Hybrid optimization algorithm for resource-efficient and data-driven performance in agricultural IoT

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ABSTRACT

The agricultural sector is undergoing a significant transformation with the adoption of the agricultural internet of things (IoT), yet it faces persistent challenges in optimizing resource efficiency and data-driven performance due to limitations in current optimization algorithms. This research assesses the effectiveness of four prominent algorithms such as ant colony optimization (ACO), genetic algorithms (GA), particle swarm optimization (PSO), and artificial bee colony (ABC) in addressing these challenges within agricultural IoT (AIoT). Introducing a novel hybrid optimization algorithm (HOA), we aim to overcome these limitations by prioritizing both resource efficiency and data-driven performance. Through a thorough evaluation, HOA demonstrates its superiority in enhancing both aspects, thereby establishing itself as a compelling solution for AIoT applications. The introduction of HOA sets the stage for sustainable, cost-effective, and data-driven precision agriculture, significantly enhancing resource efficiency and data accuracy within the IoT network.

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1. INTRODUCTION

Modern internet of things (IoT) systems are designed to collect and analyze data from various sources to make more informed decisions. This idea has been applied in many settings, including the healthcare industry, smart homes, and agriculture [1]. In agriculture, data is collected from field monitoring and time-stamped sensory data from various machinery and combined with contextual data. This data can be utilized to make numerous decisions, from matching fertilizer rates to field variability to automation of a tillage system. This can lead to higher yields, increased efficiency of input use, and maintenance of a sustainable farming operation. Time-stamped sensory data can also drive decisions and provide recommendations for when to conduct various field operations [2], [3]. An example would be monitoring soil moisture levels and receiving a notification when irrigation is required. Despite the potential for increased efficiency through the automation of these systems, increased data collection and automation in agriculture can result in higher energy expenditure. This is especially pertinent in the case of IoT systems, where additional networking and sensing devices are integrated with existing machines and systems. High energy use conflicts with sustainability goals and thus becomes an inefficiency in input use [4]. This has the potential to negate efficiency gains of data-driven decisions and automation of the system.

Adaptation of IoT in farming includes innovative employment of proficient devices, such as sensors, GPS, robots, mobile apps, and unmanned aerial vehicle (UAVs), in concert with internet connectivity. IoT technologies have advantageously transcended different job domains, and farming has not been left out in this surge. Farming incorporates wide arrays of activities, with a considerable percentage of it being reliant on manual labor. There are also job-specific activities, like the use of tractors for tillage, and milking machines for milking. IoT in agriculture captures data from farming activities using different devices to increase farm productivity. IoT enables farms to gather data with a high degree of precision in a variety of situations, helping to make better decisions. IoT-driven decisions can cause an impact ranging from optimal and precise use of fertilizers in the planting season to automatic detection and targeted treatment of diseases and increased yield during harvest. Data thus generated from farming operations have the potential to radically change decision algorithms used up until now into powerful predictions and prescriptions for raising farm productivity. The data gathered from IoT devices in agricultural farms, shown in Figure 1, encompasses both structured and unstructured data. Structured data is usually time-stamped and geo-located data from sensors, yield monitors, and other precision ag technology, while unstructured data can take the form of images, geographic information system (GIS) maps of fields, and records of agricultural practices. With data analysis, decisions, and ultimately actions being the main goal, it is a must to have high-quality data and a clear plan for using up the data effectively. High-quality data paired with the right analysis and subsequent actions can lead to increased farm productivity.

