A Hybrid Modified Ant Colony Optimization - Particle Swarm Optimization Algorithm for Optimal Node Positioning and Routing in Wireless Sensor Networks

Original Scientific Paper

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Abstract *– Wireless Sensor Networks (WSNs) have been widely deployed in hostile locations for environmental monitoring. Sensor placement and energy management are the two main factors that should be focused due to certain limitations in WSNs. The nodes in a sensor network might not stay charged when energy draining takes place; therefore, increasing the operational lifespan of the network is the primary purpose of energy management. Recently, major research interest in WSN has been focused with the essential aspect of localization. Several types of research have also taken place on the challenges of node localization of wireless sensor networks with the inclusion of range-free and range-based localization algorithms. In this work, the optimal positions of Sensor Nodes (SNs) are determined by proposing a novel Hybrid M-ACO – PSO (HMAP) algorithm. In the HMAP method, the improved PSO utilizes learning strategies for estimating the relay nodes' optimal positions. The M-ACO assures the data conveyance. A route discovers when it relates to the ideal route irrespective of the possibility of a system that includes the nodes with various transmission ranges, and the network lifetime improves. The proposed strategy is executed based on the energy, throughput, delivery ratio, overhead, and delay of the information packets.*

Keywords*: wireless network, PSO, modified ACO, HMAP algorithm, node placement, relay node selection*

1. INTRODUCTION

WSNs are structured networks with many SNs, where SNs sense, compute, and transmit data within small distance ranges [1]. SNs have low powers and cost very less. The applications of WSNs includedifferent areas, like enemy monitoring and tracking, forest fire detection, battlefield surveillance, and disaster management. The data is collected and sent back towards Base stations (BSs)or sink nodes by SNs deployed over a region in the applications of WSNs. SNs have very low communication ranges and are driven by batteries resulting in issues of coverages, energy consumptions, network lifespans, and costs during deployments of WSNs in regular/irregular terrains. For improving the WSN's performance, an effective resolution is required. In this efficient method, the optimum location for SNs is to be positioned as the NP-hard issue [2]. The energy consumption, operative lifespan, and sensing coverage are affected by the sensor node's locations [3]. Therefore, there is an essential needfor the careful placement of SNs. The trade-off exists between SNs' energy consumption and network coverage, [4]. However, the network coverage will turn smaller, and the energy consumption isreduced using nearby SNs.

As a result of its low battery life, a main problem in the WSNs are the nodes' energy consumption. Since power consumptions and transmission distances are directly proportional, data transmissions are the primary reasons for energy depletion. A solution to this problem can be the additions of expensive high-powerrelay nodes or CHs (cluster heads) that extend networklifespans, enhance network proficiencies, and minimize data transmission distances based on connections and fault tolerances [5]. The network lifespan is prolonged, and therefore by minimizing the transmission distance to its equivalent relay nodes which act as CHs for clusters of SNs transmitting data. Relay nodes are similar to SNs in that they are high-powered nodes with tiny batteries and might point toward failures. Various factors like environmental problems, external destructions, and hardware failures make networks inefficient, and similarly, relay nodes may become idle or get damaged. Therefore, BSs cannot receive sensed data of SNs that are combined towards relay nodes [6]. Thus, in the circumstance of a relay node failure, placing an appropriate quantity of relay nodes linked to a sensor is necessarily such that it is still attached to an additional relay node. By considering the connectivity problem, the number of relay nodes is minimized since the relay nodes are costly. Since both are contrary to one another, the minimization of the relay node and the connectivity are opposing ideas. Therefore, employing a method that mutually considers problems is highly significant.

WSNs are cheaper in terms of costs and require little or no maintenance costs once installed hence the need for using WSNs for various applications [7]. Routing protocols of WSNs map paths between sources and destinations. They are routing algorithms that split the network into more manageable chunks and provide mechanisms for exchanging information amongst neighbors initially followed by coverage of entire networks [8-9]. For WSNs applications to be efficient and reliable there is a need to design a routing optimization to manage the communication of WSNs in energy-aware and also traffic and distance-aware mechanisms. The focus of this research work is to optimize routing in WSNs. Based on the energy of SNs, network traffics, and the distances between source and destination SNs, this study aims to select the best ideal paths for SNs to deliver information to BSs. Hence in this work, the optimal positions of SNs (Sensor Nodes) are determined by proposing a novel hybrid algorithm HMAP algorithm for estimating the relay nodes' optimal positions that includes the nodes with various transmission ranges, and the network lifetime improves.

