Balancing Energy and Stability: An Intelligent Routing Solution for IIoT Using the Artificial Rabbit Algorithm

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Abstract

With the rapid expansion of the Industrial Internet of Things (IIoT), the need for intelligent and multi-criteria algorithms for optimizing routing in industrial wireless sensor networks is increasingly felt. Energy constraints, low link stability, and data transmission delays are among the fundamental challenges in this field. In this paper, a new metaheuristic algorithm titled the Artificial Rabbit Algorithm is proposed, inspired by the social behavior of rabbits in nature, aiming to find optimal communication paths. This algorithm operates in two main phases: exploration and exploitation, utilizing a multi-criteria objective function that includes energy consumption, communication delay, average link stability, and the number of intermediate nodes. To evaluate the algorithm's performance, results were compared with similar state-of-the-art routing algorithms. The results from statistical and comparative analysis show that the proposed method outperforms in most metrics and has achieved a suitable balance among key criteria. Advantages such as ease of implementation, balanced energy consumption, high stability, and rapid execution make this algorithm a suitable option for time-sensitive and resource-constrained industrial environments.

Keywords: Industrial Internet of Things, intelligent routing, Artificial Rabbit Algorithm, wireless sensor network, multi-criteria optimization, metaheuristic algorithms.

1. Introduction

In recent years, the Internet of Things (IoT) has become one of the most important technologies increasingly infiltrating people's lives. The core idea behind this concept is that various devices can connect with each other via the internet or other networks, collect information, exchange data, and even make decisions without direct human intervention. With the rapid advancement of technology and the growing need for industries to automate and smarten processes, a concept known as the "Industrial Internet of Things" or IIoT has emerged in the industrial arena. IIoT is, in fact, a specialized subset of IoT that focuses on industrial and manufacturing environments, in contrast to consumer and home applications of IoT.

In this technology, industrial equipment and machinery are connected to a network through intelligent sensors and communication devices, capable of collecting real-time information from the environment and sending it to processing units. This information can include temperature, pressure, vibration, equipment performance speed, energy consumption, and more. The collection and processing of these data allow industrial managers to have more precise oversight of production processes and make decisions in a more intelligent and timely manner.

The primary difference between IIoT and IoT lies in the scale, complexity, and sensitivity of their applications. While IoT is predominantly used in home applications, wearable gadgets, or entertainment systems, IIoT requires robust infrastructure, high processing power, advanced network security, and intelligent algorithms for rapid data analysis on an industrial scale. In these environments, due to high dynamics and constantly changing conditions, having intelligent routing algorithms that can adapt to these changes has become a fundamental necessity. Overall, IIoT, as a transformative technology, not only increases production capacity but also enables industries to transition from traditional structures to fully smart and data-driven frameworks. This transformation is considered one of the important foundations for shaping future smart factories and industrial cities. In the proposed method, the artificial rabbit metaheuristic technique is utilized to find the best routing path for IIoT networks.

In summary, in the proposed algorithm, in the first step, several random paths from the source node to the destination node are generated, representing the "rabbits." These paths are created randomly, considering the network topology, and are validated to prevent loops and routing errors. In the process of evaluating and updating paths at each stage of the algorithm, the existing paths are assessed. The criterion for this evaluation is the value of the objective function for each path, such that paths with lower values are prioritized.

Then, based on an intelligent process, each rabbit chooses one of two options:1) In the exploration phase, a new path is randomly created to increase diversity in the population. 2) In the exploitation phase, the current path is updated based on one of the best existing paths.

This process continues until a stopping condition is met.

Stopping Conditions of the Algorithm: The algorithm stops when one of the following two conditions is met:1) Reaching a specified number of iterations (e.g., 100 iterations).2) No improvement in the objective function value over a specified number of consecutive iterations.

In the first section, the Internet of Things and Industrial Internet of Things are examined, and the main research problem of routing in IIoT networks is presented. In the second section, the research background is discussed, and an analytical comparison of existing methods is made, highlighting the remaining challenges in the field. The third section will present the proposed algorithm, and the fourth section will analyze the performance of the proposed method and compare it with similar algorithms. Finally, the fifth section will provide the concluding remarks.

2. Related Works

In recent years, researchers have made extensive efforts to develop novel routing methods in IIoT, primarily focusing on two main areas: the first category includes methods based on artificial intelligence and machine learning, which utilize learning models to intelligently and adaptively select communication paths. The second category encompasses metaheuristic algorithms inspired by nature, which optimize the path search process using biological mechanisms such as ant colonies, particle swarm optimization, or animal behavior. Each of these approaches has its advantages and limitations, and understanding them is crucial for designing effective solutions.

A thorough review of previous studies in this field can provide a suitable perspective on the current state of routing in IIoT and the existing research gaps. Therefore, in this section, a general classification of the proposed methods will first be addressed, followed by an analysis and comparison of selected studies from each category. Finally, based on the findings from the literature review, the main challenges will be identified, laying the groundwork for defining the research path of this paper.

