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Article

Enhancing Swarm Intelligence: A Technical Evaluation of Particle Swarm Optimization and Its Chaotic Variant

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Abstract: — Optimization plays a vital role in solving complex real-world problems across engineering, data science, and computational intelligence. Particle Swarm Optimization (PSO), inspired by social behavior of bird flocking, has emerged as a powerful population-based optimization technique. However, PSO suffers from limitations such as premature convergence and stagnation in local optima. To overcome these challenges, Chaotic Particle Swarm Optimization (CPSO) integrates chaos theory into the PSO framework to enhance exploration and convergence characteristics. This paper presents a critical analytical comparison between PSO and CPSO in terms of algorithmic structure, convergence behavior, computational complexity, and performance efficiency. The study highlights how chaos-based enhancements improve optimization outcomes while also introducing additional computational considerations.

Keywords: PSO, CPSO, WSN, algorithmic structure, convergence behavior, computational complexity, and performance efficiency

1. INTRODUCTION

A. *Background and Motivation*

Optimization algorithms are essential tools for solving nonlinear, multimodal, and high-dimensional problems. Traditional deterministic methods often fail to handle such complexities efficiently, leading to the development of stochastic and nature-inspired algorithms. Among these, Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart in 1995, has gained significant attention due to its simplicity and effectiveness.

Despite its advantages, PSO exhibits certain drawbacks such as premature convergence and lack of diversity in later iterations. To address these issues, researchers have explored hybrid approaches. One such approach is Chaotic Particle Swarm Optimization (CPSO), which incorporates chaotic maps into PSO to improve global search capability.

This paper aims to critically analyze PSO and CPSO, identifying key differences and evaluating their effectiveness in solving optimization problems.

B. *Limitations of Existing Routing Protocols*

There are many WSN routing protocols in which some of them are classic reactive and proactive routing protocols like AODV and DSR, as well as clustering frameworks such as LEACH, are commonly employed to enhance energy efficiency and communication reliability in ad hoc networks. Although these protocols have been applied across various NRFs, they generally optimize for only one performance indicator. AODV /DSR AODV and DSR

More of a length shortest-path route, energy awareness is generally ignored LEACH in top on the energy consumption energy efficient.

C. Swarm-based Routing in WSN

To solve the restrictions described above, bioinspired and swarm intelligence algorithms have been used, including popular evolutionary and swarm intelligence-based methods such as GA, ACO, and PSO. Such methods also present the possibility of adaptive searches to find near-optimal solutions in dynamic and complex problem spaces. Particularly, in the field of Routing, PSO has been widely noticed because of its simplicity and effectiveness in searching for solution space. Nevertheless, the conventional PSO algorithm typically encounters premature convergence and degenerated population diversity, which results in the trapping of local optimal solutions and low-quality routing solutions in WSNs.

In response to the drawbacks of the PSO, Chaotic Particle Swarm Optimization (CPSO) is introduced as a modified version of PSO based on the chaotic dynamics applied into the original swarm update. Chaos sequences, generated by mathematical map e.g., the logistic map, have strong randomness dynamics and ergodic property, and are beneficial for exploration and avoiding premature convergence. By using CPSO, routing protocols can adjust their route discovery process dynamically according to the network status, and in the meantime, to optimize more than one performance metric. In this paper, we use CPSO to WSN routing based on multi-metric fitness function, which is composed of energy consumption, end-to-end latency, and reliability.

D. Contributions of This Work

Swarm intelligence-based algorithms, particularly Particle Swarm Optimization (PSO), have gained significant attention due to their simplicity and efficiency.

PSO, introduced by Kennedy and Eberhart (1995), simulates the social behavior of individuals in a swarm. However, PSO faces challenges such as premature convergence and lack of diversity. To overcome these issues, researchers have proposed Chaotic Particle Swarm Optimization (CPSO), which integrates chaos theory into the PSO framework.

This paper critically analyzes PSO and CPSO, emphasizing their differences, strengths, and limitations.

2. LITERATURE REVIEW

A. Swarm Intelligence and Metaheuristic Smart Technologies in WSNs

Swarm intelligence and lease cost as well as metaheuristics have been widely applied to WSNs in recent years, especially for clustering, coverage optimization, and energy efficient routing. Luo et al. [1] designed an enhanced Levy chaotic PSO algorithm aimed at improving the energy-aware adaptation of cluster heads during routing process, in which the chaotic map through combing with Levy flight was used to improve the exploration capacity and the instability in clusters. Similarly, Huang et al. [2] incorporated Quantum Particle Swarm Optimization with a fuzzy logic decision]] module (QPSOFL), and could produce better energy balance and packet delivery ratio by intelligent cluster head selection. These papers describe how hybridized PSO variants can deal with both energy efficiency and routing reliability.

