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OPTIMIZED HYBRID ROUTING ALGORITHM WITH ENHANCED TRANSMISSION SPEED IN WIRELESS SENSOR NETWORKS FOR AMI APPLICATION UNDER INDIAN GOVERNMENT ACT 1933

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Abstract

In the present digital era, data transmission plays a crucial role across diverse technological platforms. Ensuring data availability during transmission is crucial, since Wireless Sensor Networks (WSNs) in the Advanced Metering Infrastructure (AMI) domain are highly susceptible to cyber-attacks. These threats often result in inefficient routing and data breaches, raising serious security concerns. To address these challenges, this article introduces a shortest-path hybrid model that improves both the speed and security of data transmission by integrating Lion Optimization, Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO). The longer a data packet remains in transit, the higher the likelihood of it being intercepted, altered, or discarded by an attacker. Routing strategies that identify the shortest or least congested routes help lower latency, thereby decreasing the risk of blackhole, selective forwarding, and eavesdropping attacks. Similarly, algorithms that enable rapid path recovery and maintain fast transmission ensure resilience against denial-of-service (DoS) and routing loop attacks. The proposed model, Particle Bee Ant Colony Swarm (PBACS), improves transmission efficiency by identifying the optimal path between nodes, thereby reducing delay and outperforming conventional techniques. Enhancing data transmission speed explicitly diminish the attack time period for attackers and acts as impediment to cyber attacks along the transmission path and the effectiveness of this method is evaluated using five key performance metrics: throughput, packet loss, energy consumption, and delay.

Keywords: Cyber-attack, Data Transmission, Machine Learning, shortest path, Attack time, Hybrid algorithm.

1. INTRODUCTION

Speed and security remain critical challenges in the transmission of data between nodes in Wireless Sensor Networks. These networks are highly efficient for data transfer as they incorporate power sources, various types of memory, and radio frequency transceivers. Once deployed, WSNs are self-organizing and communicate wirelessly in an ad-hoc manner. However, their analysis and configuration are often complex and time-intensive. To improve data delivery speed, identifying the shortest communication path for efficient data collection is essential. WSNs face several challenges, including routing, clustering, event monitoring, fault detection, data aggregation [1], and task scheduling. Among these, routing plays a pivotal role, as it contributes to the majority of energy consumption. Machine Learning (ML) techniques present a promising solution due to their ability to perform reliable data aggregation, classification, optimization, and clustering with high accuracy and efficiency. Leveraging neural networks, swarm intelligence, and reinforcement learning, ML can exploit the distributed characteristics of the network to minimize transmission overhead and determine optimal data routes through effective aggregation and clustering. When integrated with clustering strategies, such methods can significantly enhance data security, extend network lifetime, and improve overall energy efficiency in WSNs.

Energy consumption can be prevented by using optimization techniques by collecting data and exchange through sensor nodes [2]. Concurrently, the ACO-OSTEB (ACO-Optimized Self-Organized Tree-Based Energy Balance) method is involved in performing, cluster development, multi-path formation, and data transmission through WSN. The Cluster Head (CH) is created by the formation of several sensor nodes. At first, the member nodes are enhanced to join CH and the other nodes are tend to join another nearby CH. ACO technique is used to find the multiple path between sensor nodes and CH. The hybrid PSO-CSO [3] (PSO-Cuckoo Search Optimization) and hybrid ACO-PSO [4] to transfer data through multi-hop transmission. It chooses various routing paths using CH and lengthens lifetime of the network. It provides multiple paths to overcome data traffic and thus provides efficient data delivery. The network lifetime is increased as CH is changed periodically.

Hybrid approaches that combine Particle Swarm Optimization (PSO) [5] and Ant Colony Optimization (ACO) [6] have been applied by partitioning the network into multiple clusters. In such methods, ACO enables mobile agents to sequentially traverse cluster heads, while PSO assists in selecting the anchor nodes for each CH within the communication boundary [7]. The dynamic adjustment of the communication range is achieved by merging anchor nodes in overlapping coverage areas. Another enhancement involves integrating PSO with Genetic Algorithms (GA) [8] for more effective CH selection. In this case, GA initially identifies the CH, and the fitness function is evaluated based on factors such as the number of nodes within the cluster, residual energy of the CH, distances between nodes and the CH, the CH-to-base station (BS) distance, and the total energy of all nodes [9]. Subsequently, PSO-based routing employs relay nodes between the CH and the sink, thereby reducing CH energy consumption and ensuring efficient data delivery to the BS through optimal path prediction. Hierarchical CH selection techniques have also been investigated in which, the LU-GWO (Lion Updated Grey Wolf Optimizer) [10] selects CHs by minimizing node-to-node distances, reducing transmission delay, and balancing energy consumption across the network. While such methods improve routing path optimization and energy efficiency, many still depend on relatively slow cryptographic mechanisms. To overcome this limitation, ACOPSO (Ant Colony Optimization with Particle Swarm Optimization) can be utilized to enhance CH selection, enabling efficient data transmission to the BS while simultaneously identifying optimal routing paths.