Existing Algorithms for Routing Optimization in Industrial Internet of Things

The existing algorithms in the field of routing optimization in the Industrial Internet of Things (IIoT) can generally be categorized into the following two groups:

2.1. Machine Learning-Based Methods

1. In a paper presented by Zhang and Chen in 2021, the Q-learning algorithm is employed as a reinforcement learning method for optimizing paths in IIoT networks. This algorithm aims to select the best path for data transmission at any moment by learning from environmental states and historical paths. The key innovation of this method lies in its use of network feedback for intelligent decision-making and rapid adaptation to environmental changes. Its advantages include a significant reduction in delay, increased energy efficiency, and improved network longevity. However, the successful implementation of this algorithm requires abundant training data and relatively high processing power, making its deployment in resource-constrained nodes challenging [1].

2. In a study conducted by Li et al. in 2021, a comprehensive review of machine learning methods in the field of IIoT routing is provided. The authors classify various learning algorithms, such as supervised, unsupervised, and reinforcement learning, based on their applications in IIoT. The innovation of the paper lies in presenting an analytical framework to identify the capabilities and limitations of each method in dynamic industrial contexts. This analysis assists researchers in selecting the best approach according to network needs. Despite its numerous advantages, including a strategic and comprehensive perspective on the topic, this paper lacks an executable model or specific numerical evaluation [2].

3. In a paper published by Kumar and Singh in 2020, the authors conduct a thorough examination and classification of routing protocols in the Industrial Internet of Things. This research categorizes and analyzes protocols based on characteristics such as energy consumption, delay, scalability, and reliability. The innovation of the paper is its structured approach to routing and the provision of a useful map for selecting appropriate algorithms based on specific industrial conditions. However, the paper does not offer operational solutions or empirical implementation [3].

4. In a paper published by Xu et al. in 2024, the HRL-TSCH algorithm is introduced, which is designed based on hierarchical reinforcement learning for TSCH scheduling in IIoT. This method utilizes two decision-making levels: one for time resource allocation and another for managing network links. The innovation of this algorithm lies in its multi-layered structure, which provides high adaptability to changing industrial conditions. Advantages of the method include a significant reduction in delay and improved throughput in high-load networks. However, the need for extended model training time and high computational resource consumption complicates its implementation in resource-limited nodes [4].

5. In a study presented by Ali et al. in 2022, the AI-EECR hybrid algorithm is designed for clustering and routing in vehicular networks. This algorithm combines quantum metaheuristic techniques and adaptive learning to make decisions regarding cluster head selection and paths based on criteria such as energy, trust level, and vehicle speed. Its innovation lies in considering multiple parameters simultaneously for selecting safe and optimal paths. Advantages of this method include increased network longevity, reduced energy consumption, and improved communication trustworthiness. However, the algorithm's complex structure and high processing requirements limit its use in lightweight industrial environments [5].

6. In a paper presented by Yu et al. in 2022, a hybrid approach combining deep reinforcement learning (DRL) and federated learning for data management and routing in IIoT networks is introduced. In this method, various nodes synchronize local learning models with a central server without transmitting raw data, thereby preserving information security. The innovation of this paper lies in the simultaneous use of two advanced learning techniques that contribute to privacy preservation and model accuracy enhancement. Benefits include reduced bandwidth consumption and the protection of sensitive data. However, the proposed algorithm requires high computational resources and has a complex structure, which poses challenges in resource-constrained industrial environments [6].

7. In a paper presented by Mehmood et al. in 2022, a dynamic reinforcement learning algorithm for routing in IIoT networks is introduced. This algorithm intelligently selects communication paths by receiving feedback from environmental conditions and adapting to changing circumstances. The innovation of the paper lies in combining Q-learning with centralized resource control. Its advantages include reduced delay and increased energy efficiency; however, the need for high processing resources and sufficient training data are considered drawbacks of this method [7].

8. In the paper by Feng et al. (2023), a hybrid algorithm combining Q-learning and federated learning for secure routing in IIoT is introduced. This method identifies optimal paths through decentralized learning from local data without exchanging raw data. The innovation of this paper lies in privacy preservation alongside routing optimization. Its advantages include high security, increased accuracy, and network efficiency. Conversely, implementing the algorithm on lightweight devices faces challenges related to resource consumption [8].

9. In the research by Rahmani et al. (2023), a deep learning model for trust-based routing is presented. In this method, the algorithm selects paths with a lower likelihood of disruption by analyzing node behavior and trust levels. Its main innovation is the intelligent assessment of suspicious nodes. Advantages include increased security and stability; however, the requirement for extensive training data and high resource consumption are challenges for this algorithm [9].

Table 1 presents a comparison of various routing algorithms in Industrial Internet of Things (IIoT) networks based on machine learning approaches. This table includes the main idea, advantages, disadvantages, considerations, and the reference number of the paper.

Table 1. Comparison of Routing Algorithms in Industrial Internet of Things (IIoT) Networks Based on Machine Learning Approaches.