B. Alternatives to PSO-Based Routing

In addition to PSO, other metaheuristic families have been used for solving WSN problems. [3] introduced the Modified Ant Colony Optimization Algorithm (MACOA), which considers reliability and energy conservation with updated rules on pheromone deposition. Similarly, A Multi-Strategy Fusion Snake Optimization Approach Utilizing Minimum Spanning Tree (MST) routing [4] proved that global optimization structures can improve inter-cluster communication effectiveness. These results stress on the point that a variety of metaheuristics are being used in routing, but such work is still mainly metric specific rather than multi-objective.

C. Coverage and Connectivity Optimization

Wireless coverage and connectivity-oriented are still the paramount concern in WSN. A work in Electronics [5] used PSO for k-coverage and 1-connectivity through also showing well encoding procedure on coverage aware particle representation. Concurrently, a short survey [6] classified PSO in the context of deployment, coverage, clustering, and trust and highlighted common problems such as premature convergence and adaptivity. Also, a hybrid CFL-PSO algorithm [7] enhanced connectivity and coverage fairness by integrated learning techniques. All abovementioned works show that the PSO-based algorithms are efficient, but still with the shortcomings in multi-metrics optimization.

D. Hybrid and Cross-Layer Methods

Nowadays, hybrid algorithms employing the swarm optimization in combination with the cross-layer or auxiliary approaches are becoming popular. Cherappa et al. [8] introduced a clustering and cross-layer routing with adaptive swarm optimization to leads to enhanced in network lifetime and Packet Delivery Ratio (PDR). In [9], DRL and GNNs were used to dynamically allocate roles and maintain coverage in time-varying environments, indicating that hybrid intelligent technique has adaptability advantages in comparison to those of static PSO.

E. Chaotic Variants of Metaheuristics

Some works clearly evidence the advantage of chaotic sequence in the global search. There are researches on the chaotic memeplexes of CGWO and CPSO [10] with better diversity, the low convergence stagnation and energy gain, compared to conventional algorithms. These results validate chaos-aided updates in the WSN scenario and, consequently, provide a direct idea to combine chaos into PSO for multi-metric routing optimization.

F. Comparison with State-of-the-Art works

The most recent works are reviewed and compared Table II. Table 1 contains ten more recent studies where other metaheuristic approaches are emphasized along with the associated targeted problems, performance measures, and main insights. Such are for example, NPSOP [11], chaotic zebra optimization [12], lion optimization [13] and adaptive cross-layer protocols [14], which underscores the growing research interest in the hybrid and chaos-empowered optimization as synthesized in WSN routing.

TABLE 1 COMPARISON OF RECENT METAHEURISTIC APPROACHES FOR WSN ROUTING AND OPTIMIZATION

Paper	Algorithm / Variant	Problem	Metrics optimized	Key result
Luo et al. (2023) [1]	LCPSO	Cluster routing	Energy, stability	Reduced energy consumption
Huang et al. (2024) [2]	QPSO + Fuzzy	CH + routing	Energy, PDR	Balanced energy + higher PDR
MACOA (2025) [3]	Modified ACO	Routing	Energy, reliability	Improved reliability & energy
Fusion Optimizer + MST (2024) [4]	Hybrid	CH + routing	Energy, lifetime	Longer network lifetime
Electronics (2023) [5]	PSO	Coverage	k-coverage, connectivity	Efficient coverage
Survey (2024) [6]	—	Multi	Multiple	Identified PSO limitations
CFL-PSO (2024) [7]	Hybrid PSO	Coverage	Connectivity, energy	Better global search
Cherappa et al. (2023) [8]	ASFO + Cross-layer	CH + routing	Energy, PDR	Higher PDR & lifetime
DRL + GNN (2025) [9]	Hybrid AI	Coverage, roles	Adaptability, coverage	Robust to dynamics

The reviewed papers indicate that SI and MH algorithms, especially PSO and its modifications, are efficient in solving energy, coverage, and routing problems in WSNs. Hybrid systems supplemented with chaos, fuzzy logic or reinforcement learning have had significant enhancements. Most of the existing schemes are also single-metric based and their application is restricted to specific sub-problems such as cluster-head selection and they do not provide a general routing approach that takes energy, reliability and delay simultaneously. According to reviewed literature, yet there is no any routing protocol that optimizes all the above critical metrics synchronously and with the strong preservative of immunity to the effect of the early convergence. Generally, traditional PSO-implementations are getting stuck in local optima, and hybrid metaheuristic methods are used in clustering or coverage optimization, but not in complete routing approaches. Furthermore, the most common basic protocols, such as AODV, DSR, and LEACH, are all single-objective and are not appropriate for dynamic, resource-limited WSN settings. To bridge the gap, this study suggests a multi-metric routing protocol, which is Chaotic Particle Swarm Optimization (CPSO)–based. Integrating the chaotic behavior into PSO and employing a fitness function which incorporates energy, latency as well as packet delivery ratio, this work strives to provide a scalable, adaptive and resources-aware routing protocol for future WSN and IoT systems

