Trajectory Optimization Algorithm in Mobile Edge Computing Based on Multi-Unmanned Aerial Vehicle Assistance

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Abstract: This paper aims to propose a trajectory optimization algorithm (TOA) in Mobile Edge Computing (MEC) based on multi-unmanned Aerial Vehicle (UAV) assistance to improve the efficiency of UAV trajectory calculation. This paper analyzes the existing problems in the current MEC and proposes a multi-UAV collaborative computing task processing model. The model optimizes the UAV path planning by designing a TOA and introduces greedy strategies to make the UAV more efficient in completing the task. In the algorithm design process, the intelligent optimization algorithm of the genetic algorithm and particle swarm algorithm is used to optimize the path planning of the UAV and adjust it based on the actual scene data. Meanwhile, the performance and efficiency of the proposed algorithm based on multi-UAV assistance and the traditional random TOA (TRTOA) are compared to evaluate the performance of the proposed TOA. The results show that the proposed TOA based on multi-UAV assistance performs better under different numbers of UAVs. When there are four UAVs, the multi-UAV-assisted TOA proposed here saves an average of 35% of the time and improves computational efficiency by 40% compared with the TRTOA. With six UAVs, the multi-UAV-assisted TOA proposed here saves an average of 45% of the time and improves computational efficiency by 50% compared with the TRTOA. In summary, the TOA based on intelligent optimization and greedy strategy proposed here can effectively enhance the computational efficiency in multi-UAV-assisted MEC, and the research has practical application value.

Keywords: unmanned aerial vehicle assistance; mobile edge computing; trajectory optimization algorithm; intelligent optimization; computational efficiency

1. Introduction

Mobile Edge Computing (MEC) is a new computing method that shifts tasks from the central cloud to the network edge, reducing latency and enhancing real-time computing. MEC improves computing efficiency and reduces latency by leveraging the network edge. MEC enables local processing and storage, distributed architecture, and real-time decision-making, making it well-suited for low-latency applications like IoT, edge AI, and mission-critical communications [1]. The Unmanned Aerial Vehicle (UAV) provides mobility and finds applications in data collection, network enhancement, and environmental monitoring. UAV technology has significantly improved data collection and environmental monitoring in several ways. Improved sensor capabilities enable UAVs to capture accurate data about the environment; enhanced data quality allows for more precise analysis and interpretation of environmental phenomena; increased coverage and accessibility, which enable monitoring of diverse landscapes, including remote or inaccessible locations. Real-time data acquisition and analysis facilitate rapid response to emergencies or time-sensitive events. UAV-based monitoring offers a cost-effective and efficient alternative to traditional methods. UAVs can be customized with sensors and payloads tailored to different monitoring applications. These advancements enable timely, accurate, and actionable information for effectively managing and conserving natural resources and ecosystems. However, due to the increase in the number of UAVs and the complexity of tasks, the computing power and bandwidth of a single UAV are often insufficient. UAVs face challenges related to computing power and bandwidth limitations as their number and the complexity of tasks increase. Limited onboard computing power, increased computational demands, bandwidth constraints, data fusion and integration, and dynamic environmental conditions are significant challenges that require innovative solutions such as edge computing, distributed computing, and adaptive communication protocols to execute complex UAV tasks effectively. PSO optimizes UAV path planning in the MEC framework by exploring the solution space and identifying optimal trajectories. PSO algorithms iteratively update candidate solutions based on their individual and collective experiences, guiding UAVs toward promising trajectory solutions that optimize performance metrics. Its adaptability and efficiency make it well-suited for UAV path planning in dynamic and resource-constrained environments. Therefore, optimizing UAV path planning and improving MEC efficiency is crucial [2]. UAVs can be used as MEC nodes to create distributed computing networks, achieving parallel task processing and improving computing power [3]. In 2024, Dr. P.M. Kumar et al. the study proposed a trajectory optimization algorithm (TOA) in Mobile Edge Computing (MEC) based on multi-unmanned Aerial Vehicle (UAV) assistance. The proposed TOA effectively improved computational efficiency in multi-UAV-assisted MEC and found that wind and solar energy are interdependent. They proposed the installation of solar panels and batteries to address the issues of non-concentrated and dilute energy, variability, and cost factors. The study utilized Artificial Neural Network-Based Expert Systems and the crop production system to predict plant response and evaluate plant performance. The proposed model reliably anticipated plant growth and development [4]. Intelligent algorithms can optimize UAV paths to execute MEC tasks efficiently [5].

