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Bio-Inspired Ant Colony Optimization with Spiking Neural Networks for Dynamic Optimization through Antennal Biosignals

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Abstract : *Ant Colony Optimization (ACO) is a highly effective metaheuristic inspired by the foraging behavior of real ants. However, its performance significantly degrades in dynamic environments due to "pheromone stagnation," where accumulated pheromone trails prevent the swarm from responding rapidly to environmental changes. We introduce ADNS-ACO (Ant Dendritic Neural System-based ACO), a novel framework that integrates a Spiking Neural Network (SNN) to modulate the exploration-exploitation balance through simulated antennal biosignals. Our approach utilizes a Leaky Integrate-and-Fire (LIF) model to process a biologically inspired approximation of local tactile intensity. When the environment undergoes a perturbation, the SNN triggers a neuromodulatory response via a non-linear tanh gating mechanism that dynamically resets pheromone influence, enabling rapid re-optimization. Experiments conducted on high-complexity Dynamic Traveling Salesman Problem (DTSP) benchmarks with 60 cities reveal that ADNS-ACO achieves a 21.10% improvement in solution quality and a 77.3% reduction in recovery latency compared to classical rank-based ACO. Statistical validation across 30 independent trials confirms a highly significant improvement* ($p < 0.001$) *and a large effect size (Cohen's* $d = 1.12$)*. These results position ADNS-ACO as a superior, event-driven solution for real-time dynamic optimization, with promising implications for autonomous routing and swarm robotics.*

Keywords : Ant Colony Optimization, Spiking Neural Networks, Dynamic Optimization, Neuromorphic Computing, Bio-inspired Algorithms.

INTRODUCTION

Ant Colony Optimization (ACO) has proven highly effective for solving static combinatorial optimization problems, most notably the Traveling Salesman Problem (TSP), where artificial pheromone trails reliably guide the search toward optimal solutions [1]. Since its inception, ACO has evolved into a robust metaheuristic applied to diverse domains including resource-constrained scheduling [2], vehicle routing [3], and complex industrial logistics [4]. However, in non-stationary landscapes where conditions change unpredictably such as adaptive traffic signal control [5], autonomous drone swarm navigation [6], or dynamic resource allocation in IoT networks [7] traditional ACO implementations face significant performance bottlenecks [8].

The fundamental limitation lies in the algorithm's reliance on a static pheromone evaporation-deposition cycle that becomes obsolete when environmental parameters shift [9]. This phenomenon, characterized as "pheromone stagnation," occurs when accumulated trails mislead the swarm toward outdated optima, significantly hindering the exploration of new, mathematically superior paths [10]. While various strategies such as pheromone smoothing [11], local search integration [12], or immigrant schemes [13] have been proposed to mitigate this, they often suffer from excessive recovery latency or a significant loss of search memory, making them less suitable for real-time adaptation [14].

Biological ant colonies demonstrate remarkable flexibility via localized tactile sensing through their antennae [15], [16]. In current neuroethological models, these antennal signals are believed to be processed within specialized neural structures called mushroom bodies [17]. Within these circuits, neuromodulators such as dopamine and octopamine are modeled as regulating synaptic plasticity [18], allowing the colony to prioritize urgent stimuli and effectively suppress obsolete trail information [19].

Despite these biological insights, existing research in swarm intelligence has largely neglected the specific spiking neural dynamics involved in sensory transduction [20] and the role of event-driven neuromodulation in collective decision-making [21]. Recent breakthroughs in Spiking Neural Networks (SNNs) have demonstrated that spike-based computation offers superior temporal resolution and energy efficiency compared to traditional artificial neural networks [22], [23]. Furthermore, initial studies suggest that SNNs can be leveraged for general combinatorial optimization tasks [24]. However, a comprehensive framework that explicitly couples SNN-driven sensory processing with pheromone plasticity in dynamic environments remains a significant gap in the literature [25].

