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Research on Optimization of Complex Waypoint Path Planning for UAVs Based on Computer Algorithms

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Abstract: Unmanned aerial vehicles operating in dynamic, cluttered environments face significant challenges in generating feasible, time-efficient, and energy-optimal paths through multiple complex waypoints. This study presents a unified computational framework for optimizing multi-constraint waypoint path planning for UAVs, integrating geometric feasibility, kinematic continuity, obstacle avoidance, and mission-specific objective trade-offs. A hybrid algorithm is developed that combines adaptive sampling-based exploration with gradient-informed local refinement and real-time replanning triggers. The method operates directly on high-fidelity vehicle dynamics models, enforcing bounded curvature, maximum angular velocity, and minimum turning radius constraints throughout the trajectory. Experimental validation was conducted across 12 distinct urban, forested, and mixed-terrain scenarios with varying waypoint densities (5–25 points), obstacle counts (10–68), and environmental uncertainty levels. Results demonstrate consistent reductions in total flight time (14.7%–29.3%), energy consumption (11.2%–24.8%), and path length (7.9%–18.5%) compared to baseline A* and RRT* implementations, while maintaining 100% success rate in constraint satisfaction. Computational latency remains below 180 ms per planning cycle on embedded hardware, enabling integration into onboard autonomy stacks. The framework exhibits robustness to sensor noise up to ± 1.2 m in position estimation and ± 0.3 rad/s in attitude rate measurement. These findings establish a scalable, deterministic-yet-adaptive approach for complex waypoint navigation without reliance on precomputed maps or offline learning phases.

Keywords: UAV path planning; waypoint optimization; trajectory generation

1. Introduction

1.1. Operational Challenges in Complex Waypoint Navigation

The increasing deployment of autonomous unmanned aerial vehicles across infrastructure inspection, precision agriculture, and emergency response necessitates robust waypoint path planning in geometrically intricate and dynamically constrained environments [1]. These applications demand strict adherence to spatially dense, non-convex waypoint sequences while respecting real-time operational constraints. A fundamental tension arises between path smoothness—critical for minimizing energy consumption and structural stress—and computational latency, where excessive optimization time compromises mission responsiveness. Simultaneously, dynamic feasibility must be guaranteed under bounded actuator capabilities, including maximum angular velocity, linear acceleration, and yaw rate limits. Safety integrity further complicates the problem: trajectories must maintain rigorously defined separation margins from both static obstacles—such as buildings or power lines—and unpredictable moving agents, including manned aircraft or other UAVs [2]. These interdependent requirements render conventional path-planning paradigms insufficient, particularly when waypoints exhibit high curvature, tight spacing, or time-varying constraints. Consequently, next-generation algorithms must co-optimize geometric fidelity, dynamical admissibility, and collision resilience within stringent temporal budgets—

Received: 02 January 2026

Revised: 26 February 2026

Accepted: 09 March 2026

Published: 13 March 2026



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establishing a multidimensional trade-off landscape that resists decomposition into isolated subproblems.

1.2. Scope and Technical Objectives

This section delineates the technical scope and objectives of the present work [3]. The methodology targets offline-to-online capable path optimization for fixed-wing and multirotor unmanned aerial vehicles navigating sequences of at least five non-collinear waypoints in three-dimensional space, under conditions of known or partially observable obstacle distributions. Three core technical objectives are established: first, minimization of the integrated energy cost across the entire trajectory, formulated as $\int_{t_0}^{t_f} \mathcal{E}(t) dt$; second, strict enforcement of kinematic feasibility—ensuring that velocity, acceleration, angular rate, and curvature constraints remain satisfied at every point along the path; third, achievement of sub-second replanning latency following environmental perturbations or waypoint updates, with deterministic upper bounds on computational overhead. The framework explicitly accommodates heterogeneous UAV dynamics, variable obstacle fidelity, and real-time adaptability without sacrificing solution optimality guarantees. Emphasis is placed on numerical stability, convergence robustness, and hardware-agnostic deployment across embedded flight control systems [4]. All algorithmic components are designed to operate within bounded memory footprints and deterministic timing envelopes suitable for safety-critical autonomous operations.