1.1 Problem Identification

Wireless Sensor Networks encounter significant challenges primarily due to the limited power supply of sensor nodes, which are typically battery-operated. This limitation necessitates the development of energy-efficient protocols and algorithms to prolong the network’s operational lifetime [11]. Wireless communication channels in WSNs also suffer from unreliability, often caused by interference from devices operating on similar frequencies, which results in packet loss and higher retransmission overhead. Accurate localization of sensor nodes is another essential requirement for effective data collection and synchronization; however, achieving this in a distributed environment remains complex and [12] dealt with improved solution. Furthermore, WSNs remain vulnerable to several security threats, including eavesdropping, jamming, and spoofing, while existing inefficient routing algorithms further degrade network performance. Therefore, optimization-based secure routing techniques are necessary to enhance both energy efficiency and resilience against attacks.

The key contributions of the proposed method are outlined below:

- Efficient Routing Path Detection: Application of Lion-Optimized ACOPSO for reliable identification of routing paths to improve data transmission efficiency.
- Shortest Path Data Transmission: Utilization of the PBACS methodology to determine the shortest routing path in sensor networks, enabling faster and more efficient data transfer.
- Comprehensive Performance Evaluation: Assessment of the proposed system against conventional approaches by analyzing metrics such as delay, throughput, energy consumption, and packet drop rate, thereby demonstrating improved speed and enhanced network lifetime in data communication.

1.2 Paper Organisation

The paper is organized according to the proposed framework for optimized routing and rapid data transmission. **Section 2** presents a review of conventional studies along with problem identification. **Section 3** describes the proposed methodology, ACOPSO algorithms to strengthen network lifetime and establish efficient routing paths. The dataset employed, experimental results, and comparative analysis with existing approaches are detailed in **Section 4**. Finally, **Section 5** outlines the conclusion and discusses potential directions for future work.

2. REVIEW OF LITERATURE

This section presents a review of existing methods that employ various approaches for optimized routing and secure data communication in WSNs.

2.1 WSN Routing Optimization

The efficiency of data transmission in WSNs primarily depends on factors such as energy consumption and network lifetime. Reliable communication can be achieved only when data is transmitted from the source node to the destination across multiple communication paths without delay. CH selection plays a crucial role in this process, as improper selection can lead to rapid energy depletion and network instability. To conserve energy and extend network lifetime, Particle Swarm Optimization (PSO) has been widely applied [13]. By employing PSO, data collected from sensor nodes can be transmitted to the Base Station (BS) without redundancy. PSO has also been implemented in Optical Wireless Sensor Networks (OWSNs) [14] to enhance routing paths while minimizing energy usage. To mitigate hotspot issues, mobile sinks have been introduced to collect data instead of transmitting directly to the BS, with Rendezvous Points (RP) [15] established to reduce data loss. For intra-cluster routing, the ACO-OSTEB algorithm [16] has been applied to achieve efficient data transmission. To further optimize CH selection, hybrid methods such as ACO combined with Glowworm Swarm Optimization (GSO) have been explored [17], where the fitness function is evaluated based on parameters including energy, distance, and delay. Similarly, Ant Colony Optimization has been employed to develop energy-efficient routing protocols. A dual-CH strategy, in which two CHs are selected via ACO, has been shown to balance the workload, thereby improving overall efficiency and extending network lifetime.

To address the local minima problem, Reposition PSO (RPSO) [18] has been introduced to preserve particles during the optimization process. In the context of Underwater Wireless Sensor Networks (UWSNs), clustering and routing techniques have proven effective for navigation, surveillance, and data collection. Improper placement of CHs can significantly reduce energy efficiency and overall network lifetime, while also introducing delays in data transmission. To overcome this issue, an OAFS (Opposite Artificial Fish Swarm) combined with IMFO (Improved Moth Flame Optimization) has been proposed to establish effective routing paths toward the BS [19]. This system has demonstrated improved energy efficiency, extended network lifetime, reduced delay, and enhanced detection accuracy compared to existing approaches.

Furthermore, the proposed model explicitly accounts for the energy consumed in data transmission, routing, encryption, and processing, thereby providing a comprehensive breakdown of energy utilization. The revised framework also includes a comparative analysis with existing routing and quantitatively validating the improvements achieved through the integration of PBACS algorithms. This holistic evaluation reinforces the effectiveness of the proposed approach in minimizing energy consumption while ensuring secure and efficient communication in WSNs.