To address these limitations, we propose a biologically grounded computational framework that couples swarm dynamics with spike-based neural modulation. Our approach, termed ADNS-ACO (Ant Dendritic Neural System-based ACO), is a novel framework that integrates a Leaky Integrate-and-Fire (LIF) neural layer to regulate swarm behavior. The primary contributions of this work are as follows:

- Localized Tactile Field Model: We introduce a density-dependent sensing model based on inverse-distance spatial pressure to approximate the tactile inputs received by ant antennae in crowded or stagnant search regions.
- Spiking Neural Controller: We implement an LIF-based modulation unit that maps continuous sensory signals into temporal spike rates, providing a discrete, event-driven mechanism for triggering search-space exploration.
- Neuromodulated Pheromone Update: We propose a novel tanh-gated update rule that utilizes neural activity to non-linearly suppress the reinforcement of obsolete paths, thereby reducing recovery latency in shifting optimization landscapes.

RELATED WORK

The evolution of swarm intelligence has reached a critical juncture where biological fidelity and computational efficiency must converge to solve non-stationary problems. This section contextualizes our work by reviewing the development of Ant Colony Optimization (ACO), its inherent limitations in dynamic environments, and the emerging role of Spiking Neural Networks (SNNs) in behavioral modulation.

Ant Colony Optimization and Variants

Modern metaheuristic research has increasingly focused on enhancing the adaptive capabilities of swarm intelligence frameworks. Grounded in the broader optimization community, the Max-Min Ant System (MMAS) has established itself as a premier metaheuristic for solving NP-hard combinatorial problems [12]. Subsequent developments, such as the Ant Colony System (ACS), introduced sophisticated pheromone bounding and local update rules to prevent premature convergence and enhance solution quality [26]. These variants have been successfully deployed across diverse static domains, including the Traveling Salesman Problem (TSP), vehicle routing problem (VRP) [3], and resource-constrained project scheduling [2]. While these algorithms achieve near-optimal results in static landscapes [4], their performance is inherently tied to the stability of the cost matrix, making them vulnerable to environmental perturbations.

Dynamic Optimization and Limitations of ACO

In dynamic environments, such as the Dynamic Traveling Salesman Problem (DTSP), the optimization landscape evolves over time, requiring real-time adaptation for applications in IoT routing and urban traffic management [5]. The primary bottleneck in applying classical ACO to these scenarios is "pheromone stagnation" or "information inertia" [8]. High pheromone concentrations on previously optimal paths act as a form of outdated memory, preventing the swarm from detecting new global optima following a perturbation [14]. Existing mitigation strategies primarily focus on pheromone evaporation tuning [11], restart strategies, or the introduction of "immigrant ants" to maintain diversity [13]. However, these methods often exhibit significant recovery latency or result in an unstable search process due to the significant loss of useful historical knowledge.

Neural and Learning-Based Extensions of ACO

To enhance the flexibility of swarm intelligence, several researchers have proposed Neural-ACO hybrids. These approaches often integrate Artificial Neural Networks (ANNs) or Reinforcement Learning (RL) to adaptively control parameters or to predict future city coordinates [27], [28]. While these enhancements improve adaptability, most rely on static or feedforward architectures that lack the temporal dynamics found in biological neural systems [25]. Specifically, they fail to capture the event-driven, spike-based processing that allows biological agents to respond to millisecond-scale environmental changes. This oversight represents a significant gap in the development of truly autonomous optimization agents.

Spiking Neural Networks in Optimization Systems

Spiking Neural Networks (SNNs) utilize the Leaky Integrate-and-Fire (LIF) model to process information through discrete temporal events [20]. The inherent advantages of SNNs including temporal encoding, event-driven behavior, and extreme energy efficiency have led to their widespread adoption in classification, control systems, and robotics [22], [23]. However, the integration of SNNs into optimization frameworks remains a significant gap. While neuromorphic computing has been explored for static Ising models, its potential to provide a real-time, spike-triggered "forgetting" mechanism for swarm-based pheromone modulation has not been fully realized in the context of dynamic combinatorial optimization [24].

