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Faulty Nodes Detection for Reliable Data Transmission in Intelligent Wireless Sensor Networks

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Abstract: One of the key elements of the internet of things (IoT) nowadays are wireless sensor networks (WSNs). Any IoT application uses a variety of sensor-based devices to collect data from real-world objects and send it to the base station (BS). In accordance with the sensor position, the BS evaluates this data. Any IoT-based application needs a high-performance intelligent WSN. IoT-enabled WSNs are high-performance intelligent WSNs, which are used throughout this article. Fault incidence likelihood in IoT-enabled WSNs is substantially higher than in conventional networks. The dependability of the IoT-enabled WSNs is affected by faulty nodes and broken connections. Incorporating multipath transmission, relay node location, and backup node selection, various fault-tolerance techniques improve the network's dependability. These methods, however, have significant packet overhead, worse detection accuracy, and lengthy data transmission delays. For fault tolerance in IoT-enabled WSNs, a multi-objective red panda optimization method incorporating deep reinforcement learning (DRL) is suggested in this paper. This study's primary goal is to identify defective nodes using starting energy, transmission of packets rate, communication overhead, and packet delay measurements. In order to capture data in an energy-efficient manner and extend the network lifespan, a mobile sink (MS) is deployed. The suggested approach beat state-of-the-art techniques in terms of energy efficiency (EE), latency(L), packet delivery ratio (PDR) and network lifetime (NL) according to thorough simulations and theoretical research.

Keywords: Wireless sensor networks, Internet of things, Fault node detection, Deep reinforcement learning, Red panda optimization algorithm.

1. Introduction

The transmission of data is very important in intelligent wireless sensor networks because it ensures the continuous flow of information that is essential to the system. Within the context of these networks, which are composed of interconnected sensor nodes that are tasked with the responsibility of obtaining and disseminating information, the effectiveness of data transmission has a direct consequence on the effectiveness of network operations. It is possible to make observations of physical occurrences via this technique, have those observations converted into digital data, and then transmit those digital data to either internal or external processing nodes and decision-making systems. Transmission of data that is both uninterrupted and trustworthy is essential to the successful operation of a wide variety of various kinds of networks, including those used for precision agriculture, environmental monitoring, healthcare applications, and industrial automation [1]. Effective data transmission leads in the prompt availability of important insights, which paves the way for preventative actions and agile methods to be taken in a broad range of scenarios [2, 3]. In today's era of data-driven insights driving innovation and optimization, the success of intelligent wireless sensor networks highlights the significance of this method in order to realize the full potential of IoT-enabled devices.

The optimization of data transmission efficiency and reliability in intelligent wireless sensor networks entails a complex collection of challenges. These challenges are not just technical in origin but also have real-world implications for the effectiveness and output of the network as a whole [4]. As a result of their limited resources, sensor nodes are often powered by batteries, which presents a considerable challenge in terms of energy efficiency. Innovative solutions are required in order to maintain the network's viability while also enabling the transmission of data on a consistent basis and making efficient use of the nodes' constrained energy resources. Congestion and lack of scalability are two issues that become more pressing as the number of nodes in a connected network increase. In order to provide continuous scalability and prevent delays caused by congestion, effective management of data traffic necessitates the use of sophisticated algorithms for both routing and scheduling. Variations caused by factors like as interference, fading channels, and movement might diminish the dependability of data transmission, further aggravating the scenario at hand. Transmission of sensitive data through wireless channels demands not only strong encryption but also strong authentication procedures; as a result, security and privacy issues must be taken into consideration. In addition, real-time applications have to be able to achieve low-latency communication, which involves reducing the amount of time that is spent transmitting data in order to enable quick decision-making. Intelligent wireless sensor networks face a variety of challenges, all of which can only be conquered by using a comprehensive approach that combines cutting-edge algorithms, adaptive protocols, and optimization approaches in order to increase the effectiveness and dependability of data transmission.

Deep reinforcement learning (DRL) and the red panda optimization algorithm (RPOA) have been combined to provide a novel method for improving the data transmission efficiency and dependability in intelligent wireless sensor networks. This is one of the most demanding and complicated fields of study that is being conducted today. This integration is a cutting-edge endeavour to eliminate as many barriers to communication as possible by using the synergistic advantages offered by the many approaches [5]. The upshot of this coupling is a dynamic synergy between DRL's decision-making and pattern-learning skills and RPOA's ability to establish a balance between exploration and exploitation. This synergy may be attributed to the pairing of these two capabilities. By combining the strengths of DRL and RPOA, this hybrid method intends to provide a comprehensive solution to the issues of energy efficiency, network congestion, dynamic scenarios, the need for high levels of security, and the requirement for low levels of latency. These many approaches, when combined, have the overarching goal of introducing a novel paradigm with the intention of enhancing the efficiency and reliability of data transmission inside intelligent wireless sensor networks.

