Exploration of the Application of Swarm Intelligence in Cooperative Driving

Runze Tian

School of Mechanical, Electrical & Information Engineering, Shandong University, Weihai, Shandong, 264200, China

202300800533@mail.sdu.edu.cn

Abstract. Swarm intelligence(SI), a nature-inspired distributed computational approach, has emerged as a promising solution within the domain of cooperative driving. This research paper investigates the theoretical foundations and practical implementations of classical swarm intelligence algorithms, focusing on their integration into intelligent transportation systems. Key areas of application, such as vehicle platooning, path planning, and traffic flow optimization, are examined to assess the real-world performance and technological advantages of swarm intelligence. Notably, swarm intelligence demonstrates exceptional capabilities in dynamic adaptation and global optimization, contributing significantly to improvements in both traffic efficiency and safety. The findings indicate that, through its decentralized and adaptive characteristics, swarm intelligence not only enhances the operational efficiency of cooperative driving systems but also provides critical theoretical and practical support for the development of safe, sustainable, and intelligent transportation infrastructures. Future research should focus on the deep integration of lightweight algorithm design and emerging technologies to provide support for building an efficient, safe and green transportation system.

Keywords: Swarm Intelligence, Cooperative Driving, Intelligent Transportation Systems

1 Introduction

Approximately 1.35 million people die each year in road traffic accidents, and 20 to 50 million people are injured. Globally, 93% of traffic accident deaths occur in low- and middle-income countries[1]. This data not only highlights the severity of global traffic congestion and safety issues, but also shows that traditional traffic management methods face huge challenges in meeting modern traffic needs. In this context, Intelligent Transportation Systems (ITS) have emerged as a comprehensive solution that integrates information technology, artificial intelligence and communication technology to optimize traffic efficiency, improve road safety and reduce environmental impact.

ITS has made significant progress in many areas, but its management in dynamic

J. Iqbal (ed.), *Proceedings of the 2025 2nd International Conference on Mechanics, Electronics Engineering and Automation (ICMEEA 2025)*, Advances in Engineering Research 272,
https://doi.org/10.2991/978-94-6463-821-9_25

and distributed traffic environments still faces many challenges. Swarm Intelligence(SI) as a computing paradigm inspired by nature, provides a new technical framework for further optimization of ITS. Through decentralized optimization methods, it demonstrates strong adaptability and efficiency in dynamic traffic scenarios.

Swarm intelligence is a computing paradigm based on decentralized distributed systems. Its core is to spontaneously generate complex global behaviors through local interactions of simple individuals. Compared to traditional centralized approaches, Swarm Intelligence offers significant advantages in solving complex distributed problems. Through the collaboration of simple individuals and the interaction of local information, it reduces the dependence on global information, thereby enhancing the scalability and robustness of the system. These decentralized and adaptive features make Swarm Intelligence particularly effective in dynamic and ever-changing traffic environments [2]. Therefore, Swarm Intelligence provides crucial support for the optimization and advancement of ITS.

This paper aims to systematically review the latest developments in swarm intelligence within the context of cooperative driving, with a particular focus on its application logic, typical use cases, and technical limitations. Through this review, we seek to offer theoretical support for future research and to promote the practical implementation of swarm intelligence in intelligent transportation systems.

The remainder of this paper is organized as follows: Section 2 provides an overview of the development and evolution of swarm intelligence; Section 3 discusses the algorithms and applications of swarm intelligence in cooperative driving; Section 4 presents a comparative analysis of the strengths and weaknesses of these algorithms; and Section 5 offers insights into future technological trends.

2 Development of Swarm Intelligence

2.1 Theoretical Foundations and Classical Cases

Swarm intelligence is a distributed artificial intelligence method inspired by collective behaviors observed in nature. It emphasizes how local interactions among individuals, governed by simple rules, can lead to global optimization in complex systems. The core idea is that individuals rely on local perception and limited interactions, such as neighborhood rules, local feedback, and environmental cues, to accomplish complex tasks through self-organization, adaptability, and cooperative behavior, without the need for centralized control. Classic examples in nature include pheromone communication in ant foraging, dynamic formation adjustments in bird migration, and obstacle avoidance coordination in fish schools. These local interactions collectively result in globally optimal behaviors.

2.2 Application in the field of drones and robots

In recent years, swarm intelligence has emerged in the research of unmanned aerial vehicles (UAVs) and robots, especially in distributed collaborative tasks such as formation control and task allocation, showing excellent performance.