The technical work is organized as given. Section 2 analyzes the different research approaches, which are presented to attain the Optimal Node Positioning and Routing in WSNs. Section 3 discusses the proposed research approach in detail with appropriate diagrams and examples. Section 4 discusses the suggested research approach's performance examination based on the numerical evaluation. Lastly in section 5, the research study's conclusion is studied depending on the achieved findings.

2. LITERATURE SURVEY

Network performances, the energy efficiency of Media Access Controls (MACs), topology controls, reduced energy routings, enhanced TCP, and domain-based schemes have been studied in WSNs [10]. These studies imply issues of battery powers, the density of SNs, and limitations in preferred statistical information in WSNs which are dissimilar when compared to other networks [11]. For the supply of energy, energy-limited small batteries are used by the Sensor nodes [12-13]. Hence, to extend the network operation lifetime, power consumption is the primary task. For reducing the power consumption and transmission range using the appropriate protocol design and the method of an advanced hardware application, different techniques have been proposed by increasing SNs density[14]. The development of algorithms is achieved to determine the disjoint paths of minimum energy in an all-wireless network. SEAD was proposed in [15] to reduce energy usage in both creations and dissemination of trees for delivering data to BSs. A few studies look at how the placement of sensors or coupled nodes affects the performance of WSNs.

The authors in [16] used Neuro-Fuzzy Rule-based clustering for WSNs with Internet of Things (IoTs). The study enhanced network lifespans by adopting cluster-based routing where MLTs (Machine learning techniques) and fuzzy rules updated weights to accomplish energy modeling. The study's comparative performance results with LEACH, FLCP and HEED procedures showed its superior performances.

Routings in the study [17] were based on adaptive ranks where CHs were selected by SN's ranks which were in turn based on energy residues and geographical positions.

The study in [18] suggested that ECRP-energy coverage ratio protocols were better alternatives to LEACH protocols for reducing network energy usage. The study found ideal cluster counts and CHs based on the least energy usage and maximum coverage area. Network longevities were enhanced by replacing CHs with low energy residues and high usages. Catalina A. S. and Mihaela C. extended their previous work of mobile BSs on Spatio-temporal event identifications and reports in [19].

In designing sensor networks, evolutionary algorithm grounded methods, namely Gas, EA, GP, and so on, are used effectively by several investigators [20].

Shaik Imam Saheb et al. [21] have proposed a novel and efficient self-deployment strategy, i.e. IPONP algorithm, to restrict the relay node placement issue. Two different parameters like relay nodes' deployed quantity and movement price minimization are concerned to provide the maximum coverage area.

Mao Li and Feng Jiang et al. [22] proposed two-dimensional topologies based on Optimal Transmission Distance Algorithms (OTDAs) to lower energy usage and extend the lives of networks.

Belal Al-Fuhaidi et al. [23] suggested heterogeneous sensor network deployments using Harmony Search Algorithms (HSAs) and probabilistic sensing models (PSMs) for improving maximum coverage and increasing probable coverage without interfering with each other.

Table 1. Comparison of the existing Approaches

Author	Approaches	Results	Disadvantages
Thangaramya et al (2019)	Algorithmic Energy aware clustering and neuro-fuzzy-based routings	Energy utilization, PDR, and network lifetime	All SNs were considered trustworthy, an impossible condition
Chithaluru et al (2019)	AREOR– Adaptive ranks based on energy-efficient opportunistic routing schemes	Better Message success rates, reduced energy consumption, minimized end-to-end delays, and better PDRs	Time and computational complexity
Mengjia Zeng et al (2019)	Heterogeneous Energy-based Clustering Protocol for WSNs	Enhanced Network lifetimes, reduced load balancing, and improved overall energy consumption	Applicable for heterogeneous networks only
Aranzazu-Suescun et al (2019)	Anchor-based routing protocols where dynamic clusters were used ring	Reduced energy consumptions	Computational complexity
Shaik Imam Saheb et al. (2019)	IPONP algorithm	The algorithm has achieved the best energy consumption, and delayed performance	Reduced lifetime
Mao Li and Feng Jiang et al. (2020)	optimal transmission distance (OTDA)	Minimizing energy usages and maximizing network life spans	Very meagre improvements in terms of first node death

