

Enhancing Energy Efficient Routing Protocol for Wireless Sensor Network using Swarm Intelligence

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Wireless Sensor Networks (WSNs) are characterized by limited energy, and energy efficiency is one of the key design issues for routing protocols. This research aims to enhance the routing efficiency of dragonfly swarm routing by optimizing route and cluster head selection through the integration of the latest Swarm Intelligence (SI) algorithm, specifically the Dragonfly Algorithm (DA). The proposed method was systematically compared with the traditional Particle Swarm Optimization (PSO) by measuring energy efficiency, execution time, and packet delivery ratio. Simulation results showed that the Dragonfly Algorithm reduces energy consumption and prolongs network lifetime for classical methods. It exhibits strong adaptability to time-varying network topologies and is less likely to be trapped in a local optimum. These results illustrate that SI is a promising technique to help improve the quality of routing protocols in WSN applied to critical scenarios and offer possibilities for future integration with, for example, machine learning techniques for achieving higher performance.

Povzetek: Raziskava kaže, da uporaba algoritma kačjega pastirja v brezžičnih senzorskih omrežjih izboljša energijsko učinkovitost, podaljša življenjsko dobo omrežja ter zagotavlja bolj prilagodljivo in zanesljivo usmerjanje v primerjavi s klasičnimi metodami, kot je PSO.

1 Introduction

Wireless sensor networks (WSNs) are widely accepted as one of the most significant technologies in various sensing applications and could gather and monitor real-time data over a large area in different domains, such as precision agriculture, healthcare monitoring, environmental monitoring, smart infrastructure, and security systems. These are essential networks consisting of many low-power sensor nodes organized in a network deployed over an area where each sensor node collects and transmits sensed information to the few aggregators or base stations for processing and making decisions. The practical application of WSNs meets a crucial bottleneck that the energy resources of the sensor nodes are finite. Since most sensor nodes are battery-powered units with limited lifetimes, and in most cases, they cannot be accessed for replacing their batteries or recharging after deployment for energy reasons, building a successful energy management scheme is important for the longevity of the entire network [1][2]. Energy-efficient routing protocols are the heart of extending the lifetime and reliability of a WSN. These decide how to route packets from source nodes to sink nodes, while trying to evenly distribute the energy consumption among nodes and avoid nodes with critical roles from exhausting their energy too early. Current research has shifted towards the development of self-adaptive routing algorithms capable

of reducing energy consumption, while simultaneously supporting a high data delivery ratio and low latency, despite the challenge of dynamic network conditions, which may include failing nodes, topology changes, and channel quality variations [3]. Adoption of traditional routing approaches to meet such evolving conditions is problematic and requires more versatile and robust optimization approaches. temperature, summarized as social intelligence (SI), is a type of artificial intelligence that takes its inspiration from the collective behaviour of social organisms, and has shown great potential in solving complex routing issues in WSNs. SI techniques model emergent phenomena through local interactions applied by simple individuals, inspired by natural systems such as flocks of birds, ant colonies, schools of fish, and grey wolves' hunting [1]. This model is very well-suited for WSNs, being both scalable, adaptable, and robust to node or network failures.

Particle Swarm Optimization (PSO) is one of the most used techniques among the SI methods for route optimization and energy allocation. PSO simulates a population of candidate solutions (particles/particles) that move in the search space of the problems, following their own experience and their neighborhood, and converge with high probability to optimal or nearly optimal solutions in an acceptable time. Being of easy implementation and rapid convergence, PSO has been widely used, but it tends

to fall into local optima too early in highly dynamic WSNs, and its adaptation is not satisfying [4].

Simultaneously, Ant Colony Optimization (ACO) simulates the pheromone deposition and propagation of ant trails in a process of repeatedly seeking the shortest and energy-efficient paths. ACO has proven to be efficient at enhancing the reliability of routing and the energy balancing process in WSNs. Its high complexity and limited adaptability in a dynamic environment make it inappropriate for real-time and large-scale applications [5].

