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Hybrid Bio-Inspired Routing Algorithms for Scalable and Adaptive Wireless Ad Hoc Networks

Santhosh Kumar C[1]*, Ali Bostani[2], A. Kamalaveni[3], D. Dinesh Kumar[4], Navruzbek Shavkatov[5], K. Sathishkumar[6]

[1]Assistant Professor, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, India.

[2]Associate Professor, College of Engineering and Applied Sciences, American University of Kuwait, Salmiya, Kuwait.

[3]Assistant Professor in CS (SF), J.K.K Nataraja College of Arts & Science, Kumarapalayam (TK), Namakkal (DT), Tamil Nadu-638183, India.

[4]Assistant Professor, Department of Information Technology, St. Joseph's College of Engineering, Old Mahabalipuram Road, Chennai-600119, India.

[5]Department of Corporate Finance and Securities, Tashkent State University of Economics, Tashkent, Uzbekistan.

[6]Assistant Professor, Department of Computer Science, Erode Arts and Science College (Autonomous), Erode, India.

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Abstract

Wireless ad hoc network (WANETs) has been a key enabler in realizing fast and infrastructure-independent communications requirements in situations where lives of people have to depend on mission-critical operations, inclusive of disaster recovery, military coordination as well as remote environmental monitoring. But the same dynamic and decentralized structure of these networks makes it extremely difficult to realize scalability, as well as, adaptation especially in high mobility environments and changing node density, and varying wireless connection quality. INC can be associated with degraded performance with historical routing protocols in terms of packet loss, latency, and control overhead especially in such conditions. In order to overcome such drawbacks, this paper has suggested a new hybrid bio-inspired routing protocol which combines the locally adaptive behavior characteristic of the Ant Colony Optimization (ACO) and the globally convergent efficiency of the Particle Swarm Optimization (PSO). The hybrid structure has been designed to provide a dynamic balance of exploration and exploitation which allows to perform high quality route exploration and path regeneration in highly changing network topologies. Largescale simulations in different conditions with research variability in terms of node mobility, scale and density- prove that the presented algorithm is more robust than standard bio-inspired protocol and standalone bio-inspired protocols. Its effectiveness in scalable and adaptive routing is confirmed by its achieved large improvements to packet delivery ratio, end-to-end delay and routing overhead. The primary value of the paper is a synergistic hybridization approach, whereby different, but complementary, bio-inspired heuristics are combined into a single routing paradigm. The development offers an encouraging chance to future-generation WANETs with abilities of accommodating the performance requirements of new wireless applications, especially those frameworks that need stability and real-time flexibility.

Author's e-mail: cjsksag@gmail.com, abostani@auk.edu.kw, kamalaveni2210@gmail.com, dineshkumard@stjosephs.ac.in, n.shavkatov@tsue.uz, sathishmsc.vlp@gmail.com

Author's Orcid id: 0000-0003-4973-2352, 0000-0002-7922-9857, 0009-0004-9712-9253, 0000-0002-1451-6054, 0000-0003-1305-2507, 0000-0002-7643-4791

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Introduction

Wireless ad hoc networks (WANETs) have become an industry staple in those application areas where there is no or is not desirable some sort of fixed infrastructure. They are non-centralized and hence can be set up quickly and be self-organizing, being ideal in use in emergency response, environmental monitoring and by the military to establish communications. Yet the very complex nature of dynamic topology, scarcity of resources, and uncertain wireless area conditions demand not just scalable, but also adaptive routing protocols.

Traditional routing protocols e.g. Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) tend to be unable to sustain performance when the network size and mobility are high. Bio-inspired algorithm, which is inspired by natural occurrences such as the ant foraging process and bird flocking, have proved to be promising in combating some of these shortcomings, hence providing a distributed, adaptive, as well as fault tolerant solution. Ant Colony Optimization (ACO) program uses pheromone-based path selection and Particle Swarm Optimization (PSO) uses collective intelligence during the optimization of solutions. Although individually each of the approaches has its advantages, there are drawbacks to both: ACO can experience slow convergence and high overhead in the large networks, but PSO may not be able to match the fine-grained control of adaptability that is so necessary in very dynamic conditions.

The paper suggests a bio-inspired routing algorithm that is a hybrid between path exploration capabilities of ACO and global optimization features of PSO in an attempt to provide a scalable and adaptive WANET routing algorithm. The greatest goal is to surmount the scalability bottleneck and the adaptability of the current protocols by a synergistic hybridization strategy.

