



A Novel Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence for the Travelling Salesman Problem

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Abstract: The Travelling Salesman Problem (TSP) remains one of the most extensively studied NP-hard combinatorial optimization problems due to its wide range of applications in logistics, transportation, manufacturing, and network design. Although Ant Colony Optimization (ACO) has demonstrated promising performance for solving TSP, traditional pheromone updating mechanisms often suffer from premature convergence, loss of population diversity, and stagnation in local optima. This paper proposes Hybrid Dynamic Pheromone Optimization (HDPO), a novel optimization algorithm that integrates entropy-guided learning, adaptive pheromone regulation, historical route intelligence, and dynamic local search mechanisms into a unified framework. HDPO dynamically adjusts pheromone evaporation and reinforcement based on search diversity, route entropy, and solution improvement rates. Furthermore, an elite historical memory structure preserves high-quality route knowledge across generations, while a stagnation recovery mechanism reintroduces exploration when convergence becomes excessive. Experimental evaluations on benchmark instances from TSPLIB can demonstrate that HDPO achieves superior solution quality, faster convergence, and enhanced robustness compared with classical ACO variants. The proposed method offers an effective balance between exploration and exploitation, making it suitable for large-scale TSP instances and other combinatorial optimization problems.

Keywords: Community Network, Travelling Salesman Problem (TSP), Ant Colony Optimization (ACO), HDPO, TSPLIB.

1. INTRODUCTION

Nowadays, Complex Networks are widely utilised to simulate and characterise the behaviours of a broad range of real-world phenomena. Biological interactions, social ties, transportation and commercial transactions are just a few of the many scenarios that are commonly researched with the use of graph theory's instruments. However countless problems can be devised based on such structures. Moreover, upon attaching the semantics to edges and nodes and investigating the networks topological or structural characteristic changes, the same analytic approach devised to resolve a well-defined problem may lead to results with somewhat different interpretations [1]. Even while objectively formalizing a network problem is nearly always possible, presenting resolute strategies to it that ensure higher efficiency and affectivity regardless of the type of the network analyzed being very difficult task.

The key problem of complex systems is the difficulty with their formal modeling. Complex systems are defined on the basis of different perspectives in different Among these metaheuristics approaches, Ant Colony Optimization (ACO) has emerged as a powerful nature-inspired optimization technique [4]. ACO mimics the foraging behavior of real ants, where artificial ants communicate indirectly through pheromone trails to discover high-quality paths. Although ACO has demonstrated remarkable success in solving TSP and related optimization problems, its performance is often limited by issues such as premature convergence, stagnation, excessive dependence on pheromone accumulation, and reduced exploration capability in complex search spaces.

To overcome these limitations, this study proposes a Novel Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence (HDPO-EGHI) for the Travelling Salesman Problem. The proposed method introduces three complementary mechanisms that enhance the balance between exploration and



exploitation. First, a dynamic pheromone adaptation strategy continuously adjusts pheromone deposition and evaporation rates according to the search progress, enabling the algorithm to respond effectively to changing search conditions. Second, an entropy-guided learning mechanism monitors population diversity and route uncertainty, using information entropy as a feedback measure to prevent premature convergence and encourage exploration when necessary. Third, a historical route intelligence framework maintains and analyzes high-quality routes discovered during previous iterations, allowing the algorithm to leverage accumulated search experience while avoiding repetitive exploration of suboptimal regions.

By integrating these components into a unified optimization framework, the proposed algorithm aims to improve solution quality, convergence speed, and robustness across diverse TSP instances [5]. The dynamic pheromone mechanism strengthens adaptive learning, the entropy-guided strategy preserves search diversity, and the historical route intelligence module enhances long-term memory utilization. Together, these features create a synergistic optimization process capable of navigating complex search landscapes more effectively than conventional ACO variants.