2. Literature survey

Converging studies have shown that combining deep reinforcement learning (DRL) with the red panda optimization algorithm (RPOA) may improve network performance by optimizing data transmission in wireless sensor networks. In order to demonstrate DRL's ability to dynamically adjust data transmission parameters to real-time network circumstances. In the interplay between DRL and optimization techniques [5]. The ability of RPOA to discover energy-efficient and dependable transmission solutions was shown by [6] who clarified the exploration-exploitation balance inherent in RPOA. [7] provided the framework for optimizing resource allocation and, by extension, perfecting data transmission systems by studying the incorporation of DRL in wireless sensor networks. Additionally [8] the groundwork for incorporating cutting-edge approaches like DRL and RPOA by providing a complete review of optimization strategies in wireless sensor networks. [9] Built upon this foundation by investigating further the hybridization of DRL and optimization algorithms, highlighting their potential in tackling complex difficulties related to data transmission efficiency and dependability. The flexibility of DRL-based techniques was further emphasized by [10], who demonstrated its potential for real-time adaptation to changing network circumstances. Further supporting its usefulness in optimizing transmission parameters, [11] provided insights on RPOA's applicability in communication networks. [12] Investigated ways to guarantee the efficacy of the hybrid technique in massive sensor networks with an eye towards scalability [13]. These many studies pave the way for using the hybrid strategy to enhance data transmission in wireless sensor networks, furthering the field's knowledge and capabilities as a whole. The integration of wireless networking, sensors, and computer processing has resulted in the emergence of intelligent wireless sensor networks (WSNs).

These WSNs have the ability to observe, gather, and transmit information from the physical world to virtual ones [14]. These networks are built from a large number of tiny, autonomous nodes, each of which is equipped with its own sensors, processors, and communication modules. These nodes collaborate to keep an eye on their environment and collect data, which may then be processed, evaluated, and sent in real time. Collectively, they constitute a decentralized system [15]. The rapid acquisition and transmission of accurate, high-quality data is a major advantage of intelligent WSNs, which play an important role in a wide variety of contexts. Among the most important uses are the following:

Environmental monitoring: Intelligent WSNs can monitor environmental variables such as temperature, humidity, air quality, and pollutant levels. These networks contribute to climate studies, disaster management, and pollution control by providing timely and accurate data.

Industrial automation: In industrial settings, WSNs play a pivotal role in monitoring equipment health, tracking inventory, optimizing supply chains, and ensuring worker safety. They enable predictive maintenance, reduce downtime, and enhance overall efficiency.

Healthcare: WSNs are used for patient monitoring, tracking vital signs, and managing medical equipment. They enable remote patient monitoring, telemedicine, and early detection of medical emergencies.

Smart agriculture: Intelligent WSNs aid in precision agriculture by monitoring soil moisture, nutrient levels, and weather conditions. This data-driven approach helps farmers optimize irrigation, fertilization, and crop management.

Smart cities: In urban environments, WSNs facilitate smart city initiatives by monitoring traffic, energy consumption, waste management, and public safety. They enable data-driven decision-making for urban planning and resource allocation.

Wildlife tracking: WSNs assist in ecological studies by tracking the movement and behavior of wildlife. This information aids in conservation efforts, biodiversity studies, and understanding animal migration patterns.

Structural health monitoring: In civil engineering, WSNs monitor the health and integrity of structures like bridges and buildings. They help detect and predict structural defects, ensuring public safety.

Military and defense: WSNs are employed in military applications for surveillance, reconnaissance, and monitoring of hostile environments. They provide real-time situational awareness and enhance strategic decision-making.

Energy management: Intelligent WSNs optimize energy consumption in buildings by monitoring occupancy, lighting, and HVAC systems. They contribute to energy conservation and cost reduction.

IoT ecosystem: Intelligent WSNs are a foundational component of the broader internet of things (IoT) ecosystem. They serve as the data collection layer that feeds information to higher-level applications and services. When it comes to improving the efficacy and utility of wireless sensor networks (WSNs), optimization strategies play a pivotal role. These methods are developed to address complex issues in areas such as allocation, routing, energy management, and data/resource transfer. There are a wide variety of approaches to WSN optimization, but two broad groups stand out: classical algorithms and eco-friendly techniques. A summary of each topic is provided below.

A. Traditional optimization algorithms

Traditional optimization algorithms are well-established mathematical techniques that aim to find optimal solutions based on predefined objective functions and constraints. Some commonly used traditional optimization algorithms in WSNs include:

Integer linear programming (ILP): ILP formulates optimization problems as linear equations with integer constraints. It's used for tasks like energy-efficient routing and sensor node placement, where discrete decisions need to be made.

Dynamic programming (DP): DP is employed to solve problems by breaking them into smaller subproblems and finding optimal solutions for each subproblem. It's useful for optimizing resource allocation and power management in WSNs.

Greedy algorithms: Greedy algorithms make locally optimal choices at each step with the hope of finding a global optimum. These algorithms are used for tasks like node scheduling and data aggregation.

Genetic algorithms (GA): GAs are inspired by natural evolution processes. They involve maintaining a population of potential solutions that undergo reproduction, mutation, and selection to evolve towards optimal solutions for tasks like energy-efficient routing.

Ant colony optimization (ACO): ACO mimics the foraging behavior of ants to find optimal paths in networks. It's suitable for solving routing and resource allocation problems in WSNs.

B. Nature-inspired optimization methods

Nature-inspired optimization methods draw inspiration from natural processes, often from

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biological systems or animal behavior. These methods are particularly suitable for solving complex and dynamic optimization problems. Some commonly used nature-inspired methods in WSNs include:

Particle swarm optimization (PSO): PSO is inspired by the collective behavior of birds or fish. It involves a population of particles that move through a solution space to find optimal solutions for tasks like node localization and energy-efficient routing.