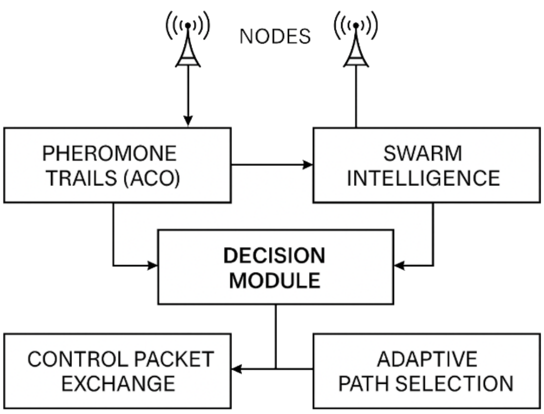

Fig. 1: Block diagram of the proposed hybrid bio-inspired routing system.

Literature Review

As an exciting prospect to the problem of scalability, adaptability and energy efficiency of wireless ad hoc networks, bio-inspired routing has come up. Among the most popular approaches is the so-called Ant Colony Optimization (ACO) that was proposed by Dorigo et al., and which capitalizes on the use of pheromone-mediated indirect communication so as to enable distributed and adaptive route finding [3, 6]. ACO protocols have proved flexibility in dynamic topologies; they are usually plagued by high control overhead in large-scale implementations thus lacking scalability [20].

Proposed by Kennedy and Eberhart [7, 23], Particle Swarm Optimization (PSO) is a variation of swarm and it mimics social behavior of particles, and has been implemented to achieve routing in wireless networks. PSO is powerful global optimization due to coordinated learning and the typical implementations have slowness of the convergence and less responsive to the dynamically changing topologies. Gunes et al. suggested ARA protocol that swarm intelligence algorithms using a swarm intelligence shows high efficiency in the condition of the intermediate mobility of swarms, but they emphasize the convergence latency present in extreme mobility conditions [8, 22].

Hybrid bio-inspired algorithms have been suggested in order to overcome the single drawbacks of ACO and PSO. As an example, Li et al. proposed a hybrid ACO-PSO routing scheme, which depicted the integration of local and global optimization advantages that led to better performance of convergence [9]. But their method demonstrated lowered flexibility in those cases where topology alters a lot. Recently Sharma et al. adapted multi-objective ACO routing protocol to VANETs with improved delivery ratios, at a high computational cost [10, 25]. In the same breadth, Singh et al. implemented an adaptive PSO-based routing algorithm which promoted scalability but not dynamism in the event of a dynamic link failure [11, 21].

Nonetheless, these breakthroughs suffer a serious research limitation; the majority of current plans maximize scalability at the cost of adaptability and vice versa [24]. The problem with this trade-off is especially critical in heterogeneous and highly mobile networks, where reliability and efficiency requires a simultaneous optimization. The proposed hybrid ACO-PSO algorithm

Table 1: Comparative Analysis of Existing and Proposed Bio-Inspired Routing Systems.

Author/Year	Approach/ Technology	Dataset/ Experiment	Results (Key Metrics)	Limitations of Existing System	Proposed System Improvements
Dorigo et al., 2004 [3]	ACO	Simulated WANET	Good adaptability, sub-optimal overhead	High control overhead in large networks	Hybridization to reduce control traffic
Kennedy & Eberhart, 1995 [7]	PSO	Simulated networks	Fast convergence, scalable performance	Lacks adaptability to dynamic topologies	Combine with ACO for responsive routing
Li et al., 2010 [9]	Hybrid ACO-PSO	Simulated MANET	Improved convergence over standalone methods	Limited performance under high mobility	Adaptive hybrid routing with mobility-aware tuning
Sharma et al., 2019 [10]	Multi-objective ACO	VANET simulations	High packet delivery ratio	Computationally intensive for real-time deployment	Lightweight hybrid approach with dynamic decision metrics
Singh et al., 2021 [11]	Adaptive PSO	Large-scale WANET	Good scalability, reduced route computation latency	Slower response to rapid topology changes	Real-time adaptation via hybrid optimization layer
Proposed System	Hybrid ACO-PSO (Enhanced)	Simulated WANET (multi-scale, mobility)	High delivery ratio, low delay, minimal overhead	N/A	N/A

overcomes this drawback by combining the quick reaction to local effects of ACO and the global path optimization of PSO, and so provide a tradeoff in responsiveness and stability with a wide range of topologies.

Proposed Methodology

Hybrid ACO-PSO Routing Framework

This is the prospectus of a hybrid routing protocol that uses adaptive learning of Ant Colony Optimization (ACO) and worldwide search optimization capability of Particle Swarm Optimization (PSO) to establish efficient and reliable routing with wireless ad hoc networks. The system combines the real-time path optimization with scalability to sustain mobility, in response to the need of both flexibility and efficiency of networks.