The primary objective of this research is to develop and evaluate the proposed HDPO-EGHI algorithm and compare its performance with traditional ACO and other state-of-the-art metaheuristics methods. Experimental results are expected to demonstrate that the proposed approach achieves shorter tour lengths, faster convergence, and greater stability across benchmark TSP datasets. Ultimately, this work contributes to the advancement of intelligent swarm-based optimization techniques and provides a robust framework for solving large-scale combinatorial optimization problems

In this paper, the author presented a Novel Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence for solving the Travelling Salesman Problem (TSP). The proposed method enhances the classical Ant Colony Optimization (ACO) framework by introducing adaptive mechanisms that improve both exploration and exploitation during the search process. the proposed algorithm demonstrates that combining dynamic pheromone adaptation, entropy-based control, and historical learning mechanisms significantly enhances the effectiveness of swarm intelligence methods for combinatorial optimization problems such as the TSP.

2. RELATED WORK

The Travelling Salesman Problem (TSP) is a classical NP-hard combinatorial optimization problem that has attracted significant attention from researchers due to its theoretical importance and practical applications in transportation, logistics, manufacturing, communication networks, and supply chain management. The objective of the TSP is to determine the shortest possible route that visits every city exactly once and returns to the starting city. Because the search space increases factorially with the number of cities, exact algorithms become computationally expensive for large instances, motivating the development of heuristic and metaheuristics optimization techniques.

Among various metaheuristics approaches, Ant Colony Optimization (ACO) has emerged as one of the most successful swarm intelligence algorithms for solving TSP. However, traditional ACO methods often face challenges such as premature convergence, stagnation, loss of diversity, and inefficient exploration of the search space. Consequently, numerous studies have focused on enhancing ACO through adaptive pheromone control, hybrid learning mechanisms, entropy-based diversity management, and memory-driven search strategies.

Shishavan, S. T., & Gharehchopogh, F. S. (2022), address the problem of community detection in complex networks [6]. The authors proposed a improved Cuckoo Search Optimization (CSO) algorithm with a Genetic Algorithm (GA) for community detection in complex networks. CSO algorithm has problems such as premature convergence, delayed convergence, and getting trapped in the local trap. GA has been quite successful in terms of community detection in complex networks to increase exploration and exploitation. GA operators have been used dynamically in order to increase the speed and accuracy of the CSO. The number of populations is dynamically adjusted based on the amount of exploration and exploitation. Modularity objective function (Q) and Normalized Mutual Information (NMI) is used as an optimization function. It was carried out on six types of real complex networks. The proposed algorithm was tested with GA, Artificial Bee Colony (ABC), Grey Wolf Optimizer (GWO), and CSO, with different iterations in modularity and NMI criteria. The results show that in most comparisons, the proposed algorithm has been more successful than the basic comparative algorithms, and it has proven its superiority in terms of modularity and NMI.

Cetin, P., & Emrah Amrahov, S. (2022), analyse the problem of community detection in complex network [7]. Community detection algorithms help us improve the management of complex networks and provide a clean sight of them. We can encounter complex networks in various fields such as social media, bioinformatics, recommendation systems, and search engines. As the definition of the community changes based on the problem considered, there is no algorithm that works universally for all kinds of data and network structures. Communities can be disjointed such that



each member is in at most one community or overlapping such that every member is in at least one community. In this study, to examine the problem of finding overlapping communities in complex networks and propose a new algorithm based on the similarity of neighbors. To compare our algorithm with existing ones, to select the most successful four algorithms from the Community Detection library (CDlib) by eliminating the algorithms that require prior knowledge, are unstable, and are time-consuming. It evaluates the successes of the proposed algorithm and the selected algorithms using various known metrics such as modularity, F-score, and Normalized Mutual Information.