For example, in the field of drone formation control, swarm intelligence has shown excellent performance. Slim et al. (2024) proposed a dynamic bandwidth allocation algorithm based on task execution measurement, which optimizes global task planning through local interaction under a decentralized framework. In the experiment, the algorithm shortened the task completion time by about 30% in a disaster relief simulation scenario and maintained a stable formation and efficient resource utilization in a dynamic environment [3].

In the practice of robot multi-task allocation, the ant colony optimization algorithm (ACO) achieved global optimization of path planning and task allocation by simulating the dynamic adjustment of pheromone concentration. Experimental data showed that the algorithm improved the task completion rate in multi-robot collaboration by about 25% and significantly reduced communication delay. In addition, its flexibility and efficiency in dynamic obstacle avoidance tasks further verified the adaptability of the algorithm in complex scenarios [3].

2.3 Transfer of Swarm Intelligence to the Intelligent Transportation Domain

Swarm Intelligence algorithms have achieved significant success in UAVs and robotics due to their distributed computing and dynamic collaboration capabilities, it provides important reference for intelligent transportation. Intelligent transportation faces the needs of multi-agent interaction and real-time optimization, which is highly similar to the path planning and task allocation problems of UAV swarms. For example, UAVs achieve formation control through local information exchange, while cooperative driving optimizes traffic flow through Vehicle-to-Everything (V2X) communication. Both systems share significant commonalities in decentralized architecture, real-time decision-making capabilities, and global optimization objectives. Therefore, SI provides a new idea for solving traffic congestion and energy consumption optimization, its applicability has been verified in multiple experimental studies.

3 Applicability of Classical Swarm Intelligence Algorithms

3.1 Application of Ant Colony Optimization in Intelligent Transportation

ACO is inspired by the path-selection behavior of ants during foraging. Its mechanism involves path construction, pheromone updating, and iterative processes, which enable dynamic optimization and the search for global optimal solutions in complex networks. ACO performs well in real-time decision-making in dynamic environments.

In the field of path planning, ACO can effectively cope with the dynamic environment in complex road networks with its strong real-time adaptability. Naheliya et al. proposed a dynamic path planning algorithm based on ACO. Experiments show that it can reduce the average travel time by 25% during urban traffic peak hours. This algorithm significantly reduces the average travel time during peak hours by dynamically adjusting the pheromone volatilization rate[4]. In a simulated urban network containing 100 nodes, ACO reduces the calculation time by 30% compared with the traditional Dijkstra algorithm, and the path efficiency is significantly improved.

In terms of traffic signal optimization, the distributed nature of ACO makes it outstanding in improving traffic flow efficiency. Yu developed an improved ACO algorithm. Experimental data show that the algorithm can reduce the average vehicle waiting time by 18% and reduce exhaust emissions by 12%. By adjusting the signal light duration in real time, the algorithm effectively improves traffic efficiency[5].
In terms of dynamic traffic management, the adaptability of ACO combined with the Internet of Vehicles (IoV) shows a strong synergistic effect. Song et al. (2024) proposed a dynamic traffic scheduling algorithm that combines ACO and the Internet of Vehicles. The algorithm achieves efficient collaboration by updating pheromone concentrations through real-time data. Experimental results show that this method can reduce the average delay of the fleet by 22% and significantly improve the overall traffic flow efficiency[6].

3.2 Application of Particle Swarm Optimization (PSO) in Intelligent Transportation

PSO efficiently solves global optimization problems by simulating information sharing between individuals. It has dynamic adaptability and multi-objective optimization capabilities, and has been widely applied in intelligent transportation scenarios such as path planning and traffic signal optimization.

In the field of path planning, PSO has demonstrated remarkable dynamic adaptability and collision avoidance capabilities. Yahia et al. proposed a PSO-based dynamic path planning method for high-density traffic scenarios, which achieves real-time path optimization and collision avoidance performance improvement by integrating global and local data. Experiments show that the algorithm can reduce the average path length by 15% and significantly reduce the collision rate[7]. It solves the problem that traditional path optimization algorithms are difficult to cope with real-time changes.

In mixed traffic patterns, PSO also shows excellent optimization capabilities. In the field of coordination of vehicle speed and distance. The experimental results of Tian et al. show that PSO can reduce the speed error by 12% and maintain the safe distance in 98% of cases[8].

