to the BS by creating clusters at the fixed sink node. Consequently, less energy is needed to collect data amongst the clusters. **Table 1** represents Related work Comparison.

Table 1. Related Work Comparison

Reference	Algorithm/ Technique	Focus	Key Features	Limitations
[3]	Virtual Force-directed Particle Swarm Algorithm (VF-PSO)	Deployment technique using node mobility distance	Utilizes virtual force to measure node interference	Node density significantly impacts performance
[4]	-	Data collection mechanism in WSN	Strategic sensor placement with the adjacent sink node	Limited to the proximity of sensors to the sink
[13]	Optimal Controllers	Network performance in WSN	Focus on delay and packet loss	High complexity and parameter dependency
[15]	-	Energy efficiency in WSN	Use of mobile energy sources and rechargeable batteries	Limited energy supply, necessitating efficient usage
[16]	Clustering-Based Energy-Efficient Routing (CBEER)	Prolong UWSN lifespan	Clustering technique for energy-efficient routing	Performance dependent on simulation parameters
[17]	Energy-Efficient Routing Based on Layers and Clusters (EERBLC)	Energy efficiency in UWSN	Multi-stage approach: layer/cluster creation, routing, maintenance	High complexity due to multiple stages
[18]	Grid Exclusion Method, Dijkstra Algorithm	Cluster formation and energy optimization	Considers energy metrics and radio range	Complexity in real-world applications
[19]	D-S Evidence Theory	Node installation and network reliability	Reduces the impact of subjective/incomplete parameters	Complexity in parameter estimation and application
[20]	Node Behavioral-Based Trust Evaluation (NBBTE)	Network Security	Combines node behavior with evidence theory	Complexity in integration and implementation
[23]	Building Information Modelling (BIM), Genetic Algorithm (GA)	Sensor placement optimization in smart buildings	Uses BIM for information and GA for optimization	Complexity in integrating sensors and barriers
[14]	Adaptive Multipath Routing	Routing efficiency and EC	Minimizes routing inefficiency with a multipath strategy	Dependent on adaptive mechanism efficiency
[05]	Competitive Clustering (CC) with Sink Mobility	Enhanced WSN performance	Uses competition-based clustering with mobile sink	Potential overhead from sink mobility management

III. METHODS AND MATERIALS

Problem Formulation

In the SSN, energy optimization is one of the most crucial challenges, mainly when nodes are battery-powered. Effective use of energy is an essential concern in increasing the working life of the network and helping to facilitate efficient data exchange. The typical routing protocols often do not account for energy management, resulting in inefficient EC and shortening the network's lifespan. This work's main problem is the energy optimization in SSN using an efficient routing protocol. More specifically, we attempt to develop a protocol that reduces the EC at the onset of communication while ensuring maximum coverage and effective data transfer among the nodes.

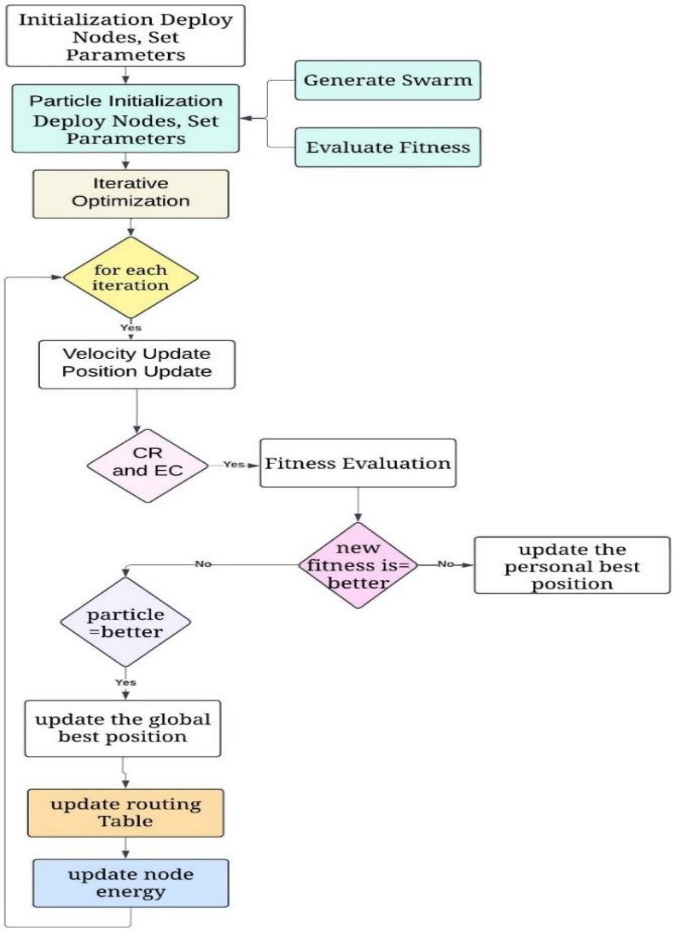

Fig 2. Flowchart of the Routing Process in RPSORP.