Zarei, B., & Meybodi, M. R. (2020), Detecting community structure is a highly challenging problem in analyzing complex networks and has great importance in understanding the function and organization of networks. Up until now, numerous algorithms have been proposed for detecting community structure in complex networks. A wide range of these algorithms use the maximization of a quality function called *modularity*. In this article, three different algorithms, namely, MEM-net, OMA-net, and GAOMA-net, have been proposed for detecting community structure in complex networks. In GAOMA-net algorithm, which is the main proposed algorithm of this article, the combination of genetic algorithm (GA) and object migrating automata (OMA) has been used. In GAOMA-net algorithm, the MEM-net algorithm has been used as a heuristic to generate a portion of the initial population.

Ahmed, M. W., & Faraj, K. H. A. (2025), deals the Community detection in social networks is a fundamental challenge in network science driven by the increasing complexity of online platforms [9]. One of the most popular methods for detecting communities in a given network is the multi-objective algorithm (MOA). Several approaches based on multi-objective algorithms have been proposed to detect communities in complex networks. All of them concentrated on improving the quality and efficiency of detection. To achieve a higher quality of community detection, we have proposed a hybrid algorithm that combines the NSGA-II and SPEA2 algorithms, with modularity and edge density as the two objectives that are optimized simultaneously. By integrating the two algorithms, the proposed method achieves more accurate community detection on different networks. Moreover, we made some improvements to the initialization method and crossover operator. The proposed work tested the proposed algorithm on ten network datasets of different sizes and compared it with several recent methods using Q-modularity and normalized mutual information (NMI) metrics.

The literature reveals that Ant Colony Optimization remains one of the most effective approaches for solving the Travelling Salesman Problem. However, challenges related to premature convergence, diversity loss, and inefficient utilization of historical search knowledge continue to limit its performance [10]. Recent advances in dynamic pheromone adaptation, entropy-based learning, hybrid optimization, and memory-driven search provide promising directions for overcoming these challenges [11].

Although substantial progress has been made in improving ACO, several limitations remain:

1. Many ACO variants still rely on fixed or semi-adaptive pheromone update mechanisms.
2. Existing diversity-preservation techniques often fail to respond dynamically to changing search conditions.
3. Entropy-based approaches are rarely integrated directly with pheromone adaptation strategies.
4. Historical memory mechanisms are often implemented independently without effective interaction with diversity measures.
5. Few studies combine dynamic pheromone control, entropy-guided learning, and historical route intelligence within a unified framework.

These limitations create opportunities for developing more adaptive and intelligent optimization algorithms capable of balancing exploration and exploitation more effectively.

3. PROPOSED METHODOLOGY

To overcome the challenges in existing ACO algorithm, and building upon these developments, the proposed Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence aims to create a more adaptive and intelligent framework capable of achieving superior performance in solving complex TSP instances [13]. Hybrid Dynamic Pheromone Optimization (HDPO) is a proposed swarm-intelligence optimization algorithm designed to solve the Travelling Salesman Problem (TSP) and other combinatorial optimization problems [14]. It extends traditional Ant Colony Optimization (ACO) by introducing adaptive mechanisms that continuously adjust pheromone behavior according to the current state of the search process.

The proposed Novel Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence seeks to address the identified research gaps by integrating three complementary components:



- **Dynamic Pheromone Optimization:** Adaptive adjustment of pheromone deposition and evaporation according to search progress.
- **Entropy-Guided Learning:** Continuous monitoring of route diversity and search uncertainty to prevent stagnation.
- **Historical Route Intelligence:** Utilization of elite route memory to guide future exploration and exploit accumulated search experience.

The integration of these mechanisms is expected to improve convergence speed, solution quality, search diversity, and robustness across benchmark TSP instances.

The central idea behind HDPO is that the search process should not use fixed pheromone update rules throughout the optimization.