PSO also plays a significant role in the combination of intelligent logistics and autonomous driving. Jia et al. proposed a PSO-based intelligent scheduling optimization scheme for shared vehicle and freight systems. This method achieves dynamic optimization of freight delivery routes and vehicle allocation. Studies have shown that transportation efficiency has increased by 15% and operating costs have been significantly reduced [9]. The technical advantage of PSO lies in the combination of real-time data analysis and multi-objective optimization technology. It not only enables efficient resource allocation in traditional logistics but also provides important reference for applications in the field of autonomous driving.

3.3 Application of Bee Algorithm (BA) in Intelligent Transportation

BA is inspired by the foraging behavior of bees. It simulates the behaviors of scout bees, worker bees, and follower bees, and uses the dynamic balance of global and local search to achieve efficient optimization.

In dynamic traffic signal control, BA has shown outstanding effectiveness. Aslan and Karaboga's research showed that optimizing traffic light phase settings based on BA can significantly reduce vehicle waiting time. In actual traffic simulations, the algorithm was able to reduce the average waiting time during peak hours by 22% and improve traffic efficiency by 18% [10]. Its technical features include a scout bee mechanism to collect traffic flow data in real time and dynamically adjust the green light duration according to traffic flow to adapt to real-time changes.

In the field of path planning and mixed traffic management, BA provides efficient solutions. The study by Jovanović et al. show that BA reduced path conflict rates by 25% and decreased network delays by 15% in scenarios when autonomous vehicles collaborate with traditional vehicles [11]. Its key features include the scout bee mechanism, which explores multiple path candidates and evaluates traffic capacity and safety, and the worker bee mechanism, which optimizes local paths to reduce vehicle conflicts, ensuring overall driving efficiency and safety.

3.4 Application of Grey Wolf Optimizer (GWO) in Intelligent Transportation

GWO is inspired by the hunting behavior of grey wolves, first proposed by Mirjalili et al. [12]. The algorithm simulates the hierarchical structure of wolves, where Alpha (leaders), Beta and Delta (collaborators), and Omega (followers) cooperate to locate, encircle, and attack prey.

GWO shows great potential in fleet collaboration and distance optimization. Li et al. proposed a fleet collaborative optimization method combining GWO and predictive control. By leveraging the global search capability of GWO and the real-time response of the prediction model, this method achieves fast and efficient dynamic adjustment of fleet spacing [13]. Experiments have shown that in a simulated highway environment, safety was improved by 25% and traffic fluctuations were reduced by 18%.

In the field of vehicle energy consumption optimization, GWO has also shown outstanding performance. Rajalingam and Kanagamalliga studied the application of GWO in optimizing electric vehicle energy consumption models and charging path selection. The results indicate that GWO can effectively extend battery life and improve energy utilization efficiency by dynamically adjusting energy allocation strategies [14]. In tests with 100 electric vehicles, the algorithm reduced energy consumption by 15% and increased the average driving range by 10%.

4 Comparative Analysis of Various Algorithms

Different swarm intelligence algorithms exhibit distinct characteristics in cooperative driving scenarios. PSO and GWO excel in terms of computational complexity, making them suitable for efficient problem-solving. The dynamic adjustment mechanisms of

BA and PSO enable them to adapt well to dynamic traffic environments. GWO and BA are particularly advantageous in multi-objective optimization and energy consumption optimization due to their effective balance of weights and dynamic search capabilities. PSO performs well in real-time and IoV applications, while GWO performs well in vehicle scheduling optimization. Table 1 discusses the advantages and disadvantages of the four algorithms from various perspectives.

Table 1. Comparison of Four Algorithms

Algorithm Dimension	ACO	PSO	BA	GWO
Computational Complexity	$O(n^2)$, increases with nodes	$O(n \cdot k)$, grows linearly with particles	$O(n^2)$, affected by population size	Moderate, between $O(n \cdot k)$ and $O(2n)$
Dynamic Adaptability	Strong, real-time pheromone concentration update	Adjustable weights and speed	Strong, optimizes scout bee mechanism	Adaptive convergence factor, fast adjustments
Multi-Objective Optimization	Moderate, relies on pheromones	Strong, excellent multi-objective ability	Strong, dynamic search capability	Strong, features weight balancing mechanism
Real-Time Performance	Moderate, requires multiple iterations	Excellent, fast convergence and short execution time	Good, after optimizing initial parameters	Moderate, influenced by initial parameter settings
Energy Optimization	Strong	Strong	Excellent	Excellent
Performance in Cooperative Driving	Moderate, may struggle with complex cooperative issues	Strong, performs well in autonomous driving and IoV	Moderate to strong, slightly weaker in large-scale collaboration compared to GWO and PSO	Strong, supports vehicle coordination and scheduling in IoV scenarios

5 Issues with Algorithms and Future Prospects

5.1 Limitations of Swarm Intelligence and Current Challenges

The application of swarm intelligence in collaborative driving still faces many challenges. At the algorithm level, SI needs to deal with problems such as path planning, resource allocation, and collision avoidance at the same time, which leads to high computational complexity and insufficient real-time performance, especially in large-scale transportation networks. In addition, although the distributed decision-making model improves local robustness, it may reduce global decision consistency. For example, in fleet formation, individual decisions based on local information may lead to inconsistencies in speed or path optimization, affecting the overall system efficiency [15].