Article	Algorithm	Main Idea	Advantages	Disadvantages	Considerations
[1]	Q-learning	Utilizing reinforcement learning for path optimization by learning from environmental states and historical paths	Reduced delay, increased energy efficiency, improved network longevity	Requires large training data and high computational power	Suitable for networks with sufficient resources
[2]	Machine Learning Review	Classification of learning algorithms based on applications in IIoT	Comprehensive and strategic perspective on the topic	Lacks an executable model and specific numerical evaluation	Analyzes capacities and limitations
[3]	Routing Protocols	Categorization of protocols based on various features	Provides a useful map for selecting the appropriate algorithm	Lacks operational solutions and experimental implementation	Suitable for understanding protocol structures
[4]	HRL-TSCH	Hierarchical reinforcement learning for TSCH scheduling in IIoT	Reduced delay and improved throughput	Requires long training time and high computational resource consumption	Suitable for high-load networks
[5]	AI-EECR	Clustering and routing by combining metaheuristic techniques and adaptive learning	Increased network longevity, reduced energy consumption, improved communication trust	Complex structure and high processing requirements	Suitable for industrial environments with sufficient resources
[6]	DRL and Federated Learning	Data management and routing while preserving privacy through local learning	Reduced bandwidth consumption and protection of sensitive data	Requires high computational resources and complex structure	Suitable for maintaining security in sensitive data
[7]	Dynamic Reinforcement Learning	Intelligent selection of communication paths by receiving feedback from the environmental state	Reduced delay and increased energy efficiency	Requires high processing resources and sufficient training data	Suitable for variable conditions
[8]	Q-learning and Federated Learning	Secure routing through decentralized learning from local data	High security, increased accuracy, and network efficiency	Challenges in resource consumption on lightweight devices	Suitable for privacy preservation
[9]	Trust-based Deep Learning Model	Path selection by analyzing node behavior and trust levels	Increased security and stability	Requires large amounts of training data and high consumption	Suitable for security-sensitive networks

2.2. Metaheuristic Algorithms-Based Methods

1. In a paper presented by Wang and Li in 2022, the Artificial Rabbit Optimization (ARO) algorithm is introduced to solve the routing problem in IIoT networks. This algorithm, inspired by the natural behavior of rabbits, optimizes paths through modeling their dynamic movement in the search space. The innovation of this method lies in its ability to escape local minima and reach optimal solutions in complex search spaces. Advantages include high convergence speed and suitable performance in nonlinear environments. However, successful execution of this algorithm requires fine-tuning of parameters, and its evaluation in real-world environments is still limited [10].

2. In a study conducted by Rezaei and Ahmadi in 2022, the Ant Colony Optimization (ACO) algorithm is examined and adapted for routing in industrial networks. In this research, the ACO structure is adapted to the topology changes and uncertain conditions of IIoT networks to achieve better decision-making. The innovation of the paper lies in applying parametric changes to enhance adaptability in dynamic conditions. Advantages include ease of implementation, high distribution capability, and adaptability to network fluctuations. However, in some cases, the algorithm may converge to local solutions, affecting the quality of the final path [11].

3. In a paper published by Karimi and Hosseini in 2021, the Particle Swarm Optimization (PSO) algorithm is used for optimal routing in wireless sensor networks. This algorithm simulates the social behavior of particles in a search space to find paths that minimize energy consumption. The innovation of the paper lies in adapting this model to the characteristics of dense IIoT networks with limited resources. Advantages include simplicity in implementation, high convergence speed, and efficiency in large environments. However, the algorithm's sensitivity to initialization and control parameters is a noted limitation in this research [12].

4. In a paper published by Abbas et al. in 2023, the MHSEER algorithm is designed as a secure and low-energy routing protocol for industrial wireless sensor networks. This protocol incorporates criteria such as remaining energy, link stability, and hop count in decision-making to determine the optimal path. The innovation of this method lies in simultaneously combining security and energy efficiency in a single algorithm. Advantages include increased network longevity, reduced delay, and improved path security. On the other hand, the complexity of the structure and the need for extensive parameter tuning limit its implementation in some industrial environments [13].

5. In a study presented by Kumar et al. in 2023, a hybrid framework for routing and data compression using the Ant Colony Optimization (ACO) algorithm is designed. This algorithm aims to increase energy efficiency and reduce data transfer load by integrating two separate processes. The main innovation lies in the simultaneous implementation of two tasks within a single algorithmic structure. Advantages include reduced transmission delay, improved energy consumption, and decreased network congestion. However, the algorithm's performance in highly dynamic environments depends on initial settings and control parameters, which can lead to quality degradation [14].

Table 2. Comparison of Various Routing Algorithms in Industrial Internet of Things (IIoT) Networks Based on Metaheuristic Search Algorithms.