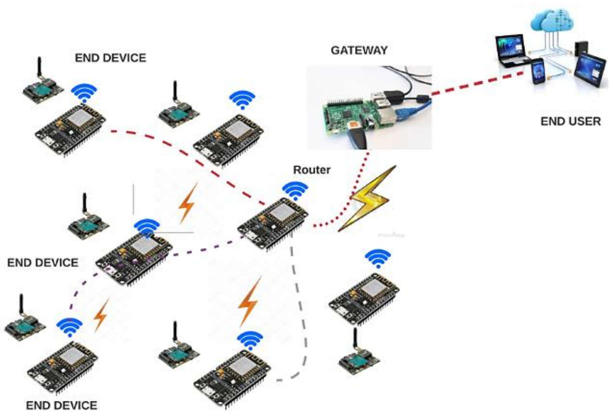


Figure 1. IoT-enabled wireless sensor network

High-quality data analysis can lead to decisions that can bring about a positive change from the present situation to a desired situation. This is performance where an action causes a change in the status of an entity. Though optimization problems provide a solution in a shorter period compared to traditional methods, for large-scale complex problems, the computational burden is much higher. Since there is a huge amount of data generated in agricultural IoT (AIoT), a demand is created for intelligent decision-making by data-driven algorithms. For large problems, it may be the case that resource-efficient algorithms may take a longer time. This article is organized as follows: section 2, provides a comprehensive overview of current research in this field. Section 3, analyzes and assesses prominent algorithms used for resource management. Section 4, dives into the details of a new approach, the hybrid optimization algorithm (HOA), designed to improve resource efficiency. Section 5, compares various optimization algorithms, details the experimental setup used to evaluate them, and presents the achieved improvements in both energy and network efficiency. Section 6, summarizes the key findings and main conclusions drawn from the discussions throughout the article.

2. LITERATURE SURVEY

Resource-efficient and data-driven performance in AIoT is crucial for optimizing crop production and improving efficiency. The use of IoT sensors and smart techniques can contribute to sustainable crop production by monitoring soil nutrients, water dynamics, and climate fluctuations [5]. Deep learning and sensor data can improve the accuracy and performance of measuring soil moisture and enable remedial measures such as irrigation [6]. Wireless sensor networks in agriculture can provide real-time data on the condition of crops and livestock, supporting efficient monitoring and management solutions [7]. Integrating IoT, machine learning, and data analytics into smart agriculture can optimize the food production process, improve quality, and help farmers avoid losses [8]. Furthermore, the concept of automatic monitoring and control tools using IoT systems such as long range (LoRa) and Arduino can contribute to the effectiveness and increase of agricultural production [9]. Efficient node deployment and data aggregation techniques can improve resource utilization in Agri-IoT (AIoT) applications. The SAREC protocol is proposed as a clustering approach for heterogeneous scenarios, which is 25% more efficient in energy utilization and network lifetime than the low-energy adaptive clustering hierarchy (LEACH) protocol [10]. An automated AIoT system is designed to optimize the use of natural resources like water and solar energy while preventing the overuse of electricity and water [11]. An IoT-based prototype is implemented to automate irrigation based on soil moisture, temperature, and humidity levels, aiming to save water and increase production efficiency [12], [13]. The CultivData platform integrates IoT devices and open data sources to support decision-making in agriculture, improving product quality and farm productivity [14]. Metaheuristic optimization techniques have been applied in AIoT to improve various aspects of the system. One study proposed a hybrid metaheuristic algorithm, whale optimization algorithm (WOA) with simulated annealing (SA), to optimize the energy consumption of sensors in the IoT network and select the optimal cluster head (CH) [15]. Another study investigated and compared different data reduction techniques for optimizing IoT data transmission in smart agriculture, including sampling, quantization, and deduplication [16]. Additionally, a swarm-optimization technique using the IoT was proposed to choose secure CH and ensure efficient data transmission in an IoT-based agriculture wireless sensor network [17]. Furthermore, a tutorial paper provided an in-depth overview of routing architectures, protocols, and performance optimization techniques in AIoT, addressing the specific requirements and constraints of the agricultural setting [18]. Finally, an optimization model for minimum service cost was established, and a collaborative Mult objective optimization algorithm was proposed for intelligent agricultural dynamic services in the IoT environment [19]. The problem being addressed is a minimization of cost over a constrained feasibility region. A genetic algorithm can be particularly effective on such a problem due to the ability to encode non-binary constraints as penalty functions and the use of repair algorithms, which can be applied within an individual generation and at the end.