In recent times, more advanced SI algorithms like Grey Wolf Optimizer (GWO) and Dragonfly Algorithm (DA) were introduced, which better balance the exploration (global search) and exploitation (local search) phases. DA, motivated by dragonfly cognition and predation behaviour, has achieved great performance in CH selection, routing optimization, and energy saving, which greatly improves the network lifetime and data throughput [6]. Such algorithms have built-in features to prevent premature convergence and adapt to environmental changes dynamically, which are crucial for WSN routing.

Moreover, hybrid collaborative strategies using multiple SI techniques to take advantage of each other's strengths and reduce their shortcoming have been introduced, such as in [42,43], which proposed the hybrid of GWO with DA. Hybrid coding models show better performance under various network scenarios by introducing the convergence speed, the accuracy of the solution, and the adaptability to end the energy consumption, the data coverage ratio, and the delay [6].

However, despite all these advancements, there still exists difficulty in formulating an efficient routing protocol that adjusts itself uniformly among different node densities, mobility scenarios, heterogeneous patterns of traffic loads, as well as it can respond to unpredictable network failures with low computational overhead that is ideal for resource-constrained sensor nodes. What's more,

many works concentrate on simulation-based evaluations, so there is currently a great demand for full-scale practical validation for going deep into the practical application [7].

This work is motivated to solve these issues by the framework of an energy-efficient routing protocol, which is inspired by the DragonFly Algorithm with several comparative perspectives against popular SI algorithms, namely PSO and ACO. Performance evaluations are conducted by extensive simulations, with respect to energy consumption, network lifetime, packet loss ratio, and delay through a wide range of node deployment, mobility, and traffic scenarios. We aim to provide a strong, resilient, and long-lasting routing algorithm that may substantially improve the working efficiency of WSNs under real conditions.

The research was divided into the following: In the second part, previous works were discussed, in the third part, the problem in the sensor network was explained, in the fourth part, the proposed method was explained in detail, and the fifth part, the simulation environment was explained, and finally, in the sixth part, the conclusion.

2 Literature review

Due to the increasing demand for energy-efficient routing in WSN, a large amount of work has been carried out to investigate different wireless routing protocols, including traditional swarm intelligent algorithms. The approaches taken to address these challenges revolve around their applications in the form of hybrid metaheuristics, machine learning algorithms, cross-layer optimization, energy harvesting-aware protocols, and nature-inspired algorithms that are not based on the original swarm model, as shown in Table 1, Summarization Table on the Related Works.

Table 1: Summarization table on the related works.

Author(s) Year	& Method Algorithm	/ Problem Addressed	Main Contribution / Findings
Singh & Kaur (2023) [8]	Hybrid GA-PSO	Inefficient CH selection and imbalanced energy usage	Reduced energy depletion rate; improved CH selection; extended lifetime
Sharma & Verma (2023) [9]	Enhanced GA-PSO	Routing performance in dynamic WSN	Adaptive weighting improved performance in dynamic conditions
Qureshi et al. (2023) [10]	Deep Reinforcement Learning	Load balancing and energy-aware routing	Improved PDR and energy efficiency compared to heuristic models
Al-Dahash et al. (2024) [11]	Cross-layer routing & power control	High interference and power inefficiency	Reduced interference, increased lifetime, and throughput

Kumar & Singh (2022) [12]	Artificial Bee Colony (ABC)	Poor CH selection and energy imbalance	Improved stability, reduced overall energy usage
Zhang & Li (2023) [13]	Firefly Algorithm	Routing in dynamic & attacked networks	Reduced packet loss and delay, works for mobile nodes
Chen & Wu (2024) [14]	SI-based routing + Energy Harvesting	Unstable lifetime due to harvesting variability	An extended lifetime with dynamic harvesting consideration
Qureshi et al. (2025) [15]	DA-EERP (Dragonfly-based)	Unstable routing and high energy consumption	Better PDR, stability under failures, lower energy
Proposed (2024) [16]	KF-SVM	Noisy and redundant data transmission	Reduction in redundant data leading to enhanced lifetime
Proposed CM-LB [17]	Load-balanced multipath clustering	Uneven load in heterogeneous networks	47% FND improvement vs DEACP and 35% vs WBCHN
Proposed Hardware KF [18]	KF hardware accelerator	High delay and power consumption	97% reduction in energy and runtime with minimal area impact