Let N be the set of SN in the network, where each node $i \in N$ has an initial energyE_i. The routing path between nodes is represented as P, Where each path consists of a sequence of SN responsible for forwarding data. The EC of a node i for transmitting and receiving data is denoted as $E_{tx}(i)$ and $E_{rx}(i)$, respectively. The total EC along a routing path P can be expressed as Eq. (1).

$$E_{total}(P) = \sum_{i \in P}(E_{tx}\,(i) + E_{rx}(ri)) \tag{1}$$

where, $E_{tx}(i)$ is the energy required to transmit data from node i, $E_{rx}(i)$ is the energy required to receive data at node i. The objective is to minimize the total EC across all possible routing paths while maximizing network coverage and maintaining effective communication. This can be formulated as Eq. (2) an optimization problem:

$$min \sum_{P} E_{total}\,(P) \tag{2}$$

Subject to the following constraints

The remaining energy at any node i must not fall below a threshold E_{min}, Eq. (3)

$$E_i - E_{total}(P) \geq E_{min} \qquad \forall i \in P \tag{3}$$

In Coverage Constraint**, t**he set of selected nodes $N_{active} \subseteq N$ must provide complete coverage of the target area N, Eq. (4).

$$\cup_{i \in N_{active}} A_i = A \tag{4}$$

where A_i is the area covered by node i.

Communication Range Constraint is the distance between any two communicating nodes i and j on a path P must not exceed the maximum communication range. R_{max}, Eq. (5)

$$d(i,j) \leq R_{max} \; \forall i,j \in P \tag{5}$$

where $d(i.j)$ is the distance between nodes i and j. To solve this optimization problem, the RPSORP is employed to iteratively search for the optimal routing paths that minimize EC while satisfying the above constraints.

Methodology

Relentless Particle Swarm Optimization-Based Routing Protocol (RPSORP)

The PSO is an approach that employs social intelligence of elements, such as bird flocks and fish schooling, to solve optimization problems with a fluctuating population. Due to this, it has been utilized to optimize particularly non-linear functions in high-dimensional spaces. Examples in this case include optimization of networks. In the context of RPSORP, the PSO finds the optimal routing paths that conserve the maximum energy in an SSN.

In this algorithm, every particle is considered a potential solution; in this case, it is a routing path/Sensor routing path set in an SN. That is, the position of each particle can be treated as an n-dimensional vector in terms of search space, where n reflects the number of interrelated parameters that define the routing path.

Let S be the number of particles in the swarm. $X_i = (x_{i1}, x_{i2}, \dots, x_{i3})$ be the position vector of the i-th particle. $V_i = (v_{i1}, v_{i2}, \dots, v_{i3})$. At each iteration t, the particles update their velocities and positions according to Eq. (6) and Eq. (7).

$$V_{ij}^{(t+1)} = w_{ij}^{(t)} + c_1 r_1 \left(p_{ij}^{(t)} - x_{ij}^{(t)}\right) + c_2 r_2 \left(g_j^{(t)} - x_{ij}^{(t)}\right) \tag{6}$$

$$X_{ij}^{(t+1)} = x_{ij}^{(t)} + V_{ij}^{(t+1)} \tag{7}$$

where, $V_{ij}^{(t)}$ is the velocity of particle i in dimension j at time t. $x_{ij}^{(t)}$ is the position of particle i in dimension j at time t. w is the inertia weight that controls the impact of the previous velocity. c_1 and c_2 are acceleration coefficients representing cognitive and social components, respectively. r_1 and r_1 are random numbers uniformly distributed in the range [0,1]. $p_{ij}^{(t)}$ is the personal best position of particle i in dimension j up to time t. $g_j^{(t)}$ is the global best position found by the entire swarm in dimension j up to time t. The inertia weight w balances the global and local exploration abilities of the swarm, Eq. (8).

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{T}\right) t \tag{8}$$

where, w_{max} and w_{min} are the initial and final inertia weights. T is the maximum number of iterations. t is the current iteration number. The fitness function evaluates the quality of each particle's position (routing path) based on Eq. (9)

$$Fitness_i = \alpha E_{total}(x_i) + \beta C_{coverage}(x_i) + \gamma D_{communication}(x_i) \tag{9}$$

where, $E_{total}(x_i)$ is the total EC of the routing path represented by particle i. $C_{coverage}(x_i)$ measures how well the routing path covers the network area. $D_{communication}(x_i)$ is the total communication distance in the routing path. α, β, γ are weighting factors that balance the importance of each term.

The objective is to minimize the fitness function, Eq. (10)

$$\min_{x_i} Fitness_i \tag{10}$$

To incorporate constraints into the PSO, apply penalty functions or repair mechanisms, Eq. (11)

$$Fitness_i = Fitness_i + P \times ConstraintViolation \tag{11}$$

where P is a significant positive constant.

In the case of the Relentless Particle Swarm Optimization based Routing Protocol (RPSORP), routing activities start from the initialization phase, where SN is placed within the designated area, and the parameters needed for the PSO are defined as shown in **Fig 2**. Afterwards, particle initialization occurs, producing a swarm of particles representing possible routing paths. The fitness of the particles is determined using a fitness function that factors in EC, coverage efficiency, and communication range, among other parameters. RPSORP incorporates iterative optimization as a vital element of the algorithm, where the velocities and portions of particles are refreshed to search through the available routing path space. After each such update, every particle fitness is recalculated, which enables the algorithm to look for the best possible routing path. When the optimization effort is over, the routing table update step takes the routing path from the best particle and refreshes the nodes' routing tables accordingly. The actual height of the sink node is taken as the anchor reference to which other nodes find their positions. With proper routing paths laid out, data transmission begins where information packets from the SN towards the sink node are sent along the shortest or optimized routes. Following transmission, the energy update phase of the framework re-estimates the energy state of nodes involved in the active transmission and reception of data packets.