3. PROPOSED SYSTEM

In this section, the proposed HMAP scheme is explained in detail. In the HMAP scheme, the optimal position of SNs is determined by a novel improved PSO algorithm that utilizes the learning strategies to increase the particle population diversity and enhance the capability to escape from local optima. The M-ACO assured the optimal data transmission, and it discovers the ideal route irrespective of the system that includes the nodes with various transmission ranges.

3.1 LOCATION ESTIMATION USING IMPROVED PSO

PSOs are an enhanced population-based stochastic optimization approach inspired by fish schooling and bird flocking. A swarm of S potential solutions is contained in the basic PSO, and they refer to particles through the problem space of D-dimension when searching for the optimum global position. Thus, the best fitness values of an objective function are generated.PSOs can be understood better by knowing elements that makeup PSOs

Particles may be defined as Pi.

Fitness Functions-These functions determine the best solutions and are generally objective functions.

Local Bests-they signifies the particle's best locations in the swarm between locations visited so far.

Global Bests-The best locations of particles based on the best fitness values amongst all particles.

Updates to Velocities—-Velocities are vectors that determine a particle's speeds and directions.

Positional Updates-Particles attempt to get into ideal positions for maximum fitness. Particles in PSOs update their locations regularly based on global optima values. The flowchart of the proposed system is shown in Figure 1.

Primarily, a position Xid is assigned by each particle i randomly, where i = 1, 2,…D and a velocity Vid(i = 1, 2, ….S). The best position of pbesti and the global best gbesti can be tracked by each particle. The particles' velocity and position are updated as follows:

$$V_{id}(t+1) = w * V_{id}(t) + L_1 * R_1 * \left(pbest_i(t) - X_{id}(t)\right) + L_2 * R_2 * \left(Gbest_i(t) - X_{id}(t)\right) \tag{1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \tag{2}$$

Where w refers to the weight factor that controls the particle's velocity, L1 and L2 are the learning factors, and r1 and r2 refer to the random variables between 0 and 1.

Design of Fitness Function:

The particle position merits are evaluated, the Fitness function guides the particle selection direction, and the calculation is given below:

$$fitness\ (i) = 1/M \sum_{j=1}^{M} \sqrt{(xi - xj)^2 + \ (yi - yj)^2} \tag{3}$$

Where, (xj, yj) refers to the location coordinates of the anchor node j, the particle i's position coordinates (xi, yi), and its fitness value is fitness i.

In PSO, the aggregation of particles contributes towards the global best position and its finest position. The population causes convergence effects and impulsive convergence, and later search stagnates in the iterative phase. Resulting in low search accurateness of PSO algorithm, it is challenging to escape from local optimal.

A learning strategy using probability selection is proposed to increase the particle population diversity and enhance the capability to escape from local optimal. In the initial iterations, the algorithm's search efficiency and convergence speed are enhanced with the help of a learning strategy. The local optimum becomes favorable, and the quality of the candidates is improved in later iterations by using a learning strategy. Every measurement that is to be chosen by the learning strategy is diverse because of various particle position vectors' qualities. Therefore, self-determining learning approaches are employed by each dimension.

3.2 The pseudo-code learning process of a particle i

The particle i's position vector is xi, the search space dimension is D, the intermediate vector is xx, the minimum and maximum particle population's j-dimensional components are max(x:,j) and min(x: j), the fitness function is f(x), and the jth dimensional component of the particle population average is mean (x:j). Here, the fitness value reciprocal average is considered as weight.

```
For j = 1:D
xx = xi;
If rand<P1,k
Xxj = 2*gbestj – xxj; //learning strategy 1
Else If rand < P1j+P2j
Xxj = 2*pbesti,j – xxj;   // learning strategy 2
Else If rand < P1,j + P2,j + P3,k
Xxj = max (x:,j) + min(x:,j) – xxj; // learning strategy 3
Else
Xxj = 2*mean(x:,j) – xxj;    //learning strategy 4
End If
If f(xx) < f(xi)
Xi= xx;
f(xi) = f(xx);
End If
End For
```

Formulas of mean (x:,j), P1, j~P4,j in the Pseudo-code are as follows:

$$mean(x,j) = \frac{\sum_{i=1}^{N} \frac{1}{f(xi)} Xxi,j}{\sum_{i=1}^{N} \frac{1}{f(xi)}} \quad (4)$$

Where N represents the number of particles in the population, the particle i's j-dimensional component in the position vector is j, and f(xi) is the particle i's fitness value.