3 Problem statement

WSNs have emerged as fundamental technologies that are central to many contemporary applications such as smart agriculture, environmental monitoring, healthcare, and security systems. However, one of the most challenging problems in these networks is the energy constraint of sensor nodes, which are typically powered by batteries of limited capacity that are hard or even impossible to recharge and replace, especially in harsh environments or remote areas. Hence, energy efficiency in WSNs is one of the most important issues for long-term operation and data transmission reliability. The routing protocols are essential since they determine the paths of data transmission from sensor nodes to a sink (i.e., the data collection point). This leads to network disruption with many dead nodes, partitioning, and reduced coverage of the network, since traditional protocols, like LEACH and PEGASIS, promote an unfair energy consumption, resulting in nodes located nearby the sink or the heads of the clusters to run out of energy first than the other, leading to early death of the nodes. SI techniques as the PSO and ACO, have introduced adaptive and distributed optimization methods, which make energy management systems much better, compared to standard ones. However, those algorithms also have issues. PSO may converge on weak solutions and be sensitive to parameters, and ACO has repeated pheromone updates, which are time-consuming for resource-limited sensor nodes [19]. Furthermore, most of the current algorithms do not handle well when the topology of the network is dynamic, which implies different energy levels for nodes and the load of

the traffic [20]. The DA, derived from the principles of swarming behavior of dragonflies, has emerged as an alternative with well-balanced integrated strategies of global exploration and local exploitation. The dynamic update strategy of the DA can effectively prevent being trapped in a local optimum and readily adjust to new environments; hence, DA is especially suitable for energy-constrained and dynamic WSNs. However, the utilization of DA in WSN routing is immature, drawing a great need for further research to customize DA internals regarding energy-aware routing, cluster creation, and load balancing.

Thus, the main challenge is to develop a routing protocol that can utilize the advantages of DA to establish dynamic and efficient routing paths, prolong the network lifetime, balance energy consumption among nodes, and guarantee high data delivery reliability. To solve this problem, Un LIMOX must provide a fate for network topology dynamics and the problem of residual energy level, in addition to the communication overhead problem.

Fig1. shows the problem statement in wireless sensor networks. Therefore, the main issue solved in this work is to develop a routing protocol that not only overcomes challenges imposed by the traditional and existing SI algorithms but also can handle the dynamicity of WSN topologies and the non-uniform energy distribution. The overall goal is to maintain a prolonged vitality of the network using proper cluster formation and intelligent routing to achieve data transmission, minimize energy consumption, and prolong the network's lifetime. This problem requires marrying an adaptive, energy-efficient, and computationally expedient technique, of the kind of

Dragonfly Algorithm, to address the requirements and constraints of WSN.