1.3. Contributions and Methodological Positioning

This work introduces three principal contributions to UAV waypoint path planning [5]. First, a curvature-bounded B-spline parameterization is developed with adaptive knot insertion, ensuring kinematic feasibility while preserving geometric smoothness. Second, a dual-layer cost function is formulated to jointly penalize traversal time, energy consumption, and jerk magnitude, thereby balancing dynamical efficiency and passenger comfort. Third, an event-triggered local replanner is designed, activating only upon exceeding predefined spatial or temporal deviation thresholds—eliminating periodic computational waste. All components are analytically proven to guarantee deterministic convergence under bounded disturbance. Implementation prioritizes hardware-aware constraints, including real-time schedulability, memory footprint minimization, and sensor latency compensation. The integrated framework bridges theoretical optimality with embedded-system deployability across heterogeneous aerial platforms [6].

2. Literature Review

2.1. Classical Approaches to Multi-Waypoint Planning

Classical approaches to multi-waypoint planning for unmanned aerial vehicles establish foundational geometric and combinatorial frameworks [7]. Dubins and Reeds-Shepp curves provide minimum-length kinematically feasible paths between waypoints under bounded curvature constraints, while polynomial interpolation—particularly cubic and quintic splines—ensures continuity in position, velocity, and acceleration across segments. Graph-based methods, including Dijkstra and A* algorithms, are adapted to waypoint sequencing by modeling the environment as a weighted graph where edge costs encode path length, turning effort, or risk exposure [6, 8]. However, these techniques exhibit structural limitations when simultaneously enforcing dynamic constraints—such as bounds on linear velocity $v_{\max}$, tangential acceleration $a_{t,\max}$, and yaw rate $\omega_{\max}$ —within spatially heterogeneous obstacle fields [9, 10]. Their decoupled treatment of geometry, dynamics, and environmental uncertainty impedes real-time feasibility verification and often necessitates post-hoc smoothing or constraint relaxation [11]. Consequently, classical methods serve as essential baselines but lack the integrated optimization architecture required for robust, high-fidelity trajectory synthesis in complex operational domains.

2.2. Sampling-Based and Learning-Augmented Methods

Sampling-based planners such as probabilistic roadmap (PRM) and rapidly-exploring random tree (RRT) variants dominate UAV waypoint path planning in complex environments due to their asymptotic optimality and probabilistic completeness [12]. However, their computational scalability degrades markedly in high-dimensional state spaces—particularly when incorporating dynamic constraints, multi-rotor aerodynamics, or real-time sensor feedback—owing to exponential growth in sampling density requirements. Empirical studies indicate that PRM construction time scales superlinearly with obstacle complexity, while RRT convergence slows significantly under sparse sampling regimes, often yielding suboptimal trajectories near narrow passages. Recent learning-augmented approaches integrate neural trajectory predictors trained on synthetic or flight-log datasets to accelerate query resolution. Yet these models lack formal safety guarantees, exhibit brittle generalization outside training distributions—especially under novel wind profiles or unmodeled actuator delays—and remain incompatible with certification frameworks requiring deterministic worst-case bounds. Consequently, hybrid architectures that embed verifiable geometric constraints within learned priors, or that enforce Lipschitz continuity on prediction residuals, represent a critical frontier for certifiable autonomy in safety-critical UAV operations [13].

2.3. Gaps in Current Practice

Critical gaps persist in contemporary UAV waypoint path planning frameworks [7]. First, no consensus exists on a unified cost metric that jointly penalizes temporal duration, energy consumption, and control effort—leading to suboptimal trade-offs across mission-critical objectives. Second, actuator dynamics are routinely modeled as symmetric, neglecting inherent physical asymmetries such as differential pitch-up versus pitch-down saturation limits, which induce systematic trajectory bias under aggressive maneuvers. Third, real-time replanning is typically implemented as an external trigger-based module rather than being intrinsically embedded within the optimization loop; this decoupling introduces latency, violates causality constraints during dynamic obstacle encounters, and prevents gradient-based adaptation of the objective landscape. Consequently, existing methods lack provable convergence guarantees under time-varying constraints and fail to maintain feasibility when subject to rapid environmental perturbations [7]. These deficiencies collectively undermine operational robustness in complex urban or cluttered natural environments where multi-objective optimality, hardware-aware actuation fidelity, and closed-loop responsiveness are simultaneously required [3]. Addressing these interdependent shortcomings necessitates a reformulation of the underlying optimization architecture—not merely algorithmic refinement.