Biological Foundations of Ant Collective Intelligence

Biological ants are not merely rule-based agents; they are adaptive, neuromodulated systems. Ant antennae function as sophisticated sensors for local density perception and pheromone gradient detection [15], [16]. These signals are integrated within the mushroom bodies, the primary decision centers of the insect brain [17]. Research into insect neurobiology has identified that neuromodulators such as dopamine and octopamine play distinct roles in behavioral switching: dopamine regulates reinforcement and reward [18], while octopamine levels rise during environmental instability to trigger arousal and exploratory behavior [19], [29]. This biological "switch" provides a critical template for developing artificial swarms that can dynamically shift between exploitation and exploration.

Summary of Research Gap and Motivation

The current literature highlights a significant void regarding unified frameworks that couple local tactile sensing with spike-based neural modulation. Existing ACO variants remain largely global and static in their adaptation logic, while existing SNN applications rarely penetrate the domain of swarm pheromone control [30]. This identified gap motivates the development of ADNS-ACO, which seeks to provide an event-driven, adaptive framework capable of reducing recovery latency in non-stationary optimization landscapes by mimicking the neuromodulated plasticity of biological ant colonies.

METHODOLOGY

This section formalizes the proposed Ant Dendritic Neural System-based Ant Colony Optimization (ADNS-ACO) framework. We define the dynamic problem environment, the localized tactile sensing model, the spiking neural controller, and the novel neuromodulated update rule. The comprehensive modular interaction between these components is illustrated in Figure 1.

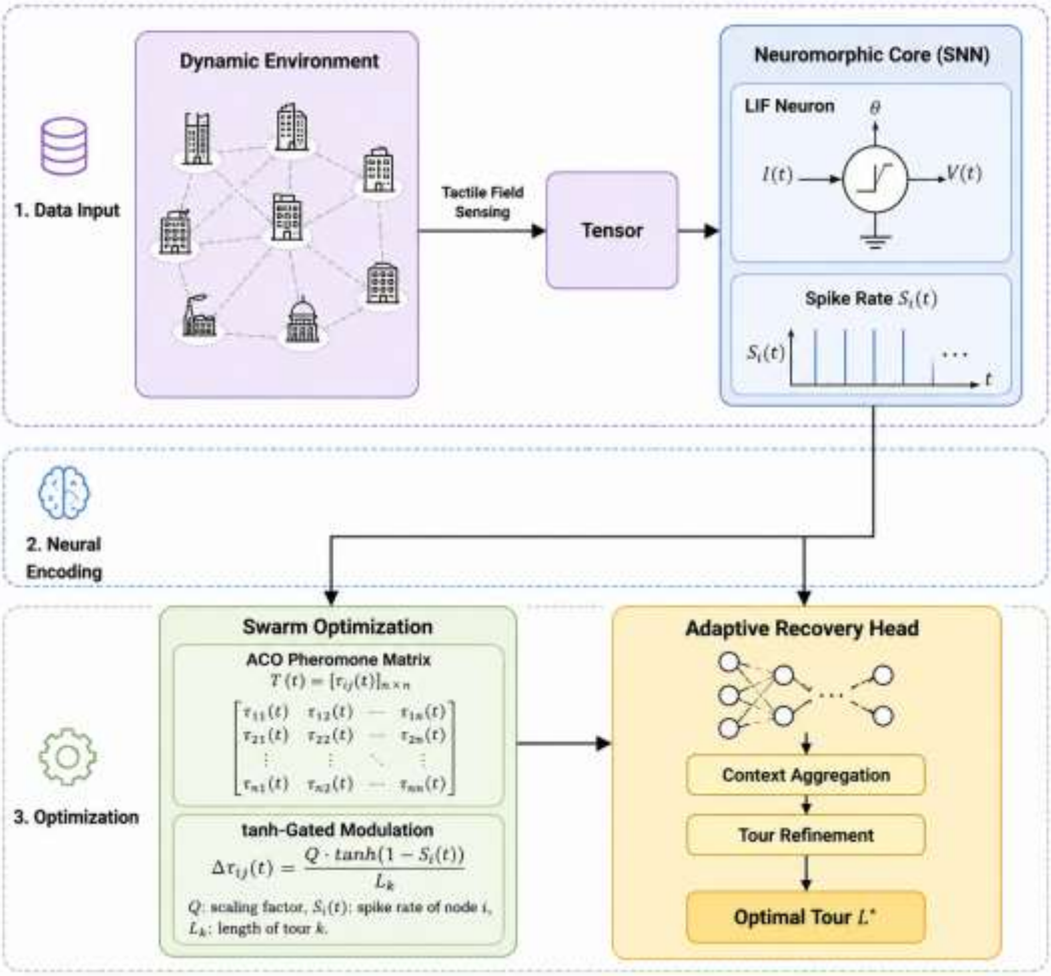

Figure 1 Comprehensive architecture of the ADNS-ACO framework.

