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"ENHANCING VANET ROUTING WITH A HYBRID BEAGLE-INSPIRED AND PARTICLE SWARM OPTIMIZATION ALGORITHM"

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ABSTRACT

The dynamic topology of Vehicular Ad-hoc Networks (VANETs) presents a significant challenge for efficient data routing. In order to identify the best communication routes, this study analyzes the multi-hop packet forwarding problem as a Traveling Salesman Problem (TSP). We present a unique Beagle-Inspired Optimization Algorithm (BIOA) and its hybrids with Differential Evolution (DE) and Particle Swarm Optimization (PSO). These are compared with various metaheuristics such as Ant Colony Optimization (ACO), Wave Optimization, a Genetic Algorithm (GA), and Snake-Skin Shedding Optimization (SSSO). By successfully balancing exploration and exploitation, the hybrid BIOA-PSO algorithm delivers excellent performance, achieving an accuracy of 76.5% and an F1-score of 72.9%, according to extensive simulations on a real-world VANET dataset. An effective substitute, ACO offers a good trade-off between computational time (1.92 seconds) and performance (74.0% accuracy). The hybrids' quick stability is demonstrated by convergence and feature importance evaluations, which also show that traffic density and erratic speed are the most important variables affecting routing choices. The findings offer a useful foundation for choosing optimization methods according to particular VANET application needs.

Keywords-VANET; Routing Protocol; Traveling Salesman Problem; Metaheuristics; Bio-Inspired Optimization; Hybrid Algorithms

I. INTRODUCTION

A key component of intelligent transportation systems, vehicular ad hoc networks (VANETs) allow communication between cars (V2V) and with roadside infrastructure (V2I)

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to improve passenger comfort, traffic efficiency, and road safety [1]. However, because of the great mobility of vehicles, the network architecture is extremely dynamic and unpredictable, which frequently results in link disconnections and makes effective routing a crucial difficulty [2]. Increased latency, packet loss, and impaired safety applications result from traditional routing protocols, which were created for more stable networks, frequently being unable to handle these quick changes [3].

There is a void in the systematic investigation and hybridization of more recent bio-inspired algorithms designed especially for VANETs, despite the use of metaheuristics such as Genetic Algorithms (GA) and Ant Colony Optimization (ACO) to network routing. The majority of research concentrates on tried-and-true techniques, largely ignoring the possibility of new metaphors.

This paper makes several significant contributions to close this gap:

- Using a unique formulation that enables comprehensive end-to-end path optimization, the multi-hop VANET routing problem is modeled as a TSP.
- Presenting a novel Beagle-Inspired Optimization Algorithm (BIOA) and creating creative BIOA hybrids with DE and PSO.
- Offering a thorough comparison of these techniques with other classical (GA, ACO) and bio-inspired (SSSO, Wave Optimization) metaheuristics.
- Assessing algorithms for correctness, computational efficiency, convergence, and feature relevance in order to provide distinctive practical insights.

The structure of the paper is as follows: Related work is covered in Section 2. The methodology is described in Section 3. The results are presented and discussed in Section 4. The job is finally concluded in Section 5.

II. RELATED WORK

A. *VANET Routing Challenges*

The two main types of VANET routing protocols are position-based and topology-based [4]. The high overhead of route maintenance in dynamic contexts is a problem for topology-based protocols like AODV. Although they rely significantly on precise GPS data, position-based protocols use geographic information for more effective routing [5]. Packet Delivery Ratio (PDR), end-to-end latency, throughput, and routing overhead are important performance indicators for assessing these protocols [6]. Scalability, dependability, and reducing latency for real-time applications continue to be the key obstacles [7].

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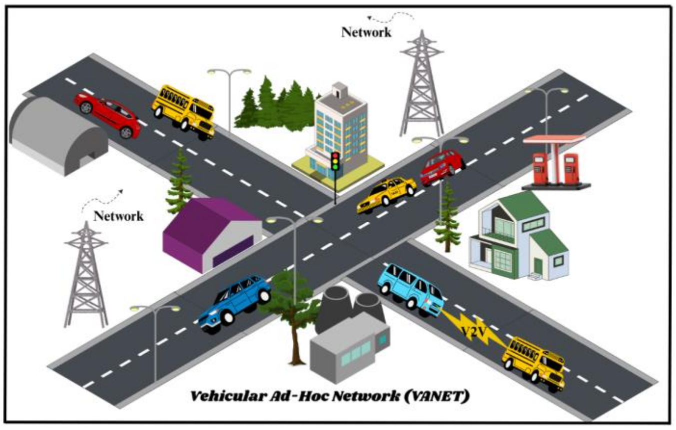

Fig. 1. Vehicular Ad-Hoc Network (VANET) architecture [Illustrating communication between vehicles (V2V) and between vehicles and infrastructure (V2I). VANETs enable intelligent transportation systems by allowing vehicles to exchange safety, traffic, and infotainment information.].