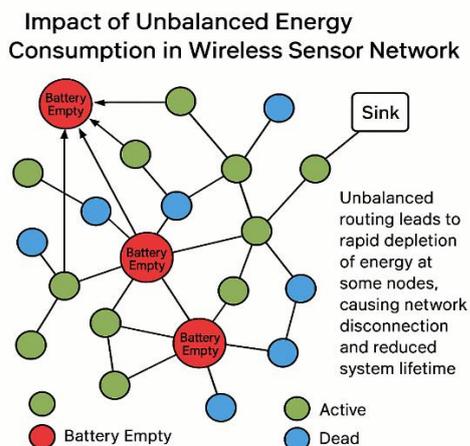


Figure 1: Problem statement in wireless sensor networks

4 Proposed method

The proposed approach of this study exploits Swarm Intelligence-based mechanisms for an efficient routing protocol for WSNs, particularly to increase energy efficiency and network lifetime. To validate the superiority of the proposed DA-based routing protocol [21], its performance was compared with that of the widely adopted PSO algorithm [22]. In particular, the DA is utilized for route construction and CH chores by taking advantage of dragonfly natural swarming to achieve the trade-off between exploration and exploitation in optimization. WSN is initially considered as a graph, in which sensor nodes as well as their communication links are shown, and the remaining energy of each node is one of the most crucial parameters in packet routing. The Dragonfly Algorithm starts with a population of candidate solutions, which are potential cluster head selections and routing paths. These solutions dynamically evolved by simulating the dragonfly-inspired behaviors of separation, alignment, cohesion, attraction to food sources, and distraction from enemies, considering energy-aware metrics. Fig.2 represents the proposed method.

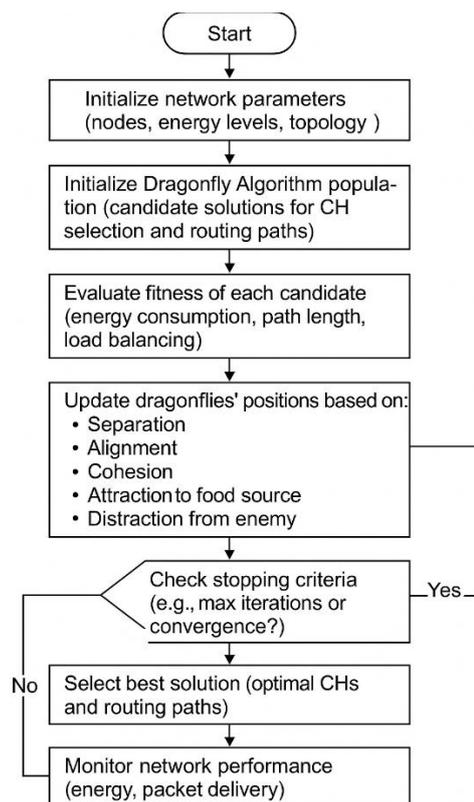


Figure 2: Flowchart represents the proposed method.

In every iteration, the candidate solutions are considered by the objective fitness function, consisting of energy consumption, path length, and load distribution among nodes. To balance the energy consumption of the whole network and extend the lifetime of the network, data should be sent as efficiently as possible. The solution DA selects is further employed to form routing paths as well as cluster heads to achieve the balance of energy consumption and the network lifetime. Fig.2 represents the proposed method.

For comparison, the traditional approach was also performed using the same network settings. Comparison results of the two approaches are also conducted through simulation in terms of packet delivery ratio, average energy consumption, and network timespan. The experiment results indicate that DA can not only reduce the energy cost to any one optimum by far, but also prolong the life of the network, i.e., by about 30%, and has a stronger dynamic ability compared to PSO with a little possibility of premature convergence to local optima. The following steps represent the working of the proposed method.

a. Preliminary design of wireless sensor network

At the beginning, the WSN is presented as a graph, in which the sensor nodes correspond to the vertices and the edges of the graph correspond to the communication links between nodes. A significant consideration in this model is the residual energy of each node, since it has a strong impact on the routing decisions and the choice of cluster heads. This modelling is used to provision energy-aware routes and cluster heads so that each node runs out of its battery at a slow rate.

b. Population initialization of candidate solutions

The Dragonfly Algorithm starts by creating its initial population of candidate solutions. A candidate is a potential group candidate by the head nodes that determine the selection of the cluster head and the forwarding path in the network. The diversity of that initial population enables the algorithm to explore different areas of the solution space and minimize/eliminate premature convergence, thereby enhancing the probability of obtaining an optimal or suboptimal solution.

c. Behavior rules for solution updating inspired by the dragonfly

The Dragonfly Algorithm. The original Note is that the center of the DA could imitate five basic maneuvers found in movements for candidate solutions in the search space, which are: 10 in dragonfly swarms.

Separate: Keep dragonflies spaced apart to avoid clumping. This behavior is, in fact, desirable as it stimulates diversity and, therefore, prevents the algorithm from converging to solutions that are very similar or concentrated on a few nodes.