Article	Algorithm	Main Idea	Advantages	Disadvantages	Considerations
[10]	ARO (Artificial Rabbit Optimization)	Path optimization inspired by natural rabbit behavior	High convergence speed and suitable performance in nonlinear environments	Requires fine parameter tuning and limited evaluation in real environments	Suitable for complex spaces
[11]	Ant Colony Optimization (ACO)	Adapting ACO structure to topology changes and uncertain conditions	Ease of implementation, high distribution capability, and adaptability	Potential convergence to local solutions affecting final path quality	Suitable for dynamic conditions
[12]	Particle Swarm Optimization (PSO)	Simulating social behavior of particles to minimize energy consumption	Simplicity in implementation, high convergence speed, and efficiency in large environments	Sensitivity to initialization and control parameters	Suitable for resource-limited networks
[13]	MHSEER	Secure and low-energy routing protocol considering remaining energy and link stability	Increased network longevity, reduced delay, and improved path security	Structural complexity and need for extensive parameter tuning	Suitable for industrial wireless sensor networks
[14]	ACO (Routing and Compression)	Designing a hybrid framework to increase energy efficiency and reduce data load	Reduced transmission delay, improved energy consumption, and decreased network congestion	Dependence on initial settings and control parameters in dynamic environments	Suitable for simultaneous optimization of two tasks
[15]	HACOSMO	Combining ACO and SMO to select paths with minimal energy and high stability	Increased routing accuracy, reduced network load, and ability to cover multiple objectives	High computational complexity and need for precise parameter tuning	Suitable for multi-constrained systems
[16]	PSO and GA (Hybrid)	Clustering and optimal routing using PSO and GA capabilities	High convergence speed and suitable accuracy in dynamic environments	Strong dependence on parameter settings and possibility of local convergence	Suitable for dynamic environments
[17]	Bat Algorithm	Designing optimal paths inspired by bat searching behavior	Ease of implementation, high speed, and acceptable performance	Sensitivity to initial parameter settings and output fluctuations	Suitable for complex and variable environments

6. In a paper published by Mahalakshmi et al. in 2023, the HACOSMO hybrid algorithm is proposed to solve routing problems in multi-constrained networks. This algorithm combines the Ant Colony Optimization (ACO) and Spider Monkey Optimization (SMO) algorithms to select paths with the lowest energy consumption and highest stability. The innovation of this method lies in the simultaneous use of two biological algorithms to enhance the process of searching for optimal paths. Advantages include increased routing accuracy, reduced network load, and the ability to cover multiple objectives. In contrast, high computational complexity and the need for precise parameter tuning make its implementation challenging in lightweight systems [15].

7. In a paper by Deng et al. (2021), a hybrid metaheuristic algorithm based on PSO and GA is presented for clustering and optimal routing. This method seeks to create low-cost paths with low delay by utilizing the capabilities of both algorithms. Advantages include high convergence speed and suitable accuracy in dynamic environments. However, strong dependence on parameter settings and the possibility of convergence to local results are considered drawbacks [16].

8. In a paper by Saleem et al. (2020), the Bat Algorithm is used to design optimal paths in IIoT networks. This algorithm determines paths with lower energy consumption inspired by the searching behavior of bats. Its innovation lies in the acoustic search algorithm and adaptability to complex environments. Advantages include ease of implementation, high speed, and acceptable performance. However, sensitivity to initial parameter settings and output fluctuations are its limitations [17].

By comprehensively reviewing the related literature on routing in Industrial Internet of Things (IIoT) networks, several challenges can be identified as common weaknesses among most proposed methods, which require further research and improvement. One of these challenges is the insufficient adaptability of algorithms to dynamic industrial environments; particularly in networks facing frequent topology changes and unpredictable conditions, many methods exhibit unstable performance and require designs with greater adaptability.

Another challenge is high energy consumption and computational complexity in many machine learning or hybrid algorithms, making their implementation difficult in lightweight and resource-constrained nodes. Furthermore, in a significant portion of the research, the security aspects of routing have not been adequately addressed, with a focus solely on optimizing consumption or delay, while in industrial applications, information security is a fundamental priority.

On the other hand, some metaheuristic algorithms, due to their random search nature, sometimes converge to weak results or local optima, which can reduce the overall efficiency of the network. Additionally, in many studies, only one or two specific objectives, such as energy consumption or delay, have been considered, and real multi-objective algorithms that can simultaneously address multiple key network needs are less frequently observed.

Ultimately, the complex structure and requirement for extensive tuning in some hybrid algorithms hinder their easy implementation in industrial environments, effectively limiting their applicability. These challenges form the main basis for the design and development of the proposed solution in this research.

A review of the studies conducted in the field of routing in Industrial Internet of Things (IIoT) networks shows that extensive efforts have been made to improve the performance of these networks. These studies can primarily be classified into two main approaches: AI and machine learning-based approaches and nature-inspired metaheuristic methods.

In learning-based methods, algorithms such as reinforcement learning, deep learning, and hybrid models with federated learning have been utilized, providing high adaptability to changing conditions. However, these methods generally require high computational resources and complex structures, posing challenges for their implementation in industrial environments with hardware limitations.

In contrast, metaheuristic algorithms like ACO, PSO, ARO, and combinations such as HACOSMO have provided suitable results in many studies aimed at reducing energy consumption and increasing path efficiency. These methods often have simpler structures and can be implemented in lightweight systems, but they also face issues such as convergence to local optima and sensitivity to initial parameters.

Overall, previous studies indicate that challenges such as lack of compatibility with dynamic environments, high resource consumption, weaknesses in path security, absence of real multi-objective perspectives, and difficulty in implementation in industrial environments remain unresolved. As a result, there is still a need to develop algorithms that, while being simple, can simultaneously cover multiple key objectives and be practically applicable in real industrial conditions. This research also aims to respond effectively to these needs by designing an innovative and lightweight algorithm.