B. *Optimization in VANET Routing*

In order to adjust to the dynamic nature of VANETs, optimization techniques are essential. Successful applications of metaheuristic techniques that provide flexibility and scalability include ACO [8] and Reinforcement Learning (RL) [9]. Inspired by natural processes, bio-inspired algorithms offer robust and adaptable search techniques appropriate for the dynamic, large-scale structure of vehicle networks [10].

A well-researched combinatorial paradigm for network routing is offered by the Traveling Salesman Problem (TSP) [11]. By reframing the problem from finding a path to finding the best relay node sequence that minimizes a cost function (such as latency or packet loss), modeling multi-hop routing as a TSP enables the integration of several constraints into a single objective function.

III. METHODOLOGY

A. *Problem Formulation and Data*

The VANET routing problem is modeled as a TSP. Given a set of n nodes (vehicles), the objective is to find the shortest closed tour visiting each node exactly once. The tour length for a permutation π is:

$$L(\pi) = \sum_{k=1}^{n-1} d_{\pi k,\pi k+1} + d_{\pi n,\pi 1} \qquad (1)$$

Where d_{ij} is the Euclidean distance between nodes i and j.

The experiments utilized the VANET Real-Time Route Optimization Dataset [12], containing 2000 records with 11 features (e.g., vehicle_speed, traffic_density, packet_loss_rate, signal_strength) and a binary target variable optimal_route_chosen. Data was normalized, and imbalance was handled using SMOTE.

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B. *Solution Encoding and Fitness*

Population-based continuous optimizers (BIOA, PSO, DE, SSSO, Wave) used a random-keys representation, decoded into a permutation by sorting vector indices. Combinatorial approaches (GA, ACO) worked directly with permutation encoding. The fitness of a candidate solution was the total tour length L(π). A 2-opt local search was optionally applied to refine solutions.

C. *Algorithmic Frameworks*

Beagle-Inspired Optimization (BIOA): The Beagle-Inspired Optimization Algorithm (BIOA) [13] is a metaheuristic that combines exploration (looking for new regions) and exploitation (refining existing good areas) to replicate the foraging behavior of beagles. The algorithm shows that solutions using random keys, which the TSP decodes into permutations. In order to reach the best-known solution, each agent makes a Gaussian-based exploration move and a focused exploitation move. New positions are only accepted if they lengthen the tour.

Algorithm 1 Beagle-Inspired Optimization Algorithm (BIOA) for TSP

Data: *TSP instance, population size N, max iterations Tmax*

Result: *Best tour π∗*

Initialize population X = {x1,x2,...,xN} using random-keys Decode each xi into

permutation πi and evaluate f(πi) = L(πi) Select best solution π∗for t = 1 to

Tmax do

for each agent xi do

x′ ← xi +N(0,σ2) ; // Exploration step

Decode π′ and evaluate f(π′) if f(π′) < f(πi) then

xi←x′

End

x′′ ← xi +α(x∗ −xi)+N(0,σ2) ; // Exploitation step

Decode π′′ and evaluate f(π′′) if f(π′′) < f(πi) then

xi←x′′

End

Update best π∗

End

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return best solution π∗

Hybrid BIOA-PSO: This hybrid algorithm combines the social learning mechanics of PSO [14] with the exploratory power of BIOA. To find new areas in the search space, the population first does a BIOA exploration step. The population is then guided toward promising solutions by using a PSO step, in which each agent's velocity is changed depending on both its individual best experience and the swarm's global best experience.