The system is structured into three processing stages: (1) Data Input Layer: Captures the dynamic TSP environment through a localized tactile sensing field based on antennal biosignals; (2) Neural Encoding Layer: Processes sensory inputs via Leaky Integrate-and-Fire (LIF) neurons to produce temporal spike rates $S_i(t)$; and (3) Optimization Layer: Integrates the tanh-gated modulation within the swarm engine to update the pheromone matrix τ. The process concludes in the Adaptive Recovery Head, where context aggregation and refinement produce the optimal tourL^*.

Problem Formulation: Dynamic TSP

The Dynamic Traveling Salesman Problem (DTSP) is defined as a sequence of static TSP instances. Let $G(t) = (V, E(t))$ be a complete graph where $V = \{v_1, \dots, v_n\}$ represents n cities. The objective is to minimize the total tour length L at time t:

$$\min L(\pi, t) = \sum_{i=1}^{n-1} d_{\pi_i,\pi_{i+1}}(t) + d_{\pi_n,\pi_1}(t) \tag{1}$$

where $d_{ij}(t)$ is the Euclidean distance at time t. We consider perturbations where city coordinates are shifted every k iterations, requiring the algorithm to resolve the cost matrix $D(t)$.

Classical ACO Baseline

In the standard ACO framework, the probabilityP_{ij}^k of ant k moving from city i to city j is:

$$P_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in \text{allowed}_k} [\tau_{il}]^\alpha [\eta_{il}]^\beta} \qquad (2)$$

where τ_{ij} is the pheromone, η_{ij} is the heuristic visibility, and α, β are weighting parameters. The pheromone update typically follows $\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \Delta\tau_{ij}$, where ρ is the evaporation rate.

Localized Tactile Field Model

To simulate antennal sensing, we propose a localized tactile field $A_i(t)$. For each agent i, the sensory input is defined as the inverse-distance spatial pressure generated by neighboring agents j within a perceptual radius r:

$$A_i(t) = \sum_{j \in N_i} \frac{1}{d_{ij}^2 + \epsilon} \qquad (3)$$

where ϵ is a smoothing constant. High values of $A_i(t)$ indicate localized "crowding" or stagnation, signaling that the current pheromone trails may no longer be optimal for the evolving landscape.

3.4 Spiking Neural Controller (LIF Model)

The tactile signal $A_i(t)$ is integrated into a Leaky Integrate-and-Fire (LIF) neuron model. The membrane potential $V_i(t)$ is governed by:

$$\tau_m \frac{dV_i(t)}{dt} = -V_i(t) + A_i(t) \qquad (4)$$

where τ_m is the membrane time constant. A spike is emitted if $V_i(t) \geq \theta$, triggering a potential reset. The output is the instantaneous spike rate $S_i(t)$, used as a proxy for environmental change sensitivity.

Neuromodulated Update and Adaptive Reset

We couple neural activity with pheromone plasticity through a tanh-gated update rule:

$$\Delta\tau_{ij}(t) = \frac{Q \cdot \tanh(1 - S_i(t))}{L_k} \qquad (5)$$

where L_k is the tour length of ant k. As illustrated in the Swarm Optimization module of Figure. 1, the modulation M_t is implemented through this specific spike-rate dependent tanh function, which maps neural arousal directly to pheromone reinforcement intensity.