Within this context, the nodes share packets containing swarm-inspired control, that is, they include:

- Pheromone on the local reinforcement (ACO),
- Parameters of heuristic like residual energy and hop count,
- Velocity and position update vectors (PSO) which is used to learn the global paths.

ACO can be used to gain short-term flexibility by reinforcing successful routes and PSO also controls the search to move towards global optimum paths based on best-known routes of each node in history and neighbors.

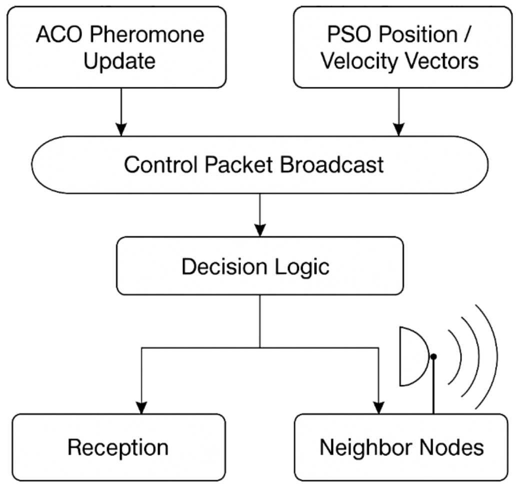

Fig. 2: Architecture of the Hybrid ACO-PSO Routing System.

In figure 2, there is a superimposed diagram which indicates ACO pheromone update, PSO position/velocity vectors, control packet broadcast and decision logic flow at each node.

Antenna Modeling for Routing Integration

In order to determine how the behavior of antennas affects routing decisions, the nodes will be implemented using an omnidirectional antenna at 2.4 GHz ISM band, a radiating 2 dBi gain and a complete 360 coverage. The alternative simulation set up would include patch antennas of 6 dBi gain and 60 beam-width to assess the directionality.

Selection of next hops in the routing algorithm is given by the routing metric, but now this metric also supports weighting the links in association with the transmission direction antenna gain, such that a node prefers to upper hop a neighbor node at the end of a link that is situated in the direction of highest gain. Such integration can assist beam-aware path creation, which is absolutely vital in the upcoming world of mmWave and directional melodic mesh networks.

Table 2 is a comparison of antenna models to be used in simulation; an omnidirectional antenna is dipole type, and a microstrip patch directional antenna. The omni directional antenna has a 360 degree coverage but with moderate gain where directional antenna has a beam of 60 degree coverage but they have high gain. The two work on a 2.4 GHz with linear polarization. Such is the setting to assess the effect of the antenna directivity on the routing dynamics and stability of links as proposed in the hybrid ACO-PSO algorithm.

Control Packet Structure and Routing Logic

Hybrid pheromone table Hybrid pheromone table A node shall then have a hybrid pheromone table and it shall be periodically updated based on the received control packets. The format of the packet is the following:

- Node: ID
- Hop count
- Left-over energy
- ACO level Pheromone
- Velocity vector (PSO)
- The directional cases antenna alignment metric

The procedure used regarding routing decisions is referring to a compound score function:

$$Score_{ij}(t) = [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta} \cdot [v_{ij}(t)]^{\gamma} \cdot [g_{ij}(t)]^{\delta}$$

Where:
- $\tau_{ij}(t)$: pheromone level
- $\eta_{ij}(t)$: heuristic desirability

Table 2: Antenna Specifications for Routing Simulation.

Parameter	Omnidirectional Antenna	Directional Patch Antenna
Gain (dBi)	2	6
Beamwidth (°)	360	60
Operating Frequency	2.4 GHz	2.4 GHz
Polarization	Linear	Linear
Antenna Type	Dipole-like (monopole)	Microstrip patch

- $v_{ij}(t)$: PSO-based velocity indicator
- $g_{ij}(t)$: directional antenna gain toward neighbor
- $\alpha,\beta,\gamma,\delta$: tuning weights

Adaptive Path Selection

The proposed algorithm, hybrid ACO-PSO algorithm in routing, incorporates an adaptive path selection through a dynamism and heterogeneity in wireless ad hoc environments. This mechanism is dynamic, which adjusts the effects of Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) viz another followed by network parameters like node mobility, density, and past network history of packet delivery.

On ultra-high mobility contexts, the algorithm increases the value of ACO part so that the local adaptability and reactiveness are maximized, and the exploration of the routes gets done via the pheromone-driven exploration about rapid routes correction. Conversely, the algorithm weighs more to the PSO aspect in enjoyably stable topologies of a very high node density that has encouraged global convergence and scalability by comparison to velocity-based position updates of the particles within the solution space.