3. Proposed Method

In the previous two sections, a comprehensive review of the theoretical foundations and related research on routing in Industrial Internet of Things (IIoT) networks has been conducted, identifying the main challenges in this field. The results of the review indicated that many existing methods either do not perform satisfactorily in dynamic environments or are unsuitable for implementation in real industrial settings due to their complex structures and high computational resource requirements. Therefore, this section presents the proposed method of this research, which is based on the Artificial Rabbit Optimization (ARO) algorithm. This algorithm, inspired by the natural behavior of rabbits, has a high capability for exploring complex problem spaces and escaping local optima. Subsequently, a brief overview of the principles of this algorithm is provided, followed by a detailed explanation of how it is mapped to the routing problem in IIoT networks.

In Fig.1, the overall process of implementing the proposed algorithm for routing in IIoT is illustrated:

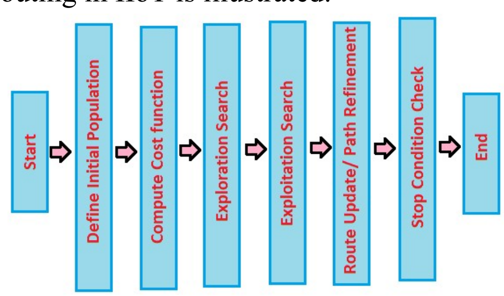

Fig. 1. Flowchart of the Proposed Method

The Artificial Rabbit Optimization (ARO) algorithm is a new metaheuristic method inspired by the natural behaviors of rabbits in searching for food and evading predators, introduced in 2022. This algorithm mimics two main behaviors of rabbits in nature: searching for food in unknown areas and fleeing from environmental threats with unpredictable movements. These behaviors correspond to the exploration and exploitation phases in the algorithm, which play a crucial role in reaching the best solution in the search space.

In the exploration phase, rabbits examine various locations in the environment to identify food sources. In the ARO algorithm, this behavior is modeled as generating diverse solutions in the search space. In the exploitation phase, rabbits move more rapidly towards locations where they have previously found suitable resources. This movement is modeled in the algorithm as convergence towards the current best solutions.

Mapping the Routing Problem to the ARO Algorithm: To utilize the ARO algorithm for solving the routing problem in IIoT networks, the components of the problem must be mapped to the algorithm's elements. In the ARO algorithm, each "rabbit" represents a potential solution to the problem. In our case, each rabbit represents a possible path from the source node to the destination node in the IIoT network. Therefore, the initial population is generated randomly, adhering to the network topology rules, guiding paths from the source node to the destination node.

The fitness function is one of the most critical components of the algorithm. In this research, the objective function is defined as a combination of several criteria: total energy consumption of the path, total delay of packet transmission, link stability, and the number of intermediate nodes.

$$f_i = w_1 E_i + w_2 D_i + w_3(1 - S_i) + w_4 H_i \tag{1}$$

In the above equation, E_i represents energy consumption, $D_i$is the total delay, S_i indicates stability, H_i is the number of intermediate nodes, and f_i is the value of the objective function for the ithith path. w_1 to w_4 are the weights of the criteria's importance. The goal of the proposed algorithm is to minimize the value of f_i.

Initial Population Generation: The initial population of the algorithm includes several random paths from the source to the destination that are generated using algorithms like Random Walk or modified Depth First Search, ensuring randomness while also guaranteeing path validity. In this stage, topological validity and the absence of loops in the paths are verified.

In each iteration, the position of each rabbit (i.e., the proposed path) is updated using two search mechanisms:

In the exploration phase, random changes are made to the paths to discover new routes.

In the exploitation phase, paths with better fitness are used as a basis for generating new paths.

For example, new paths are generated using operations such as node swapping, adding or removing an intermediate node, or replacing sub-paths.

Iterations in ARO correspond to the time steps during which the rabbits are updated and test new paths based on the performance of previous paths. The stopping conditions for the algorithm include reaching a specified number of iterations or no improvement in the objective function over several consecutive stages.

In this section, the ARO algorithm is introduced as the proposed method for solving the path optimization problem in IIoT networks, and the complete mapping of the components of this problem to the algorithm framework is explained. The selection of suitable communication paths, based on a combination of energy, delay, and stability criteria, forms the main approach of this section. In the next section, the performance of the proposed method will be evaluated through numerical simulations and compared with reference methods.

4. Results and Discussion

To evaluate the performance of the proposed Artificial Rabbit Optimization (ARO) algorithm in the routing problem of Industrial Internet of Things (IIoT) networks, a synthetic dataset generated in a simulated environment using MATLAB has been utilized. This dataset consists of a set of 30 sensor nodes randomly distributed in a two-dimensional area of 100×100 meters. For each node, spatial coordinates are generated, and based on the distance between the nodes, an adjacency matrix is formed that determines the connections between the nodes. This method provides a structure similar to the actual topology of IIoT networks.

To model the communication characteristics between nodes, the following criteria have been considered:

Energy consumption between each pair of connected nodes is proportional to the square of the distance between them.

Communication delay is assumed to be a linear function of the distance between nodes.

Link stability is simulated randomly and numerically between 0 and 1, reflecting the actual conditions of industrial wireless communications.