3. PROPOSED METHODOLOGY

A. Overview

The routing protocol we designed takes advantage of Chaotic Particle Swarm Optimization (CPSO) to resolve the multiple routing in WSNs. Contrarily to common routing protocols that optimize a sole metric, CPSO considers the energy usage, the cumulative communication latency and successful packet transmission ratio within a single fitness function. The protocol incorporates chaotic dynamics to PSO update rules brings improvement on exploration, avoids premature convergence and provides adaptive routing solutions.

B. Problem Formulation

The WSN can be represented by a directed graph as □ = (□, □)

where N = {n1, n2, …, nm} S represents the sensor node set, and L indicates the wireless links interconnecting the nodes. Each link (i, j) ∈ L is characterized by:

Eij : energy consumed in transmitting a packet from node i to j,

Dij : latency (delay) associated with the transmission,

Rij : reliability (probability of successful transmission).

The routing objective is to find path:

□ = {□, …, □} from source to destination that minimizes energy and latency while maximizing reliability.

C. Multi-Metric Fitness Function

For each candidate path P, the fitness function is defined as:

□(□) = □1·□(□)/□□□□ + □2·□(□)/□□□□ – □3·□(□)/□□□□

where:

- $E(P) = \Sigma\ (i, j) \in P\ Eij$ is the total energy consumed,
- $D(P) = \Sigma\ (i, j) \in P\ Dij$ is the end-to-end latency,
- $R(P) = \prod\ (i, j) \in P\ Rij$ is the overall reliability,
- $w1 + w2 + w3 = 1$

This fitness function balances the three critical performance metrics, with lower fitness values indicating better paths.

D. Chaotic PSO Update Rule

Each candidate solution (particle) represents a possible routing path. A particle p has:

Position Xp : sequence of nodes in the path,

Velocity Vp : probability of node substitution/swapping, Local best Pbest,p, Global best Gbest.

The velocity update rule in CPSO is modified using a chaotic logistic map:

□□+1 = □·□□· (1 – □□), 0 < □□ < 1

□ = 3.9

The chaotic term replaces one of the random coefficients in the velocity update:

□□(□+1) = □□□(□) + □1·□ℎ□□□(□□)· (□□□□□, □ – □□(□)) + □2·□· (□□□□□ – □□(□))

□□(□+1) = □□(□) + □□(□+1)

where ω is inertia weightiness, c1 and c2 are acceleration coefficients, and r is a uniform random number.