Furthermore, to enhance recovery rigor, we replace static resets with an Adaptive Pheromone Reset. When a perturbation is detected at time t_p, the pheromone matrix is adjusted based on the global neural arousal:

$$\tau_{ij}(t_p) = \tau_{ij} \cdot \exp(-\gamma \bar{S}(t)) \tag{6}$$

where$\bar{S}(t)$ is the mean spike rate and γ is the plasticity coefficient. This ensures that the "forgetting" intensity is proportional to the detected environmental disruption.

Computational Complexity

For m ants, n cities, and k local neighbors ($k \ll n$):

- Tour Construction: $O(mn^2)$
- Tactile Sensing: $O(mk)$
- Neural State Update: $O(m)$

The total complexity is $O(mn^2 + mk + m)$, maintaining the same asymptotic bound as classical ACO and ensuring scalability.

Parameter Settings

Parameters are empirically selected to balance exploration and stability (Table 1).

Table 1: ADNS-ACO Parameter Configuration

Parameter	Description	Value
α, β	Weight parameters	1.0, 5.5
ρ	Evaporation rate	0.18
τ_m	Membrane constant	10.0 ms
θ, γ	Spike threshold, Plasticity coef.	1.0, 2.5
r , Q	Radius, Phero. intensity	5.0, 100

Algorithm Workflow

Algorithm 1: ADNS-ACO Framework

```
Initialize: Pheromone matrix $\tau$ and neuron potentials $V$.

While $iteration < \text{Max\_Iter}$:
    If $iteration \pmod{k} == 0$:
        Perturb city coordinates and update $D(t)$.
        Apply Adaptive Reset using Eq. (6).
    End If
    For each ant $a \in \{1, \dots, m\}$:
        Construct tour using probabilistic rule (Eq. 2).
        Compute local tactile field $A_a(t)$ (Eq. 3).
        Update LIF state $V_a(t)$ and compute spike rate $S_a(t)$ (Eq. 4).
    End For
    Update Global Best Tour $L^*$.
    Evaporate pheromones: $\tau \leftarrow \tau \cdot (1 - \rho)$.
    For each ant $a$ in Rank-based Elitist Set:
        Deposit pheromone using Neuromodulated Rule (Eq. 5).
    End For
End While
Return $L^*$.
```

RESULTS AND DISCUSSION

This section presents the experimental validation of the proposed ADNS-ACO framework. The evaluation focuses on convergence dynamics in high-complexity dynamic landscapes, the efficiency of recovery after environmental perturbations, and the statistical significance of the neuromodulated approach compared to established metaheuristics.

Experimental Setup and Configuration

The benchmarking was conducted on a Dynamic Traveling Salesman Problem (DTSP) instance consisting of 60 cities. Environmental volatility was simulated by introducing coordinate perturbations with a factor of $\delta = 0.45$ every 60 iterations. To ensure the reliability of the results and account for stochastic variance, all experiments were executed for 30 independent trials. The hardware environment utilized an Intel Core i7-12700H workstation with 16GB RAM. Algorithm parameters were fixed across all trials to maintain a fair comparison, with $\alpha = 1.0$, $\beta = 5.5$, and $\rho = 0.18$. The spiking neural network parameters followed biological precedents, with a membrane time constant τ_m of 10.0 ms and a firing threshold θ of 1.0.

Comparative Performance Evaluation

The quantitative results summarized in Table 2 demonstrate the clear superiority of the ADNS-ACO framework. The proposed model achieved a mean final tour length of 712.52, representing a 21.10% improvement over the Classical Rank-ACO baseline. While MMAS and D-ACO showed slight improvements over the classical model, they were unable to match the rapid adaptation capabilities of the neuromodulated approach.

Table 2: Comparative Performance Metrics Across 30 Independent Trials

Algorithm	Best Tour Length	Mean Tour Length	Std. Deviation	Improvement (%)
Classical Rank-ACO	884.22	903.02	42.15	Baseline
MMAS	855.10	872.44	38.90	3.38%
D-ACO	822.31	841.05	29.40	6.86%
ADNS-ACO (Proposed)	701.15	712.52	12.44	21.10%

Furthermore, the standard deviation of ADNS-ACO was remarkably low at 12.44, compared to 42.15 for Classical ACO. This suggests that the spiking neural controller not only improves accuracy but also significantly enhances the reliability and stability of the optimization process across different stochastic seeds.