The local development low capacity can improve the accuracy and convergence of the optimal solution and other shortcomings in the later stage and disturbances to the current position as the PSO algorithm falls into the local optimum. The mutation of any dimension can be done as the current position's each dimension is not the best. For mutating the current best value, the step of Levy distribution is used based on the mutation formula as follows:

$$g_{best} = g_{best} + \alpha * s \quad (5)$$

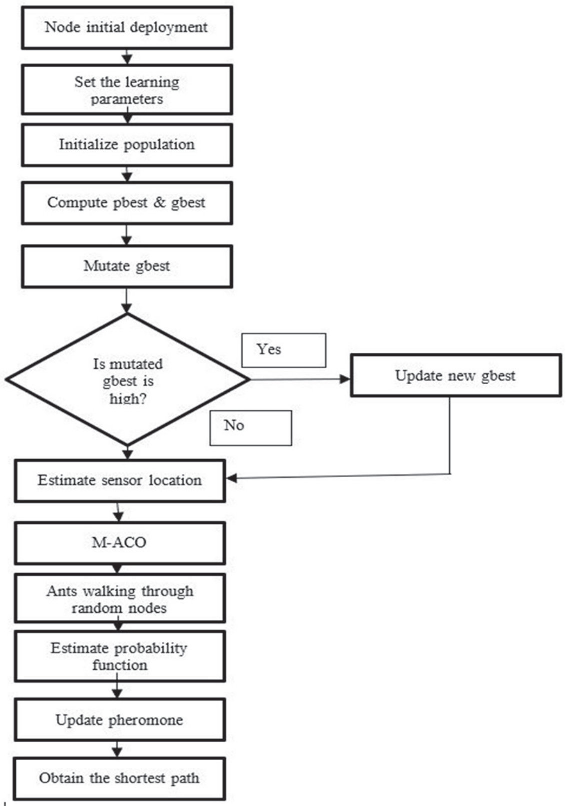

Fig. 1. Flowchart of the proposed system

Where, a represents the step size factor, whose value is 0.1 and s refers to the step subject to Levy's distribution.

Algorithm process: The process involves below

Step 1: Several SNs are placed at random in target regions, and distances between SNs are computed.

Step 2: Learning factors are set along with maximum iterations counts Tmax and maximum and lowest counts of particles.

Step 3: The population is initialized. The particle i's initial position xi = (xi1, xi2, …, xiD), best position is pbesti = xi, and speed is vi = (vi1, vi2, …viD). The swarm fitness value of a particle is evaluated based on equation (3). The best initial position of particle population is the global best position gbest.

Step 4: The particle speed v and position x are updated using the formula (1) & (2)

Step 5: The learning strategies implemented for particles based on pseudo-code

Step 6: The global best position and best position of particles are updated.

Step 7: The optimal position gbest mutates based on equation (5), and gbest is updated when the position of mutation is better

Step 8: The steps are repeated until all nodes' estimated location is determined.

3.3 ACO-BASED OPTIMAL ROUTE SELECTION

To determine the surmised answers for optimization challenges, the ACO could be used because it is a populace-based meta-heuristic algorithm. From the concept of ants' conduct, the ACO's vital thought has been considered. In a self-assertive way, each ant would be crossed the region while researching the synthetic substance in the first place. The chemical is called a pheromone, and it is the preface details of a neighborhood at each node. The pheromone quantity would be deposited based on the number of ants on the path and its length. The measure of higher pheromone will get by the shortest path. The ants with more increased pheromone obsession would be taken away and brace on the path they have considered. For handling various combinatorial issues, it is utilized as a masses-based scan practice. The network directions would imitate the way followed by ants. As a part of the position of ants, ant packets could be used. Each node's likelihood could be supplanted by the synthetic substance 'pheromone'. In ACO, pheromone trails would be helpful as dispersed and numerical data. The ants create the answers probabilistically for the comprehended challenge, and the ants have been adjusted to implement the algorithm for mirroring the pursuit encounter. At each ant packet's entry, the pheromone ought to be refreshed or modified as it is a volatile substance.