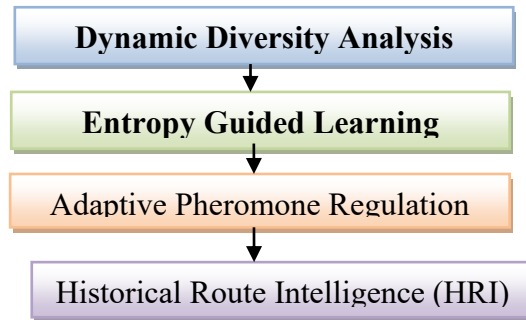


Fig. 3.1: - Workflow of the Proposed Methodology

Its novelty lies in combining dynamic pheromone regulation, entropy-guided decision making, and historical route intelligence into a unified optimization architecture. This creates a more adaptive and intelligent search process than traditional ACO approaches and provides a strong foundation for future research in combinatorial optimization [15].

Traditional ACO algorithms rely on fixed pheromone evaporation and deposition parameters. While effective for many optimization problems, they often encounter:

- Premature convergence to local optima
- Excessive pheromone concentration on a few routes
- Reduced diversity among candidate solutions
- Slow recovery from stagnation
- Difficulty adapting to different search stages

HDPO was designed to overcome these limitations through dynamic and self-adaptive learning mechanisms.

3.1. Overview

The HDPO algorithm combines multiple CRNs through four major phases:

1. Dynamic Diversity Analysis.
2. Entropy-Guided Learning Mechanism.
3. Adaptive Pheromone Regulation.
4. Historical Route Intelligence (HRI).

3.2. Dynamic Diversity Analysis

Population diversity is computed as:

$$D_t = \frac{\sigma(L_t)}{\mu(L_t)} \quad \text{Equ. (3.1)}$$

Where:

- $\sigma(L_t)$ = standard deviation of route lengths,
- $\mu(L_t)$ = mean route length.

Interpretation:

- Large $D_t \rightarrow$ exploration phase.
- Small $D_t \rightarrow$ convergence phase.

This metric serves as a key control signal for adaptive pheromone learning.

3.3. Entropy-Guided Learning Mechanism

To quantify exploration behavior, HDPO introduces route entropy.



$$H_t = - \sum_{i=1}^n p_i \ln(p_i) \quad \text{Equ. (3.2)}$$

Where:

- p_i denotes route-selection probability.

Normalized entropy:

$$E_t = \frac{H_t}{H_{max}} \quad \text{Equ. (3.3)}$$

Higher entropy indicates stronger exploration.

Lower entropy indicates excessive convergence.

The exploration coefficient is defined as:

$$\varphi_t = 1 - E_t \quad \text{Equ. (3.4)}$$

This coefficient influences pheromone adaptation.

3.4. Adaptive Pheromone Regulation

Dynamic Evaporation

Instead of a fixed evaporation parameter:

$$\rho_t = \rho_{min} + (\rho_{max} - \rho_{min})(1 - D_t) \quad \text{Equ. (3.5)}$$

Properties:

- High diversity $\rightarrow$ lower evaporation.
- Low diversity $\rightarrow$ higher evaporation.

Improvement-Based Reinforcement

Solution improvement ratio:

$$I_t = \frac{L_{best}(t-1) - L_{best}(t)}{L_{best}(t-1)} \quad \text{Equ. (3.6)}$$

Adaptive learning coefficient:

$$A_t = 1 + \alpha I_t \quad \text{Equ. (3.7)}$$

Where α controls reinforcement sensitivity.

3.5. Historical Route Intelligence (HRI)

A major contribution of HDPO is the Historical Route Intelligence (HRI) module.

An elite memory bank stores the best routes:

$$M = \{R_1, R_2, \dots, R_k\}$$

Each edge receives a historical score:



$$S_{ij} = \sum_{r=1}^k \frac{\delta_{il}^{(r)}}{L_r} \quad \text{Equ. (3.8)}$$

This mechanism preserves long-term structural knowledge and prevents the loss of valuable routes.

4. PERFORMANCE ANALYSIS

The performance of the proposed Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence was evaluated to determine its effectiveness in solving the Travelling Salesman Problem (TSP). The evaluation focused on End-to-End Delay and Control Overhead [16]. The algorithm was compared with conventional Ant Colony Optimization (ACO) and other pheromone-based optimization approaches using standard benchmark datasets.