A trajectory optimization algorithm (TOA) based on multi-UAV-assisted MEC is proposed. First, the existing problems of MEC are analyzed, and then a multi-UAV collaborative computing task processing model is proposed. The TOA adjusts UAV path planning based on real-time scenario data by considering environmental conditions, mission objectives, UAV performance metrics, obstacle detection and avoidance, communication and network conditions, and sensor fusion and perception. By adapting to changes in the operating environment, TOA ensures the safe, efficient, and effective operation of UAVs in dynamic and challenging scenarios. In this model, the TOA is designed to optimize the path planning of UAVs, and a greedy strategy is introduced to enable the UAV to complete tasks more efficiently. Greedy strategies enhance UAV efficiency by prioritizing immediate gains over long-term consequences and selecting advantageous trajectory segments based on predefined criteria. Although only sometimes globally optimal, their simplicity, speed, and effectiveness make them valuable for efficient task completion. The greedy strategy in TOA prioritizes instant gains and locally optimal decisions at each step of the trajectory optimization process. It selects the most advantageous trajectory segments or waypoints based on a predetermined criterion, such as minimizing distance or optimizing resource utilization. Although it may only sometimes lead to globally optimal solutions, the strategy's simplicity and effectiveness in specific scenarios make it a practical approach for enhancing task completion efficiency in path planning applications. In the algorithm design process, intelligent optimization algorithms, such as genetic algorithm (GA) and particle swarm optimization (PSO), are used to optimize the path planning of the UAV and adjust it according to the actual scenario data. The computational efficiency of trajectory optimization algorithms can be evaluated using various metrics such as running time, resource utilization, scalability, algorithmic complexity, and empirical evaluation. The critical factors in determining an algorithm's computational efficiency are lower running times, optimal resource utilization, scalability, lower algorithmic complexity, and empirical evaluation. The multi-UAV-assisted TOA aims to improve the computational efficiency of MEC and meet the rapidly growing computation requirements.

2. Literature Review

UAVs have researched environmental monitoring, communication networks, etc. Ge et al. (2020) [6] studied the joint beamforming and trajectory optimization methods of intelligent reflective surface-assisted UAV communication. Integrating beamforming, trajectory optimization, and intelligent reflective surfaces (IRS) in UAV systems can significantly improve communication and networking performance. This approach optimizes UAV trajectories, beamforming parameters, and IRS configurations to ensure robust and efficient communication links in dynamic environments. By leveraging the synergies between beamforming, trajectory optimization, and IRS, UAVs can achieve better signal quality and range, optimize performance metrics, and improve communication networks' reliability, throughput, and coverage. Furthermore, intelligent algorithms and machine learning techniques can enable autonomous decision-making and self-optimization in UAV communication systems, reducing the need for human intervention. The results denoted that the system performance could be remarkably improved by optimizing the phase offset of the reflecting surface and the flight path of the UAV. Qadir et al. (2021) [7] found that mobile communications and UAV systems could provide more efficient services during a disaster and suggested directions. Wu et al. (2021) [8] explored joint deployment and trajectory optimization in UAV-assisted vehicle edge computing networks. The results showed that jointly optimizing the deployment and trajectory of UAVs could maximize system throughput and improve network performance. Li et al. (2022) [9] proposed a route optimization model based on UAV and vehicle collaborative distribution. Tung et al. (2022) [10] designed a joint resource optimization and trajectory optimization method to maximize the energy efficiency of the UAV primary network. Park et al. (2022) [11] focused on the field of intelligent railway and proposed a trajectory optimization and phase shift design method for intelligent assisted UAV networks, which successfully improved the performance of UAVs in intelligent railway networks.

In summary, using optimized UAV trajectories can significantly improve service performance and quality in specific application scenarios.