Although several hybrid algorithms—such as Ant Colony Optimization (ACO) combined with Particle Swarm Optimization (PSO), Genetic Algorithm–PSO (GA-PSO), and Cuckoo Search Optimization (CSO)-based methods—have been explored in prior studies to improve routing efficiency, most of these techniques primarily focus on either minimizing energy consumption or accelerating routing performance. However, they often lack integrated mechanisms and exhibit limited adaptability to dynamic network conditions. In contrast, the proposed Particle Bee Ant Colony Swarm (PBACS) algorithm integrates ACO, PSO, and Lion Optimization to simultaneously enhance routing efficiency, conserve energy, and dynamically adapt to variations in network topology and residual node energy. By addressing routing optimization and rapid data transmission, the proposed system offers a comprehensive solution well-suited for real-world applications where energy efficiency, network lifetime, and data availability are equally critical. The comparative analysis further demonstrates the superiority of the proposed method over existing hybrid approaches in terms of adaptability, efficiency, and availability.

2.2 Problem Identification

The key issues identified from the analysis of conventional studies are as follows:

- Although energy-efficient routing protocols have been developed to improve security through QoS, their performance can be further optimized by applying fuzzy techniques to effectively manage uncertainty in data communication [16].
- Clustering has been shown to enhance routing efficiency and reduce energy consumption; however, Genetic Algorithms (GAs) often require longer computation time to reach optimal solutions, which limits their practicality [20].
- The role of cluster heads is critical for effective communication, typically achieved through clustering with techniques such as TFL-BOARS. Nevertheless, network lifetime can be further extended by incorporating data compression mechanisms [21].

Energy efficiency and routing optimization remain enduring challenges in WSNs. Traditional methods often fail to achieve an effective balance between minimizing energy consumption and ensuring reliable routing, particularly in dynamic environments with fluctuating node connectivity and variable traffic patterns. Most existing techniques emphasize either energy conservation or routing efficiency in isolation, leading to suboptimal outcomes in real-world deployments. To address these limitations, the proposed framework integrates advanced algorithms Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Lion Optimization combined as Particle Bee Ant Colony Swarm (PBACS) to provide a comprehensive solution. This integrated approach not only optimizes routing paths and reduces energy consumption but also strengthens data availability. Experimental results demonstrate superior performance across key metrics, including throughput, delay, and packet drop rate, underscoring the adaptability and effectiveness of the proposed system for practical WSNs in AMI.

3. PROPOSED METHODOLOGY

Data transmission in wireless sensor networks is typically achieved by organizing sensor nodes into clusters, which facilitates data aggregation and the selection of cluster heads. This clustering process enables the identification of shortest paths for efficient routing. Although conventional approaches have improved data transmission, they often incur high energy consumption at the node level, thereby limiting overall network lifetime. To address this issue, the present study emphasizes secure data transmission through shortest-path routing while optimizing network longevity by effectively managing node energy levels. The motivation for this work arises from the inherent resource constraints of WSNs, where sensor nodes are restricted in both battery capacity and processing power. Traditional routing protocols frequently overlook energy efficiency, leading to premature node failures and reduced network sustainability. To overcome these challenges, the proposed framework introduces PBACS (Particle Bee Ant Colony Swarm), a hybrid optimization algorithm that integrates Particle Swarm Optimization, Ant Colony Optimization, and Lion Optimization. By combining the exploratory capabilities of PSO with the exploitative strengths of ACO and Lion Optimization, PBACS efficiently determines energy-optimal routing paths while dynamically adapting to variations in network topology and residual node energy.

The integration of the proposed algorithm enables real-time adaptability to dynamic network conditions, ensuring efficient data transmission even under high traffic loads or node failures. To further enhance overall performance, this work explores three hybrid algorithms specifically designed to achieve both accelerated routing and secure data transmission, as illustrated in Figure 1, which presents the system flow model for achieving end-to-end data availability within a node, utilizing the hybrid PBACS algorithm to optimize routing and improve energy efficiency. The process begins with agent initialization, followed by the selection of potential routing paths. Through iterative tour construction, the algorithm progressively identifies the most optimal path, with agents updating their velocity and position until convergence is reached at the final iteration. This ensures the selection of the most energy-efficient routing path. Supporting processes—including fitness evaluation, energy estimation, and performance analysis—further reinforce the optimization.

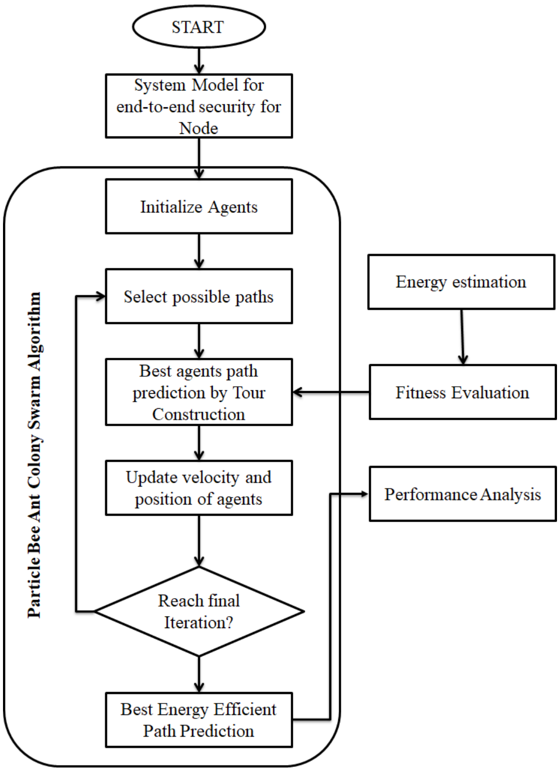

Figure.1 Overall Flow of Data transmission

At the outset, potential routes for data transmission are identified using Lion Optimization, which evaluates the energy levels of network nodes. Paths are established by selecting nodes with comparable energy levels, ensuring faster transmission while minimizing the risk of premature energy depletion. With these enhancements, the system ensures greater efficiency, accuracy, and resilience in rapid data routing and transmission.