3. Materials and Methods

3.1. System Modeling and Constraint Formulation

The UAV dynamics are modeled as a six-degree-of-freedom rigid body governed by Newton–Euler equations, incorporating time-varying mass, full inertia tensor $\mathbf{J} \in \mathbb{R}^{3 \times 3}$, thrust vectoring actuation limits, and quadratic aerodynamic drag parameterized by coefficients $C_{D,x}$, $C_{D,y}$, and $C_{D,z}$. Hard kinematic and dynamic constraints are formulated as inequality conditions to ensure physical feasibility and operational safety [5]. The maximum longitudinal acceleration is bounded at $a_{x,\max} = 3.2 \text{ m/s}^2$; the minimum turning radius is constrained to $R_{\min} = 12.5 \text{ m}$, which implicitly restricts lateral acceleration and yaw coupling; the yaw rate is limited to $\omega_{z,\max} = 1.8 \text{ rad/s}$; and obstacle avoidance mandates a uniform clearance margin of $d_{\text{clear}} = 3.0 \text{ m}$ from all static and dynamic obstacles. All constraints are encoded in the optimization problem as nonlinear inequality functions of state and control variables. As detailed in Table 1, these four key parameters—maximum longitudinal acceleration, minimum turning radius, yaw rate limit, and obstacle clearance margin—are explicitly tabulated with their corresponding symbols, nominal values, and SI units. This constraint set ensures that generated trajectories remain executable under realistic actuator saturation, structural loading, and environmental interaction limits while preserving numerical tractability for

gradient-based and sampling-based solvers. The model further supports modular integration of sensor noise models and communication latency effects without altering the core constraint structure.

Table 1. Key UAV Dynamic Parameters Used in Optimization

Parameter	Symbol	Value	Unit
Maximum longitudinal acceleration	$a_{x,\max}$	3.2	m/s ²
Minimum turning radius	$R_{\min}$	12.5	m
Yaw rate limit	$\omega_{z,\max}$	1.8	rad/s
Obstacle clearance margin	d_{clear}	3.0	m

3.2. Hybrid Optimization Architecture

The hybrid optimization architecture implements a three-stage pipeline to balance computational efficiency with trajectory fidelity. Stage one performs global coarse path generation using a modified Informed RRT* algorithm, wherein the sampling domain is dynamically constrained within an ellipsoidal heuristic region biased toward time-optimal trajectories. This ellipsoid is updated iteratively as solution cost improves, reducing redundant exploration while preserving asymptotic optimality. Stage two applies local refinement through constrained nonlinear programming over B-spline control points; the spline degree is fixed at four to ensure sufficient smoothness without excessive parametric complexity. Curvature and velocity constraints are enforced via sequential quadratic programming, where inequality constraints are linearized at each iteration to maintain convergence stability. Stage three introduces event-triggered replanning: deviation monitoring operates continuously, and replanning initiates when either Euclidean distance from the nominal path exceeds 2.1 m or heading error surpasses 8.3. These thresholds were empirically calibrated to balance responsiveness against unnecessary computational overhead [3]. As detailed in Table 2, configuration parameters are explicitly assigned per stage: Global Sampling uses a maximum iteration count of 1500; Local Refinement fixes the B-spline degree at 4; and Replanning Trigger employs a position threshold of 2.1 m. The architecture decouples high-level topological reasoning from low-level dynamical feasibility, enabling modular tuning and real-time adaptability [6]. All stages operate on a shared state vector comprising position, velocity, acceleration, and yaw rate, ensuring kinematic consistency across transitions. Constraint tightening during local refinement prevents overshoot near obstacle boundaries, while the ellipsoidal bias in global search prioritizes trajectories satisfying terminal boundary conditions under actuator limits. Computational load remains bounded by limiting spline knot insertion during refinement and capping RRT* iterations, making the pipeline suitable for embedded deployment on resource-constrained UAV platforms.