In the last stage, the system goes into the repeat phase, progressing from the routing intervals and evaluating the routing paths from time to better cope with changing conditions in the network, such as energy depletion or node failure, so that efficiency can be maintained. Focusing on this process method indicates how RPSORP can impact computation processes in improving routing decisions and using energy in SSN.

Proposed RPSORP Protocol

The RPSORP aims to enhance SSN-based EC by automatically adapting the routing paths to be the most efficient. The PSO is used in the protocol to navigate amongst various possible routing paths and employ the least amount of energy possible while meeting the set requirements. Let $N = \{ n_1, n_2, \dots, n_M\}$ represent the set of $'M'$, SN deployed over an area A. Each node n_i has Initial Energy, $E_i^{(0)}$. Communication Range, R_i . Coverage Range, C_i. A routing path P_k is represented as a sequence of nodes connecting a source node n_s to the sink node n_{sink} :

$$P_k = (n_s, n_{k1}, n_{k2}, \dots, n_{sink}) \tag{12}$$

The set of all possible routing paths is denoted as $'P'$. The fitness function in RPSORP evaluates the quality of routing paths based on three key factors: EC (E_{total}), Coverage Efficiency (C_{eff}), Communication Distance (D_{total}). The fitness function for a routing path P_k is defined as:

$$Fitness(P_k) = \alpha \cdot E_{total}(P_k) + \beta \cdot (1 - C_{eff}(P_k)) + \gamma \cdot D_{total}(P_k) \tag{13}$$

where α, β, γ are weighting coefficients satisfying $\alpha + \beta + \gamma = 1$, and they determine the relative importance of each component.

The total EC for transmitting data along the path P_k is calculated as:

$$E_{total}(P_k) = \sum_{i=1}^{L_K-1}\left(E_{tx}(n_{k_I}, n_{k_{i+1}}) + E_{Rx}(n_{k_{i+1}})\right) \tag{14}$$

where L_k is the length (number of nodes) of the path P_k. $E_{tx}(n_{k_I}, n_{k_{i+1}})$ is the EC by the node n_{k_I} to transmit data to the node $n_{k_{i+1}}$. $E_{Rx}(n_{k_{i+1}})$ is the EC by node $n_{k_{i+1}}$ to receive data. The transmission energy is modelled as follows:

$$E_{tx}\left(n_{k_I}, n_{k_{i+1}}\right) = \mathrm{E_{elec}} \cdot \mathrm{l} + \mathrm{E_{amp}} \cdot \mathrm{l} \cdot \mathrm{d}^{\mathrm{m}}_{k_i,k_{i+1}} \tag{15}$$

where, $\mathrm{E_{elec}}$ is the energy dissipated per bit to run the transmitter or receiver circuit. $\mathrm{E_{amp}}$ is the energy dissipated per bit per m^m by the transmitter amplifier. l is the size of the data packet in bits. $\mathrm{d}^{\mathrm{m}}_{k_i,k_{i+1}}$ is the Euclidean distance between nodes $k_i$and k_{i+1}. m is the path loss exponent (typically m=2). The reception energy is:

$$E_{Rx}\left(n_{k_{i+1}}\right) = \mathrm{E}_{elec} \cdot \mathrm{l} \tag{16}$$

Coverage efficiency measures how well the routing path contributes to the overall network coverage

$$C_{eff}(P_k) = \frac{Area\ covered\ by\ nodes\ in\ P_k}{A} \tag{17}$$

Alternatively, the formula can be adjusted if the coverage is represented in terms of coverage probability or the number of covered targets. The total communication distance along the path P_k is:

$$D_{total}(P_k) = \sum_{i=1}^{L_k-1} d_{k_i,k_{i+1}} \tag{18}$$

Minimizing D_{total} helps reduce EC due to lower transmission distances.

Algorithm 1 for RPSORP

1. Initialization:

a. Deploy SN as $N = \{n_1, n_2, \dots, n_M\}$ in the target area A.

- Assign initial energy E_i^0 to each node n_i .
- Define communication range R_{max} and coverage range C_i for each node.

b. Initialize PSO parameters:
- Swarm size S (number of particles).
- Maximum number of iterations T.
- Inertia weight w, cognitive coefficient c_1, social coefficient c_2.
- Weighting factors α, β, γ for the fitness function.

c. Generate Initial Swarm:
FOR $i = 1$ TO S DO
- Randomly generate a feasible routing path P_i.
  - Ensure P_i connects source node n_s to sink node n_{sink}.
  - Satisfies communication range and energy constraints.
- Initialize particle position x_i to represent P_i .
- Initialize particle velocity v_i (could be zeros or small random values).
- Evaluate fitness Fitness (x_i) using the fitness function.
- Set personal-best position $p_i = x_i$.

End For

d. Determine the global best position:
- g = argmin(Fitness(p_i)) FOR all particles i = 1 TO S.