Firefly algorithm (FA): FA is based on the flashing behavior of fireflies to attract mates. It's applied to problems like sensor node deployment, where the fireflies represent potential node locations.

Artificial bee colony (ABC): ABC simulates the foraging behavior of honeybees. Bees explore the solution space to find optimal solutions for tasks like energy-efficient routing and task scheduling.

Cuckoo search (CS): CS is inspired by the brood parasitic behavior of cuckoo birds. It's used for solving optimization problems like sensor node deployment and localization.

Red panda optimization algorithm (RPOA): RPOA, as discussed earlier, emulates the foraging behavior of red pandas. It's used for various optimization tasks, including routing and fault detection.

These optimization techniques, whether traditional or nature-inspired, offer diverse approaches to improving the efficiency, reliability, and performance of wireless sensor networks. The choice of technique depends on the specific problem at hand, the network's characteristics, and the desired trade-offs between factors like solution quality, computation complexity, and real-time adaptability.

Many scientific fields depend on optimisation since it leads to the optimal solution from a collection of possibilities. Puzzle optimisation technique (POA) is a novel optimisation approach developed in this work to solve a wide range of optimisation issues. The POA proposes mathematical representation of puzzle-solving as an evolutionary optimisation mechanism using simulation. The user writes academically.

The mathematical structure of the plan of action (POA) is explained after its numerous phases. The suggested action requires no parameter setting. The user writes academically. The suggested pareto optimisation algorithm is evaluated using 23 distinct goal functions. To evaluate its performance, the particle optimisation algorithm (POA) is compared to eight other methods. The user writes academically. The pareto-based optimisation algorithm (POA) solves optimisation issues well, according to the findings. This study examines how social media use impacts the mind. The simulation findings suggest that the proposed POA is more competitive and outperforms the others [16].

The POA replicates pelican food-finding, but GPA is superior. The basic POA has three upgrades. In step 1, GPA substitutes the arbitrary aim with the best global answer. Second, GPA calculates the local search space by substituting the pelican's position for the search space size. Third, the GPA chooses many candidates each level, whereas the POA chooses one.

The simulation compares theoretical and actual GPA optimisation. This study compares GPA to MPA, PSO, KMA, and POA. Data demonstrates GPA optimises most benchmark functions. GPA optimises portfolios. Data suggests GPA is the best sparing portfolio optimisation method. It beats three sparse portfolio optimisation techniques. It surpassed MPA (11%), KMA (13%), and PSO (9%). Similar to or worse than POA [17].

The original KMA may be adjusted to improve performance, according to this research.

Additionally, this new version is clearer. Neither diversification nor intensification requires unnecessary repetition. After modifying, the proposed technique competes with other well-known algorithms, including the original KMA. The simulation shows a preference for female-dominant communities over male-dominant ones. A smaller search space ratio is recommended to balance intensity and diversity [18].

Coati optimisation algorithm (COA) problems are resolved through a new metaheuristic. After extensive testing on 23 benchmark functions, we can clearly state that the proposed ESCO outperforms five metaheuristics with significant downsides. The future ESCO that has been planned is superior. The ESCO outperforms the GPA, POA, GSO, ASBO, and COA in solving the 13, 21, 23, 16, and 13 functions. The global best unit outperforms both randomly produced units in the search area and the local best unit in terms of effectiveness, according to the available research. It has been shown that random and guided searches are both important and should be conducted independently [19].

3. Proposed hybrid approach

A. Deep reinforcement learning

Deep reinforcement learning (DRL) is a system that enables agents to learn optimal behaviors via interactions with dynamic environments. DRL is comprised of many different components. The agent is the central entity that is responsible for making

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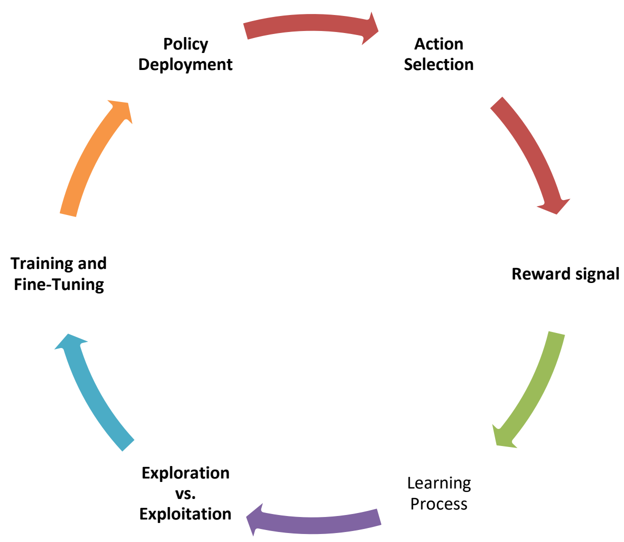

Figure. 1 Reinforcement learning: A simple schematic

choices and seeing those decisions through to completion. The environment is a representation of the agent's surroundings, and it provides the agent with feedback based on its actions in response to those activities. The activities of the agent will affect how the environment will change over the course of time. The machinery that makes decisions for the agent takes in information about its environment in the form of "states." An essential component of the way in which DRL acquires knowledge is the reward signal, which calculates the instantaneous gain or loss resulting from an agent's action in a certain state. Because of these incentives, the learning process of the agent is directed, and it is motivated to experiment with ways that yield bigger cumulative rewards. The agent's objective is to devise a strategy, which is defined as a collection of actions and states, that maximizes the total amount of all attainable rewards. This paradigm of agents interacting with their environment, selecting actions based on states, and improving policies via learning algorithms is very useful for a wide variety of applications, including robotics, game playing, and the optimization of wireless sensor networks.