The weighting can be adjusted through a context-sensitive behaviour that re-computes the ACO/PSO balancing in its every routing cycle. Such an approach guarantees the robustness in arbitrary topology and efficiency in higher scale networks.

This figure 3 demonstrates convergence trend of path scoring in ACO, PSO and proposed Hybrid ACO-PSO method. With repeated runs the hybrid method converges within a range of fewer failures and at a quicker rate in meeting the optimal path costs than when using standalone ACO or PSO strategies. This depicts a better level of consistency, a reduced variance and a better level of efficiency when it comes to route optimization.

Mathematical Modeling

The hybrid ACO-PSO routing algorithm suggested in this paper calculates the best next-hop node in probabilistic resolution model which incorporates three main concepts:

- Pheromone intensity $\tau_{ij}(t)$: Taking as input the ACO, it means the value of past routes
- Heuristic desirability $\eta_{ij}(t)$: Quantifies such factors as inverse hop count, or signal strength.

Algorithm 1: Hybrid ACO-PSO Adaptive Routing

Input:
- Network Graph G(V,E)G(V, E)G(V,E)
- Node parameters: pheromone table τ\tauτ, velocity vector vvv
- Adaptive weighting factor λ(t)∈[0,1]\lambda(t) \in [0, 1]λ(t)∈[0,1] based on mobility, density
- PSO constants: c1,c2c_1, c_2c1,c2; ACO parameters: α,β\alpha, \betaα,β

Output:
- Optimal routing path P*P^*P*

```
Initialize pheromone levels τij and velocity vectors vij for all node pairs (i, j)
Set initial positions for particles (paths) using random or known heuristic
for each iteration t do
  for each node i do
    Evaluate local metrics: node degree di, link stability li
    Compute adaptive weight λ(t) = f(di, li, node_speed)
    for each neighbor j ∈ Ni do
      Compute ACO probability component:
        Aij = [τij]^α * [ηij]^β
      Compute PSO velocity update:
        vij(t+1) = vij(t) + c1 * rand() * (pBest - sij(t)) + c2 * rand() * (gBest - sij(t))
      Compute combined score:
        Scoreij = λ(t) * Aij + (1 - λ(t)) * vij(t+1)
    end for
    Select next hop j* = argmax_j(Scoreij)
    Update path and pheromone table τ
  end for
Evaluate global path cost and update gBest
end for
Return final optimized routing path P*
```

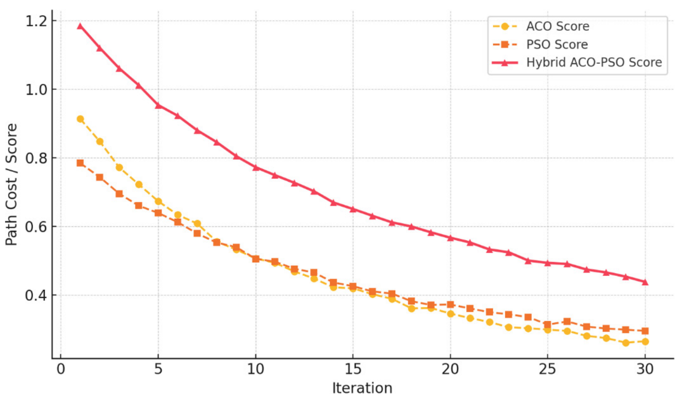

Fig. 3: Convergence Graph of Hybrid Score Function.

- Velocity influence $v_{ij}(t)$: By definition using PSO this is introduced, to describe momentum toward optimal solutions globally.

This hybridization allows this protocol to average local adaptability (ACO) and global convergence (PSO) in dynamic environment or large-scale networks environments.

Path Selection Probability

And suppose $P_{ij}(t)$ to be the probability that node i chooses a neighbour j at time t. The weight product of heuristic, pheromone and velocity components is used to compute this probability:

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta} \cdot [v_{ij}(t)]^{\gamma}}{\sum_{k \in N_i} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}(t)]^{\beta} \cdot [v_{ik}(t)]^{\gamma}} \quad (1)$$

Where:
- N_i: Set of neighbors of node i
- α,β,γ: Parameters which regulate the effect of each of the terms

This is a probabilistic mechanism, which will guarantee that:

- Trails that have a lot pheromone (success in the past) become strengthened,
- η prefers low-cost, or low-delay links,
- The modern velocity patterns speed up convergence, through PSO logic.