3.1 Shortest Route Selection- PBACS (Particle Bee Ant Colony Swarm Algorithm)

To determine the most efficient routing path for data transfer, this study introduces the PBACS algorithm, which integrates Lion Optimization with ACO and PSO. The optimization model is inspired by the social dynamics of lions, where different roles and behaviors are mapped to specific optimization processes. In the initialization phase, a population is generated within the search space, with each member represented as a "lion." The algorithm incorporates mechanisms such as lagging lions, territorial dominance, evaluation, nomadic movement, survival contests, and pride formation—ensuring a balanced trade-off between exploration and exploitation. Within each pride, the fittest solution is identified, representing the optimal or near-optimal routing path.

Within this framework, the ACO module employs a probabilistic strategy inspired by the food-searching behavior of ants. This approach reduces computational overhead while efficiently identifying routes in a graph-based environment. Ants construct solutions incrementally by traversing graph edges, with their choices guided by pheromone intensity and heuristic information. In each cycle, ants explore possible paths and then evaluate their quality. Following this evaluation, pheromone levels are updated—reinforcing promising routes while reducing the likelihood of selecting less efficient ones. Through repeated iterations, the algorithm progressively converges toward the shortest and most energy-efficient transmission path.

Particle Swarm Optimization is a widely recognized meta-heuristic technique used to solve complex optimization problems. As a population-based method, it iteratively improves candidate solutions based on a defined fitness function. In this approach, each candidate solution is represented as a particle that moves through the search space by updating its velocity and position using mathematical equations. The movement of each particle is influenced by two key factors: its own best-discovered position and the global best position found by the swarm. By sharing information and adjusting trajectories accordingly, the swarm gradually converges toward the optimal solution, ensuring an effective balance between exploration and exploitation of the search space.

The integration of ACO and PSO is driven by the need to balance their complementary strengths while mitigating their individual limitations. ACO excels in exploration, as its probabilistic path-construction mechanism effectively identifies diverse potential routes; however, it often suffers from slower convergence and redundant iterations. In contrast, PSO emphasizes exploitation, refining solutions by guiding particles toward promising regions of the search space, but it may converge prematurely. By combining ACO and PSO, the hybrid model leverages the explorative capability of ACO with the exploitative strength of PSO. While ACO discovers diverse candidate paths, PSO accelerates convergence toward the best solution. Moreover, ACO's pheromone update mechanism guides the swarm to reinforce efficient routes, thereby reducing redundant computations and ensuring faster convergence.

This global path obtains the final population of the data transmission. Fitness value is needed to find for the fast transmission. It is accomplished through PSO algorithm as it is a computational technique that enhances a problem by constant process to develop a contender result with respect to a specified amount of quality feature. It resolves a problem by taking a population of contender results. It moves the dubbed particles in the exploration space with measured formula over the elements speed and position. The movement of the particle is inclined by position. It also suggest the suitable position in the search space. This will assign the swarm near the finest results.

In the proposed methodology, the algorithm begins with a population of candidate solutions that evolve according to fundamental mathematical rules. The movement of these solutions is directed by their positions within the search space. The integration of Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) is motivated by the need to overcome their individual limitations while harnessing their complementary strengths. ACO is particularly effective for exploratory searches, while PSO excels in exploitative refinement. Their combination enhances the overall search process: ACO minimizes redundant iterations through its pheromone-guided mechanism, whereas PSO accelerates convergence, thereby improving data transmission efficiency. The Figure 2 gives the Pseudocode for proposed Particle Bee Ant Colony Swarm (PBACS) Algorithm which comprised six steps.

```
//General Pseudocode for Combined Three Routing Algorithms.//
// Each algorithm runs separately and produces its own shortest-path estimates.//
//Combination Phase compares results and picks the best one per destination.//
//Ensures optimality, Adapts to local changes and Backup path ensures redundancy if failure.//
```

```
//Combination Phase: Particle Bee Ant Colony Swarm (PBACS).//

    Algorithm CombinedThreeRouting(NetworkGraph, Source):

    Input:
       NetworkGraph = (V, E, Cost)     // Graph with nodes, edges, and link costs//
       Source                          // Starting node (router)//
    Output:
       FinalRoutingTable[ ]            // Best next-hop and cost to all destinations//

    Steps:
    1. Initialization:
         For each node v in V:
            distance[v] := ∞
            nextHop[v] := NULL
         distance[Source] := 0

    2. Phase 1 – Algorithm Lion Optimization (A):
         Run Algorithm A
         Store results in distanceA[ ] and nextHopA[ ]

    3. Phase 2 – Algorithm Ant Colony Optimization (B):
         Run Algorithm B
         Store results in distanceB[ ] and nextHopB[ ]

    4. Phase 3 – Algorithm Particle Swarm Optimization C:
         Run Algorithm C
         Store results in distanceC[ ] and nextHopC[ ]

    5. Combination Phase:
         For each destination d in V:
            bestCost := min(distanceA[d], distanceB[d], distanceC[d])
            If bestCost == distanceA[d]:
               FinalRoutingTable[d] := (nextHopA[d], distanceA[d])
            Else if bestCost == distanceB[d]:
               FinalRoutingTable[d] := (nextHopB[d], distanceB[d])
            Else:
               FinalRoutingTable[d] := (nextHopC[d], distanceC[d])

    6. Return FinalRoutingTable      //Efficient updated routing table//
```