Algorithm 2 Hybrid BIOA–PSO for TSP

Data: *TSP instance, population size N, max iterations Tmax*

Result: *Best tour π∗*

Initialize population X and velocities V Set personal bests pbesti = xi and global

best gbest for t = 1 to Tmax do

for each agent xi do

x′ ← xi +N(0,σ2) ; // BIOA exploration

Evaluate f(x′) if f(x′) < f(xi) then

xi←x′

end

Update pbesti if improved

end

for each agent xi do

vi ← wvi +c1r1(pbesti − xi) +c2r2(gbest − xi) ; // PSO velocity update

xi ←xi +vi ; Evaluate f(xi) Update pbesti if improved end Update gbest

end

return best solution π∗

Hybrid BIOA-DE: This hybrid approach makes use of Differential Evolution (DE) [15] for its potent mutation and crossover operations to refine solutions and BIOA for global exploration. The DE cycle starts with a standard BIOA phase. For each agent, a mutant vector is made from three different parents. This vector then crossovers with the current agent to form a trial solution, which replaces the original if it is superior.

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Algorithm 3 Hybrid BIOA–DE for TSP

Data: *TSP instance, population size N, max iterations Tmax*

Result: *Best tour π∗*

Initialize population X and evaluate Set best solution π∗ for t = 1 to Tmax

do for each agent xi

do x′ ← xi +N(0,σ2) ; // BIOA exploration

Evaluate f(x′) if f(x′) < f(xi)

then xi←x′ end end for each agent xi

do Choose distinct random indices

r1,r2,r3/ = i u ← xr1+F(xr2−xr3) ; // DE mutation trial ← crossover(xi,u,CR) ;

// DE crossover Evaluate f(trial)

if f(trial) < f(xi) then xi←trial

end

Update π∗

end

return π∗

Snake-Skin Shedding Optimization (SSSO): Inspired by the process of snake molting, the Snake-Skin Shedding Optimization algorithm [16] is a new metaheuristic. The population is ranked and split into top, middle, and bottom groups. Each group uses a unique movement strategy that mimics various snake locomotion types, such as rectilinear and serpentine. From aggressive refining to exploratory motions, this framework encourages a variety of search behaviors.

Algorithm 4 SSSO for TSP

Data: *TSP instance, population size N, max iterations Tmax*

Result: *Best tour π∗*

Initialize population X and evaluate fitness for t = 1 to Tmax do

Rank solutions and divide into top, middle, and bottom groups for each agent

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xi do

if agent in top group then

xi ←xi +λ(x∗ −xi);// Rectilinear movement

end

else if agent in middle group then

xi ←xi +βsin(θ)(x∗ −xi) ;

end else

xi ←xi +Concertina/Sidewinding(x∗) ;

end

Evaluate updated xi

Update best π∗

return π∗

Wave Optimization: Wave propagation and attenuation are modeled by the Wave Optimization Algorithm [17]. A wave-like function that decays exponentially with time and oscillates with a sine wave updates each solution. Large initial explorations that become finer, more precise motions as the algorithm converges are made possible by the wave's amplitude, which is proportional to the distance from the optimal solution.

Algorithm 5 Wave optimization for TSP

Data: *TSP instance, population size N, max iterations Tmax*

Result: *Best tour π∗*

Initialize population X and best π∗

for t = 1 to Tmax do γ ←2(1−t/Tmax) ; // Calculate decay factor

for each agent xi/= x∗

do r ∼U(0,1) ;

∆←|x∗−xi| ;

xi ←xi +βe−γtsin(2πr)∆ ;

Evaluate xi

Update best

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if improved

end

end

return π∗

Genetic Algorithm (GA): Natural selection serves as the inspiration for the population-based evolutionary algorithm known as the Genetic Algorithm [18]. It works with a population of chromosomes, or candidate tours. To produce new offspring, it employs selection, crossover (like Order Crossover-OX), and mutation (like swap mutation) operators. Elitism is employed to conserve the optimal solution across generations, and an optional 2-opt local search can be used to refine people.

Algorithm 6 Genetic Algorithm for TSP

Data: *TSP instance, population size N, max generations G*

Result: *Best tour π∗*

Initialize population of permutations Π Evaluate fitness of each permutation for

g =1 to G do

Select parents using tournament selection

Apply crossover (e.g., OX) with probability pc to produce offspring Apply mutation (e.g., swap) with probability pm to offspring Apply 2-opt local search to offspring optional) Form new population from offspring and elites Evaluate new population

end

return

best solution found

- Ant Colony Optimization (ACO): Ants construct tours probabilistically based on pheromone trails and heuristic desirability (inverse distance) [19].