ACO-based algorithm: The assumption of random circulation of SNs in a rectangular locale is considered in the network model to detect the purpose of using the algorithm. For applying the principle behind the fundamental ACO, the outlines would be given by the fragment. Each node in the graphical issue would represent a point or vertex. The nodes or vertices that are joining the line are called edges.

Step 1: Random Deployment

The source over the framework would communicate the ant packets. In addition to the pheromone concentration, each path distribution is done randomly.

Step 2: Solution set generation

Based on the previous studies, the random deployment of the incalculable number of ants would be commenced, and the random path is strolled along these lines that constructed each set of solutions. Based on the provided constraints, each solution would be generated.

Step 3: Node selection

From the present node, the following node's selection would have relied on the probability function. Along the network edges, the associated pheromone would be considered while selecting the nodes. As a part of the Markov chain, each move of the ant could consider that the possibility of the move will be relying on the present value and not on the initial value.

Step 4: Probability estimation for the selection of a node

The equation below provides the possibility of selecting the next node 'j' from the present node 'i'.

$$\text{Pij} = \frac{[Tij]^{\alpha} * [nij]^{\beta}}{\sum k\in Ni\ [\{Tik\}^{\alpha} * \{nik\}^{\beta}]} \quad (6)$$

Here, α & β are control constraints Tij would represent the pheromone concentration along with the edges nij is going to signify the information of heuristic. It is equivalent to 1/dij, where dij is the distance between 2 nodes, Pij characterizes the node j probability to be selected from node i, and Ni would be represented the nodes' set.

Step 5: Pheromone update

Any node receives each ant packet and updates the pheromone while each node travels over all ants formerly using the below equation,

$$Tij(t+1) = (1-p)Tij(t) + \sum_{k=1}^{m} Tijk(i,j) \quad (7)$$

Where ρ is the pheromone rate of evaporation for avoiding the accumulation of pheromone, which would represent the pheromone quantity that would require be adding or subtracting to the path traveled by the ant k. As these results are made as particles, these k particles are selected randomly from the particle population and the k particles' appropriate positions are compared. Rather than choosing the global position for guiding the particle motion, it selects its individual best position. Based on the iteration, the k value increases gradually. The high-grade solution is made worse by a smaller k value that performs better towards the global search, and the population diversity rises. A larger k value attains high quality.

4. RESULTS AND DISCUSSION

Network simulator-2 was used to perform simulations based on the AODV routing protocol that focuses on the technique of node deployment. The network's energy consumption is discussed through the simulation results after carrying out the routing packets via AODV [24]. The network lifetime is increased by covering the maximum area using the proposed algorithm that saves the network energy. For nodes' deployment, the results are plotted using different parameters [25]. The proposed H-MAP system was compared to the Intersection Point Based Optimal Node Placement (IP-ONP) Algorithm, optimal transmission distance (OTDA) Algorithm, and harmony search algorithm using the network simulator NS2 (HSA). End-to-end latency, energy usage, and throughput characteristics were utilized to compare and appraise this example. The simulation parameters are shown in Table 2.

Table 2. Simulation parameters

Simulation Parameters	Values
Simulation Tool	NS-2.35
No. of nodes	50
Simulation time	100 sec
Simulation area	1500*1500 m
Pause time	2-20 S
Mobility model	Random waypoint model
Routing protocol	HMAP
Packet rate	1000 bytes/0.1ms
Transmission Protocols	UDP, NULL
Channel type	Wireless
Mac layer	802.11, SMAC
Traffic type	constant Bit Rate (CBR)
Antenna type	Antenna/Omni antenna
Initial energy	100 j

End-to-end delays: Average time taken by packets to get transferred from network's sources to destinations and based on Equation (8).

$$End - to - enddelay = \frac{\sum_{i=1}^{n}(t_{ri}-t_{si})}{n}$$

Where t_{ri} – ith packet delivery time, t_{si} – a time when an ith packet was sent, n – number of packets.