Figure 2. Pseudocode for proposed Particle Bee Ant Colony Swarm (PBACS) Algorithm

To further strengthen performance, machine learning–based classifiers are incorporated to predict the location of CHs, ensuring more reliable data transfer across the network. The uniqueness of this enhanced work stems from the combined use of LO, ACO, and PSO, which collectively enhance both security and transmission efficiency in wireless sensor networks. More specifically, the proposed PBACS algorithm fuses the strengths of PSO, ACO, and Bee algorithms to optimize routing by dynamically selecting the most energy- and time-efficient path. This hybrid approach not only reduces energy consumption and transmission delay but also provides a robust layer of security for data communication.

Unlike existing approaches, such a combination has been scarcely explored in the literature, particularly for secure and efficient data transmission. The proposed framework therefore delivers a holistic solution by unifying optimization and cryptographic techniques in a single configuration, significantly improving routing efficiency while mitigating security risks. The following discussion highlights the advantages of PBACS and its contributions to achieving superior performance compared to conventional methods.

4. RESULT AND DISCUSSION

This section presents the results of the proposed system, along with a detailed description of the dataset, exploratory data analysis (EDA), evaluation metrics, predicted outcomes, and comparative performance analysis.

4.1 Simulation Configuration

The proposed study was implemented in Anaconda Spyder using Python 3.9 to evaluate the system's efficiency and performance. Network simulation was performed with the NetworkX package to model the topology and test routing protocols. The simulated environment comprises 100 sensor nodes uniformly deployed within a 100 m × 100 m area, with randomized node positions and varying energy levels to closely resemble real-world conditions. Node mobility is incorporated to represent dynamic scenarios, while additional factors such as node failures, interference, and traffic load are introduced to emulate practical WSN environments. This experimental setup establishes a reliable and realistic foundation for assessing the effectiveness of the proposed routing and security optimization algorithms. To ensure more efficient data transmission, the proposed PBACS integrates three highly effective algorithms, incorporating selected parameters from each, as illustrated in Figure 3.

Ant Colony Optimization (ACO) Number of ants 50

Parameter	Pheromone Decay Rate	Number of Iterations	Alpha (pheromone influence)	Beta (heuristic influence)
Value	0.95	100	1	2

Particle Swarm Optimization (PSO) population size is 30

Parameter	Particle Population Size	Cognitive Coefficient (C1)	Social Coefficient (C2)	Maximum Velocity	Maximum Iterations
Value	30	2	2	0.1	200

Proposed Particle Bee Ant Colony Swarm (PBACS) population size are 30

Parameter	Ant Population Size	Bee Population Size	Convergence Criteria
Value	30	30	Fitness improvement threshold of 0.01 or maximum iterations of 150

Figure 3. Algorithm Parameter values and Description

4.2 Performance Metrics

The performance evaluation of the proposed data transmission system is carried out using several key criteria: throughput, energy consumption, packet drop rate and delay.

- **Throughput:** The amount of data successfully delivered from source to destination within a specific time frame, serving as an indicator of system efficiency.
- **Energy Consumption:** The total energy required for operations such as signal generation, amplification, and reception. Wireless communication generally consumes more energy than wired transmission, with usage influenced by factors including signal frequency, modulation type, environmental interference between sender and receiver, hardware configuration, and data rate.
- **Packet Drop Rate:** The percentage of data packets that fail to reach their intended destination. A high packet drop rate reduces reliability and degrades overall system performance.
- **Delay:** The time taken to transmit packet bits across the communication link. Transmission delay is primarily affected by channel bandwidth and the size of the data being transmitted.

4.3 Simulation Result

The proposed system was implemented, and its overall performance was evaluated through simulation. Routing paths were determined based on the selected source and destination nodes.