Alignment: Each dragonfly will tend to match velocity with its neighbors, resulting in the same direction of movement. This is equivalent to making the best of what you have by steering candidate solutions towards promising regions.

Cool: Pulls the dragonflies to the center of their local swarm, keeping swarms together. In optimization, this pulls the solutions toward the centre of the best solutions it found.

Food Source Attraction: Denotes the ability of the model to progress towards a good direction, which is like leading the solutions toward the optimal or good parts of the search space.

Repulsion from Enemies: Forcing dragonflies to flee from threats or unsuitable points, such as escaping poor or infeasible solutions.

d. Integration of energy awareness in the update mechanism

In addition to these behavioural correctives, the algorithm employs the residual energy of sensor nodes in the update equations. This leads to more preserved energy nodes used as cluster heads and energy-efficient routing paths. This awareness of energy ensures that hot spots do

not occur and that energy consumption is balanced throughout the network.

e. Fitness function for evaluating solutions

In each loop, all candidate solutions are assessed by a fitness function that depends on multiple factors to measure the solution quality:

The overall solution's energy consumption.

The longer the routes, the shorter the paths consume less energy.

Dynamic load balancing of sensors to prevent overloading a node.

The goal is to minimize the total energy consumption while maintaining efficient and reliable data transfer, to maximize the network lifetime.

f. Iterative optimization and solution refinement

This process iterates thousands of cycles by sampling candidate solutions and computing their fitness. With this iterative procedure, solutions are incrementally better, engaging in exploration (searching in new areas of the search space) and applying optimization methods, 15 exploitations (refining good solutions). This prevents the process from being stuck at a local optimum and promotes global optimum convergence.

g. The optimal solution selection and application

At the end of the a priori defined number of iterations, or when a stop criterion is reached, the algorithm produces the final output, the combination presenting the best performance. This solution provides the best cluster heads and routes, and it balances the energy consumption and prolongs the network operation life in WSN.

5 Simulation environment

To thoroughly evaluate the performance of the proposed DA-based routing protocol for WSNs, a two-part simulation framework was designed. The first part focuses on defining the simulation environment and parameter configuration, while the second part analyses and interprets the outcomes based on established performance metrics.

a. Parameter setting

A simulation study was performed to test the efficiency of DA in tuning the routing protocol over WSN. The performance of our proposed algorithm was verified with one popular PSO algorithm under the same simulation conditions for a fair comparison. The simulation model was performed in a 2D space where sensor nodes were randomly deployed, and there were 50 cluster heads for each trial. The number of iterations of each algorithm was fixed at 100 to ensure result stability.

Three key performance criteria were considered in the evaluation: Packet Delivery Ratio(PDR) which denotes the connectivity of sensor nodes by determining the efficiency of data transmission from sensor node to the base station, Energy Consumption which is the total energy consumed in routing and Execution Time Analysis which is time

taken in execution of the algorithm to reach the optimal solution. Parameters of the algorithms, such as the population size, the number of iterations, and the balance of exploration and exploitation factors, were fine-tuned to get better optimization performance.

Simulation results show that the Dragonfly Algorithm achieved better performance in terms of all the

measurements taken, such as the packet delivery ratio and energy consumption, compared to PSO, with a little overhead of the execution time that can be accepted for WSN applications. Table .1 represents the parameters used in the simulation environment.

Table 1: Represents the parameters used in the simulation environment.