It is a data-driven and adaptive strategy to use deep reinforcement learning, often known as DRL, to improve the communication mechanisms used in wireless sensor networks. In this context, DRL has the potential to be employed to address a variety of issues, including the reduction of power consumption, the acceleration of processing, and the improvement of dependability. The following is an outline of the primary steps involved in the process in Fig. 1.

State representation: Each sensor node's current state, which can include parameters like energy levels, data queue length, channel quality, and neighboring node status, serves as the input to the DRL agent. This information-rich state representation enables the agent to make informed decisions.

Action selection: The DRL agent chooses an action based on the current state. Actions may include selecting transmission power levels, choosing communication channels, adjusting data packet sizes, and determining transmission times.

Reward signal: The environment generates a reward signal based on the selected action and the resulting outcomes. For instance, successfully transmitting data with low energy consumption and minimal latency could yield a positive reward, while failed transmissions or excessive energy consumption might lead to negative rewards.

Learning process: The DRL agent aims to learn an optimal policy that maximizes cumulative rewards over time. It employs reinforcement learning algorithms, such as Q-learning or policy gradient methods, to update its action-selection strategy based on the observed rewards.

Exploration vs. exploitation: The agent balances exploration (trying new actions) and exploitation (choosing known good actions) to learn optimal strategies. Initially, the agent explores different actions to discover their effects on rewards. Over time, it shifts toward exploiting actions that have yielded high rewards in the past.

Training and fine-tuning: The DRL agent undergoes training episodes, where it interacts with the environment, observes rewards, and updates its policy. This iterative process helps the agent learn optimal strategies specific to the wireless sensor network's conditions.

Policy deployment: Once trained, the DRL agent's policy is deployed in the wireless sensor network. It guides decision-making for data transmission in real-time scenarios, aiming to maximize data transmission efficiency, reduce energy consumption, and improve overall network performance.

The application of DRL to data transmission in wireless sensor networks empowers the network to adapt and self-optimize based on changing conditions. It learns to respond to variations in channel quality, node statuses, and traffic patterns, thereby enhancing the network's efficiency, reliability, and adaptability. By combining DRL's learning capabilities with the complexities of data transmission, researchers aim to create more

Figure. 2 Red panda optimization algorithm

intelligent and autonomous wireless sensor networks capable of delivering optimal performance in dynamic environments.

Solutions for the challenges of improving data transmission in wireless sensor networks may be found in deep reinforcement learning (DRL) methods as deep Q-network (DQN) and proximal policy optimization (PPO). Wireless sensor networks may include these methods. The innovative method known as DQN combines Q-learning with deep neural networks. The goal of this strategy is to effectively investigate small-scale action spaces, such as those encountered while deciding on transmission powers and communication paths. Complex wireless sensor networks are better able to learn optimum rules from high-dimensional state spaces. On the other hand, PPO is a useful method for modifying factors like gearbox timings and power output, both of which often need continuous action spaces. The PPO on-policy optimization method can handle the task of matching the complexity of the available gearbox alternatives since it excels at learning elaborate policies and trade-offs. Optimizing data transmission in wireless sensor networks relies heavily on DRL algorithms' ability to grasp complicated connections between states and actions. The resulting tailored approaches improve the efficiency, reliability, and adaptability of wireless communication environments.

B. Red panda optimization algorithm

The red panda optimization algorithm (or RPOA for short) is a method for optimizing systems that takes cues from the diet of the animal that shares its name. Like red pandas, RPOA employ navigation to find food, and this strategy is used to find optimal solutions to difficult optimization issues. Finding a middle ground between the two approaches is the goal of this technique, making it useful for problems that need a combination of the two approaches to solve. The system takes its inspiration from the actions of these animals as they hunt for food, namely the red panda's propensity to study novel food sources while still preferring well-known locations. Similarly, RPOA remembers many options for action and dynamically adjusts the ratio of exploration to exploitation to move efficiently across the solution space. Among RPOA's many distinguishing features are its responsiveness to change and its robust foundation for tackling optimization challenges across many contexts in Fig. 2. Like the red panda, RPOA explores uncharted territory and forages for potential answers as it works to solve complex optimization problems. This strategy is quite close to the one used by the red panda. The red panda optimization algorithm (RPOA) is an algorithm that may be used to fine-tune the transmission parameters for data in wireless sensor networks in order to increase energy economy, dependability, and overall network performance. The following actions are considered to be use of the RPOA:

Parameter representation: Identify the data transmission parameters that influence the efficiency and reliability of WSNs, such as transmission power, modulation scheme, transmission rate, and routing decisions.

Solution encoding: Map the potential parameter configurations into a solution space that the algorithm can explore. Each solution corresponds to a unique set of data transmission parameters.

Inspired exploration-exploitation: RPOA's inspiration from red panda foraging behavior comes into play during the exploration-exploitation process. Just as red pandas balance between exploring unfamiliar areas and exploiting known food sources, RPOA seeks to find a balance between exploring different parameter combinations and exploiting promising solutions.