2. Iterative Optimization:
For t = 1 to T **Do**
For i = 1 to S **Do**
a. Update inertia weight (if using dynamic inertia):
- w = w_{max}- ((w_{max}- w_{min}) * t) / T

b. Update particle velocity v_i :
For each dimension d in particle i, **Do**
- Generate random numbers r_1 and r_2 uniformly distributed in [0, 1].
- $v_i[d] = w * v_i[d] + c_1 * r_1 * (p_i[d] - x_i[d]) + c_2 * r_2 * (g[d] - x_i[d])$

End For

c. Update particle position x_i:
- For discrete PSO, update $x_i$based on v_i using a suitable method (e.g., probability mapping, position swap operations).

d. Ensure particle position $x_i$represents a feasible routing path:
- If $x_i$violates communication range constraint:
  - Repair $x_i$by adjusting node sequences to satisfy $d_{\{k_i k_{\{i+1\}}\}} \leq R_{max}$.
- If x_i violates energy constraints:
  - Remove nodes with $E_i < E_{min}$ from x_i.
  - Find alternative nodes with sufficient energy.

e. Evaluate fitness Fitness (x_i):
- Compute $E_{total}(x_i), C_{eff(x_i)}, D_{total(x_i)}$
- $Fitness(x_i) = \alpha * E_{total(x_i)} + \beta * \left(1 - C_{eff(x_i)}\right) + \gamma * D_{total(x_i)}$

f. Update personal best position p_i:
- If $Fitness(x_i) < Fitness(p_i)$ Then
  - $p_i = x_i$

End IF

End For

g. Update global best position g:
- $g = argmin(Fitness(p_i))$ FOR all particles i = 1 TO S.

h. Check termination criteria:
- **If** convergence is achieved (e.g., minimal improvement over several iterations) OR t equals maximum iterations T, **Then**
  - Break loop

End If

End For

3. Update Routing Tables:
a. Extract optimal routing path P_{best} from global best position 'g'.
b. Update routing tables of SN:
- **For Each** node n_i in P_{best}, update its routing information to forward data accordingly.

4. Data Transmission: Nodes transmit data packets using the optimized routing paths in their routing tables.
5. Adaptation and Iteration:
a. Periodically or upon significant network changes (*e.g.*, node failure, energy depletion):

- Return to Step 2 to re-optimize routing paths.

End RPSORP Algorithm

In the Relentless Particle Swarm Optimization based Routing Protocol, the algorithm for node selection, deployment, and distribution (the Relentless Particle Swarm Optimization based Routing Protocol) starts by setting the area of interest as well as the specific parameters concerning the SN like energy capacity, communication, and sensing range. Each node is scattered randomly among the appropriate zones and noted in its coordinates. The next step involves determining the effectiveness of the deployed nodes in terms of coverage areas by measuring the distances between the deployed nodes and identifying any zones that could be exposed. If these zones exist, these nodes will be relocated to reduce the number of uncovered areas. Now, the algorithm formulates a database of each deployed node and its corresponding attributes to achieve a desirable node density and energy distribution, preparing the ground for sound routing policies in RPSORP.

Algorithm 2 for Node_Selection_Deployment_Distribution(A, N, E_i^0, R_max, C_i):

Step 1. Initialize NodeList = [ ]
Step 2. For i from 1 to N:
Step 3. Create node n_i with:
E_i^0, C_i, R_max
Step 4. Generate random coordinates (x_i , y_i) in A
Step 5. Assign n_i.position = (x_i , y_i)
Step 6. While NodeList is not empty:
Step 7. For Each Node n_i in NodeList:
For Each Node n_j in NodeList:
Calculate distance $d_{ij} = \sqrt{\left((x_i - x_j)^2 + (y_i - y_j)^2\right)}$
Evaluate coverage and identify gaps
If gaps exist
Reposition $n_i$to a new random location, maximizing coverage
Step 8. For Each node n_i:
Step 9. Append $n_i$to NodeList with its final attributes
Step 10. Return NodeList

Simulation Setup

Simulations performed extensive assessments to measure the effectiveness of RPSORP. This section briefly describes the simulation settings, parameters, and methodology adopted to compare RPSORP and traditional routing protocols. The simulations were conducted in MATLAB R2021a since it is a versatile tool that allows one to design WSN and implement advanced functions such as PSO. The simulation area is a model for the 2-D square area with randomly deployed SN. The network consists of 'N' as SN randomly distributed over 100×100 square meters. The sink node is deployed at the geographical centre of the entire deployment zone. The key network parameters are summarized in **Table 2.**

Table 2. Network Parameters

Parameter	Symbol	Value
Deployment Area	—	100×100 m²
Number of SN	N	100
Initial Energy Per node	$E_i^{(0)}$	2 Joules
Communication range	R_{max}	20 meters
Sensing Range	C_i	10 meters
Data Packet Size	l	4000 bits
Sink Node Position	—	Centre of area
Path Loss Exponent	m	2 (Free space)

The EC model is based on the first-order radio model, in which EC is used during the transmission and reception of data packets. Such parameters, which are found in the energy model, are presented in **Table 3.**

Table 3. Energy Model Parameters

Parameter	Symbol	Value
EC Per Bit (Tx/Rx)	E_{elec}	50 nJ/bit
Transmit Amplifier Energy	E_{amp}	100 pJ/bit/m²
Data Aggregation Energy	E_{DA}	5 nJ/bit

The parameters for the PSO used in RPSORP are listed in **Table 4**.