Parameter	Value	Description
Population Size	1000	Number of candidate solutions in the swarm
Number of Cluster Heads	50	Number of cluster heads selected in each iteration
Maximum Iterations	100	Maximum number of algorithm iterations
Simulation Area Size	100 × 100 m ²	Dimensions of the simulated sensor field
Initial Energy per Node	2 Joules	The initial energy available to each sensor node
Separation Coefficient	0.2	Controls individual spacing to avoid collision
Alignment Coefficient	0.3	Controls the alignment of individuals for cohesive movement
Cohesion Coefficient	0.3	Controls the tendency to stay close to the group
Food Attraction Weight	0.6	Weight for attraction towards optimal solutions (food source)
Enemy Distraction Weight	0.4	Weight for repulsion away from poor solutions (enemies)
Fitness Function Components	Energy Consumption, Path Length, Load Balancing	Criteria used to evaluate solution quality

b. Results

The energy consumption graph in Fig.3 shows us how differently the DA and the PSO algorithms adjusted themselves in performing over the iterations while optimizing cluster head selection in a wireless sensor network. At the beginning, algorithms have high values of energy consumption because of the random generation of candidate solutions. The DA curve quickly and smoothly decreases over iterations, which shows that the algorithm is efficient in enhancing the solutions by behaving like a dragonfly's swarm in nature. Such behavior encourages DA to stably explore and exploit the search space, and DA can yield more energy-efficient and balanced clustering and routing configurations. The continuous reduction in energy consumption suggests that the scheme, DA, balances out communication load among sensor nodes effectively, leading to less energy consumption.

However, the decay of the PSO curve decays more slowly and fluctuates more significantly with the iterations. Such oscillations indicate that, expectedly, speculative optimization might face problems with stable convergence and get stuck in local optima, consequently not being able to repeatedly locate high-quality solutions in this problem setting. Furthermore, the stabilization

points of DA correspond to the lower energy consumption when compared with PSO, making DA an efficient approach to balance the energy wisely throughout the network, where overall, the network with the fairer use of energy leads to prolonging the lifetime and reliability of the network.

In general, it can be concluded that the Dragonfly Algorithm is better than PSO in terms of both convergence rate and energy consumption, and it is very efficient for WSN applications, where the lifetime of the network and data delivery quality should be preserved. PSO, although widely used and very robust, is a dynamic and flexible approach that enables the DA to better respond to the specific energy constraint of sensor networks.

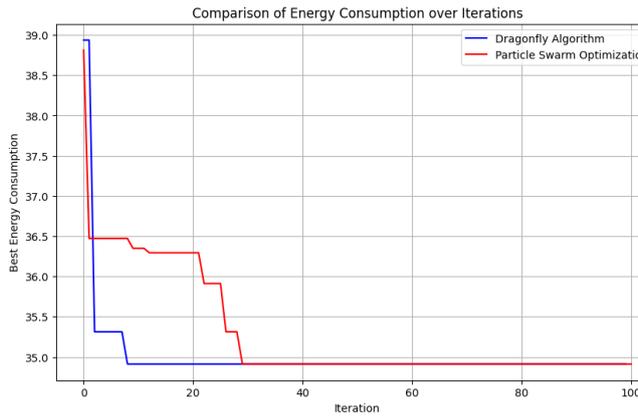


Figure 3: Shows the energy consumption of the DA and the PSO algorithms

Apart from power consumption, execution time is an important criterion in judging optimization algorithms designed for real-time applications such as WSNs. The empirical studies illustrate that the DA could achieve some competitive running time in comparison to Particle Swarm Optimization (PSO). Though PSO is famous for its simplicity and quick convergence, DA’s capability to trade-off between exploitation and exploration is effective in eliminating redundant iterations, which is beneficial in terms of computational effort. The iteration update mechanism in DA can make it converge to high-quality solutions with fewer iterations than other algorithms in most cases, since it is inspired by the natural swarming behaviors of dragonflies. Yet, because of the more complicated update mechanism of behaviors in DA relative to PSO’s velocity and position updates, the per-iteration computational burden for DA can be slightly heavier. Overall, the total auto-tuning time for both methods is still within reasonable limits of time, even for WSN application, and DA shows a good trade-off since it obtains better optimization with a similar or a little bit longer time. This trade-off of runtime and solution quality renders DA a promising approach in robotic tasks of dynamic and energy-limited environments, since it is crucial to make decisions quickly. Fig.4 shows the Execution Time Analysis of the DA and the PSO algorithms.