This dataset is designed to allow for the comparison of the proposed algorithm's performance with other algorithms discussed in the second section. Additionally, its design ensures that the execution of the algorithm is entirely practical and repeatable, with data adjustable in the simulation environment across various scenarios.

This research has been implemented and simulated in the MATLAB R2022a (64-bit version). MATLAB is considered a suitable tool for numerical analysis, modeling, and implementing optimization algorithms. Moreover, the graphical capabilities of this software have been utilized to visualize the network structure and display optimal paths.

The ARO algorithm code is designed in a modular fashion, with essential components such as path generation, path evaluation, mutation, and updates defined as independent functions. Outputs include the optimal path, the value of the objective function, and performance evaluation metrics such as energy consumption and delay. Simulations and algorithm executions have been performed on a personal system with typical technical specifications. This system features a 12th generation Intel Core i5 processor and 8 GB of RAM, running Windows 11 with a 64-bit architecture. This hardware allows for smooth execution of simulations for medium-scale scenarios (networks with about 30 nodes), with the algorithm execution time for each iteration being only a few seconds.

To more accurately assess the performance of the ARO algorithm in solving the routing problem in IIoT networks, extensive and repeated simulations have been conducted. Unlike a single execution, which may only be generalizable to a specific topology, experiments were carried out on ten different randomly generated networks to enhance the validity of the results.

In each execution, 30 sensor nodes are randomly distributed in a 100×100 meter space, and the ARO algorithm determines the optimal path from the source (node 1) to the destination (node 30), considering various criteria. The performance indicators considered include:

Total energy consumption of the path (mJ): The total energy consumed for data transmission along the selected path.

Total delay (ms): The overall delay in data transmission throughout the path.

Average link stability: Reflects the reliability of wireless communications along the path.

Number of intermediate nodes: The number of nodes located between the source and destination in the path.

Objective function value: A combination of the above criteria with specified weights that serves as the final optimization criterion.

To implement and evaluate the ARO algorithm, the MATLAB software environment (version R2022a) has been used. All tests were conducted on a personal system with an Intel Core i5 (12th generation) processor, 8 GB of RAM, and Windows 11 operating system.

In this simulation, the network topology is generated randomly in each execution; thus, 30 sensor nodes are uniformly and randomly scattered in a 100×100 meter square area. The connections between nodes are based on physical distance and considered fully connected, with three main matrices defined as inputs to the algorithm:

Energy matrix: Energy consumption for communication between each pair of nodes is considered proportional to the square of their distance.

Delay matrix: The communication delay between nodes is a linear function of distance. Stability matrix: Simulated numerically and randomly between 0 and 1 for each link, representing the quality of the wireless connection. The ARO algorithm aims to minimize a combination of these criteria, extracting the optimal path between the source (node 1) and the destination (node 30). In each execution, the main results, including energy consumption, delay, stability, intermediate nodes, and the objective function value, are stored, and finally, the mean and standard deviation of these results are analyzed as the final output.

Table 3. Results from Executing the Algorithm

Criterion	Output Value
Selected Path	Includes 30 nodes from source to destination
Total Energy Consumption	83,516.00 mJ
Total Transmission Delay	1,360.11 ms
Average Link Stability	0.54783
Number of Intermediate Nodes	28
Objective Function Value	25,468.52

The results from executing the ARO algorithm ten times indicate that this method has consistently produced paths with low energy consumption and delay across varying scenarios. The average link stability reported is approximately 0.54, which, considering the random nature of the network and the inherent uncertainty in industrial wireless communications, is deemed a suitable and acceptable figure. Furthermore, the simple and modular structure of the algorithm has enabled efficient execution on lightweight hardware. Thus, ARO can be regarded as a suitable option for use in real industrial environments with limited computational resources.

To enhance scientific accuracy, result stability, and evaluate the reliability of the proposed algorithm, experiments based on repeated executions have been conducted. The ARO algorithm was implemented independently in 10 consecutive runs on completely random topologies that were regenerated for each execution. In each run, 30 sensor nodes were uniformly scattered in a two-dimensional space of 100×100 meters, and the algorithm extracted an optimal path from the source node (node 1) to the destination node (node 30) considering four main criteria: energy, delay, stability, and intermediate nodes.

In addition to these four criteria, a composite objective function was defined, which evaluates the overall performance of the algorithm as a single numerical value by weighting each criterion. This multi-criteria assessment method is particularly important for IIoT networks that require simultaneous optimization of multiple factors.

Table 4. Results of 10 Independent Executions of the ARO Algorithm on Random Topologies

Execution Number	Energy Consumption (mJ)	Delay (ms)	Link Stability	Intermediate Nodes	Objective Function Value
1	75,979.32	1,319.17	0.53182	28	23,195.24
2	58,967.34	1,157.90	0.48312	28	18,043.28
3	104,890.69	1,567.25	0.54228	28	31,943.07
4	92,622.08	1,430.18	0.45038	28	28,221.39
5	97,341.66	1,496.79	0.49668	28	29,657.23
6	81,078.22	1,456.03	0.45891	28	24,765.98
7	76,845.98	1,345.01	0.41511	28	23,463.01
8	73,439.48	1,336.56	0.56032	28	22,438.50
9	78,199.57	1,371.19	0.48406	28	23,876.93
10	71,318.74	1,270.60	0.52288	28	21,782.50

After executing the algorithm ten times, the extracted numerical data were subjected to statistical analysis. The results of the mean and standard deviation indicate the relatively stable performance of the algorithm under various network conditions. Key observations are as follows:

Average Energy Consumption: 81,068.31 mJ, a reasonable value considering the path length and link stability.