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Algorithm 7 ACO for TSP

Data: *TSP instance, number of ants m, max iterations Tmax*

Result: *Best tour π∗*

Initialize pheromone matrix τij = τ0 for all edges (i,j) Initialize heuristic information

ηij = 1/dij for t = 1 to Tmax

do Place each ant on a random city for each ant k

do Construct a complete tour by choosing next city j from city i with probability:

Pk ij = [τij]α[ηij]β

l∈allowed[τil]α[ηil]β

Compute tour length Lk

end

Update global best tour

if improved Evaporate pheromones:

τij ← (1 − ρ) · τij

for all (i,j) for each ant k do

for each edge (i,j) in the ant's tour do

Deposit pheromone: τij ← τij + Q/Lk

end

return

global best tour

Algorithms were run for a maximum number of iterations, and performance was assessed over 30 independent runs based on best, mean, and standard deviation of tour lengths.

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IV. RESULTS AND DISCUSSION

A. *Overall Performance and Computational Time*

Table I summarizes the total performance as determined by training time and classification measures. With the best accuracy (76.5%) and F1-score (72.9%), the Hybrid BIOA-PSO algorithm proved to be the most successful. This is explained by its synergistic architecture, in which PSO facilitates effective exploitation and BIOA offers strong exploration. Nevertheless, the computing cost was larger (3.46 s).

Among the higher-performing algorithms, ACO achieved competitive accuracy (74.0%) with the lowest computation time (1.92 s), demonstrating an outstanding balance and emphasizing its intrinsic efficiency for combinatorial tasks. Additionally, GA and Hybrid BIOA-DE demonstrated excellent performance. The fastest, but less accurate, methods were SSSO and Wave Optimization, which makes them appropriate for situations that call for quick, adequate answers.

TABLE I. OVERALL PERFORMANCE COMPARISON

Algorithm	**Accuracy**	**F1 Score**	**Time (sec)**
Hybrid BIOA-PSO	0.765	0.730	3.462
Genetic Algorithm (GA)	0.750	0.714	3.913
Hybrid BIOA-DE	0.752	0.708	3.701
BIOA	0.745	0.702	3.087
Ant Colony Opt. (ACO)	0.740	0.698	1.915
SSSO	0.668	0.634	1.567
Wave Optimization	0.648	0.591	1.484

There is an obvious trade-off between computational cost and solution quality (Fig. 1). A high-accuracy/higher-time cluster is formed by GA and high-performing hybrids (BIOA-PSO, BIOA-DE). While SSSO and Wave Optimization create a lower-accuracy/low-time cluster, ACO provides an attractive middle ground.

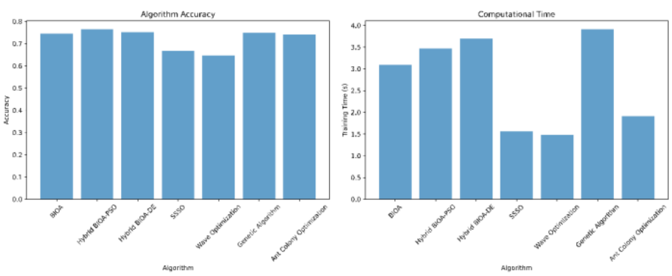

Fig. 2. Algorithm performance vs. computational time trade-off [The chart juxtaposes the accuracy of each algorithm against its computational time. A clear Pareto front is observed,

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where the Hybrid BIOA-PSO, GA, and Hybrid BIOA-DE form a group of high-accuracy/higher-time solutions.].

B. Feature Importance and Convergence

'Volatile Speed' and 'Traffic Density' were consistently the most influential features across all algorithms, according to the feature importance analysis (Fig. 2), confirming their basic influence on routing in dynamic environments. Notably, network-quality indicators like "Packet Loss Rate" and "Signal Strength" were given greater relative weight by the top-performing algorithms (Hybrid BIOA-PSO, ACO), indicating that explicitly quantifying communication reliability is a crucial success element.