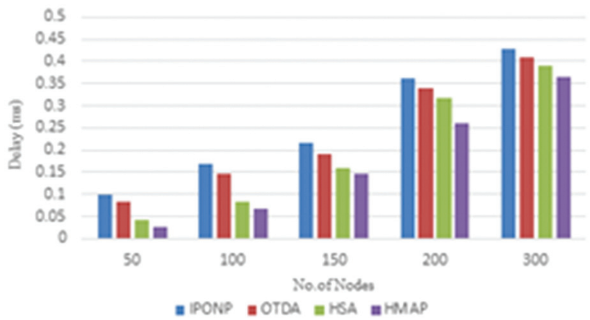

Fig. 2. End-to-end delay vs number of nodes

The simulation results in Figure 2 show the evaluation of the proposed HMAP method's end-to-end delay time. Table 2 shows how effective node placement using a learning technique and optimum relay selection using ACO, which guarantees that only high-quality nodes are chosen as relays, helped to reduce end-to-end latency. The proposed HMAP approach achieved the shortest average latency in the network 0.25ms for 50 numbers of nodes, whereas the previous methods like IPONP, OTDA, and HSA are 0.98ms, 0.84ms, and 0.41 which are higher delays than the proposed method.

Table 2. Comaprision of end to end delay

Nodes	IPONP (ms)	OTDA (ms)	HSA (ms)	HMAP(ms)
50	0.098	0.084	0.041	0.025
100	0.169	0.146	0.084	0.068
150	0.217	0.191	0.160	0.148
200	0.362	0.338	0.316	0.259
300	0.429	0.409	0.390	0.365

Energy consumptions: These refer to average energies required for transmitting packets to nodes within particular time frames in Equation (9)

$$Energy\ (e) = [(2 * pi - 1)(e_t + e_r)d \tag{9}$$

Where pi – data packet, e_t - packet i's source energy, e_r – energy needed for the receipt of packet i, d – distance among source and destination nodes.

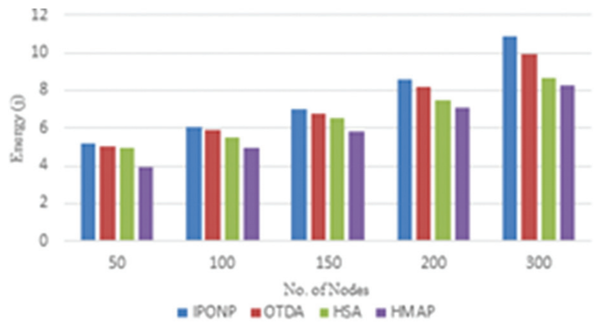

Fig. 3. Energy consumption against counts of SNs

The simulation results in Figure 3 and Table 3 show that the proposed approach saves a significant amount of energy compared to the prior existing methods. The proposed HMAP method attains minimum energy consumption obtained in the network was 3.920 for 50 numbers of nodes, whereas the previous methods like IPONP,OTDA, and HSA are 5.23, 5.01, and 4.954 which are higher values of energy consumption when compared to the proposed method.

Table 3. Comparison of energy consumption

Nodes	IPONP (j)	OTDA (j)	HAS (j)	HMAP (j)
50	5.23	5.01	4.954	3.920
100	6.071	5.93	5.480	4.933
150	7.027	6.80	6.540	5.811
200	8.619	8.20	7.510	7.067
300	10.8544	9.90	8.70	8.296

Network lifetime: network lifespan can be expressed in eqn (10)

$$Lifetime\mathbb{E}[L] = \frac{\varepsilon_0 - \mathbb{E}[E_w]}{P + \lambda\mathbb{E}[E_r]} \tag{10}$$

here P - constant network power consumption and continuous, ε_0 - total non-rechargeable initial energy, λ- average sensor reporting rate, $\mathbb{E}[E_w]$ – expected energy wastage or non-utilized energy till the death of the network, and $\mathbb{E}[E_r]$ –reported energy consumption of nodes.