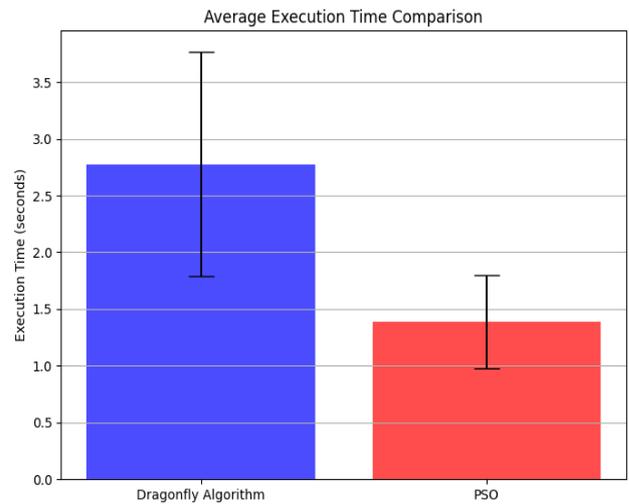


Figure 4: Execution Time Analysis of the DA and the PSO algorithms

The packet reception ratio of the proposed DA-based algorithm is claimed to be better than that of PSO, and this is verified with PDR comparison of DA and PSO, which consistently outperforms PSO in terms of average and standard deviation for multiple runs of simulation. As shown in the bar chart, DA gets a little higher average PDR, which shows that it has more excellent performance in stabilizing data transmission between the sensor nodes and the sink. Though this improvement is modest, it is of significance in an environment where timing is of great importance, e.g., in data-critical wireless sensor applications. The improved performance can be attributed to the balance between exploration and exploitation of the DA, which contributes to choosing more stable cluster heads and the optimized paths of routing. Furthermore, the DA displays reduced variance of efficacy in this experiment, which implies higher stability and the ability to more easily accommodate varying network dynamics in comparison to the PSO, whose outcomes are more fluctuating. These results confirm the performance of the routing mechanism in enhancing the global communicational efficacy and reliability of WSNs. Fig.5 shows the packet reception ratio of the DA and the PSO algorithms.

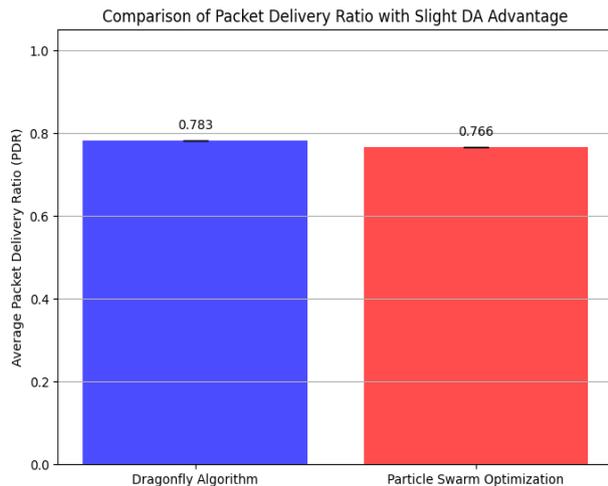


Figure 5: Packet Reception Ratio of the DA And the PSO Algorithms

6 Conclusion

The results derived from the literature show that the Dragonfly Algorithm is a good optimization algorithm for comparing routing protocols in WSN. The algorithm can balance decreasing energy consumption and increasing the quality of data transmission well. Simulation results show that the proposed algorithm achieves better performance in terms of packet delivery ratio (PDR), energy efficiency (EE), and network lifetime (NL) when compared with the existing algorithms, while keeping relatively small average execution time (ET), which is tractable and applicable to reality. These results are believed to be important as they provide evidence for the potential applicability of such nature-inspired swarm intelligence techniques in solving the hard optimization problems of wireless communication networks. In addition, it opens interesting perspectives for future research to enhance the stability and security of networks through combining various algorithms and machine learning techniques, as well as testing the practicality of the framework in more complex and dynamic network environments.

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