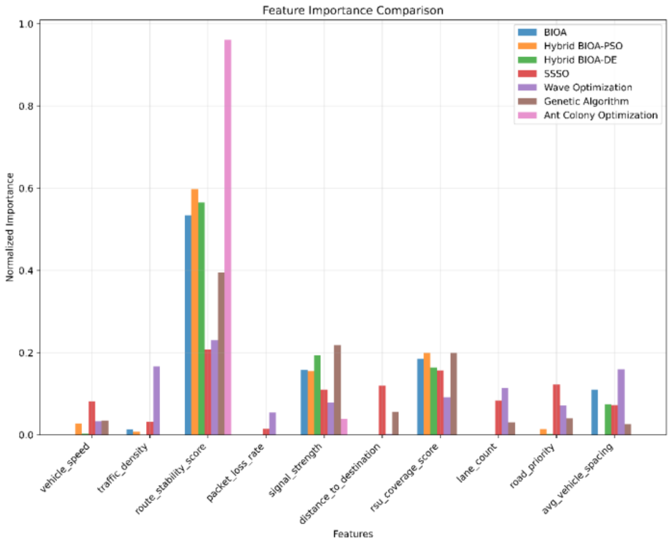

Fig. 3. Normalized feature importance across algorithms [The analysis reveals that 'Volatile Speed' and 'traffic density' are consistently among the most influential features for determining an optimal route in the VANET environment, underscoring the dynamic and congested nature of the urban mobility scenario.].

Hybrid BIOA-PSO had a quick initial descent and stable convergence, as seen by the convergence analysis (Fig. 3), supporting its high ranking. The hybrid models successfully blended exploitation and exploration. While SSSO and Wave Optimization converged quickly but plateaued at larger error values, indicating their exploratory nature, ACO's convergence remained steady and smooth.

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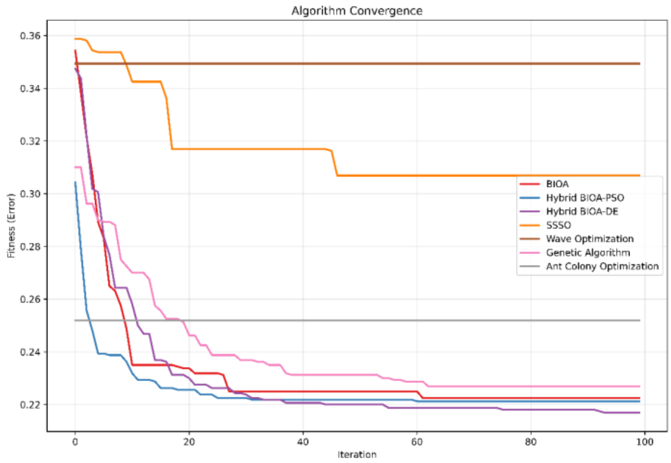

Fig. 4. Convergence behavior of the evaluated algorithms [The Hybrid BIOA-PSO algorithm demonstrates not only the best final performance but also a rapid and stable convergence, reaching a near-optimal solution within approximately 40 iterations.].

V. CONCLUSION

In order to optimize VANET routing, which is modeled as a TSP, this work provided a thorough comparison of innovative and hybrid metaheuristics. There are three main conclusions. First, because of its synergistic combination of PSO's local exploitation and BIOA's global exploration, the recently suggested Hybrid BIOA-PSO algorithm proved to be the most successful, attaining the highest accuracy (76.5%) and F1-score (72.9%). Second, ACO turned out to be a very effective option, providing the best-in-class trade-off between computational speed (1.92 s) and performance (74.0% accuracy). Third, the analyses verified that top algorithms prioritize network-quality measures and that dynamic aspects such as traffic density and vehicle speed are crucial for routing decisions.

The results illustrate a clear performance-efficiency trade-off, providing a practical guide for algorithm selection:

- For maximum routing accuracy (e.g., emergency services): Hybrid BIOA-PSO or GA are recommended.
- For a balance of accuracy and efficiency (e.g., general purpose routing): ACO or Hybrid BIOA-DE are ideal.
- For ultra-low latency applications (e.g., real-time collision avoidance): Wave Optimization or SSSO provide rapid solutions.

The effectiveness of hybrid metaheuristics for intricate VANET routing is confirmed by this study. In the future, large-scale city simulations will be used to evaluate adaptive frameworks that dynamically alter algorithms based on current network conditions.

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