3. METHOD

To compare HOA with existing algorithms, it is necessary to evaluate the strengths and weaknesses of the specific established algorithms. Therefore, this section discusses a comprehensive evaluation of the strengths and weaknesses of ant colony optimization (ACO), which is a typical algorithm proposed for solving optimization problems by simulating the natural activities of ant colonies. According to the existing literature, ACO shows advantages in terms of global optimization, combinational and modular optimization methodology, and autonomous distributed optimization process [20]. However, this kind of algorithm requires extensive memory and computational efforts, and it is more suitable to solve stochastic optimization problems. Then comes the second existing algorithm genetic algorithms (GA), which is based on the theory of natural selection and evolution. Compared with the traditional ACO, GA has a wider adaptation for solving combinatorial and optimization problems due to its sophisticated and intelligent genetic operators. However, under the current situation, the main drawback of GA is the relatively high demand for computational effort and memory space, and it is not suitable for real-time optimization practices which require high efficiency and reliable performance and the same problem is faced in particle swarm optimization (PSO) [21], [22]. PSO is a population-based stochastic optimization algorithm, and it is a kind of swarm intelligence technique. It has been extensively studied and widely recognized by researchers and experts in the field of optimization algorithms. The good thing about PSO is its simple procedure. However, just like the inherent defects in ACO and GA, PSO also has its main limitations - it is quite easy for the algorithm to fall into local optima and the calculation of parameters c1 and c2 is not straightforward for various kinds of optimization problems. Finally, the literature review discusses a brief drawback of artificial bee colony (ABC). ABC is a relatively new, population-based stochastic optimization algorithm. Just like ACO, it is featured by superior swarm independence and intrinsic distributed structure [23]. However, the main drawback of ABC is its slow convergence speed, and it is difficult to balance between the exploration and exploitation abilities. When reviewing the strengths and weaknesses of all established algorithms, it is noteworthy that different algorithms show their unique advantages for various kinds of optimization problems. The proposed HOA integrates the merits of existing prominent algorithms and eliminates the prevalence of certain limitations.

3.1. Proposed hybrid optimization algorithm

The concept of a HOA involves the integration of multiple optimization techniques to address complex challenges more effectively. In the context of enhancing energy efficiency in AIoT, HOA combines the strengths of various optimization algorithms, including ACO, GA, PSO, and ABC, to create a comprehensive and versatile approach. HOA leverages the strengths of individual optimization algorithms such as ACO, GA, PSO, and ABC to create a robust and versatile approach. Each algorithm brings its unique expertise: ACO efficiently explores different solutions and excels at global search, GA improves adaptability through its selection, crossover, and mutation mechanisms, PSO optimizes continuous parameters by mimicking particle behavior, and ABC exploits the foraging behavior of bees for effective exploration purposes, dealing with discrete and continuous variables. HOA devises these algorithms in a series of steps, starting with defining the optimization goals and adjustable parameters. Solutions are then represented as device configuration decision sets, followed by initialization with a diverse population specific to each algorithm. At each iteration, individual algorithms create solutions based on their mechanisms, update information based on solution quality, and balance local exploration with global usage. This process continues until the algorithm reaches optimal or near-optimal configurations for energy-efficient IoT operations in agriculture. Finally, the solutions are evaluated based on energy efficiency, data quality, and other relevant metrics. By combining the strengths of individual algorithms, HOA offers several advantages. It explores the solution space more comprehensively through the different approaches of each algorithm, resulting in improved convergence toward optimal solutions. Furthermore, compared to individual algorithms, HOA offers a more robust and versatile approach capable of tackling complex optimization challenges in the context of AIoT. HOA represents a powerful tool for improving the energy efficiency of IoT devices while ensuring the reliability and quality of data, contributing to sustainable agricultural practices and efficient resource management.

Algorithm 1. Hybrid optimization algorithm

```
    Data: Network Terrain, initial energy, Efs, Eelec, Eamp, Dcritical, Dmax
    Result: bestSolution, bestCost, hybridMetrics
1   Initialize parameters and variables
2       - Initialize bestSolution to an empty solution
        - Initialize bestCost to a high-value
        - Initialize pheromoneMatrix for ACO
        - Initialize particle positions for PSO
        - Initialize population for GA
        - Initialize colony for ABC
        - Initialize other algorithm-specific parameters
3   for iteration ← 1 to hybridIterations do
4       Run ACO Algorithm to obtain acoBestSolution, acoBestCost
5           Pheromone MatrixUpdate ← Calculate pheromone updates
6   End for
7   Run PSO Algorithm to obtain psoBestSolution, psoBestCost
8       particleUpdateEquation(p, d)
9       particleVelocities(p, d) ← particleUpdateEquation(p, d)
10      particlePositions(p, d) ← particlePositions(p, d) + particleV elocities(p, d)
11  Run GA Algorithm to obtain gaBestSolution, gaBestCost
12      tournamentSelection(),crossover(),mutation()
13  Run ABC Algorithm to obtain abcBestSolution, abcBestCost
14      colonySize ← Size of the bee colony
15      colony ← Initialize bee colony
16  Combine the results using the hybrid strategy
17      hybridBestSolution = CombineSolutions(ACO, P SO, GA, ABC)
18      hybridBestCost = CostFunction()
19          if hybridBestCost < bestCost then
20              bestSolution ← hybridBestSolution
21              bestCost ← hybridBestCost
22          end if
23  Calculate hybridMetrics
24      hybridMetrics = CalculateMetrics()
25  Return bestSolution, bestCost, hybridMetrics
```