In addition, the limitation of hardware resources is also an important bottleneck for the development of swarm intelligence. The operation of complex algorithms places extremely high demands on energy consumption, and drones or vehicle-mounted equipment often find it difficult to meet this demand when performing long-term tasks. In addition, the dependence on high-precision sensors further exacerbates the instability of the system. Low-quality or failed sensors may not be able to accurately capture real-time traffic information, resulting in deviations or lags in data input, affecting local interactions between individuals and environmental perception, leading to decision-making errors or reduced efficiency.

Communication issues directly impact the practical effectiveness of Swarm Intelligence applications. The real-time nature and stability of information sharing are limited by the latency and bandwidth issues of the network environment, especially in complex scenarios or weak signal areas. The lack of unified communication protocols between different manufacturers and platforms leads to incompatibility in data transmission, further limiting cross-platform collaboration capabilities. As the scale of the system expands, the demand for information sharing surges, which intensifies the load pressure on the communication network and has an adverse impact on real-time performance and efficiency.

5.2 Future Prospects

SI still face challenges in terms of real-time performance and resource usage, which has promoted the development and research of lightweight and high versatility, so that they can run efficiently in an environment with limited computing resources. Studies have shown that swarm intelligence optimization algorithms based on lightweight agents have significant computational efficiency advantages in multi-scenario traffic networks [16]. On the other hand, the high versatility improvement direction of SI algorithms benefits from the development of multimodal collaborative optimization technology. Experiments show that the generalization performance of the hybrid swarm intelligence model combined with deep learning is improved by about 18% and remains stable under different traffic flow conditions[17].

Swarm intelligence algorithms are gradually deeply integrated with emerging technologies, providing strong support for the future development of collaborative driving.Its integration with communication technologies such as v2x and 5G/6G further strengthens the algorithm's collaborative and large-scale link capabilities. For example, in complex traffic environments, V2X-based swarm intelligence algorithms can achieve rapid response to vehicle-to-vehicle path adjustment, obstacle avoidance, and emergencies. This collaborative mechanism enables vehicles to complete status updates and optimal path decisions within milliseconds, significantly reducing the interference of emergencies on traffic flow and improving the stability and efficiency of the overall system.

In addition, digital twin technology provides a new dimension of dynamic optimization and real-time decision-making for swarm intelligence algorithms. It builds a virtual simulation platform that runs synchronously with the real traffic environment, providing high-precision prediction support for swarm intelligence algorithms[18]. For example, by embedding PSO into the digital twin model, the system can quickly respond to emergencies in complex traffic environments and dynamically adjust path planning.

6 Conclusion

This study shows that swarm intelligence, with its decentralized and adaptive characteristics, has shown excellent application potential in the field of collaborative driving. Classic algorithms such as ACO and PSO have significantly improved the efficiency and safety of the system in scenarios such as path planning, convoy formation and traffic flow optimization. At the same time, the integration with V2X, digital twin and other technologies further enhances the system's collaborative capabilities and real-time decision-making performance.

Although the application of swarm intelligence in intelligent transportation has made important progress, further breakthroughs are still needed in computational complexity, hardware resource limitations and communication stability. Future research should focus on the deep integration of lightweight algorithm design and emerging technologies to provide support for building an efficient, safe and green transportation system.

References

1. WHO: Global Status Report on Road Safety 2023.
2. Mavrovouniotis, M., Li, C., Yang, S.: "A survey of swarm intelligence for dynamic optimization: Algorithms and applications," Swarm and Evolutionary Computation, 2017, 33, pp. 1-17. DOI: 10.1016/j.swevo.2016.05.001.
3. Slim, M., Daher, N., Elhajj, I. H.: "Dynamic Bandwidth Allocation for Collaborative Multi-Robot Systems Based on Task Execution Measures," J Intell Robot Syst, 2024, 110, pp. 114. DOI: 10.1007/s10846-024-02126-y.