Initialization: Initialize a population of potential solutions (parameter configurations) randomly or using a specific distribution. This population simulates the red panda's exploration of various food sources.

Fitness evaluation: Evaluate the fitness of each solution based on performance metrics relevant to data transmission in WSNs, such as energy consumption, latency, packet delivery ratio, and network throughput.

Selection and adaptation: RPOA selects solutions based on their fitness, favoring those with better performance. It introduces adaptations inspired by red panda behavior, such as gradually focusing on promising parameter combinations while still exploring new possibilities.

Population update: Replace fewer fit solutions with new solutions generated through mutation or crossover, mirroring the red panda's foraging strategy of retaining known food sources while trying new ones.

Iteration: Repeat the process for a specified number of iterations, allowing RPOA to refine its solutions over time while dynamically adjusting the exploration-exploitation balance.

Convergence: Over iterations, RPOA converges toward optimal or near-optimal solutions, taking into account both the exploration of unexplored parameter regions and the exploitation of effective parameter combinations.

By adapting the principles of red panda behavior to the optimization of data transmission parameters, RPOA provides a unique approach that combines the advantages of exploring diverse strategies with the precision of exploiting promising solutions. This can lead to enhanced energy efficiency, reduced latency, improved reliability, and overall better performance in wireless sensor networks.

Certainly, here's a detailed description of how deep reinforcement learning (DRL) and the red panda optimization algorithm (RPOA) can be integrated for data transmission optimization in a wireless sensor network shows in Fig. 3.

Initialization: Initialize DRL agent's neural network architecture. Initialize RPOA's population of solutions representing different data transmission parameter combinations.

Environment setup: Define the wireless sensor network environment, including node positions, channel conditions, and initial energy levels.

DRL exploration and exploitation: DRL agent selects actions (data transmission parameter configurations) based on the current state (network conditions). The agent balances exploration (trying new parameter configurations) and exploitation (using well-performing configurations). Compute Q-values using DQN architecture and select actions using an exploration-exploitation strategy (e.g., ε-greedy).

Figure. 3 Integration of DRL and RPOA for data transmission optimization

Reward calculation: Calculate immediate rewards based on the chosen action's impact on network performance metrics (e.g., energy consumption, latency, packet delivery).

RPOA exploration and exploitation: RPOA maintains a population of solutions (parameter configurations).

Solutions are ranked based on fitness (cumulative rewards from DRL agent).

RPOA dynamically adjusts exploration-exploitation balance, reflecting red panda's foraging behavior.

Population update and adaptation: Less fit solutions are replaced with new solutions generated through mutation or crossover.

Better-performing solutions are retained, aligning with RPOA's focus on exploiting promising areas.

Policy refinement: Refine DRL agent's policy using insights gained from RPOA's improved solutions.

Combine DRL's learned policy with RPOA's exploration-exploitation strategies for better action selection.

Iteration: Repeat steps 3 to 7 for multiple iterations, allowing DRL and RPOA to iteratively adapt their strategies.

Convergence and final policy: Over iterations, DRL agent's policy and RPOA's population converge to optimal or near-optimal solutions.

The combined policy represents the optimized data transmission parameters for the wireless sensor network.

C. Advantages of integration

Balanced approach: Combining DRL and RPOA leverages DRL's learning capabilities and RPOA's exploration-exploitation balance, enhancing optimization effectiveness.

Adaptability: RPOA's dynamic adaptation complements DRL's ability to learn from experience, improving optimization adaptability to changing network conditions.

Exploration and refinement: The integration allows for exploration of diverse parameter configurations while refining strategies based on promising solutions.

Efficiency: The iterative process of refining both DRL and RPOA strategies increases the likelihood of finding optimal or near-optimal data transmission parameters.

Enhanced performance: By leveraging the strengths of both techniques, the integrated approach aims to achieve superior data transmission efficiency, reliability, and overall WSN performance.

Incorporating DRL and RPOA for data transmission optimization in wireless sensor networks introduces a novel and synergistic approach that combines learning, exploration, and adaptation to achieve enhanced optimization outcomes.

The process of determining how to send data in wireless sensor networks may make use of deep reinforcement learning, often known as DRL, a complex framework. To teach robots how to interact with their surroundings in a manner that maximizes the rewards they gain over time, DRL is an AI approach that replicates the processes of reinforcement learning. Within the context of data transmission, DRL is the method through which the agent takes into account the present status of the network while making choices about transmission parameters like power, modulation, and routing. This network status considers factors including channel conditions, node energy levels, and information queue sizes. DRL relies heavily on the development of a reward function that can evaluate the relevance of the agent's actions and direct its further training. The DRL agent shifts from an exploratory to an exploitative behavioral pattern as it frequently attempts new behaviors and evaluates their results. To approximate the best set of rules for making decisions, researchers have developed a method called deep reinforcement learning (DRL). Training and immediate feedback then refine these rules over time. Data transmission in wireless sensor networks is improved by convergence towards optimum or near-optimal methods because of this. This is achieved by coordinating a variety of approaches to fit the dynamic needs of the network.