Table 4. PSO Parameters

Parameter	**Symbol**	**Value**
Swarm Size	S	30
Maximum Iterations	T	100
Inertia Weight	w	Linearly decreasing from 0.9 to 0.4
Cognitive Coefficient	c_1	2.0
Social Coefficient	c_2	2.0
Velocity Clamping	—	Applied
Position Update Method	—	Discrete PSO

The inertia weight w decreases linearly over iterations to balance exploration and exploitation. The weighting factors in the fitness function balance the importance of different optimization objectives **Table 5.**

Table 5. Fitness Function Weights

Component	**Symbol**	**Weight (α, β, γ, δ)**
EC	α	0.4
Coverage Efficiency	β	0.3
Communication Distance	γ	0.2
Energy Balance	δ	0.1
Total	—	1.0

Many simulation scenarios were designed to evaluate RPSORP comprehensively. Scenario A involved comparing traditional routing protocols, such as LEACH and AODV, under identical network conditions to assess relative performance. In Scenario **B**, the number of SN was varied (N=50,100,150N=50, 100, 150N=50,100,150) to assess the scalability of RPSORP in networks of different sizes. Scenario **C** examined the protocol's performance under different energy constraints by varying the initial node energy levels ($E_i^{(0)}$=1,2,3 Joules). Lastly, Scenario **D** tested the robustness of RPSORP against communication limitations by varying the communication range (R_{max}=15,20,25meters).

The simulation procedure proceeds with the initialization phase first. In this phase, SNs are uniformly placed over the designated area, and an initial energy is assigned to each node, which is 6 times the average amount from the previous section. The execution of the RPSORP follows this, and the first step is the initialization of the PSO. The swarm of particles is built, and routing paths are optimized with the help of the fitness function, which attempts to optimize the EC, coverage efficiency, communication distance, and energy balance of each node. After the optimization, each SN's routing table is exemplified with the best routing paths obtained. In the data transmission phase, SN generates packets and sends the data to the sink node via the optimized routing paths. During the phase in which data are transmitted and received, EC for both acts is determined with a first-order radio model, and energy residues of the nodes are updated.

The RPSORP algorithm runs periodically (*e.g.,* after every 20 rounds) with repetitive execution so that the network can adjust to node energy exhaustion or even topological shifts. Throughout the simulation, primary performance indicators, including total EC, network lifetime, coverage ratio, PDR, and average energy reserve per node, are measured at the end of each round. Running the simulation continues until a stopping criterion is pointed out. An example could be energy depletion of specific nodes up to some preset level (*e.g.,* 50%). In order to provide reliable results, the same scenario is repeatedly executed several times with different random seeds, and the performance metrics are averaged.

IV. RESULT AND DISCUSSION

This section of the paper discusses the results obtained during the evaluation of the routing protocol RPSORP and places the results in the context of the traditional routing protocols. Performance metrics that were measured include total EC, Network Lifetime (NL), Coverage Ratio (CR), Packet Delivery Ratio (PDR), and Average Residual Energy (ARE). It is evident from the results that RPSORP is well suited to promoting EC and increasing the useful lifetime of SSNs.

Scenario A: Comparison With Traditional Routing Protocols

The total EC of RPSORP was compared to LEACH and AODV's under the same networking conditions. These results for RPSORP are listed in **Table 6**, which indicates that RPSORP substantially decreases EC. **Table 6** represents Total EC Comparison.

Table 6. Total EC Comparison

Protocol	**Total EC (Joules)**
RPSORP	120
LEACH	180
AODV	200

As seen in **Fig 3**, the EC by each protocol, the drug performs relatively better as time progresses than other protocols' EC profiles. RPSORP exhibited decreased EC throughout the simulation period owing to its effective routing path, which reduces the distance to be covered and reclines the EC on nodes**.**

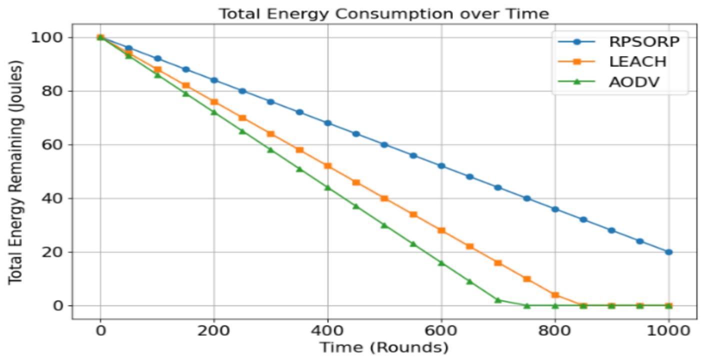

Fig 3. Total EC Over Time.

The number of rounds measures the network lifetime until the First Node Dies (FND) and until 50% of High Nodes Die (HND). As shown in **Table 7**, RPSORP extends the network lifetime significantly compared to LEACH and AODV.

Table 7. Network Lifetime Comparison

Protocol	Rounds until FND	Rounds until HND
RPSORP	500	900
LEACH	350	600
AODV	300	550

The extended network lifetime in RPSORP is featured in its energy-aware routing decisions, which prevent early energy depletion of critical nodes. The coverage ratio over time is depicted in **Fig 4.** RPSORP maintains a higher coverage ratio than LEACH and AODV, ensuring that the monitoring area remains effectively covered even as nodes deplete their energy.