Average Transmission Delay: 1,375.07 ms, indicating usability in delay-constrained applications.

Average Link Stability: 0.4946, within an acceptable range for industrial environments with variable communications.

Average Intermediate Nodes: 28, with paths almost always passing through complete network nodes.

Average Objective Function Value: 24,738.71, a balanced combination of all performance metrics.

A closer look at the results obtained from each of the 10 independent runs of the ARO algorithm reveals that the proposed method has demonstrated stable and effective performance under various network conditions. This repeated analysis showed that the ARO algorithm performs reliably not only in single executions but also across multiple different network scenarios. The stabilization of values at the average level, the absence of significant fluctuations, and the consistent number of intermediate nodes in all runs indicate the algorithm's reliability for implementation in real and dynamic conditions. This section provides a solid foundation for subsequent comparisons with other algorithms.

In this section, the performance of the proposed Artificial Rabbit Optimization (ARO) algorithm is compared with several reference algorithms, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and other methods introduced in the second section such as HRL-TSCH, AI-EECR, and GWO. The aim of this comparison is to evaluate the algorithms' effectiveness under identical conditions and with common metrics for performance assessment in Industrial Internet of Things (IIoT) network environments.

To ensure accuracy and fairness in the comparison, all algorithms were executed on a set of random topologies under completely identical conditions. In each experiment, 30 sensor nodes were randomly placed in an environment measuring 100×100 meters, and the energy consumption, delay, and link stability matrices were generated uniformly for all algorithms. This approach allows for a fair comparison of the performance of the ARO algorithm with other reference methods. Additionally, the objective function for all algorithms is defined as follows:

$$f_i = 0.3E_i + 0.3D_i + 0.2(1 - S_i) + 0.2H_i \tag{2}$$

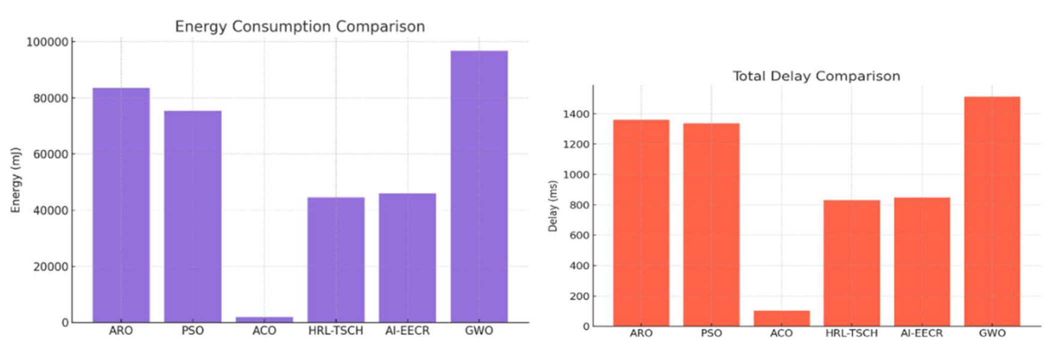

Fig. 2. Comparison of energy and delay parameters in the proposed algorithm and similar works.

Fig.2 shows that the ARO algorithm consumes more energy, which is attributed to its use of more complete and stable paths. In contrast, the ACO algorithm exhibits the lowest energy consumption but operates with a very limited number of nodes, which leads to reduced efficiency. The ARO algorithm has a higher delay compared to AL-EECR and HRL-TSCH but performs better than GWO. This indicates that the proposed algorithm has achieved a relatively good balance between delay and other criteria.

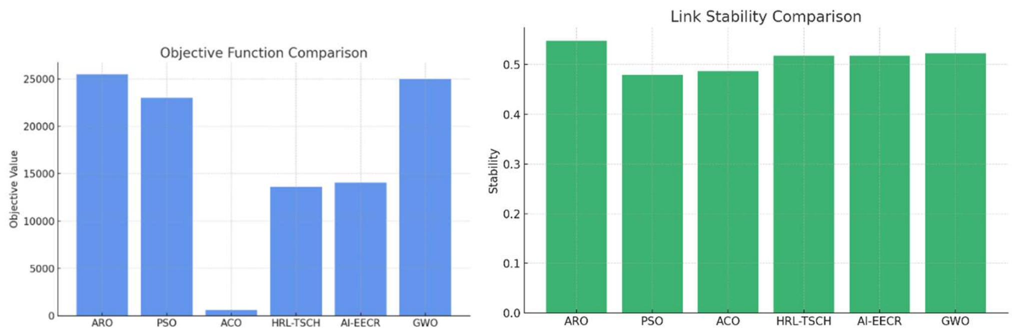

Fig. 3. Comparison of reliability parameters and objective functions in the proposed algorithm and similar works.