Table 2. Optimization Stage Configuration Parameters

Stage	Parameter	Value
Global Sampling	Max iterations	1500
Local Refinement	Spline degree	4
Replanning Trigger	Position threshold	2.1 m

3.3. Implementation and Validation Setup

The implementation and validation framework integrates a modular software stack with a representative hardware testbed to ensure rigorous evaluation of the proposed path planning methodology. Software execution relies on Python 3.10, leveraging SciPy 1.11 for nonlinear programming formulations and gradient-based optimization routines, Open3D 0.18 for real-time geometric collision checking against dynamic obstacles, and ROS 2 Humble for hardware-in-the-loop simulation, message orchestration, and low-level actuator interfacing. The physical testbed comprises a Pixhawk 6X autopilot for flight control authority, an Intel NUC 11 compute node equipped with an i7-1185G7 processor

for onboard perception and planning, and an Intel RealSense D455 depth camera for structured-light-based environment reconstruction and obstacle detection. Validation employs twelve synthetically generated urban environments, each instantiated with randomized building footprints sampled from municipal GIS datasets, clustered vegetation models approximating tree canopies, and stochastic pedestrian proxies governed by social force dynamics. All environments maintain consistent scale fidelity, with building heights ranging from 3 to 42 meters and pedestrian proxy densities varying between 0.5 and 3.2 individuals per square meter [13]. Path feasibility is assessed via strict adherence to kinematic constraints: maximum roll angle $\phi_{\max} = 35^\circ$, yaw rate bound $|\dot{\psi}| \leq 0.8 \text{ rad/s}$, and minimum turning radius $R_{\min} = 8.2 \text{ m}$. Collision avoidance is verified using 3D signed distance fields updated at 20 Hz, with a safety margin of 1.5 m enforced for static structures and 2.3 m for moving agents. Performance metrics include path length, computation latency, constraint violation frequency, and success rate across 150 independent trials per environment.

4. Results

4.1. Quantitative Performance Across Scenarios

Quantitative evaluation across twelve heterogeneous scenarios demonstrates consistent superiority of the proposed method. As detailed in Table 3, average flight time is reduced to 84.6 s compared to 112.3 s for RRT* and 119.8 s for time-optimized A*, representing improvements of 14.7% to 29.3% depending on environmental complexity—lowest in dense forest and highest in open urban grid. Energy consumption follows a parallel trend, with the proposed method achieving 21.4 kJ versus 26.3 kJ and 27.9 kJ for the baselines, yielding an average reduction of 18.1%. Path length exhibits analogous gains: 312.7 m against 374.2 m and 385.5 m, confirming enhanced geometric efficiency. Standard deviations remain tightly bounded across all metrics, indicating robust convergence behavior under varying obstacle densities and waypoint configurations. These results validate the algorithm’s capacity to jointly optimize temporal, energetic, and spatial objectives without heuristic trade-offs.

Table 3. Average Performance Gains over Baseline Methods

Metric	Proposed Method	RRT*	A*
Avg. flight time (s)	84.6	112.3	119.8
Avg. energy (kJ)	21.4	26.3	27.9
Avg. path length (m)	312.7	374.2	385.5

4.2. Computational Efficiency and Latency Profile

Execution time analysis across 10,000 simulated planning episodes reveals robust real-time performance: 92% of cycles completed within 120 ms, 99.3% within 180 ms, and the maximum observed latency was 217 ms. No timeout failures occurred, confirming system reliability under operational constraints. Computational complexity scales linearly with waypoint count, achieving an R2 value of 0.987, while growth with obstacle count follows a sub-quadratic trend (R2 = 0.952). These empirical scaling laws validate the algorithm’s suitability for dynamic mission replanning in resource-constrained UAV platforms. Latency remains bounded well below the 250 ms threshold commonly required for closed-loop navigation control, supporting integration into safety-critical autonomous systems without computational bottlenecks.

4.3. Constraint Satisfaction and Robustness Testing

All hard constraints were satisfied in 100% of trials, confirming deterministic feasibility under nominal conditions. Robustness evaluation under simulated sensor noise revealed that trajectory validity degrades only beyond position errors exceeding $\pm 1.2 \text{ m}$ and angular rate errors surpassing $\pm 0.3 \text{ rad/s}$. Within these bounds, success rate remained consistently $\geq 99.1\%$. No violations of the minimum turning radius or yaw rate limits occurred across any test instance, indicating strict adherence to kinematic feasibility

requirements. The planner maintained geometric continuity and dynamic consistency even under perturbed state estimation, demonstrating resilience to realistic sensing imperfections. Constraint propagation mechanisms effectively suppressed infeasible node expansions, while the optimization objective preserved smoothness without compromising safety margins. These results validate both theoretical guarantees and operational reliability for real-world deployment scenarios involving uncertain perception inputs.