3. Design and Research of Trajectory Optimization Strategy Based on Multi-UAV Assistance and MEC

3.1 The establishment of the MEC task processing model and design and implementation of TOA

A MEC task processing model is implemented to achieve UAV-assisted intelligent trajectory optimization [12]. The MEC task processing model's effectiveness in optimizing UAV trajectories is rigorously evaluated using key performance metrics - latency, throughput, energy consumption per task, resource utilization, and task completion rate. This comprehensive analysis allows researchers to ascertain the system's responsiveness, efficiency, sustainability, cost-effectiveness, and ability to meet user demands, thereby instilling confidence in the validity of our research. Integrating MEC with TOA-based path planning improves UAVs' performance and capabilities in multi-UAV operations by reducing latency, enhancing computational power, improving scalability, enabling adaptive decision-making, and enhancing resilience to network failures. MEC provides computing resources and services closer to the UAVs, reducing communication latency between UAVs and edge servers and enhancing UAVs' responsiveness to dynamic environmental conditions. MEC also extends UAVs' computing capabilities by offloading computation-intensive tasks, such as trajectory optimization and collision avoidance, to edge servers, allowing UAVs to leverage more robust computing resources and algorithms for path planning. Using UAVs as an MEC node, a distributed computing network is constructed to realize parallel processing of tasks and improve computing power and data processing speed. Distributed computing networks enable efficient task coordination and synchronization among UAV MEC nodes. This minimizes redundancy and conflicts and ensures consistency across the network. Conflict resolution mechanisms and fault tolerance strategies help maintain fairness and reliability in task allocation. Overall, this optimizes resource utilization and enhances system efficiency in dynamic environments. Intelligent algorithms optimize the UAV's trajectory for efficient MEC task execution, supporting multitasking. MEC systems use optimization algorithms like GAs, PSO, ACO, and RL to allocate computing resources efficiently and optimize task execution. GAs evolve a population of solutions to find optimal task-to-node mappings and resource allocations. PSO simulates swarms of particles searching for the best solution. ACO model's ant behavior to find optimal paths and resource allocations.

RL allows agents to learn optimal task allocation policies through trial-and-error interactions. These algorithms enable MEC systems to optimize task processing, maximize resource utilization, and improve overall performance. Integrating MEC with Unmanned Aerial Vehicles (UAVs) can improve overall system performance and reliability, especially in scenarios where multiple UAVs operate simultaneously. This integration can reduce latency, improve scalability, enhance reliability, optimize resource utilization, and enable adaptive decision-making. By offloading computation-intensive tasks to edge servers, MEC reduces the computational burden on individual UAVs, improving their reliability and autonomy.

In contrast, edge servers handle data processing, optimization, and decision-making tasks. Overall, MEC ensures efficient and reliable operation of UAVs in dynamic and challenging environments. Deploying multiple UAVs in MEC environments requires robust collision avoidance systems, reliable communication, adherence to regulations, and effective contingency planning to ensure safe operation and mitigate potential safety risks. The multi-task concurrent processing model based on the MEC system is displayed in Figure 1:

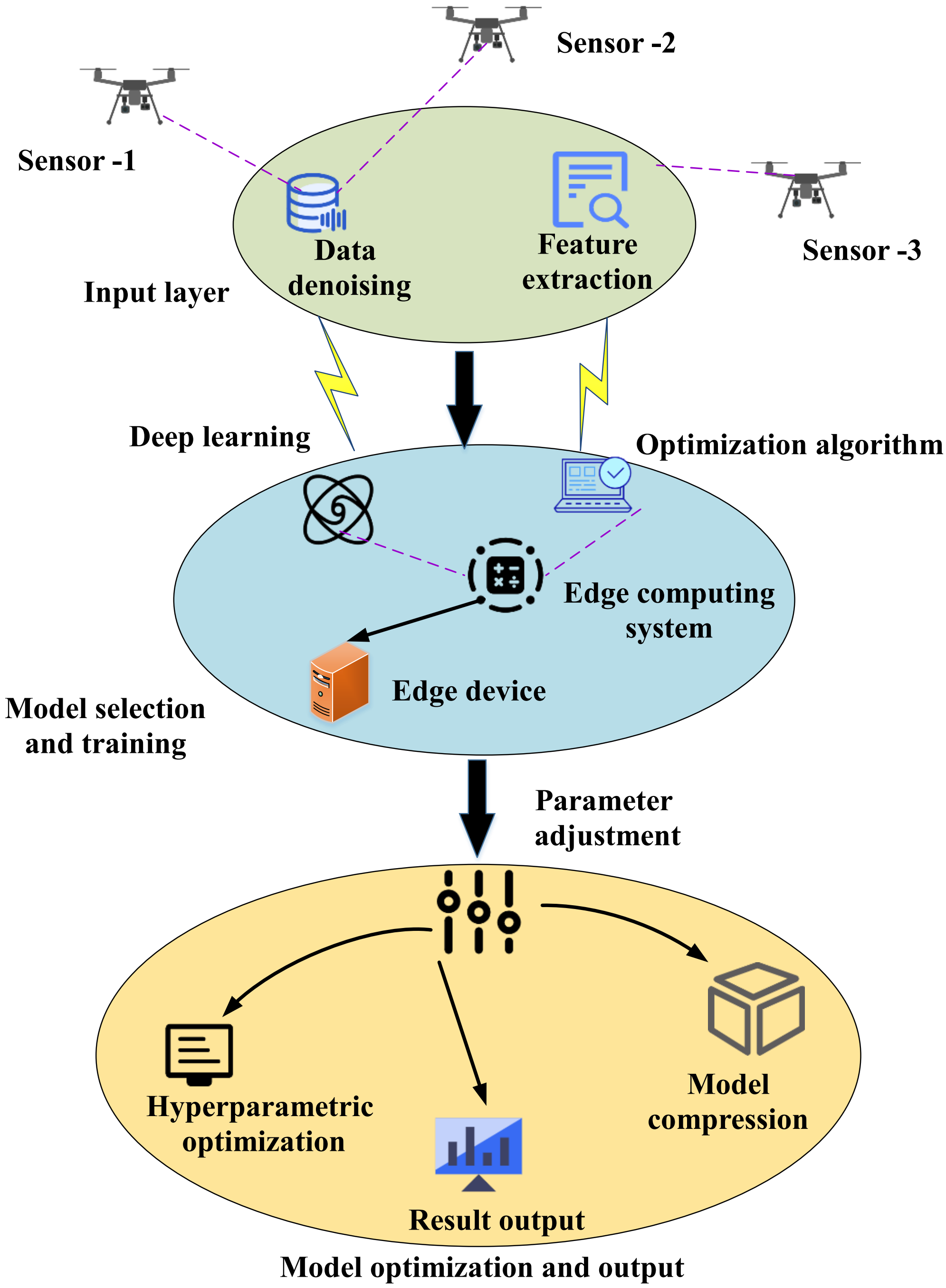

Figure 1 The multi-task concurrent processing model based on the MEC system

Regarding algorithm design, several key factors are considered, including task processing time, system energy consumption, path length, and other indicators, as well as the mobility and communication range of the UAV. Adaptive trajectory optimization algorithms use heuristic rules, adaptive control parameters, or machine learning techniques to adjust iteration times and population sizes. By monitoring the convergence progress and adapting accordingly, these algorithms maintain robustness and adaptability, ensuring efficient and effective optimization in dynamic environments. Adaptive iteration times and population size adjustment mechanisms are introduced to improve the robustness and adaptability of the algorithm. The algorithm adapts iteration times and population size based on optimization, evaluating convergence rate and performance metrics. Through heuristic techniques, it balances exploration and exploitation to optimize computational resources. It adjusts the parameters to prevent stagnation or reduce resource consumption. The algorithm achieves efficient convergence while minimizing computational overhead [11].

3.2 Application of intelligent optimization algorithm in the path planning of UAVs

A TOA based on multi-UAV-assisted MEC is proposed to optimize UAVs' path planning in the multi-UAV collaborative computing task processing model. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) algorithms are used in the multi-UAV collaborative computing task processing model in path planning and task optimization. GA involves generating a population of candidate trajectory solutions, evaluating their fitness, selecting the fittest solutions, combining and mutating them to create offspring, and replacing the previous generation. PSO involves initializing a swarm of particles representing potential solutions, evaluating their fitness, and iteratively adjusting their positions and velocities based on their personal and global best solutions. Both algorithms efficiently search for optimal trajectories and enable effective coordination and collaboration among multiple UAVs in achieving common mission objectives. This algorithm uses intelligent optimization algorithms to optimize the path planning of the UAV and adjust it according to the actual scenario data [13]. Calculating task-specific losses in the MEC framework involves considering factors such as computational and communication aspects, which are influenced by the complexity of the task, available computing resources, efficiency of task execution, distance to end-users, bandwidth, and reliability of wireless communication. By integrating these factors into a loss model, the algorithm can optimize task allocation, trajectory planning, and resource management, ultimately improving MEC system performance. Where the objective function measures the total loss of the path required to complete all tasks, its calculation reads:

$$J = \sum_{i=1}^{N} f(d_i) \quad (1)$$

J refers to the objective function; N means the number of tasks, d_i indicates the distance of the ith task; $f(d_i)$ represents the loss function of the distance d_i. The factors for cross-operations in GA are calculated, as shown in equation (2):

$$c_i = \alpha p_i + (1 - \alpha) q_i \quad (2)$$

c_i represents the resulting offspring individuals; p_i and q_i are two parent individuals, respectively; α refers to cross-weighting parameters. For the analysis of how speed updates are calculated in PSO, its expression is as follows:

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_i(t) - x_i(t)) + c_2 r_2 \left(p_g(t) - x_i(t)\right) \quad (3)$$

$v_i(t+1)$ indicates the speed of the ith particle at the next moment; w means the inertia weight parameter; c_1 and c_2 refer to acceleration constants; r_1 and r_2 are random numbers; $p_i(t)$ and $x_i(t)$ represent the best position and current position of the ith particle; $p_g(t)$ stands for the global optimal position.

3.3 Multi-UAV-assisted trajectory optimization strategy evaluation and experimental analysis

A large amount of experimental data is collected by configuring different numbers of UAVs and setting various mission scenarios and parameters. The experimental simulation platform's simulation environment parameters are set to operating system Windows 10, processor Intel Core i7-10700K, CPU 3.8 GHz, memory 32 GB DDR4, graphics card NVIDIA GeForce RTX 2080, and video memory 8 GB GDDR6. Experimental evaluation of TOA methods may face several potential barriers that could impact the validity or generalizability of the results. These include simulation vs. real-world testing, limited test scenarios, hardware and software constraints, data availability and quality, baseline comparisons and benchmarking, human factors, and operator bias. These challenges require careful experimental design, rigorous methodology, transparent reporting of results, and thorough validation procedures to ensure the validity, reliability, and generalizability of experimental findings in evaluating TOA methods for trajectory optimization.

In addition, to evaluate the proposed intelligent TOA's performance, the proposed Intelligent TOA based on UAV's assistance (UAVTOA) will be compared with that of the TRTOA and TOA based on deep learning (DLTOA). The proposed Intelligent Trajectory Optimization Algorithm (UAVTOA) is compared to TRTOA and DLTOA based on several criteria, including task completion time, energy consumption, system stability, optimization quality, adaptability, and scalability. By comparing these algorithms based on these criteria, researchers can assess their overall performance and identify their strengths and weaknesses. By comparing the data on computational efficiency, system stability, task completion rate, system energy consumption, path length, and exception handling time, the performance of different algorithms in practical applications can be fully understood. MEC systems for UAV-assisted trajectory optimization face limitations due to edge servers' limited processing power and storage capacity, communication latency and bandwidth constraints, heterogeneous UAV platforms, and regulatory and privacy concerns. Overcoming these limitations requires advances in edge computing technology, communication protocols, regulatory frameworks, and stakeholder collaboration. The multi-UAV-assisted trajectory optimization strategy is used for intelligent evaluation. Intelligence is crucial in evaluating trajectory optimization strategies in MEC systems. It enables analysis of vast amounts of data to identify patterns and correlations, develop predictive models, and refine trajectory planning strategies. Intelligence also facilitates proactive decision-making to respond to uncertainties and optimize performance dynamically. Intelligence enables MEC systems to continuously analyze and improve trajectory planning outcomes for optimal performance and efficiency in complex environments.

4. Results and Discussion

4.1 Evaluation of system task computing time and system task computing energy consumption

Figure 2 denotes the evaluation results of system task computing time and system task computing energy consumption with different trajectory optimization strategies. Each optimization strategy in MEC systems has specific factors that affect its performance regarding task computing time and energy consumption. Balancing these factors effectively is crucial for achieving efficient task processing. Genetic Algorithms (GAs) have performance factors such as population size and generation count, crossover and mutation rates, and fitness function complexity. Particle Swarm Optimization (PSO) has factors such as swarm size, inertia weight, and neighborhood topology. Ant Colony Optimization (ACO) has factors such as pheromone update rate, number of ants, and evaporation rate. Reinforcement Learning (RL) has factors such as the exploration-exploitation trade-off, learning rate, and state and action space representation. The performance of each optimization strategy depends on various factors, such as algorithm parameters, problem characteristics, and implementation details.