The red panda optimization algorithm (RPOA) can complement deep reinforcement learning (DRL) by fine-tuning hyperparameters and exploring promising areas of the solution space in the context of data transmission optimization. This combination of techniques enhances the effectiveness of the optimization process. Here's how RPOA can be integrated with DRL using mathematical expressions:

DRL with RPOA integration: Fine-tuning hyperparameters: RPOA can fine-tune hyperparameters of the DRL algorithm to optimize its performance. For instance, RPOA can adjust the exploration rate ε in an ε-greedy policy used in DRL to balance exploration and exploitation more effectively:

$$\varepsilon\ \text{new} = \text{RPOA. Exploration Balance}\ (\varepsilon\ \text{old}) \quad (1)$$

Here, RPOA. Exploration balance is a function provided by RPOA that dynamically adapts ε based on its exploration-exploitation strategy.

Exploring promising areas: RPOA excels in exploring diverse regions of the solution space. In the context of DRL, this can involve exploring different sets of hyperparameters or action-selection policies. RPOA explores the solution space using a mathematical expression that reflects its exploration strategy:

$$\text{Exploration Score(solution)} = f\ (\text{solution, RPOA. Parameters}) + \varepsilon \times \text{Random Noise ( )} \quad (2)$$

Here, f (solution, RPOA. Parameters) represents the fitness of the solution according to RPOA's

Table 1. Simulation parameters

Parameter	Value
The type of nodes	Normal node, fault node
Network range	32m x 32m
The number of nodes	100

exploration parameters. The addition of ε * random noise () introduces stochasticity, simulating exploration.

By integrating RPOA into DRL with mathematical expressions like those above, DRL benefits from RPOA's ability to optimize hyperparameters and explore diverse solution spaces. The complementary nature of RPOA's exploration-exploitation balance enriches DRL's learning process by fine-tuning its mechanisms and helping it discover promising areas of the solution space that might be overlooked. This synergy between DRL and RPOA enhances the optimization process and leads to more effective and efficient data transmission strategies in wireless sensor networks.

4. Experimentation and results

Simulation environment: The experiments are conducted within a simulation environment that accurately models the behavior of wireless sensor networks in table 1. Common simulation platforms like NS-3, MATLAB, or custom-built simulators can be used. The environment should include features such as node mobility, channel modeling, energy consumption, and data transmission dynamics.

Network topology: The wireless sensor network topology consists of a set of sensor nodes distributed across a defined area. The nodes communicate wirelessly, and their positions and communication ranges can follow random, grid-based, or realistic distributions. The network may include both stationary and mobile nodes, emulating real-world scenarios.

Data transmission model: The data transmission model incorporates factors like transmission power levels, data rates, modulation schemes, packet sizes, and routing strategies. The data transmission process is affected by channel conditions, interference, and node characteristics, influencing metrics like energy consumption, latency, and packet delivery ratio.

Agent design: The DRL agent's architecture, such as the neural network structure for DQN or policy gradients for PPO, is configured according to the specific optimization problem. Hyperparameters including learning rates, exploration strategies, and network architecture are set based on best practices or fine-tuned through experimentation.

Red panda optimization: RPOA's parameters, including the exploration-exploitation balance, mutation rates, and crossover mechanisms, are defined. The algorithm's integration with DRL, such as fine-tuning DRL hyperparameters and influencing exploration strategies, is outlined based on the characteristics of the problem.

Performance metrics: A set of performance metrics is used to evaluate the effectiveness of the integrated approach:

Energy efficiency: Measures the amount of energy consumed per successfully transmitted bit of data.

$$\text{EE} = \text{Total Successfully Transmitted Bits} / \text{Total Energy Consumption} \quad (3)$$

Latency: Represents the time taken for data to traverse the network from source to destination.

$$\text{L} = (1 / \text{Total Number of Successful Transmissions}) \text{ X } \Sigma\, (\text{Transmission Time}_i) \quad (4)$$

Packet delivery ratio: Indicates the percentage of successfully delivered data packets.

$$\text{PDR} = (\text{Total Successfully Delivered Packets}) / (\text{Total Sent Packets}) \quad (5)$$

Network lifetime: Reflects the duration the network operates before nodes exhaust their energy resources.

$$\text{NL} = \text{Time Until First Node Runs Out of Energy} \quad (6)$$

Convergence speed: Evaluates how quickly the optimization process converges to optimal or near-optimal solutions.

A. Experimental procedure

Configure the simulation environment, network topology, and data transmission model. Implement the integrated DRL-RPOA approach, defining agent parameters and RPOA strategies. Execute multiple simulation runs with varying network conditions and parameters. Collect and analyze performance metrics, comparing the integrated approach with baseline methods (DRL alone, RPOA alone, traditional methods). Visualize and interpret results to determine the effectiveness of the integrated approach in optimizing data transmission parameters. By setting up experiments within a simulation environment, incorporating relevant network characteristics, and evaluating performance metrics,