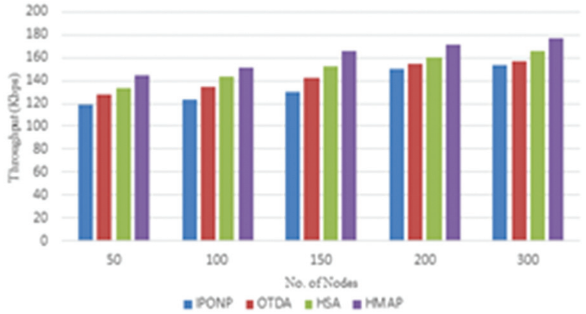

Fig. 4. Network performance vs number of nodes

Throughput metric refer to the amount of data transmitted between SNs. High throughputs ensure higher amounts of data deliveries. Table 4 and figure 4 show that, when compared to existing approaches, the suggested method has a high throughput rate. The high throughput rate was due to the efficient node placement strategy and optimal relay node selection, which always selects the interference-free paths. In the experiment, the suggested approach kept the average throughput rate at up to 160kbps, whereas current methods kept it at less than that and maintained low throughputs than the results of the proposed method.

Table 4. Comparison of network performance

Nodes	IPONP (Kbps)	OTDA (Kbps)	HSA (Kbps)	HMAP (Kbps)
50	119.34	127.93	133.42	144.13
100	122.88	133.98	143.17	151.42
150	129.88	142.88	152.46	165.75
200	149.59	154.68	160.42	171.01
300	153.58	157.37	165.64	177.39

PDR: indicates the proportion of total lost packets to overall sent packets can be expressed in eqn (11)

$$\text{Packet loss ratio} = \frac{N^{tx} - N^{rx}}{N^{tx}} \times 100\% \qquad (11)$$

Where N^{tx} - transmitted packets, N^{rx} - received packets. This evaluation was carried out through the extraction of all real-time packet sizes, which are sent and obtained.

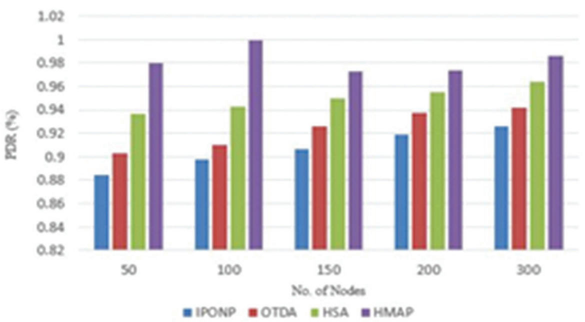

Fig. 5. Packet delivery ratio vs number of nodes

PDRs: They refer to the ratio of successful delivery of packets to intended destinations.

PDRs describe the network's data transmission quality. The successful delivery of packets was aided by the selection of reliable relay nodes and the optimal placement of relay nodes using learning algorithms. The proposed approach obtained a maximum PDR of 0.97 percent, whereas previous methods averaged 0.93 percent. The packet delivery ratio is shown in Figure 5, and a comparison of existing approaches is shown in Table 5.

Table 5. Comparision of Packet delivery ratio

Nodes	IPONP (%)	OTDA(%)	HSA (%)	HMAP (%)
50	0.8847	0.9026	0.9369	0.9795
100	0.8973	0.9103	0.9430	0.9991
150	0.9065	0.9256	0.9497	0.9726
200	0.9186	0.9370	0.9548	0.9739
300	0.9255	0.9417	0.9635	0.9861

5. CONCLUSIONS

In this work, the optimal position of SNs is determined by proposing a novel hybrid algorithm HMAP algorithm. In the HMAP method, the improved PSO utilizes learning strategies for estimating the relay nodes' optimal position. The M-ACO assures the data conveyance, and a route is discovered that is very close to the ideal route irrespective of the system with nodes of various transmission ranges. The probability-based selection scheme used in ACO improves the self-node selection strategy. The experimental results prove the effectiveness of the HMAP scheme over the IPONP, OTDA, and HSA schemes. The proposed HMAP method attains minimum energy consumption experienced in the network was 3.920 for 50 numbers of nodes, whereas the previous methods like IPONP, OTDA, and HSA are 5.23, 5.01, and 4.954 which are the higher value of energy consumption when compared to the proposed method. The suggested approach appears to have a good chance of being implemented in a static WSNs system. Future research should look at the possibilities of implementing the proposed method in a dynamic WSNs system, so that its full potential may be used to solve real-world challenges like sensor lifetime and geographical conditions.

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