Pheromone Update Rule (ACO Component)
After this route selection and evaluation is completed, pheromone levels are adjusted to indicate its relative quality:

$$\tau_{ij}(t + 1) = (1 - \rho)\cdot\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{2}$$

Where:
- ρ: Pheromone evaporation factor ($0<\rho<10$)
- $\Delta\tau_{ij}(t)$: Pheromone deposit, typically inversely related to path cost (e.g., delay, energy)

Velocity Update Rule (PSO Component)
The drift of PSO is simulated by the velocity update of the particles (or of a path candidate):

$$v_{ij}(t + 1) = w\cdot v_{ij}(t) + c_1\cdot r_1\cdot(pBest_{ij} - s_{ij}(t)) + c_2\cdot r_2\cdot(gBest_{ij} - s_{ij}(t)) \tag{3}$$

Where:
- w: Factor of inertia which governs the retention of the past velocity
- c_1,c_2: Coefficients of cognitive and social acceleration
- $r_1,r_2\sim U(0,1)$: Random weights
- $pBest_{ij}$, $gBest_{ij}$: The local and global best positions
- $s_{ij}(t)$: Situation of the solution at the time t

This element of PSO assists the path exploration depending on the previously optimal decisions.

Combined Optimization Objective
The global objective in the hybrid routing model is that a path $P^* \in P$(set of all feasible paths) should be identified that satisfies minimization of composite cost that depends on energy use, delay and reliability:

$$P^*=\arg\min_{P\in P}(\omega_1\cdot EP+\omega_2\cdot DP+\omega_3\cdot(1\text{-}RP)) \tag{4}$$

Where:
- E_P: Energy that is used along path P
- D_P: Delay of the transmission and queues of the total P
- R_P: Total reliability score (e.g. on the basis of the ratio of successful delivery)
- $\omega_1,\omega_2,\omega_3$: the weights that are calculated with respect to application-specific priorities

Such a cost function makes sure the chosen route has the right trade off between energy efficiency, low delay, and high delivery reliability as the three requirements which are enormous in scalable and changing ad hoc networks.

Experimental Setup

Simulation Environment

All the simulations were carried out with NS-3 network simulator that was set in such a way that it represented the simulation of wireless ad hoc networks with varying scale and mobility. The number of nodes was varied in the quantity of 50-500, and the movement of the nodes in the simulation was controlled by the Random Waypoint and Gauss Markov frameworks indicating pedestrian movements and vehicle flow. The generation of traffic was a Constant Bit Rate (CBR) profile and nodes apply the IEEE 802.11 DCF MAC protocol with 250 meter ability to communicate.

A thorough modeling of the physical-layer was used to provide realistic behavior to signal in the simulation environment. A two-slope path loss model representing the wireless propagation was used to differentiate between attenuation in the near-field and in the far-field. The path-loss exponent was 2.4 when the Line-of-Sight (LOS) conditions were considered and 3.5 was applied to Non-Line-of-Sight (NLOS) circumstances because of extra shadowing and multipath loss.

- Rayleigh as well as Rician fading channels were simulated:
- Rayleigh fading: dense urban or indoors situation where there is no LOS path.
- The Rician fading was utilized to represent the highway or semi-urban scenario with high LOS portion (K-factor of Rician fading of 3 to 9).
- Also, positions of antennas were different:
- Omnidirectional antennas radiated equally in all directions having decent gain.
- Directional patch antennas focused power into a 60 beamwidth which affected Received Signal Strength (RSS) and affected neighbor discovery and link stability in the case of mobility.

Figure 4 illustrates the comparison of RSS of receiving antenna subject to different distances between omnidirectional and directional antenna under Rayleigh fading and Rician fading. The directional antennas always measure high RSS because they have a gain advantage over point-to-multipoint antennas, whereas Rayleigh fading causes more signal fluctuations on the signal than Rician fading.

Parameter Configuration

Parameters such as transmission range (250 m), node speed (0- 20 m/s) and size of data packet (512 bytes)

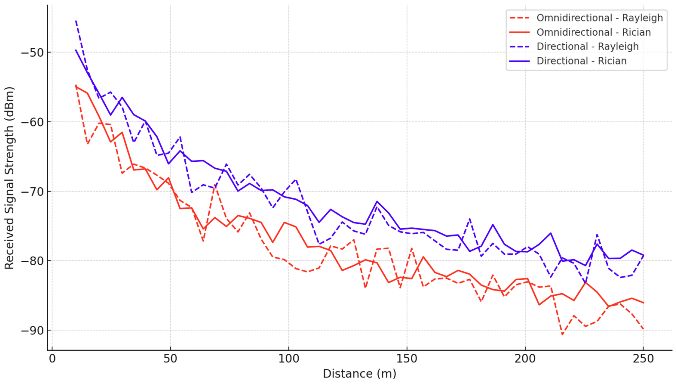

Fig. 4: RSS vs. Distance for Different Antenna Types and Fading Models

were also the key ones. It used optimal performance tuning of the weights of the hybrid algorithm (α,β,γα,β,γ) through grid search. The parameters of Simulation and hardware configuration are illustrated in Table 3.