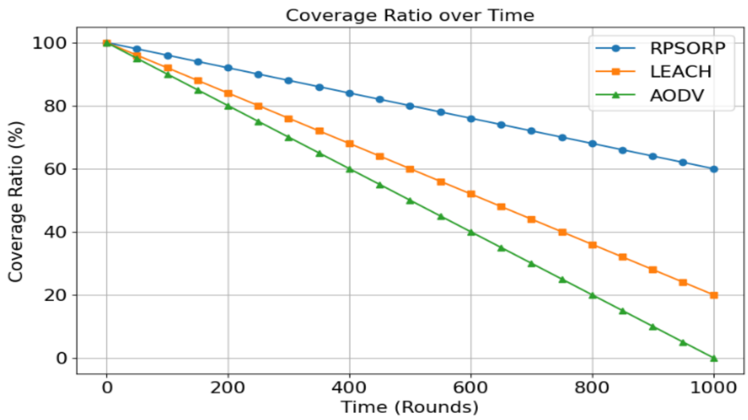

Fig 4. Coverage Ratio Over Time.

As shown in **Table 8**, RPSORP achieves a higher PDR, indicating more reliable data transmission to the sink node.

Table 8. PDR Comparison

Protocol	PDR (%)
RPSORP	95
LEACH	88
AODV	85

Scenario B: Scalability Analysis

The performance of RPSORP was evaluated by variable the number of SN (N=50,100,150) to assess scalability. **Fig 5** shows that as the number of nodes increases, the total EC of RPSORP scales linearly, demonstrating its ability to handle more extensive networks efficiently.

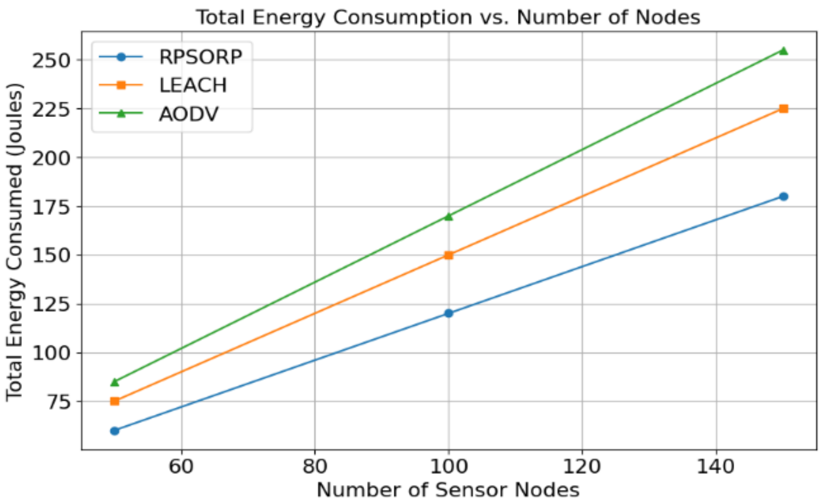

Fig 5. Total EC vs. Number of Nodes.

Table 9 presents the network lifetime for different network sizes. RPSORP consistently outperforms traditional protocols, with the network lifetime slightly decreasing as N increases due to higher energy demands. Despite the increase in network size, RPSORP maintains a high coverage ratio, as illustrated in **Fig 6**, due to its efficient routing and energy-balancing mechanisms.

Table 9. Network Lifetime with Varying Number of Nodes

Number of Nodes (NNN)	RPSORP Rounds until FND	LEACH Rounds until FND	AODV Rounds until FND
50	550	400	350
100	500	350	300
150	450	300	250

Despite the increase in network size, RPSORP maintains a high coverage ratio, as illustrated in **Fig 4**, due to its efficient routing and energy-balancing mechanisms.

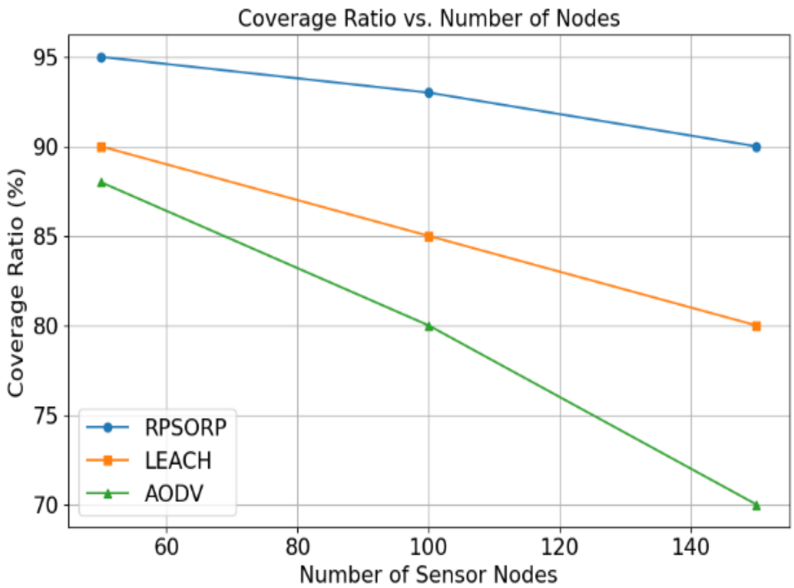

Fig 6. Coverage Ratio vs. Number of Nodes.