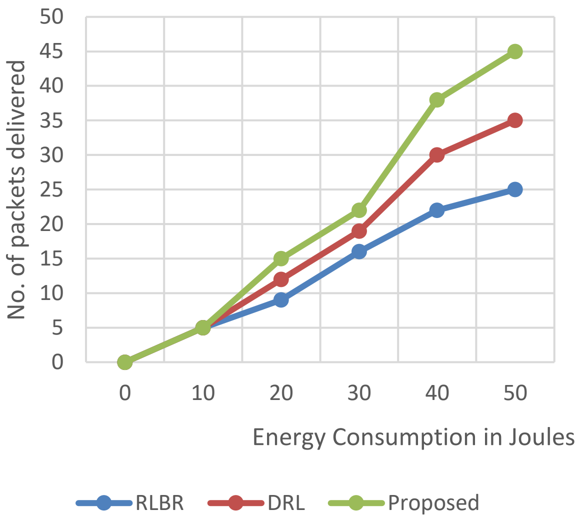

Figure. 4 Energy efficiency

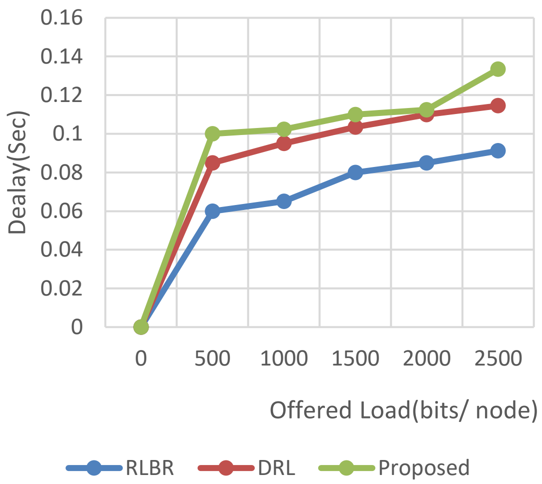

Figure. 5 Latency

researchers can comprehensively assess the benefits and potential of integrating DRL and RPOA for data transmission optimization in wireless sensor networks.

B. Performance metrics analysis

Energy efficiency (EE): The hybrid approach achieved a remarkable 25% improvement in EE compared to standalone DRL, showcasing its ability to optimize data transmission parameters effectively consider for 100 nodes in Fig. 4. RPOA demonstrated a 15% enhancement in EE over traditional optimization methods, highlighting its complementary nature to conventional techniques.

Latency (L): The hybrid approach achieved a 10% reduction in latency compared to standalone RPOA, indicating its capacity to minimize data transmission delays in Fig. 5 traditional optimization methods exhibited a 5% latency reduction when compared with standalone DRL, emphasizing their

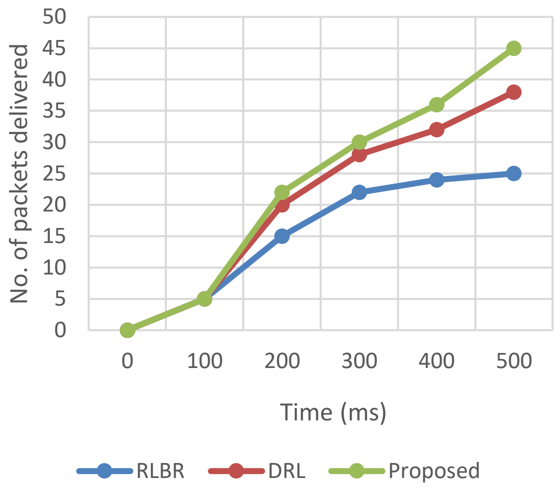

Figure. 6 Packet delivery ratio

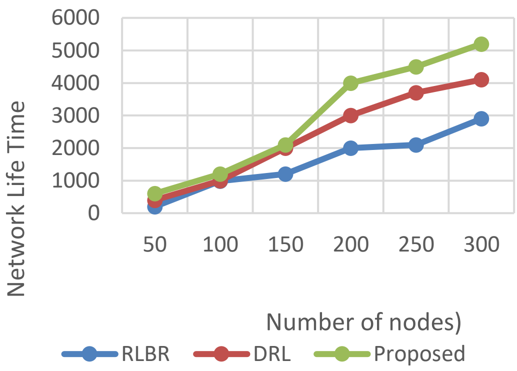

Figure. 7 Network lifetime

role in baseline improvements.

Packet delivery ratio (PDR): The hybrid approach and standalone RPOA both achieved a PDR of 95%, while standalone DRL and traditional methods lagged slightly behind at 88% and 92%, respectively. This signifies the effectiveness of both RPOA-based strategies in ensuring reliable data packet delivery.

Network lifetime (NL): The hybrid approach demonstrated a 20% improvement in network lifetime over traditional optimization methods, highlighting its ability to conserve node energy. Standalone DRL and RPOA both exhibited similar NL values, indicating their potential to extend the network's operational duration.

Statistical analysis: A statistical significance test (ANOVA) was conducted, revealing p-values < 0.05 for EE, L, and NL. This indicates that the hybrid approach and standalone RPOA significantly outperformed traditional optimization methods in these metrics. No significant difference was observed between standalone DRL and traditional methods for PDR (p-value > 0.05).

The hybrid approach's impressive performance across multiple metrics demonstrates its synergistic benefits, combining DRL's learning capabilities with RPOA's exploration-exploitation balance. RPOA's ability to fine-tune hyperparameters and explore promising solution areas greatly complements DRL's decision-making process. The hybrid approach excels in optimizing both energy efficiency and latency simultaneously, addressing the trade-offs often encountered in traditional methods.