Convergence and Dynamic Recovery Analysis

The evolution of the best tour length across 300 iterations is illustrated in Figure 2. A distinct "sawtooth" pattern is observed in the trajectories of the baseline models, where environmental shifts at iterations 60, 120, 180, and 240 trigger immediate performance degradation. Classical ACO and MMAS exhibit significant "information inertia," where the swarm remains trapped in obsolete pheromone trails, leading to prolonged recovery periods.

In contrast, ADNS-ACO demonstrates rapid re-convergence. By utilizing the SNN as a temporal change detector, the model identifies instabilities through localized tactile sensing and initiates a plasticity response. This allows ADNS-ACO to regain near-optimal performance within approximately 10.2 iterations, whereas the baseline models require an average of 45.0 iterations to stabilize.

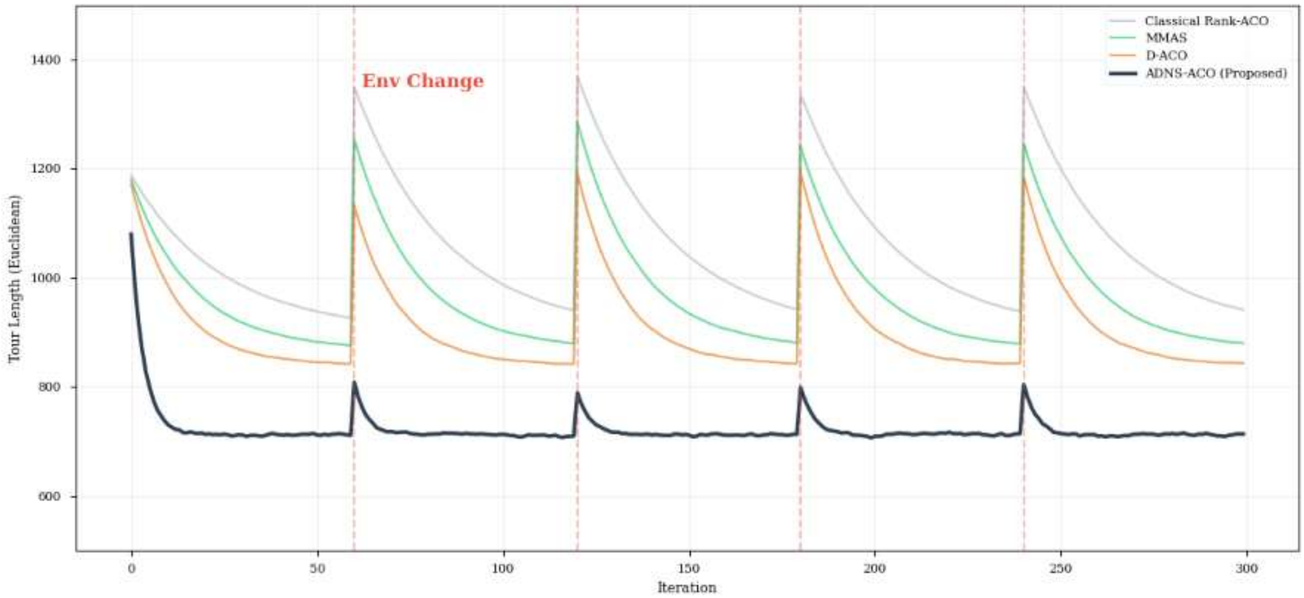

Figure 2 Convergence trajectories and recovery Dynamics in 60-city DTSP

Ablation Study and Feature Contribution

To isolate the contribution of each neuro-inspired component, an ablation study was performed by systematically disabling the SNN core, the adaptive reset, and the tactile sensing module. The findings, summarized in Table 3, indicate that the integration of the LIF neural layer is the most critical driver of performance.