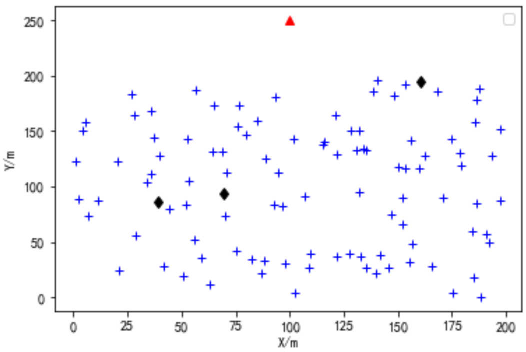

Figure.4 The Nodes Location of Proposed Method

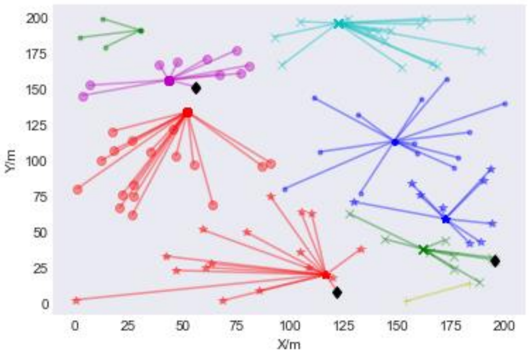

Figure.5 Various Cluster Heads Connected With Nodes

Figure 4 illustrates the network layout, where the sensor nodes are depicted in blue. The three black nodes represent the source nodes from which data transmission originates. Data is routed from these sources to the red destination node via the identified shortest paths. The selection of cluster heads, which play a vital role in determining the optimal routing paths, The cluster head, which is responsible for aggregating data from its associated sensor nodes and forwarding it to the base station (BS) is presented in Figure 5. To ensure balanced energy consumption, the role of the cluster head is typically rotated among the nodes within a cluster. Based on the interconnections between nodes, Figure 6 illustrates the communication duration of recurrent nodes selected for data transmission. Over successive communication rounds, the load on certain nodes gradually decreases, and nodes that are no longer able to participate in transmission are classified as dead nodes.

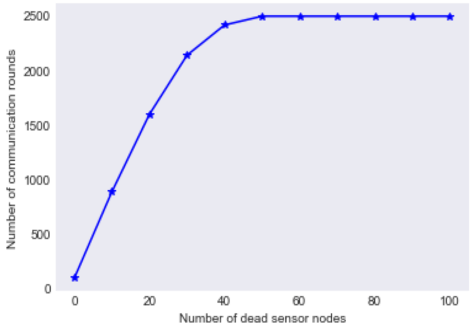

Figure.6 Communication Time Between the Adjacent Nodes

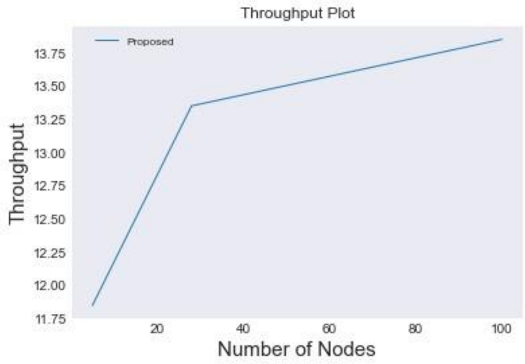

Figure.7 Throughput of the Proposed System

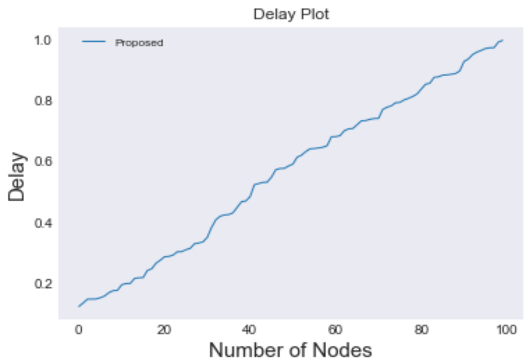

Figure.8 Transmission Delay in Data Transmission

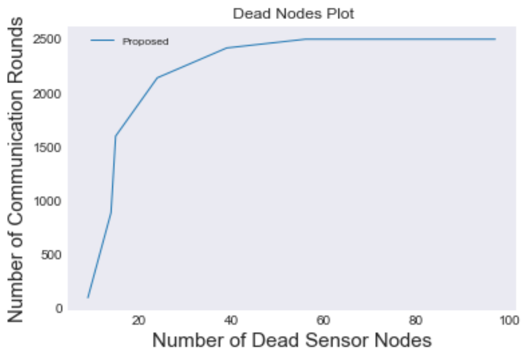

Figure.9 The Representation of Dead Nodes in WSN

Figure 7 depicts the system's efficiency across multiple communication rounds, showing the volume of data successfully transmitted within a given time period, which directly reflects system throughput. Related performance indicators include the rate at which tasks are completed during a specific time frame. In this context, data transmission delays primarily result from network traffic.