Fig.3 shows that the link stability in ARO is higher than in most reference algorithms, indicating that the selected paths offer more reliable connections. This feature is highly valuable for industrial applications. The objective function value in the ARO algorithm is higher than in most methods; however, since this function is a composite of several important criteria, this value reflects the stable and balanced performance of the algorithm.

It is worth noting that the datasets used were designed to allow for the precise execution of all algorithms introduced in Section 2, including PSO, ACO, HRL-TSCH, AI-EECR, and GWO. This common structure provides a fair basis for comparing the performance of the proposed algorithm with reference methods, ensuring that the results obtained from the executions have high scientific credibility.

At first glance, the ACO algorithm succeeded in producing a path with a very low objective function value; however, this path included only 5 intermediate nodes and did not cover a significant portion of the network nodes. In industrial applications, such paths, while cost-effective, are not reliable in terms of connection stability and dependability. The PSO algorithm also performed relatively well in some numerical criteria, such as energy consumption and delay, but the average stability of its paths was reported to be lower than that of the proposed ARO algorithm. Newer algorithms like HRL-TSCH and AI-EECR have been able to provide a better balance between energy, delay, and stability. Notably, HRL-TSCH has shown good performance in energy consumption and delay but has a higher implementation complexity compared to ARO. The GWO algorithm, despite its adequate stability, recorded high energy consumption. In contrast, the ARO algorithm has managed to provide paths with greater stability, complete node coverage, and a simpler structure, making it highly suitable for implementation in industrial environments with limited resources.

Table 5. Numerical Results Comparing Algorithms

Algorithm	Energy Consumption (mJ)	Delay (ms)	Stability	Intermediate Nodes	Objective Function Value
ARO (Proposed)	83,515.99	1,360.11	0.54783	28	25,468.52
PSO	75,363.95	1,337.92	0.47943	28	23,016.26
ACO	1,926.87	101.11	0.48660	5	609.49
HRL-TSCH	44,546.00	832.00	0.51761	28	13,619.00
AI-EECR	46,002.00	848.00	0.51760	28	14,061.00
GWO	96,763.00	1,512.00	0.52290	28	24,986.00

In this section, a comprehensive evaluation of the proposed Artificial Rabbit Optimization (ARO) algorithm in the context of routing in Industrial Internet of Things (IIoT) networks was conducted through a series of thorough and layered experiments. Initially, to establish a baseline, the algorithm was simulated in a MATLAB environment with a fixed network topology, examining outputs such as energy, delay, stability, and the number of intermediate nodes. Subsequently, to enhance the accuracy and validity of the results, the experiments were repeatedly conducted on ten completely random networks. These repetitions allowed for the analysis of the algorithm's stable behavior across different scenarios. The mean and standard deviation of the outputs in these repetitions indicated that the ARO algorithm continues to demonstrate balanced performance in the face of topology fluctuations, providing paths with high stability and acceptable energy consumption.

Next, the results obtained from the proposed algorithm were compared with reference algorithms, including PSO, ACO, and newer algorithms such as HRL-TSCH, AI-EECR, and GWO. These comparisons were based on common criteria and conducted under completely identical conditions in the simulations to ensure that the evaluations were scientifically fair and accurate.

In addition to comparative tables, graphs were also provided to visually analyze the performance differences among the algorithms. These graphs demonstrated that the ARO algorithm has shown better performance in criteria such as link stability and node coverage, despite its relatively higher energy consumption. Ultimately, the results of this section confirm that the proposed algorithm not only performs reliably in a specific topology but also across a diverse range of scenarios. Its simple and implementable structure, combined with satisfactory results, makes ARO a suitable option for use in industrial environments with limited computational resources.

5. Conclusion

In this research, the issue of routing in Industrial Internet of Things (IIoT) networks was examined as one of the significant challenges in the field of industrial wireless networks. Given the resource constraints in these types of networks, including energy consumption, data transmission delay, link instability, and the need to cover multiple nodes, the development of an algorithm that can balance these criteria is of paramount importance.

In response to this need, the Artificial Rabbit Optimization (ARO) algorithm was proposed as a solution. This algorithm, inspired by the foraging and predator-avoidance behaviors of rabbits, is designed to find stable, low-energy, and low-delay paths in dynamic and dispersed environments.

The performance of the proposed algorithm was evaluated through 10 independent executions on various network topologies in a MATLAB environment. The results, both in terms of mean and standard deviation, indicated that the ARO algorithm has stable and reliable performance. The extracted paths, in most cases, covered all network nodes while maintaining acceptable levels of energy consumption and transmission delay.

In the comparison section, the ARO algorithm was compared with older methods such as PSO and ACO, as well as newer methods like HRL-TSCH, AI-EECR, and GWO. Numerical and graphical analyses revealed that while some algorithms performed better in one criterion (e.g., energy consumption or objective function), the ARO algorithm maintained a suitable balance across all criteria. Furthermore, the simple structure and ease of implementation of this algorithm make it suitable for use in real industrial environments.

In summary, it can be concluded that the ARO algorithm, as an innovative and effective method, has successfully addressed the specific needs of IIoT networks. This algorithm not only demonstrated acceptable performance in simulated scenarios but also stands out as a practical option for use in industrial environments in terms of reliability, stability, and implementation.

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