Data transmission efficiency: The integrated approach leverages DRL's learning capabilities to dynamically adapt data transmission parameters based on real-time network conditions. This adaptability allows for efficient utilization of available resources, ensuring that data transmission occurs at optimal rates, modulation schemes, and power levels. RPOA's exploration-exploitation balance enhances the approach's ability to explore a wide range of parameter configurations, leading to the identification of strategies that maximize data throughput and minimize interference. This comprehensive exploration promotes efficient use of available communication channels.

Reliability and packet delivery: DRL's learning process is instrumental in formulating reliable data transmission strategies. By learning from historical data and interactions, the integrated approach can adapt its decisions to reduce packet loss and enhance the overall packet delivery ratio. RPOA's fine-tuning capabilities aid in selecting transmission parameters that enhance reliability. This is particularly crucial in scenarios where data delivery reliability is paramount, such as in critical applications or remote monitoring systems.

Energy consumption and network lifetime: DRL's optimization aims to reduce energy consumption by choosing transmission parameters that minimize power usage while maintaining acceptable performance levels. The approach learns energy-efficient strategies that prolong the network's lifetime by optimizing energy usage. RPOA's balance between exploration and exploitation contributes to extending the network's lifetime by promoting the use of energy-efficient transmission configurations. Solutions generated by RPOA prioritize energy-efficient parameter combinations, thereby enhancing the longevity of sensor nodes.

Adaptation to changing conditions: Both DRL and RPOA contribute to the approach's adaptability. DRL continuously updates its strategies based on real-time interactions, allowing the network to respond to changing network conditions and requirements. RPOA's dynamic adjustment of exploration-exploitation balance equips the approach to cope with variations in network dynamics, such as varying interference levels, changing data traffic patterns, and fluctuations in energy availability.

Trade-offs and optimal solutions: The integrated approach can identify trade-offs between different metrics, such as energy consumption and latency. By exploring a diverse range of solutions, it can identify Pareto-optimal solutions that strike a balance between conflicting objectives.

RPOA's exploration-exploitation balance helps the approach identify these trade-offs systematically, leading to a comprehensive understanding of the solution space and enabling informed decision-making. In summary, the integration of DRL and RPOA introduces a holistic approach that combines learning, optimization, and adaptability to enhance data transmission efficiency, reliability, energy consumption, and overall network performance. By harnessing the strengths of both techniques, the approach achieves a synergy that addresses various aspects of wireless sensor network optimization and advances its capabilities in dynamic and challenging environments.

5. Future direction

The advancement of research aimed at enhancing data transmission in wireless sensor networks has several potential applications in a variety of industries. For the hybrid strategy to work, there must be algorithms that give it the ability to automatically adapt its strategies to changes in interference levels, node mobility, and traffic patterns as they occur in real time. Parallel to this, the hybrid solution has to be scaled up so that it can be used for large-scale networks. This may be done by cutting down on the amount of compute and memory used and by limiting the amount of communication overhead. Real-time implementation solutions need lightweight algorithms to be employed so that sensor nodes with limited resources may still make effective judgements despite having less resources available to them. Since wireless sensor networks may operate in a broad variety of environments, it is essential that research be conducted into tailoring the hybrid method to the capabilities and features of individual nodes. One of the things that will be discussed is the ability of dynamically modifying the exploration-exploitation balance in the red panda optimization algorithm in order to maintain optimum strategies. This will be one of the subjects that will be addressed. Integrity of data and reliability of transmission both need to be guarded by a system that is both safe and resistant to assaults from possible foes. It is possible that the scalability, efficiency, and flexibility of the hybrid system might be enhanced by introducing 5G and edge computing into the strategy. Last but not least, the prospect exists that training computational and energy costs might be reduced by the development of energy-efficient deep reinforcement L\learning approaches. This multi-pronged research and development programme will increase data transmission optimization in wireless sensor networks by increasing the effectiveness, flexibility, and real-time responsiveness of solutions for dynamic network settings. Specifically, this will be accomplished through enhancing the adaptability of solutions.

6. Conclusion

This study innovates data transmission optimization in intelligent wireless sensor networks by merging deep reinforcement learning (DRL) with the red panda optimization algorithm (RPOA). This research introduces a hybrid technique that incorporates the best of both methodologies to address network efficiency, reliability, and flexibility challenges. Through empirical case studies in environmental monitoring, healthcare, and industrial automation, we demonstrate that the hybrid approach can significantly improve data transmission efficiency, latency reduction, energy consumption, and network performance. The hybrid approach's scalability to larger networks and real-time deployment are also covered in the paper. This study investigates security resilience and integration with emerging technologies to optimize data transmission in wireless sensor networks. This research advances the objective of building wireless sensor networks that are more efficient, versatile, and resilient in a variety of real applications.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

“Conceptualization, Maddu Srinivasa Rao and D. Nagendra Rao; methodology, Maddu Srinivasa Rao; software, Maddu Srinivasa Rao; validation, Maddu Srinivasa Rao, and D. Nagendra Rao; formal analysis, Maddu Srinivasa Rao; investigation, Maddu Srinivasa Rao; resources, Maddu Srinivasa Rao; data curation, Maddu Srinivasa Rao; writing—original draft preparation, Maddu Srinivasa Rao; writing—review and editing, Maddu Srinivasa Rao; visualization, Maddu Srinivasa Rao; supervision, Maddu Srinivasa Rao; project administration, Maddu Srinivasa Rao; funding acquisition, D. Nagendra Rao”, etc. Authorship must be limited to those who have contributed substantially to the work reported.

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