Figure 8 presents the transmission delay observed in the proposed system to transmit data packets from the source to the destination.. Throughput is affected by several critical factors, including energy consumption, network congestion, and the overall effectiveness of the data transmission process. Transmission delay is defined as the duration needed to transfer a packet, measured in bits, across the network. This delay is primarily influenced by factors such as network traffic, transmission link capacity, and the availability of outgoing channels. Figure 9 presents the number of dead nodes observed during successive communication rounds. As communication progresses, the workload on certain nodes decreases, while nodes that exhaust their energy resources become inactive. These inactive nodes, referred to as dead nodes, directly affect the overall efficiency and lifetime of the network.

4.4 Performance Analysis

Evaluating performance metrics is essential for enhancing system efficiency. Accordingly, the performance of the proposed work is assessed. Table 1 presents the performance analysis of the results obtained from the proposed system with respect to key metrics. The measured outcomes for packet drop rate, energy consumption, delay and throughput are 3.4%, 0.265 J, 0.419 ms, and 13.35 Mbit/sec respectively. From this analysis, it is evident that the proposed study achieves satisfactory performance in data transmission and enhancing data transmission speed directly reduces the time available for attackers and serves as a barrier against cyber attacks along the transmission path.

Table.1 Packet Transmission Rate Analysis of the Proposed System with Existing Methods

Sl. No.	Method	Packet drop rate (%)	Avg. Energy Consumed (J)	Delay (ms)	Throughput (Mbit/sec)
1.	Bee-PSO	4.2	0.355	1.08	12.58
2.	ACO-AIS	4.7	0.362	0.6	11.25
3.	PSO-GA	3.8	0.315	1.16	12.44
4.	Proposed	3.4	0.265	0.419	13.35

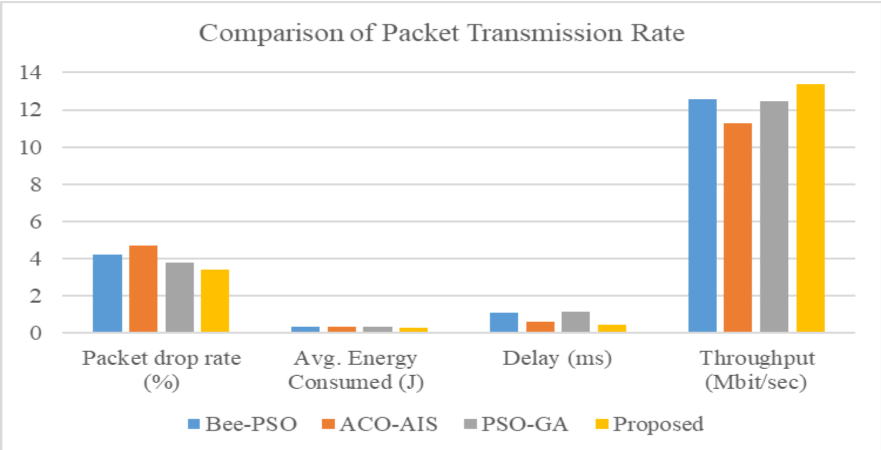

Figure 10. Comparison of Packet Transmission Rate Analysis of the Proposed System

Figure 10 illustrate the comparison of different combined algorithms with proposed system with respect to packet drop rate, average energy consumed, delay and throughput. The proposed method PBACS consistently outperformed them across all four metrics. These features contribute to the enhanced performance of the system, resulting in more reliable and robust outcomes.

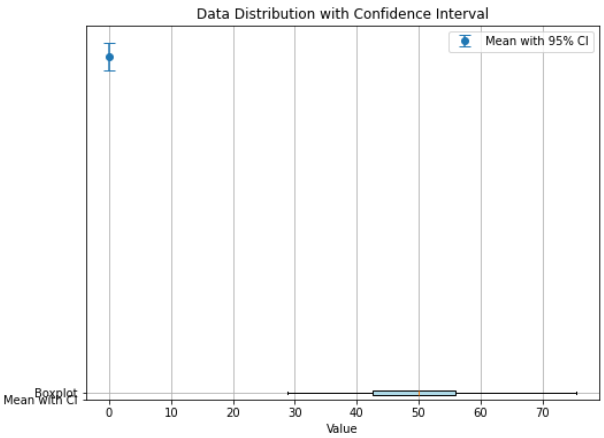

Figure 11. Data Distribution with Confidence Interval

Figure 11 presents a combined visualization of data distribution using both the mean with a 95% confidence interval (CI) and a box plot. The error bars, representing the 95% CI, illustrate the precision and reliability of the estimated mean by defining the range within which the true population parameter is likely to fall. This provides insight into the degree of uncertainty associated with the data. The accompanying box plot offers a concise summary of the distribution, highlighting the median, inter quartile range, and potential outliers. Together, these visual elements provide a comprehensive representation of the dataset's central tendency, variability, and statistical reliability.