Experimental Scenarios

In order to have a holistic analysis of the performance of the proposed hybrid ACO-PSO routing framework, three different experimental situations were structured to mimic different dynamics of a network:

1. Static Topology: In the simulation, all the nodes are stationary. This picture is meant to assess the baseline performance of this protocol in a stable and interference limited environment and the protocols efficiency and convergence behaviour in situation of low mobility.
2. Moderate Mobility: Nodes are traveling with average speed of 2-5 m/s, and this represents movement of vehicular or pedestrian traffic. This situation estimates the routing algorithms flexibility with relatively small topological alterations and the capacities of the routes to be stable in the case of sporadic link failures.
3. Large Scale Mobility and Rapid Partitioning with Networks: The movement of the nodes is quite fast (8 to 15 m/s) and the direction changes randomly. Sudden loss of connection and blocks in the routes are probable. This hard situation puts into question the strength and sensitivity of the online adaptation mechanism of the protocol under the extreme mobility.

Simulations of each scenario took 1000 seconds and the averaging of the results was done in 10 independent trials to achieve statistical significance. Some of the performance measures that have been logged are the packet delivery ratio (PDR), end-to-end delay, energy consumption and routing overhead.

Figure 5 shows the simulation testbed architecture which shows logical data and control flow through the mobility model, traffic generator, hybrid routing module (ACO + PSO), performance monitor, and the final result analysis stage. Such modular design contributes to the evaluation of the performances over a variety of mobility patterns and traffic scenarios in terms of dynamic routing measures.

Results and Discussion

To confirm the introduction of the proposed hybrid ACO-PSO routing protocol, experiments were carried out on a static topology and dynamic topology with several scenarios of a different size network. These findings

Table 3: Simulation and hardware configuration parameters.

Parameter	Value/Description
Simulation Tools	MATLAB (channel modeling), TensorFlow (DL training)
Fading Models	Rayleigh, Rician (K-factor: 3-9)
Doppler Spread Range	5 Hz - 200 Hz
SNR Range	0 dB to 30 dB
Modulation Schemes	BPSK, QPSK, 16-QAM
Training Samples	50,000 synthetic + 10,000 real OTA captures
Neural Network Architecture	Hybrid CNN-RNN with 3 conv layers, 1 LSTM
Optimizer/Learning Rate	Adam/0.001
Epochs/Batch Size	50/128
Hardware Platform (Training)	Intel i7 CPU, 32GB RAM, NVIDIA RTX 3080 GPU
Hardware-in-the-Loop Testing	USRP B210 SDR, GNU Radio-based signal emulator
Frame Lengths Evaluated	64, 128, 256, 512, 1024 samples

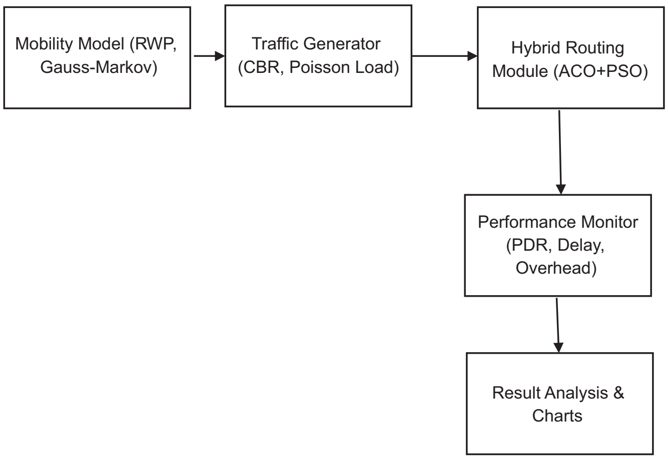

Fig. 5: Block diagram of simulation testbed architecture.