Scenario C: Impact of Initial Node Energy

By varying the initial node energy levels ($E_i^{(0)}$=1,2,3 Joules), the protocol's performance under different energy constraints was evaluated. **Fig 7** shows that network lifetime increases proportionally with higher initial energy levels. RPSORP makes better use of the available energy, resulting in longer network lifetimes than LEACH and AODV at each energy level.

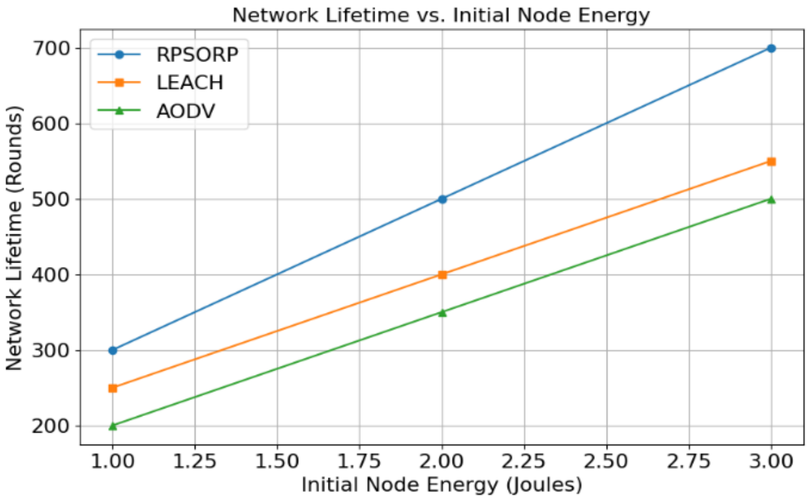

Fig 7. Network Lifetime vs. Initial Node Energy.

The energy efficiency of RPSORP is highlighted by its ability to extend network lifetime without a proportional increase in total EC, indicating effective energy optimization.

Scenario D: Robustness Against Communication Limitations

The communication range (R_{max}=15,20,25 meters) was wide-ranging to test the protocol's robustness. The PDR typically decreases as the communication range decreases due to limited connectivity. However, **Table 10** shows that RPSORP maintains a higher PDR than traditional protocols, even at shorter communication ranges.

Table 10 represents PDR with Variable Communication Range.

Table 10. PDR with Variable Communication Range

Communication Range (m)	RPSORP (%)	LEACH (%)	AODV (%)
25	96	90	88
20	95	88	85
15	92	80	78

RPSORP adapts to reduced communication ranges by optimizing routing paths considering communication constraints, thereby maintaining network connectivity and performance.

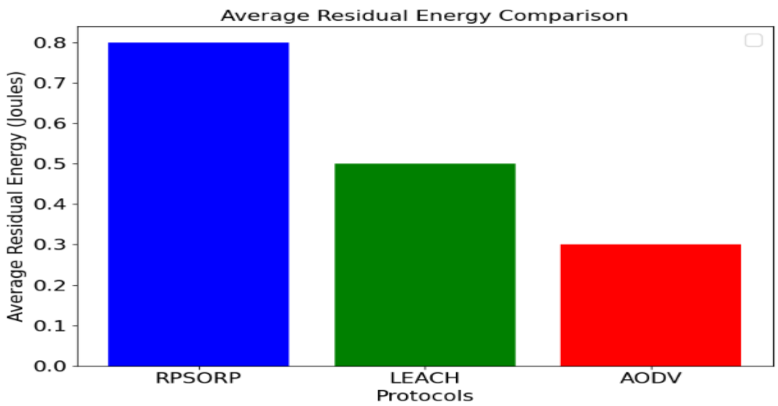

Fig 8. The Average Residual Energy of Nodes.

At the end of the simulation for each protocol, **Fig 8** presents the average residual energy of nodes. This visualization displays the energy efficiency level of the system during operation concerning the protocols. The bar chart shows that RPSORP performs well in energy efficiency among nodes by showing a higher average residual energy than the conventional routing protocols of LEACH and AODV. This points out that RPSORP reduces the total EC while simultaneously providing and maintaining better EC equilibrium among the nodes in the network, increasing the network lifetime.

According to the simulation results, RPSORP outperforms standard routing protocols such as LEACH and AODV regarding EC and prolonging network lifetime. RPSORP's improved performance can be attributed to its succession of routing paths, which effectively shortens transmission distances and balances the EC on the networks' nodes. Using PSO, RPSORP can determine paths that use less energy without exhausting some nodes faster than others. The lack of a dynamic average coverage ratio in standard protocols makes RPSORP significantly valuable for applications that need regularly located area tracking. Network protocols based on RPSORP and similar structures will use significant energy to avoid networking disparity and enhance productive domain coverage for extended periods. Run-of-the-mill interactions along these lines are featured by limited protocols that hardly deploy the global optimization approach elucidated above, and as such, shorter network lifespans are experienced.