The HOA presented here aims to address the challenges of resource efficiency and data-driven performance in AIoT applications. The algorithm combines four prominent optimization algorithms ACO, PSO, GA, and ABC to find an optimal solution for AIoT systems.

- Initialization: the algorithm initializes necessary parameters and variables, including the solution space and algorithm-specific parameters for ACO, PSO, GA, and ABC.
- Iterative optimization:

a. ACO phase: ACO is executed in each iteration to find the best solution and its cost. Pheromone updates are calculated to guide the search process.
b. PSO phase: PSO is employed to update particle positions based on a predefined equation, optimizing the solution space.
c. GA phase: GA utilizes tournament selection, crossover, and mutation operations to evolve the population towards better solutions.
d. ABC phase: ABC is executed to explore the solution space using employed, onlooker, and scout bees to find optimal solutions.
e. Hybrid strategy: the results from ACO, PSO, GA, and ABC are combined using a hybrid strategy to obtain the best solution and its cost. If the hybrid solution improves upon the current best solution, it is updated along with its cost.
f. Metrics calculation: after combining the results, hybrid metrics are calculated to evaluate the performance of the hybrid algorithm.
g. Output: the algorithm returns the best solution found, its cost, and hybrid metrics, providing insights into the efficiency and performance of the AIoT system.

3.2. Enhanced resource efficiency in internet of things network

The proposed HOA algorithm provides a solution for enhancing the resource efficiency in the IoT network. Resource management in the IoT network environment focuses on the allocation of limited resources to network services effectively. With the advent of more and smaller devices, such as sensors and actuators, being connected to the IoT network, resource management becomes more challenging. Traditionally, the resources in the IoT network were allocated based on either a static manner - using a predefined schedule - or a centralized dynamic manner the resource allocation decision is made by a central controller based on the current network transmission conditions. With static resource allocation, the maximum delay incurred is predictable, but the resource is under-utilized. On the other hand, the scheduled resource re-allocation process in a centralized manner causes a long initial delay and frequent disruption to the network services. These problems have been unresolved for a while until the proposal of applying the HOA algorithm to resource efficiency optimization. First, the structure of the IoT network for resource allocation is redefined. By introducing a service encapsulation and decoupling control plane from the data plane, the IoT network can be virtually divided to several resource management domains [24], [25]. Each domain has its domain head and a dynamic resource manager. This allows a distributed manner for the application of the HOA algorithm as well as an isolated environment for the usage of resource allocation strategies: if one strategy fails, the network can still reconfigure and adapt to the changes. Secondly, the HOA algorithm can initialize the resource allocation based on the historical network traffic data and the synchronization, so that the energy waste in the static resource allocation can be largely reduced. Thirdly, the HOA algorithm provides a self-adaptive and dynamic allocation mechanism. The proposed HOA can truly achieve the goal of optimizing resource allocation by ensuring minimum delay and maximum utilization of resources. Finally, as the constantly changing network conditions are monitored and reflected in the resource allocation decision, resource efficiency maintenance in the long run can be guaranteed. By allowing the network to adapt to the changes, the network can engage in sleep mode to save energy or to reallocate resources to other active services. All these features make the HOA algorithm particularly suitable for resource efficiency optimization in the large-scale IoT network.

4. RESULTS AND DISCUSSION

The comparative analysis of different optimization algorithms based on evaluation criteria and performance metrics. Although all the algorithms are well evaluated by following standard procedures, these criteria may not be directly used in practical applications. The selection of an appropriate algorithm primarily depends on the successful implementation of the intended application which is reflected through the performance and results. The evaluation of optimization algorithms within the context of AIoT devices aimed to address the paramount challenge of enhancing energy efficiency while preserving the integrity of data collection and transmission. Through a comprehensive set of performance metrics, the effectiveness of five optimization algorithms, namely ACO, GA, PSO, ABC, and HOA, was thoroughly assessed. The results and analysis reveal key insights into each algorithm's performance and provide a basis for informed recommendations.