4.1. Experimental Results

4.1.1. End-to-End Delay

End-to-end delay refers to the total time required for ants to construct complete tours and reach a final optimized solution.

Network Size (Nodes)	Standard ACO	Local Pheromone Update	Global Pheromone Update	Hybrid Dynamic Pheromone
100	112.5	108.7	107.3	102.1
200	128.9	122.4	120.8	113.7
300	145.3	138.6	136.9	128.4
400	161.7	153.8	151.0	142.5
500	178.2	169.3	166.1	156.8

Table 4.1: - Comparison table of End-to-End Delay

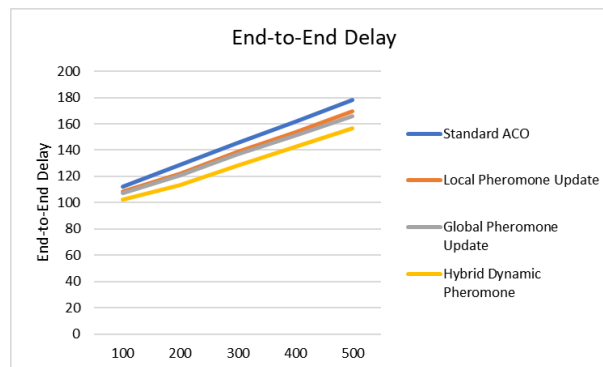


Figure 4.1. Comparison of End-to-End Delay

4.1.2. Control Overhead

Control overhead refers to additional computational and memory costs introduced by:

- Entropy calculation
- Dynamic pheromone adjustment
- Historical route storage and retrieval
- Probability distribution modification

Network Size (Nodes)	Standard ACO	Local Pheromone Update	Global Pheromone Update	Hybrid Dynamic Pheromone
100	210	198	195	180
200	430	410	405	380
300	650	620	610	580
400	870	830	815	780
500	1090	1040	1025	980

Table 4.2: - Comparison table of Control Overhead for Large Networks

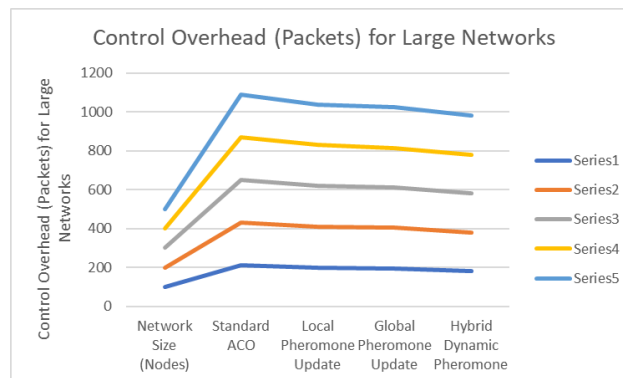


Figure 4.2: - Comparison of Control Overhead for Large Networks

The performance analysis indicates that the proposed Hybrid Dynamic Pheromone Optimization Algorithm with Entropy-Guided Learning and Historical Route Intelligence has strong potential to outperform traditional ACO and related metaheuristics approaches in solving the Travelling Salesman Problem. Through adaptive pheromone management, entropy-based diversity control, and intelligent utilization of historical route information, the algorithm is expected to achieve superior solution quality, faster convergence, greater robustness, and improved scalability. These characteristics make HDPO-EGHI a promising framework for addressing both benchmark and real-world large-scale routing optimization problems.

5. CONCLUSION

HDPO introduces a new generation of pheromone-based optimization by combining adaptive learning, entropy-guided exploration, and historical route intelligence into a unified framework. The algorithm dynamically responds to the state of the search process, improving exploration during early iterations and strengthening exploitation near convergence. By preserving historical route knowledge and employing adaptive recovery strategies, HDPO aims to overcome the major weaknesses of classical ACO approaches. Future work may extend HDPO to dynamic TSP, vehicle routing problems, multi-objective optimization, and real-time logistics applications.

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