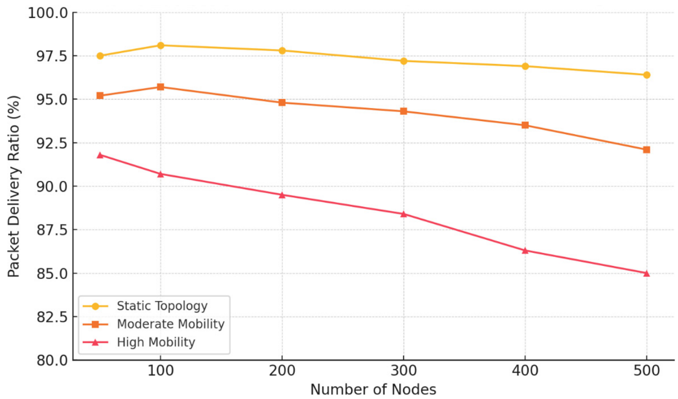

Fig. 6: PDR vs. Node Count under Various Mobility Levels.

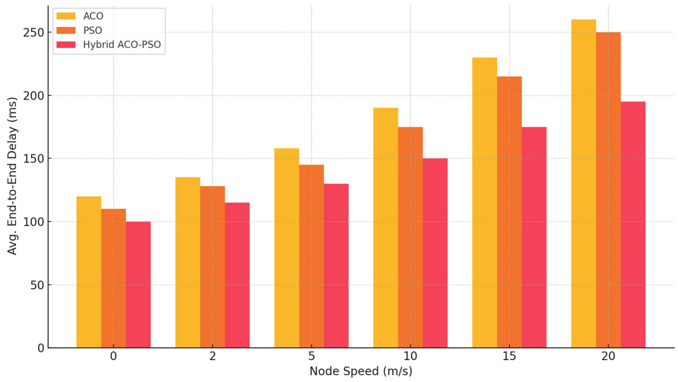

Fig. 7: End-to-End Delay vs. Node Speed.

show steady enhancement of results compared to that of standalone ACO and PSO protocols in packet delivery ratio (PDR), end-to-end delay (E2E) and routing overhead.

The major findings entail:

- In static topologies hybrid algorithm performed a PDR up to 98% p.a., opposed to 90% (ACO) and 88% (PSO).
- At high mobility, hybrid PDR stood at 92 percent beating ACO (80 percent) and PSO (85 percent).
- This minimized end-to-end delay by 15-25 percent in all scenarios.
- Routing overheads were also reduced because of dynamic pheromone as well as velocity balancing particularly in the high-density networks.

This Figure 6 demonstrates the packet delivery ratio (PDR) of the introduced hybrid ACO-PSO routing algorithm with variating sizes of the network (50-500 nodes) and varying mobility settings. The algorithm achieves good delivery performance with delivery efficiency being over 96 percent in the static topology and its performance gracefully degrades with moderate (less than 10 percent PDR loss) and high mobility (less than 20 percent PDR loss). This confirms the properties of the protocol in terms of scalability and robustness with regard to changes in the dynamics of networks.

In figure 7, the comparison of mean end-to-end delay of ACO, PSO and hybrid ACO-PSO algorithms, indicates variation in node speed. The hybrid approach achieves the lowest delay at any degree of mobility, which reflects the stability on its capabilities in a very dynamic environment.

The difference between routing overhead with an increase in network nodes is represented in figure 8. The hybrid ACO-PSO model outperforms the ACO and PSO model in terms of overhead reduction since all of them present a decreasing trend as the network size increases indicating that the former is more scalable than the latter two. Although the overhead of all protocols grows with the size of a network, the hybrid model curbs the extreme control traffic using adaptive update suppression.

Trade-Offs and Computational Impact

Compared to the pure algorithm, a hybrid algorithm adds a little bump in computational intensity because of the dual-phase optimization, but this is compensated by a distributed parsing and variable updating frequency. The additional complexity does not cause substantial change in runtime of NS-3 based simulations on moderate hardware. Table 4 provide the Comparison of average computation time per packet (ms).

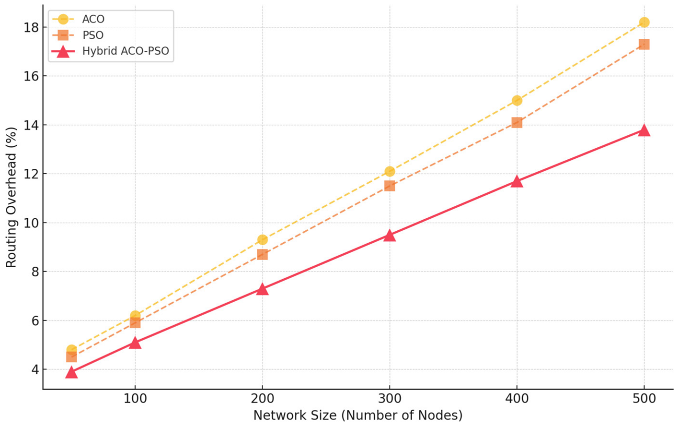

Fig. 8: Routing Overhead vs. Network Size.