4.1. Experimental setup

The experimental setup detailed involves the thorough configuration of a multitude of parameters and metrics to replicate a network environment within an AIoT system. This thoroughly constructed setup as shown in Table 1 serves as the foundational framework for scrutinizing the performance of the HOA, as outlined in the algorithm overview. Within this setup, various network parameters are established, including the delineation of a 250 square meter area to encapsulate the physical domain in which sensor nodes and the base station operate. Sensor nodes are endowed with an initial energy level of 10 joules, denoting the available power for data transmission and processing. Additionally, parameters such as the probability to become CH and energy models for transmission and amplification are defined to encapsulate the intricacies of communication dynamics within the network. The critical and maximum communication distances are set at 20 and 100 meters, respectively, while data packets are standardized at 500 bytes, affecting both energy consumption and communication efficiency. The positioning of the base station at coordinates (100, 100) and the variation in sensor node numbers from 100 to 500 enable the assessment of algorithm performance across different network densities. Furthermore, the iterative execution of the hybrid algorithm 100 times facilitates the refinement of optimization processes and the evaluation of convergence behavior and efficiency. This comprehensive experimental setup provides a structured foundation for evaluating the effectiveness and scalability of the proposed HOA in enhancing resource utilization and data transmission efficiency within AIoT networks.

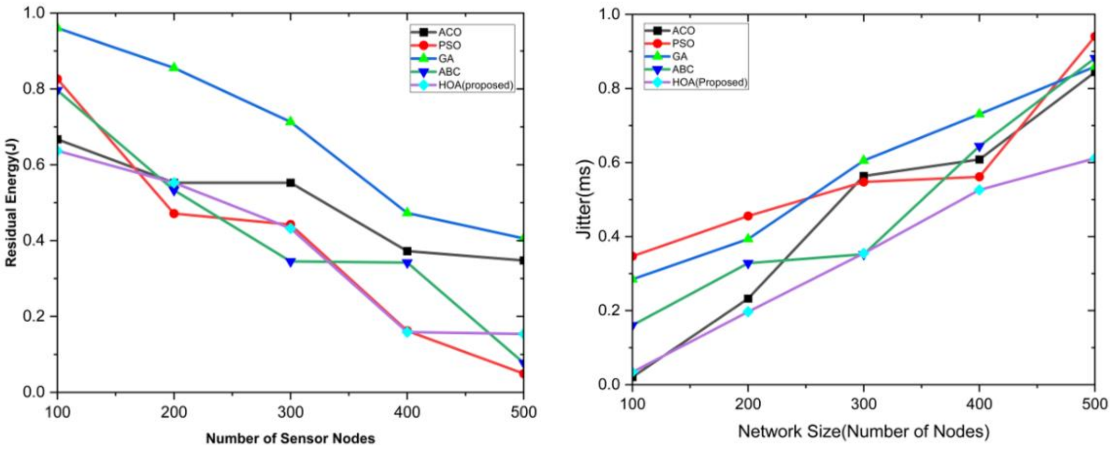
Table 1. Network parameters

Parameter	Value
Network terrain	250 m^2
Initial energy of sensor nodes	10 J
Probability to become CH	0.1
Free space energy model (Efs)	10e-12 J/bit/m^2
Electronic energy model (Eelec)	50e-9 J/bit
Amplification energy model (Eamp)	0.0013e-12 J/bit/m^4
Critical distance (Dcritical)	20 m
Maximum distance (Dmax)	100 m
Data packet size	500 Bytes
Base station position (x, y)	[100, 100]
Number of sensor nodes	[100, 200, 300, 400, 500]
HybridIterations	100