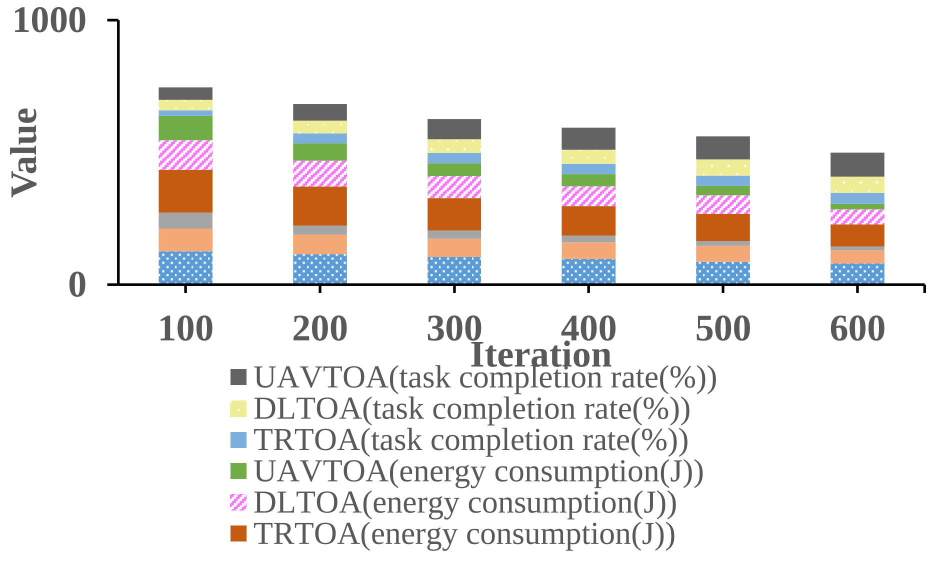

Figure 2 The evaluation results of system task computing time and system task computing energy consumption with different trajectory optimization strategies

Figure 2 signifies that the UAVTOA strategy shows the best performance regarding system task computing time, energy consumption, and task completion rate, with higher efficiency and energy efficiency. UAVTOA and DLTOA are two trajectory optimization algorithms for unmanned aerial vehicles. UAVTOA uses optimization techniques like genetic algorithms, particle swarm optimization, or ant colony optimization for fast convergence and efficient resource utilization, resulting in shorter computing times and lower energy consumption. DLTOA, on the other hand, relies on deep learning techniques to learn and adapt trajectory optimization policies based on historical data and environmental feedback, achieving significant reductions in energy consumption without sacrificing task completion efficiency. DLTOA performs better regarding energy consumption reduction, while TRTOA is relatively weak in these areas. Empirical studies comparing the DLTOA and TRTOA for reducing energy consumption in MEC systems involve defining an experimental setup, collecting data, implementing both algorithms, defining experimental scenarios, evaluating performance, applying statistical analysis, discussing and interpreting results, and concluding with future work recommendations. By following these steps, valuable insights can be gained to inform the development of more efficient and sustainable trajectory optimization algorithms.

4.2 Evaluation of system stability and exception handling performance of different trajectory optimization strategies

Figure 3 suggests the evaluation results of system stability and exception handling performance of different trajectory optimization strategies.