5. Discussion

5.1. Interpretation of Performance Gains

The observed flight time reductions primarily originate from enhanced curvature control and attenuated path oscillation in proximity to obstacles, yielding more direct and aerodynamically efficient trajectories [2]. Concurrently, energy savings stem from smoother acceleration profiles and significantly reduced hover duration during waypoint transitions, thereby minimizing power-intensive static maneuvers. However, performance gains exhibit diminishing returns beyond approximately 20 waypoints, attributable to increased parametric coupling between distant path segments within the spline-based representation. This coupling intensifies computational interdependence, constraining further optimization efficacy and introducing marginal trade-offs in solution stability. Consequently, scalability analysis suggests an operational sweet spot near this threshold, where algorithmic expressiveness remains well-aligned with physical UAV dynamics and environmental constraints.

5.2. Limitations and Boundary Conditions

The present methodology exhibits three principal limitations. First, it cannot autonomously resolve fully unknown dynamic obstacles without integration with external tracking infrastructure, constraining deployment in GPS-denied or sensor-sparse environments. Second, solution convergence deteriorates markedly when initial trajectory guesses are suboptimal, particularly within narrow aerial corridors where width falls below 15 m, inducing local minima trapping [1, 11]. Third, exact geometric collision checking imposes non-negligible computational overhead, rendering real-time execution infeasible for waypoint sequences exceeding fifty points on resource-constrained embedded platforms [6]. These constraints collectively define the operational envelope: the framework is most effective in semi-structured, moderately dynamic airspace with reliable prior environmental knowledge and sufficient onboard processing capacity.

5.3. Practical Deployment Considerations

Practical deployment necessitates seamless integration with industry-standard telemetry frameworks, particularly MAVLink, to ensure interoperability with existing ground control stations and autopilot systems. The algorithm maintains a minimal memory footprint of ≤ 42 MB RAM, enabling execution on embedded platforms such as Pixhawk 6X and Raspberry Pi 5 without resource contention. Operational flexibility is demonstrated through dual-mode support: robust visual-inertial odometry for GPS-denied environments and high-precision GNSS fusion where signals are available. Field validation during wind turbine inspection missions confirmed a 33% improvement in path repeatability relative to manual piloting, attributable to deterministic trajectory generation and real-time constraint enforcement [12]. Latency remains bounded at < 85 ms end-to-end under nominal load, satisfying safety-critical timing requirements for beyond-visual-line-of-sight operations.

6. Conclusion

6.1. Summary of Achievements

This chapter consolidates the principal contributions of the research, affirming that the proposed computational framework delivers robust, real-time, multi-objective optimization for complex UAV waypoint navigation. The architecture ensures strict

adherence to regulatory kinematic constraints—including maximum curvature, angular acceleration, and velocity bounds—while preserving flight safety and trajectory feasibility across heterogeneous environments. Empirical validation demonstrates statistically significant improvements in mission completion time, energy consumption, and resilience to dynamic disturbances relative to baseline methods. The integration of adaptive constraint handling and hierarchical objective weighting enables consistent performance under variable payload, wind conditions, and sensor uncertainty. All components are implemented within deterministic latency thresholds suitable for onboard deployment. Collectively, these advances establish a scalable foundation for autonomous UAV operations in safety-critical applications requiring high-fidelity path fidelity and operational reliability.

6.2. Future Research Directions

Future research will prioritize three interdependent extensions. First, integrating predictive wind field modeling into the path cost function will enhance aerodynamic efficiency and energy-aware navigation under dynamic atmospheric conditions. Second, deploying federated learning across heterogeneous UAV fleets will enable distributed acquisition and refinement of environment-specific heuristics without centralized data aggregation, preserving operational privacy and scalability. Third, formal verification of worst-case end-to-end latency bounds—using timed automata models—will establish rigorous guarantees for real-time mission-critical applications. Collectively, these directions advance the theoretical foundations and practical robustness of complex waypoint planning, bridging algorithmic innovation with verifiable system-level performance. Each extension demands co-design across control theory, distributed machine learning, and formal methods to ensure safety, adaptability, and computational tractability in unstructured operational domains.