4.2. Energy efficiency improvement

Energy efficiency is a critical concern in AIoT, as it directly impacts the lifespan of IoT devices and, consequently, the sustainability of precision farming practices. The evaluation of the optimization algorithms' impact on energy efficiency was central to this study. Residual energy is one of the most essential metrics in such systems, as the sensor nodes often work in the resource-constrained environment that requires the long-term efficiency. The above results reveal that PSO performs the worst in terms of energy efficiency and residual energy. Therefore, the overhead of PSO is too high to work in large networks. More specifically, larger networks result in more energy consumption by PSO, rendering this algorithm not scalable. Although ACO and GA perform moderately, their energy efficiency degrades in large networks. Therefore, the scalability of ACO and GA is limited when it comes to large-scale agricultural applications. On the other hand, the energy efficiency of ABC is promoted in the beginning and then degrades beyond 250 nodes. In terms of energy efficiency, HOA outperforms all other algorithms. The above result shows that HOAs perform the best in terms of the energy efficiency in large networks. The gradual energy consumption by HOA in Figure 2(a). clearly shows that even in large-scale AIoT deployments, the residual energy remains high. Therefore, HOA is the best-suited algorithm to operate sensor nodes long-term and resource-efficiently in an agricultural environment. HOA can become the best algorithm to extend the lifetime of AIoT networks by reducing maintenance and keeping the data-driven monitoring operational for a long time.

A key performance indicator for stable and predictable communication in AIoT networks is jitter. Figure 2(b) illustrates the jitter vs number of sensor node graph for the mentioned algorithms, while it depicts that the jitter increases with the number of sensor nodes for all algorithms but at different rates, PSO has the highest jitter, particularly, it performs unstable in a large network, especially after 300 nodes. The same can be observed for ACO and GA which have a moderate increase in jitter, this makes them suitable for small and medium networks but not more suitable for large ones. ABC starts well and is one of the most stable algorithms until it reaches 200 nodes. After that, it sharply increases the jitter, making it very unsuitable for many nodes, demonstrating scalability issues. In contrast, HOA shows the least jitter for all sizes of networks, hence demonstrating its stability even as the size of the nodes increases. Thus, it is the most effective in reducing jitter, making it suitable for large, low latency, and highly energy-efficient AIoT networks.



(a) (b)

Figure 2. Energy efficiency analysis: (a) residual energy and (b) jitter

4.3. Network efficiency

AIoT networks must be efficient in transmitting data while conserving energy. The study assessed the optimization algorithms' impact on network efficiency, as characterized by metrics such as throughput, packet delivery ratio (PDR), and packet loss ratio (PLR). HOA enhances network efficiency, demonstrating significant advantages in terms of throughput and reduced packet loss. Its ability to find optimal configurations for data transmission schedules ensures that data is delivered effectively and with minimal losses. As shown in Figure 3(a) as the number of sensor nodes increases from 100 to 500, all algorithms exhibit an upward trend in throughput, but their performance varies significantly. The HOA demonstrates the best scalability, achieving around 9 Kbps at 500 sensor nodes, making it the most efficient among the algorithms. The ABC algorithm follows, showing a steady increase and reaching approximately 7 Kbps at 500 nodes, indicating strong performance with higher node densities. PSO performs moderately, achieving about 6 Kbps with 500 nodes, slightly behind ABC. The GA shows lower throughput, reaching around 4-5 Kbps at 500 nodes, with relatively stable performance but lagging the top-performing algorithms.

The ACO algorithm consistently provides the lowest throughput, peaking at approximately 4 Kbps, indicating its limited scalability compared to the other algorithms. As shown in Figure 3(b) The HOA achieves the highest PDR, nearing 0.9 as the network grows, showcasing excellent reliability even in dense networks. ABC follows closely with a PDR of around 0.8 at 500 nodes, making it the second most reliable. PSO performs moderately, reaching about 0.7, while GA lags slightly behind with a PDR of 0.6. ACO struggles with lower PDR, particularly at smaller node counts, improving to 0.5 at 500 nodes.

Overall, HOA outperforms others in large-scale networks, with both HOA and ABC proving highly reliable, while all algorithms improve in PDR as the node count increases. As shown in Figure 3(c) the HOA has the lowest PLR, staying below 2% even with 500 nodes, making it the most efficient and reliable algorithm. ABC performs well but reaches a 5% PLR at 500 nodes, while PSO shows moderate performance with a 7% PLR. GA experiences higher packet loss, reaching 8%, and ACO has the worst performance, peaking at 9%. Overall, HOA excels in minimizing packet loss, making it ideal for applications requiring low data loss, while other algorithms struggle as node density increases.