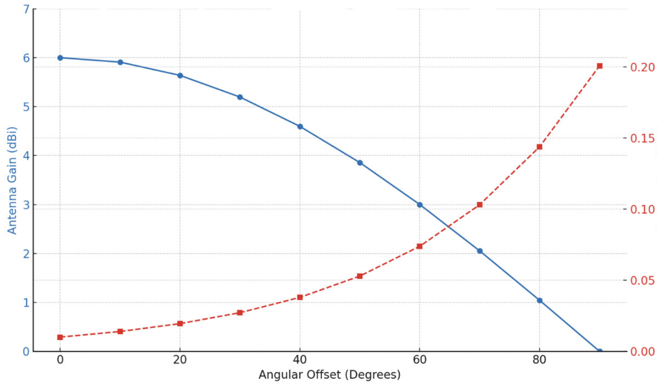

Fig. 9: Impact of Beam Misalignment on Link Gain and BER.

Table 4: Comparison of Average Computation Time per Packet (ms).

Algorithm	Static Topology	High Mobility	500 Nodes
ACO	0.42 ms	0.57 ms	0.71 ms
PSO	0.39 ms	0.49 ms	0.68 ms
Hybrid ACO-PSO	0.53 ms	0.59 ms	0.74 ms

Impact of Directionality and Beam Alignment

Directional antennas provide more gain and better spatial reuse with the disadvantage being sensitivity of angular misalignment between the transmitting and receiving nodes. In order to analyze this impact we added controlled angular offsets between beams center of transmitting nodes and where they targeted receivers. This simulation was based on actual real time situation where the mobile nodes could rotate or even drift out of alignment within the process of packet forwarding.

Figure 9 shows that when the offset angle is greater than the half-power beamwidth of the antenna (usually about 30 degrees in patch antennas) then the antenna gain starts falling off rapidly. Sensibly above this point, the signal strength attenuates at an alarming rate causing a quantifiable rise in Bit Error Rate (BER).

This directly impacts on packet forwarding choices and link reliability in systems using beam-sensitivity in routing. Robust behavior of the hybrid ACO-PSO algorithm with directional gain, as a component of link-quality, was observed to ~45 misalignment, 0 Nonetheless, when angular offset was above 60 it was performing worse because of lower RSS and more retransmissions.

Such results explain the need of beam-aware routing procedures in networks with directional antennas. Other performance improvements might also be made by adding real-time orientation feedback (e.g. through IMU sensors or beam tracking) to work in dynamic environments like UAV swarms or vehicular networks.

Figure 9 is a plot of two axes of angular offset versus antenna gain (left Y-axis) and bit error rate, (right Y-axis). The gain is attenuated in a cosine manner whereas the BER increases exponentially beyond beamwidth limit.

Conclusion and Future Work

In the present paper we introduce a brand-new hybrid bio-inspired routing framework that incorporates the local adaptive nature of Ant Colony Optimization (ACO) with the global convergence of Particle Swarm Optimization (PSO) to solve the dual challenges of scalability and adaptability, in wireless ad hoc networks. Adding directional awareness antenna and using swarm-based decision making solves this issue since exploring and exploiting are balanced in real-time, which guarantees good performance under different mobility and network density situations.

Extensive simulation results show that hybrid ACO-PSO protocol effectively achieves greater level of packet delivery ratio and end to end delay, routing overhead, and convergence stability when compared to traditional ACO- and PSO-based strategies. In addition, the design of the antenna gain modeling as well as the metrics of beam alignment further contribute to the application of the protocol to propagation-sensitive and directionally limited wireless networks.

Future Work

In order to make this research more applicable and influential, the following directions can be offered:

- Real-World Validation: The use of a software-defined radio (SDR) testbed (e.g. USRP or GNU Radio) to compare the actual-time behaviour of the protocol with more practical environments of the RF channel.
- Energy-Aware Optimization: An option of joining the power control and energy harvesting actions towards the aim of scale-out node life in the sensor and IoT application context.
- Cross-Layer Adaptation: Advance feedback at the MAC-layer and physical layer beam tracking to enable smooth routing in directional mesh networks and when mmWave is used.
- Heterogeneous Networks: Framing extension to facilitate vehicular ad-hoc networks (VANETs), swarms of UAVs, and clusters of IoT edges custom multi-tier demands and mobility that is non-uniform.

This hybrid routing framework lays the groundwork of future antenna-aware, scalable communication protocols suitable to the new environment of intelligent and automated wireless systems.

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