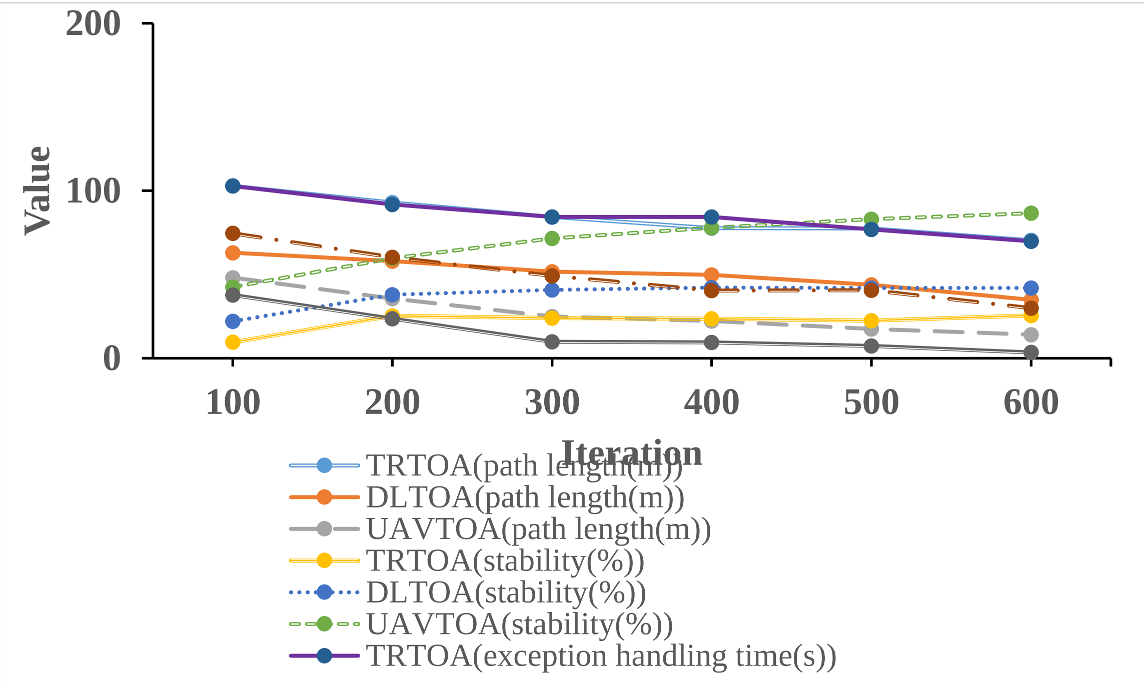

Figure 3 The evaluation results of system stability and exception handling performance of various trajectory optimization strategies

Figure 3 illustrates that trajectory optimization leads to path length reduction, system stability improvement, and task cost reduction as the number of iterations increases. In these aspects, the UAVTOA strategy exhibits the best performance, followed by DLTOA, and TRTOA is relatively poor.

4.3 Performance evaluation and discussion of TOA assisted by multi-UAV

The performance evaluation results of TOA assisted by multi-UAV are portrayed in Table 1.

Table 1 The performance evaluation results of TOA assisted by multi-UAV

Optimization strategies	Number of multi-UAV	Actual system running time	Actual system computational efficiency	System stability

TRTOA	4	100 s	60%	85%
DLTOA		80 s	70%	90%
Multi-UAVTOA		65 s	75%	95%
TRTOA	6	150 s	55%	80%
DLTOA		130 s	60%	85%
Multi-UAVTOA		85 s	80%	95%