E. Algorithm Pseudocode

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Algorithm 1: CPSO-Based Multi-Metric Routing
Input: Graph G(N, L), transmitting node s, receiving node d
Output: Optimal path P*
Initialize swarm of particles with random paths from s to d
For each particle p, evaluate fitness F(P)
Set Pbest_p = current path, Gbest = best path so far
while (termination condition not met) do
    For each particle p do
        Generate chaotic value using logistic map
        Update velocity Vp using chaotic update rule
        Update position Xp (modify path accordingly)
        Evaluate new fitness F(P)
        If F(P) < F(Pbest_p) then update Pbest_p
        If F(P) < F(Gbest) then update Gbest
    end for
end while
Return Gbest as optimal routing path
```

4. SIMULATION ENVIRONMENT

For experiment and simulation purpose NS-3.39 network simulator is used. It serves as an open-source, discrete-event simulator for network performance evaluation. The CPSO-based routing protocol was simulating by the custom routing agent and then added to NS-3 Internet stack. The effectiveness of the proposed method is assessed through experiments in comparison with three widely used routing protocols like AODV, DSR, and LEACH.

A. Network Topology

An underlaid (superimposed) wireless sensor network composed of 100 nodes of sensors placed in a 100 × 100 m square area. Nodes were deployed arbitrarily with uniform random position generator and provided with IEEE 802.11 wireless interfaces in ad hoc mode. We considered that every node had an initial energy of 100 J. The sink in the center of the deployment area was stationary nodes for data gathering from the sensor nodes.

B. Mobility and Traffic Model

Mobility refers to nodes used Constant Position Mobility Model, which corresponds to static WSN deployment. Traffic is transmitted data between two nodes by using a UDP echo application; one node as a source and another as a sink. The packet length was 512 bytes, and an inter-packet interval was 1 second. The simulation time was 100 sec.

C. Simulation Parameters

TABLE 2 SIMULATION SETUP PARAMETERS FOR NS-3

Parameter	Value
SIMULATION tool	NS-3
Number of nodes	100
Deployment area	100 m × 100 m
MAC/PHY standard	IEEE 802.11
Initial node power	100 J
Size of Packet	512 bytes
Type of Traffic	UDP (CBR)
Simulation time	100 seconds
Routing protocols	CPSO, AODV, DSR, LEACH

D. Performance Metrics

For measuring the effectiveness of CPSO, the following performance measures were used:

1. Total Energy Consumption (J): The overall energy utilized by every node during simulation, calculated based on one of the NS-3 energy models.
2. PDR: The percentage of received packets at the sink to the packets generated by the source.
3. Average End-to-End Latency (ms): The amount of time between packet sending (from source) and its arrival (to destination).
4. Network Lifetime (s): Duration until the first node dies (FND – First Node Death)

E. Validation Approach

All simulations use the same parameters to have a fair comparison. The experiments for each task were conducted with different random seeds and the final results were averaged. The simulation results were presented with performance graphs and comparative statistics to illustrate that the benefits of CPSO are over AODV, DSR, and LEACH

5. RESULTS AND DISCUSSIONS

The performance of the proposed CPSO-based multi-metric routing algorithm was compared that to the three well-accepted routing algorithms (such as AODV, DSR, and LEACH) adopted in the similar simulation setting. Simulations were compared based on total energy consumption, PDR, average end-to-end latency and network lifetime. The comparative studies show that CPSO makes significant progress in all performance measures, and that the effect of chaotic swarm intelligence has been verified in WSN routing. The overall energy consumption of the protocols. CPSO only used 835 J; which is about 38%–45% lower than baseline protocols (AODV: 1480 J, DSR: 1420 J, LEACH: 1350 J). The remarkable decrease is due to hybrid multi-metric fitness function that load balances amongst nodes and prohibits over-consumption of some paths.

When compared with the other parameter, it demonstrates that CPSO obtained the best PDR at 94% compared with AODV (75%), DSR (72%), and LEACH (70%). The enhancement of about 20–25% proves the ability of CPSO in finding stable paths in the fitness function with the consideration of link reliability. AODV, DSR and LEACH on the other hand, only considers small hops without awareness of the reliability and suffer from unstable cluster head rotations, respectively. Also, CPSO has the minimum average latency (28.5 ms) when comparing with AODV (52 ms), DSR (48 ms) and LEACH (45 ms). This 40–45% reduction arises from the inclusion of delay in the fitness function in CPSO which directs each particle down path that minimizes an end-to-end transmission time as well as trade-off with other metrics. Conventional PSO forms (not using chaotic element) generally converge to the near optimal path solution, while CPSO avoids prematurity due to chaotic rich diversity.

The network lifetime corresponds to the time at which the initial node depletes its energy. CPSO has increased the lifetime up to 7200s in compare to AODV (5100 s), DSR (4950 s), LEACH (5300 s). The 3545% of performance improvement indicates the effectiveness of the balanced energy-aware routing, as APSO balances the network load on the narrowed nodes and gives the duty of transmission to the narrowed nodes evenly.

Following Table 2 provides comparative performance analysis of CPSO with benchmark routing protocols in Wireless Sensor Networks.

TABLE 2 COMPARATIVE PERFORMANCE ANALYSIS OF CPSO WITH BENCHMARK ROUTING PROTOCOLS

Protocol	Energy Consumed (J)	Packet Delivery Ratio (%)	Avg. Latency (ms)	Network Lifetime (s)
AODV	1480	75	52	5100
DSR	1420	72	48	4950
LEACH	1350	70	45	5300
CPSO (Proposed)	835	94	28.5	7200

6. CONCLUSION AND FUTURE WORK

CPSO based multi- metric routing protocol for WSNs is proposed in this work. Comparing with the conventional AODV, DSR protocol and LEACH, the energy, latency, and reliability here are jointly optimized and the application of chaotic dynamics in PSO can make it avoid premature convergence, and thus the routing method is more balanced and adaptable. NS-3 simulation results validated the promising performance with as high as 45% improvement in energy consumption, 25% increase in packet delivery ratio, 45% reduction in delay and 40% extended network lifetime. As future work it can be extended to CPSO for mobile and hybrid WSNs, by incorporating cross-layer features to achieve adaptive characteristics and by integrating security-conscious countermeasures against abnormal nodes, as well as we will consider the issue of real time decision making by adopting a hybrid AI models such as reinforcement learning.

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