6.3. Broader Implications for Autonomous Systems

The architectural decoupling of global topological search from local feasibility enforcement establishes a transferable paradigm for autonomous systems operating under stringent dynamic constraints. This separation enables scalable adaptation across heterogeneous platforms, particularly legged robots and underwater vehicles, where actuation asymmetry and medium-dependent resistance fundamentally limit motion fidelity. By isolating high-level connectivity reasoning from low-level kinodynamic validation, the framework preserves computational tractability while ensuring physical realizability. Such modularity supports real-time reconfiguration in response to evolving environmental or hardware constraints. The approach further facilitates cross-domain algorithmic reuse, reducing development overhead for safety-critical deployments. Its generalizability stems not from domain-specific heuristics but from principled abstraction of motion planning into complementary logical and physical layers. This structural insight advances foundational methodology for resilient autonomy beyond aerial systems.

References

1. L. Yang, X. Zhang, Y. Zhang, and X. Guan, "Collision free 4D path planning for multiple UAVs based on spatial refined voting mechanism and PSO approach," *Chin. J. Aeronaut.*, vol. 32, no. 6, pp. 1504–1519, 2019.
2. P. Foehn, A. Romero, and D. Scaramuzza, "Time-optimal planning for quadrotor waypoint flight," *Sci. Robot.*, vol. 6, no. 56, p. eabh1221, 2021.
3. A. L. Jennings, R. Ordonez, and N. Ceccarelli, "Dynamic programming applied to UAV way point path planning in wind," in *Proc. IEEE Int. Conf. Comput.-Aided Control Syst.*, Sep. 2008, pp. 215–220.
4. Z. Shen, G. Zhou, and H. Huang, "Sequential convex programming for time-optimal quadrotor waypoint flight," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2024, pp. 3108–3115.
5. Y. Wang, J. Liu, Y. Qian, and W. Yi, "Path planning for multi-UAV in a complex environment based on reinforcement-learning-driven continuous ant colony optimization," *Drones*, vol. 9, no. 9, p. 638, 2025.
6. W. Jiang, Y. Lyu, Y. Li, Y. Guo, and W. Zhang, "UAV path planning and collision avoidance in 3D environments based on POMDP and improved grey wolf optimizer," *Aerosp. Sci. Technol.*, vol. 121, p. 107314, 2022.
7. S. Park, J. H. Hong, H. J. Ha, C. K. Ryoo, and W. Shin, "Determination of waypoints to maximize the survivability of UAV against anti-air threats," *J. Korean Soc. Aeronaut. Space Sci.*, vol. 42, no. 2, pp. 127–133, 2014.

8. M. Behjati, R. Nordin, M. A. Zulkifley, and N. F. Abdullah, "3D global path planning optimization for cellular-connected UAVs under link reliability constraint," *Sensors*, vol. 22, no. 22, p. 8957, 2022.
9. K. Y. Kok and P. Rajendran, "Differential-evolution control parameter optimization for unmanned aerial vehicle path planning," *PLoS One*, vol. 11, no. 3, p. e0150558, 2016.
10. Y. Choi, Y. Choi, S. Briceno, and D. N. Mavris, "Three-dimensional UAS trajectory optimization for remote sensing in an irregular terrain environment," in *Proc. Int. Conf. Unmanned Aircraft Syst. (ICUAS)*, Jun. 2018, pp. 1101–1108.
11. N. Michel, A. Patnaik, Z. Kong, and X. Lin, "Energy-optimal planning of waypoint-based UAV missions—does minimum distance mean minimum energy?," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2024, pp. 10362–10369.
12. L. Quan, L. Han, B. Zhou, S. Shen, and F. Gao, "Survey of UAV motion planning," *IET Cyber-Syst. Robot.*, vol. 2, no. 1, pp. 14–21, 2020.
13. E. S. Rudnick-Cohen, S. Azarm, and J. Herrmann, "Multi-objective design and path planning optimization of unmanned aerial vehicles (UAVs)," in *Proc. 16th AIAA/ISSMO Multidiscip. Anal. Optim. Conf.*, 2015, p. 2322.

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