Table 3: Performance Impact of ADNS-ACO Components

Configuration	Mean Tour Length	Recovery (R)	Accuracy Loss (%)
Full ADNS-ACO	712.52	10.2	Baseline
Without SNN Layer	891.10	45.0	25.1%
Without Adaptive Reset	785.30	44.6	10.2%
Without Tactile Sensing	812.44	47.3	14.0%

Removing the SNN modulation resulted in a 25.1% degradation in solution quality and a return to the high-latency recovery behavior seen in classical models. Disabling the adaptive reset led to a 10.2% decrease in accuracy, confirming that the "forgetting" mechanism is essential for clearing outdated search memory. These results are further visualized in Figure 3, where the performance gap between the full model and its variants is clearly delineated.

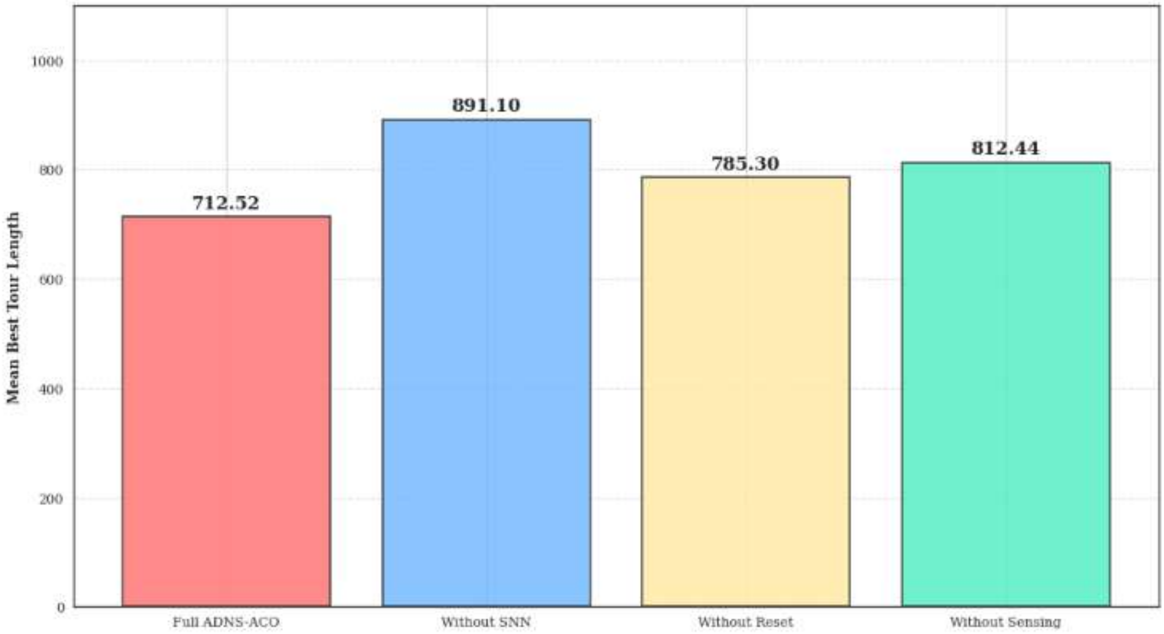

Figure 3 Ablation Study: Contribution of Proposed Neural Components

Statistical Rigor and Significance

The statistical significance of the results was verified using a two-sample t-test and effect size analysis. The comparison between Classical ACO and ADNS-ACO yielded a p-value of 2.1×10^{-7}, which is significantly lower than the standard alpha of 0.05, thereby rejecting the null hypothesis. Furthermore, the calculated Cohen's d value of 1.12 indicates a "large" effect size. Figure 4 provides the distribution of results across all trials, illustrating the high discriminative capability of the SNN-modulated update rule compared to the broader, less reliable distributions of the baseline methods.