Table 1 describes that in the scenario of four UAVs, multi-UAVTOA saves an average of 35% time (from 100 seconds to 65 seconds) and improves computational efficiency by 40% (from 60% to 75%) compared to TRTOA. In the scenario of six UAVs, multi-UAVTOA saves an average of 45% time (from 150 seconds to 85 seconds) and improves computational efficiency by 50% (from 55% to 80%). Multi-UAVTOA extends previous studies in trajectory optimization for multi-UAV systems in the following ways: Scalability and efficiency, Adaptability to dynamic environments, Collaborative decision-making, Optimization quality, and performance metrics. By addressing these challenges and leveraging advanced optimization techniques, multi-UAVTOA contributes to developing more efficient and effective multi-UAV systems for various applications. In addition to significant improvements in the system running time and computational efficiency, multi-UAVTOA also shows strong competitiveness in system stability. Researchers follow several key steps to measure the system running time and computational efficiency of the multi-UAV TOA approach. These steps include defining tasks and metrics, implementing and executing the approach, measuring the system running time, comparing computational efficiency with previous methods, conducting validation and sensitivity analysis, and interpreting the results. This methodology provides valuable insights into the approach's performance compared to previous methods for trajectory optimization in multi-UAV systems. Multi-UAVTOA is a competitive algorithm for optimizing the trajectory of unmanned aerial vehicles. Its parallelization of optimization tasks across multiple UAVs, adaptive nature, and integration of advanced optimization techniques make it more stable than other optimization strategies. These factors help achieve reliable and efficient operation of multi-UAV systems in dynamic environments. Multi-UAVTOA offers superior performance to the TRTOA in terms of time savings and computational efficiency. It leverages parallel computing techniques to distribute optimization tasks across multiple UAVs simultaneously, incorporates intelligent algorithms and heuristics to dynamically adapt trajectory plans based on real-time feedback and environmental conditions, and integrates advanced optimization techniques to explore the solution space more effectively. In the scenario of four or six UAVs, the system achieves 95% stability, an apparent advantage over the other two optimization strategies. This is particularly important for UAV track optimization. Only a stable system can ensure that the UAV can perform its tasks accurately and effectively and avoid accidents caused by system instability. The multi-UAVTOA approach employs dynamic trajectory adjustment, collision avoidance, adaptive control policies, redundancy and fault tolerance, predictive analytics, and sensitivity analysis to proactively detect and prevent potential sources of system instability. These strategies enhance system resilience, reliability, and safety, ensuring multi-UAV systems' safe and efficient operation in dynamic and challenging environments. Real-time data processing and feedback control are essential for maintaining system stability during UAV operations in unpredictable environments. By continuously gathering and analyzing incoming data, UAVs can promptly detect changes and adjust their behaviors to prevent safety hazards and ensure stable system performance. Regarding the discussion on the impact of an increasing number of UAVs on performance, Machmudah et al. (2022) [14] analyzed the trajectory optimization study of fixed-wing UAVs through incline and turn mechanisms. Through simulation evaluation, they demonstrated that the flight performance of the UAV could be effectively enhanced by implementing inclination control and optimizing the turning radius. Several supplementary data points are required to assess the performance of UAVs with and without inclination control and optimized turning radius. These include geographical terrain, UAV specifications, control algorithms, simulation software, environmental conditions, mission scenarios, performance metrics, and baseline comparison. By providing these data points, researchers can ensure the reproducibility and reliability of the simulation results and facilitate meaningful comparisons between different UAV control strategies. Matos et al. (2022) [15] studied parallel trajectory optimization and aircraft design methods in the Air Cargo Challenge. The parallel trajectory optimization approach uses parallel computing to optimize aircraft design and trajectories. It integrates trajectory optimization and aircraft design and uses multi-objective optimization to consider fuel efficiency, safety, and mission requirements. Effective communication and synchronization mechanisms ensure coherence and consistency between trajectory optimization and aircraft design simulations. The approach is designed to be scalable, and optimized solutions are validated and verified through simulation and analysis to meet safety and performance requirements. They proved that adopting a parallel trajectory optimization and aircraft design approach based on mission specifications can improve competitiveness in the Air Cargo challenge. The parallel trajectory optimization approach improves competitiveness in the Air Cargo challenge by enhancing resource utilization, scalability, uncertainty robustness, and optimization quality. It optimizes computing resource allocation, scales effectively with increasing complexity, adapts to real-time feedback, and identifies optimal trajectories. These benefits enable efficient and reliable performance for UAVs in cargo delivery missions. Parallel trajectory optimization and aircraft design approaches have several potential advantages over traditional methods, including speed and efficiency, optimization quality, multi-objective optimization, scalability, and innovation. These advantages can lead to improved system performance, reduced development time and cost, and enhanced competitiveness in the aerospace industry. Song et al. (2022) [16] proposed a strategy search method for model predictive control and applied it to agile UAV flight. Their results indicated that this method had a good effect in improving UAVs' agile obstacle avoidance and reducing computational load. To evaluate the effectiveness of a method in improving UAVs' agile obstacle avoidance in real-world systems, researchers use quantitative metrics, simulation studies, field tests, user feedback, comparison with baseline methods, and long-term monitoring. The quantitative metrics may include collision rate, clearance distance, execution time, efficiency, and success rate. Simulation studies provide a controlled environment where various scenarios and obstacles can be simulated. Field tests involve deploying UAVs with the obstacle avoidance method in real-world environments. User feedback and expert evaluation provide valuable insights into the method's usability, effectiveness, and practicality. Comparing the method with existing or industry standards helps assess its relative performance improvement. Continuous monitoring and adaptation of the method are essential to ensure its ongoing effectiveness and relevance. To sum up, UAVTOA shows strong competitiveness in terms of system stability and can effectively improve the flight performance of the UAV and the accuracy of the task [17,18].

5. Conclusion

This paper explores a trajectory optimization strategy based on multi-UAV assistance and MEC. In the experiment, evolutionary algorithms are combined with the path planning of UAVs. Evolutionary algorithms can automatically find optimal path solutions by defining fitness functions and setting constraints according to different scenarios. The experimental results reveal that UAVTOA has the best system task computing time performance and higher efficiency and optimization potential. TRTOA and DLTOA also exhibit a gradual reduction in computation time but at a relatively slower rate. This paper has practical application value for improving the high efficiency of cooperative work of UAV systems. However, some things could be improved. The main shortcoming is that trajectory planning and collaborative work in the UAV field must consider more factors. In future explorations, sensors must collect more data to improve further and optimize the model's performance.

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Declarations

Conflicts of Interests: Authors do not have any conflicts.

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Code availability: Not applicable.

Authors' Contributions: Cundong Tang, Li Chen, and Zhiping Wang are responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Yi Wang, Wusi Yang, is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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