4.5 Comparative Analysis

A comparative analysis was conducted to demonstrate the superior performance of the proposed system over existing approaches. Conventional studies have applied various algorithms, and their results were evaluated against those of the proposed method. Table 2 lists different existing techniques along with their corresponding key metrics, providing a basis for comparison with the proposed approach. The experimental results indicate that the proposed method outperforms traditional algorithms such as K-Nearest Neighbors (KNN), Random Forest (RF), Naïve Bayes, and Decision Tree (DT). Performance evaluation, summarized in Table 2, is based on standard classification metrics, including precision, recall, accuracy, and F1-score. Since precision and recall often exhibit inverse trends, the F1-score—representing the harmonic mean of precision and recall—is adopted as a balanced indicator of classification quality. Figure 10 illustrates the comparative performance of the proposed system against existing methods across different metrics, clearly highlighting its effectiveness.

Table.2 Comparative analysis with performance metrics of proposed method with existing methods .

Sl.No.	Method	Precision	Recall	Accuracy	F1 Score
1.	KNN	98.8%	98.1%	91.6%	98.5%
2.	RF	98.7%	97.8%	92.7%	98.3%
3.	Naive Bayes	64.5%	54.9%	95.8%	59.1%
4.	DT	97.9%	97.8%	98.1%	97.8%
5.	**Proposed**	99.5%	99.87%	99.2%	99.2%

From Table 2, it is evident that the proposed method achieves higher accuracy compared to existing approaches [22]. Figure 12 illustrates the performance of different classifiers with respect to precision, recall, accuracy and F1-score. The comparative analysis shows that although conventional studies employed various classification algorithms, the proposed method consistently outperformed them across all four metrics. Moreover, the PBACS algorithm demonstrates the ability to cluster nodes in a flexible manner while enabling efficient data aggregation. These features contribute to the enhanced performance of the system, resulting in more reliable and robust outcomes.

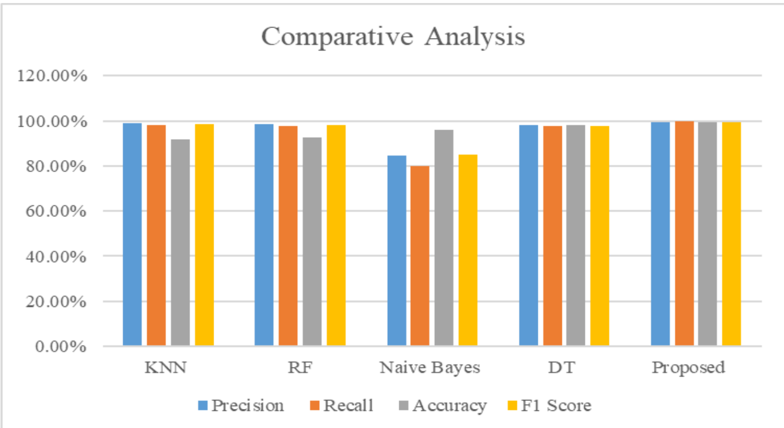

Figure 12. The Comparative Analysis of Existing Model With Proposed Work

The analytical results confirm that the proposed approach delivers optimal performance when compared to traditional methods. Experimental findings demonstrate that the proposed model significantly outperforms existing techniques, achieving 99.92% accuracy, 13.35 Mbits/s throughputs, 0.419 ms delay, 0.265 J energy consumption, and a packet drop rate of 3.4%. Comparative analyses confirms the superiority and reliability of the model in ensuring both efficient and secure data transmission. In conclusion, the integration of Lion Optimization with ACO, PSO, and PBACS enables efficient routing and ensure robust data protection.

5. CONCLUSION

High-speed and secure data transmission is a critical requirement in the modern digital era, as cyberattacks can result in severe data breaches and operational losses. This study addresses the challenge of identifying the shortest routing path among transmission nodes by implementing PBACS integrated with the ACOPSO algorithm. Furthermore, traffic flow detection is carried out using the AR algorithm, which efficiently manages large datasets, thereby reducing transmission delays and enhancing overall accuracy. This synergy enhances both the speed and security of wireless sensor networks. For future research, algorithm parameters can be fine-tuned using adaptive learning strategies to further optimize performance. Scalability testing in larger and more complex network environments will also be pursued. Additionally, evaluating the system under real-time cyber attack scenarios and integrating emerging technologies such as edge computing and block chain may further strengthen both security and efficiency. The proposed model, Particle Bee Ant Colony Swarm (PBACS), enhances transmission efficiency by determining the optimal path between nodes, thereby minimizing delay and outperforming conventional techniques. By accelerating data transmission, it effectively shortens the window of opportunity for attackers, serving as a deterrent to cyber threats along the transmission path. The effectiveness of this approach is assessed using five key performance metrics: throughput, packet loss, energy consumption, and delay. The next phase of work will involve real-world deployment in collaboration with industry partners, along with the development of hybrid encryption models designed to minimize processing delays without compromising security.

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