The RPSORP exhibits consistent strategic advantages as the network size increases, which points out its scalability. The efficiency of the PSO increases the size of the search space without increasing the level of computation, which proves helpful for RPSORP in large WSNs. It also adapts to different communication ranges and is still functional despite these communication limits. The routing paths disagree to enable communication and data transfer if these nodes' communication capabilities are lowered, thus still operating the network under communication constraints. Nevertheless, a few weaknesses of RPSORP, in particular, need to be addressed. These nodes are assumed to be other corresponding sensors executing the PSO, which adds unnecessary computations and can be a limiting factor for SN with low power or low resources. This problem, however, is countered by the extended network life. Networks cause this overhead and the implementation of efficient algorithms to execute our risk. Other molds made in the simulations, such as no movement of nodes and the existence of ideal scenarios, will hold in highly dynamic settings, such as moving node mobility or changing channel conditions where the protocol performance may suffer. Dealing with dynamics such as these will be the area of extending RPSORP and studying hybrid methods, which RPSORP will integrate with other optimization methodologies to alleviate UPR in future performance.

As agreed in an earlier discussion, there are several developments where the use of RPSORP has practical consequences in such fields as environmental monitoring, smart healthcare, and security surveillance. Longer network lifetimes translate to lower operational expenditure as fewer batteries must be changed, hence a smaller infrastructure footprint. Furthermore, the protocol's effectiveness can be improved using adaptive parameter tuning and energy harvesting techniques. This would render RPSORP an up-and-coming, efficient energy management protocol solution for SSNs. To summarize, the presented results leave no doubt that RPSORP poses excellent potential in overcoming the limitations of the conventional routing method in the area of EC, network lifespan, extent of reach, and network durability. In the same method as routing figdecisions, which require the embedding of PSO, these aspects have been integrated into the optimization of the EC in RSOPRPM by RPSORP.

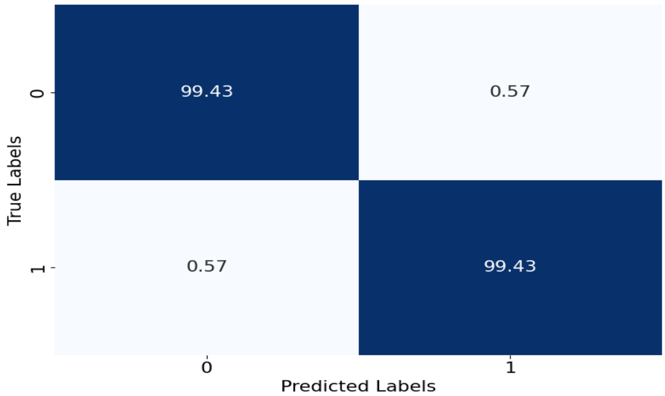

Fig 9. Confusion Matrix.

Fig 9 is the Confusion Matrix, which contains all-inclusive details of the classification of successful and failed data transmission with the RPSORP. The matrix summarizes the actual and percentage shares of TP and FN and open-handed ideas about RPSORP's performance in managing data packet classification. True Positive (TP) and True Negative (TN) are crucial determinants of protocol usability. Such high figures make it understandable that all the positive and negative attempts are captured. FP represents the unfortunate situation of a failed transmission being interpreted as a success, whereas the other method could enhance energy waste and lower efficiency. The same reasoning applies to FN, which refers to misclassifying a successful message transmission as a failure. The percentage reading on the confusion matrix makes drawing reports on the protocol's performance easy, as most percentages averaged out number nine as a balance. The more evenly spread the percentage was, the better the performance of the PSO algorithm in making routing decisions.

V. CONCLUSION AND FUTURE WORK

This paper introduces RPSORP, a technique that addresses energy efficiency in wireless SSNs. It integrates the advantages of PSO in routing decisions, allowing it to adaptively search for fewer ECs at any specified time while ensuring acceptable network coverage and connectivity. In most performance parameters, RPSORP is more effective than traditional routing protocols like LEACH and AODV. It provides an energy-efficient network operation by routing communication distances, reducing communication travel distances, and evenly distributing energy depletion across nodes. It makes the operational time longer, increases the time constant area coverage ratio, and advances the over-percent PDR to the sink node, all of which means better data transfers. RPSORP is flexible and extendible, preserving performance benefits even when network sizes and conditions change. It can endure communication restrictions and promotes sustainability in the entire set-up by rerouting communication links.

Future work should explore RPSORP's probable in dynamic networks, increasing its use in complex environments and encompassing its lifetime. When PSO is combined with other routing optimization methods, the result can be better routing solutions because these technologies can restore node energy and increase network lifetime. This method can enhance the network's performance.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Ali A Ibrahim Alasadi, Vijayanandh T, Showkat A Dar, Arulmozhiselvan L, Tanweer Alam and Virender Singh**; Methodology:** Ali A Ibrahim Alasadi, Vijayanandh T and Showkat A Dar; **Software:** Arulmozhiselvan L, Tanweer Alam and Virender Singh; **Data Curation:** Ali A Ibrahim Alasadi, Vijayanandh T and Showkat A Dar; **Writing- Original Draft Preparation:** Ali A Ibrahim Alasadi, Vijayanandh T, Showkat A Dar, Arulmozhiselvan L, Tanweer Alam and Virender Singh; **Writing- Reviewing and Editing:** Ali A Ibrahim Alasadi, Vijayanandh T, Showkat A Dar, Arulmozhiselvan L, Tanweer Alam and Virender Singh; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Competing Interests

There are no competing interests

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