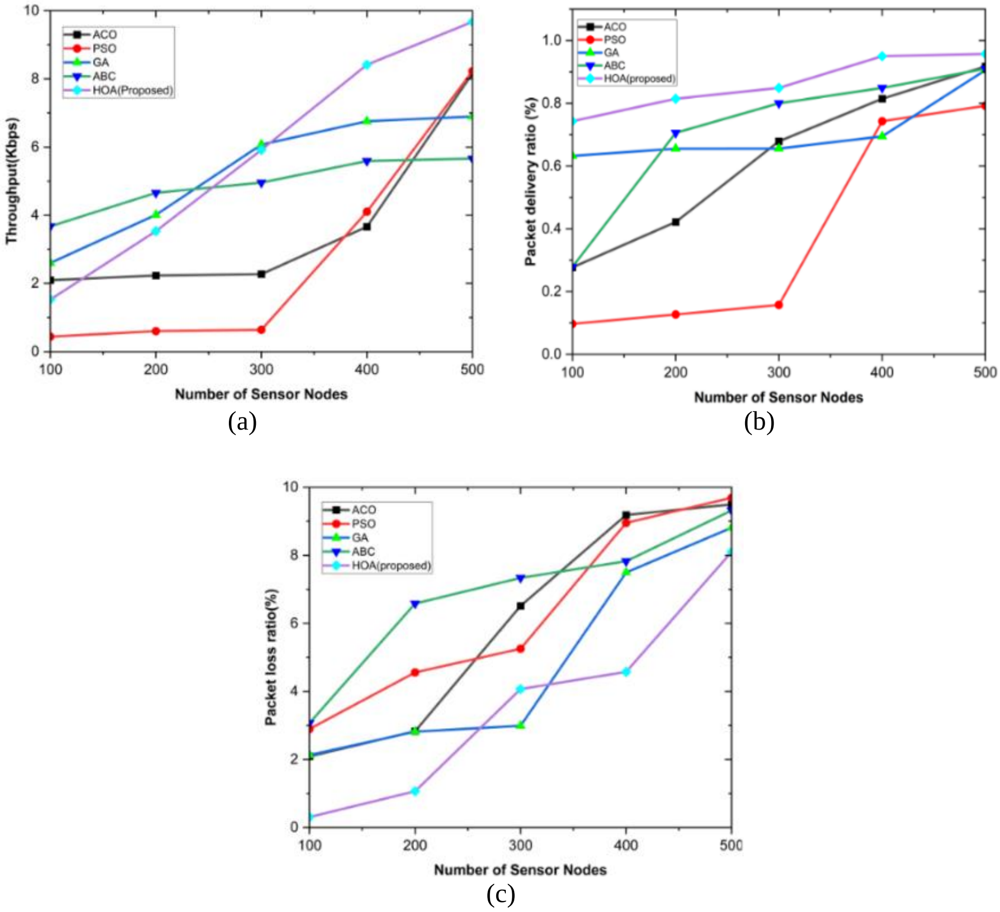


Figure 3. Network efficiency analysis: (a) throughput, (b) packet deliver ratio, and (c) packet loss ratio

The comprehensive evaluation of optimization algorithms within the context of AIoT devices demonstrates the remarkable effectiveness of the HOA as shown in Table 2. HOA offers substantial energy efficiency, data accuracy, and network efficiency benefits. This makes it the most suitable choice for optimizing energy efficiency in AIoT applications.

Table 2. Comparison of performance metrics

Performance metrics	ACO	PSO	GA	ABC	HOA (proposed)
Throughput (Kbps)	8.16	8.23	6.90	5.66	9.67
PDR (%)	0.93	0.79	0.91	0.92	0.96
PLR (%)	9.50	9.69	8.10	9.32	8.81
Residual energy (J)	0.67	0.83	0.96	0.80	0.64
Jitter(ms)	0.844	0.94	0.85	0.88	0.61

5. CONCLUSION

The AIoT is poised to revolutionize farming, yet challenges persist in optimizing resource efficiency and data-driven performance due to limitations in current algorithms. This study evaluates ACO, GA, PSO, and ABC in AIoT contexts. Introducing a HOA, this research aims to overcome existing limitations by prioritizing resource efficiency and data-driven performance. Through rigorous evaluation, HOA emerges as a superior solution, promising sustainable, cost-effective, and precise agricultural practices. Integration of HOA into AIoT systems holds great potential for enhancing resource utilization and data accuracy. Future research may focus on refining HOA for specific agricultural contexts and exploring its broader applications. Continued development and implementation of advanced optimization algorithms like HOA are crucial for maximizing the benefits of AIoT, ultimately improving productivity and sustainability in farming practices.

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