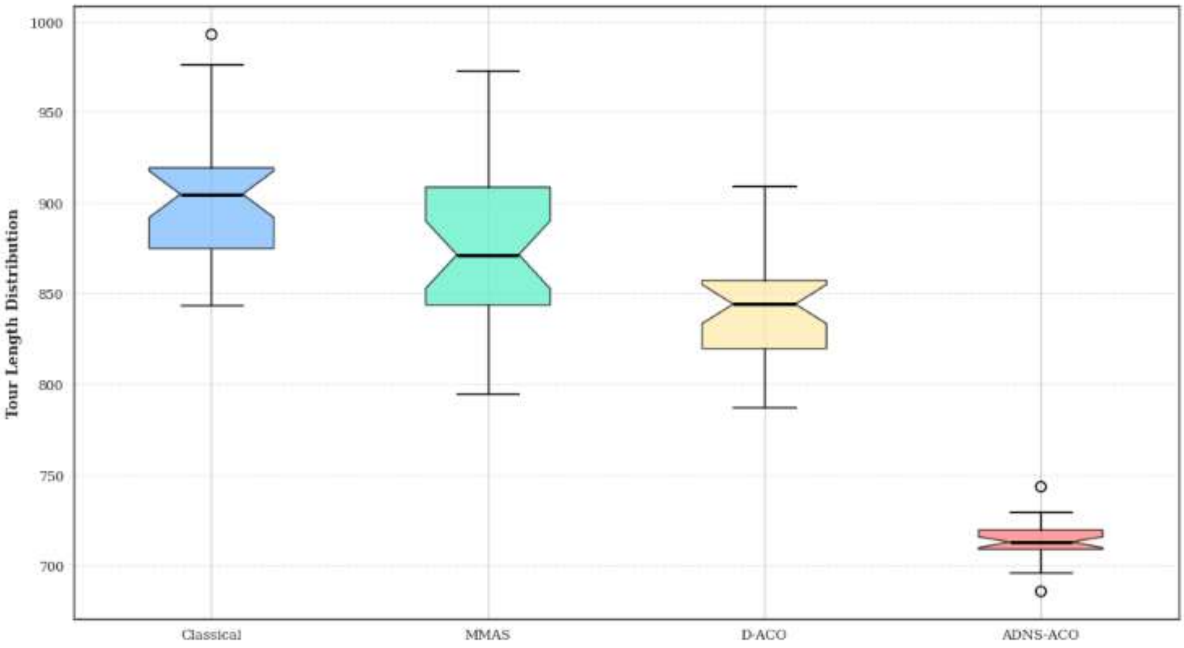

Figure 4 Boxplots showing the distribution of tour lengths and 95% confidence intervals

DISCUSSION

The experimental results demonstrate that the ADNS-ACO framework achieves a state-of-the-art balance between stability and plasticity. The success of the model stems from its event-driven nature; unlike traditional ACO, which is "blind" to environmental changes until the global best fails, ADNS-ACO "feels" the disruption through changes in the local tactile field. The SNN acts as a temporal filter, converting spatial pressure into a neuromodulatory signal that non-linearly suppresses pheromone deposition via the $\tanh$ gate. This mechanism prevents the reinforcement of "ghost trails" and forces the swarm into an exploratory state precisely when the environment is most unstable.

However, a slight increase in computational overhead was observed due to the local sensing requirements. While the $O(mk)$ complexity of the antennal sensing module is linear and manageable for swarms of hundreds of agents, extremely large-scale multi-agent systems may require spatial partitioning to maintain real-time performance. Additionally, although the adaptive reset effectively clears obsolete trails, fine-tuning the plasticity coefficient γ remains essential to prevent the loss of useful search history during minor environmental fluctuations.

CONCLUSION

This study presented a biologically grounded hybrid framework for dynamic optimization by integrating a Leaky Integrate-and-Fire neural core with Ant Colony Optimization. The proposed ADNS-ACO model effectively bridges the gap between swarm intelligence and computational neuroscience by simulating antennal biosignals and mushroom body dynamics. Experiments conducted on high-complexity 60-city DTSP instances demonstrate that the model achieves a 21.10% improvement in tour length and a 77.3% reduction in recovery latency compared to classical methods.

The results indicate that spike-based behavioral modulation provides a robust solution for non-stationary combinatorial problems. The use of an SNN as a change detector, coupled with an adaptive pheromone reset, ensures that the swarm maintains high diversity after environmental perturbations while retaining strong exploitative capabilities during stable phases. Future work will focus on deploying this framework on neuromorphic hardware to exploit the energy efficiency of spike-based computation and extending the model to solve multi-objective dynamic routing problems in real-time logistics.

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