4. Naheliya, B., Redhu, P., Kumar, K.: "A Review on Developments in Evolutionary Computation Approaches for Road Traffic Flow Prediction," Arch Computat Methods Eng, 2024. DOI: 10.1007/s11831-024-10189-1.
5. Huan, Y.: "The Impact of Path Planning Model Based on Improved Ant Colony Optimization Algorithm on Green Traffic Management," International Journal of Advanced Computer Science and Applications (IJACSA), 2024, 15(6). DOI: 10.14569/IJACSA.2024.01506109.
6. Song, M., Xiao, F., Liu, H., Wu, S., Zhao, X., Sui, G.: "Research on the application of ant colony algorithm in optimal path planning according to the concept of intelligent transportation," Proc. SPIE 13251, Ninth International Conference on Electromechanical Control Technology and Transportation (ICECTT 2024), 132513W, 28 August 2024. DOI: 10.1117/12.3039951.
7. Yahia, M. A., Gueye, M. M., Jaafar, W., Langar, R.: "On the Joint Placement of Blockchain and Users' Virtualized Services in the Internet of Vehicles," Proceedings of the 2024 7th Conference on Cloud and Internet of Things (CIoT), Montreal, QC, Canada, 2024, pp. 1-8. DOI: 10.1109/CIoT63799.2024.10757064.
8. Tian, Z., He, Y., Tian, B., Zhong, R., Foorginejad, E., Shi, W.: "ICAT: An Indoor Connected and Autonomous Testbed for Vehicle Computing," Proceedings of the 2024 IEEE International Conference on Mobility, Operations, Services and Technologies (MOST), Dallas, TX, USA, 2024, pp. 242-250. DOI: 10.1109/MOST60774.2024.00033.
9. Jia, W., Bin, D.: "Exploring Applications of Artificial Intelligence Technology in Modern Intelligent Logistics Development," Proceedings of the 2024 IEEE 7th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chongqing, China, 2024, pp. 1359-1364. DOI: 10.1109/ITNEC60942.2024.10733205.
10. Aslan, S., Karaboga, D.: "A genetic Artificial Bee Colony algorithm for signal reconstruction based big data optimization," Applied Soft Computing, 2020, 88, pp. 106053. DOI: 10.1016/j.asoc.2019.106053.
11. Jovanovic, A., Teodorović, D.: "Fixed-Time Traffic Control at Superstreet Intersections by Bee Colony Optimization," Transportation Research Record: Journal of the Transportation Research Board, 2021, 2676, pp. 036119812110581. DOI: 10.1177/03611981211058104.
12. Mirjalili, S., Mirjalili, S. M., Lewis, A.: "Grey Wolf Optimizer," Advances in Engineering Software, 2014, 69, pp. 46-61. DOI: 10.1016/j.advengsoft.2013.12.007.
13. Li, J., et al.: "Experience-Shared Variable-Step Predictive Control of Range-Extended Electric Vehicles Using Transferable Driver Model," IEEE Transactions on Intelligent Transportation Systems, 2024. DOI: 10.1109/TITS.2024.3489018.
14. S., R., S., K., R., K., A. R. K.: "Optimizing Electric Vehicle Energy Consumption with Artificial Intelligence," Proceedings of the 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Coimbatore, India, 2024, pp. 553-557. DOI: 10.1109/ICoICI62503.2024.10696080.
15. Bayindir, L.: "A review of swarm robotics tasks," Neurocomputing, 2016, 172, pp. 292-321. DOI: 10.1016/j.neucom.2015.05.116.
16. Fatemidokht, H., Rafsanjani, M. K., Gupta, B. B., Hsu, C.-H.: "Efficient and Secure Routing Protocol Based on Artificial Intelligence Algorithms With UAV-Assisted for Vehicular Ad Hoc Networks in Intelligent Transportation Systems," IEEE Transactions on Intelligent Transportation Systems, 2021, 22(7), pp. 4757-4769. DOI: 10.1109/TITS.2020.3041746.
17. Zedadra, O., Guerrieri, A., Jouandeau, N., Spezzano, G., Seridi, H., Fortino, G.: "Swarm intelligence-based algorithms within IoT-based systems: A review," Journal of Parallel and Distributed Computing, 2018, 122, pp. 173-187. DOI: 10.1016/j.jpdc.2018.08.007.

18. Zhao, L., Li, T., Zhang, E., Lin, Y., Wan, S.: "Adaptive swarm intelligent offloading based on digital twin-assisted prediction in VEC," IEEE Transactions, 2023.