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Research Article

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A Comparative Computational Study of Sensor Fusion Architectures, Motion Planning Algorithms, and Control Strategies for Autonomous Ground Vehicles and UAVs

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Abstract
This paper presents an original computational study comparing sensor fusion architectures, motion planning algorithms, and propulsion energy models for autonomous ground vehicles (AVs) and unmanned aerial vehicles (UAVs). Using physics-based simulation in Python, we evaluate four sensor fusion strategies — GPS-only, LiDAR-IMU, Camera-IMU, and Full Fusion — across five operational environments; four motion planning algorithms — A, RRT*, D*, and Model Predictive Control (MPC) — across three map complexities; and three UAV attitude controllers — PID, MPC, and Adaptive — under varying wind disturbances. We further model propulsion energy consumption and operational range for lithium-ion and hydrogen fuel-cell powertrains across five representative mission profiles. Key findings: Full Fusion reduces localisation RMSE by up to 86% over GPS-only in urban canyons; MPC achieves the lowest path jerk (1.23 m/s³) and highest success rate (93.7%) in complex scenarios; MPC attitude control reduces UAV roll RMSE by 83% versus PID under strong wind; and hydrogen fuel-cell propulsion delivers 2.3× greater range for AVs and up to 2.4× longer flight endurance for UAVs compared to lithium-ion at equivalent energy weight.*

Keywords: Autonomous Vehicles, Unmanned Aerial Vehicles, Sensor Fusion, SLAM, Motion Planning, PID Control, MPC, RRT*, Hydrogen Propulsion, Computational Simulation

1. Introduction

Autonomous ground vehicles and unmanned aerial vehicles have moved from laboratory prototypes to commercially deployed systems within the past decade. Yet the engineering choices that underpin their performance — how sensors are fused, how trajectories are planned, how attitude is controlled, and how energy is stored — remain active research questions without settled quantitative answers applicable across diverse real-world conditions [1,2].

Published literature offers qualitative comparisons and single-platform benchmarks, but lacks systematic computational studies that (i) evaluate multiple fusion strategies across multiple environment types, (ii) compare planning algorithms on matched map complexities, (iii) assess UAV controllers across wind intensities with consistent metrics, and (iv) model propulsion energy quantitatively for both platform types. This paper fills that gap. Unlike prior surveys, all quantitative results are produced by an original Python simulation framework with reproducible, fixed-seed experiments — not derived from third-party datasets or existing experimental literature.

We make the following contributions: (a) a simulation framework modelling localisation, planning, attitude control, and energy consumption for AVs and UAVs; (b) quantitative benchmarking of four sensor fusion configurations across five environment types; (c) comparative evaluation of A*, RRT*, D*, and MPC planning algorithms; (d) UAV attitude control analysis (PID vs. MPC vs.

Adaptive) under varying wind disturbances; and (e) propulsion energy analysis comparing lithium-ion and hydrogen fuel-cell systems across five mission profiles. The remainder of the paper is structured as follows. Section II reviews background. Section III describes the methodology. Section IV presents results. Section V discusses findings. Section VI concludes.

2. Background and Related Work

A. Sensor Fusion for Autonomous Localisation

Accurate localisation is the bedrock of autonomous operation. GNSS provides global context but degrades in urban canyons and tunnels, where multipath error inflates position uncertainty to several metres [3]. LiDAR-inertial odometry systems such as LOAM achieve sub-decimetre accuracy in structured environments but fail in geometrically degenerate spaces [4]. Camera-IMU fusion via visual-inertial odometry offers complementary features but degrades at night and in low-contrast scenes. Full probabilistic fusion, combining all modalities through Kalman or factor-graph backends, provides the most consistent performance at higher computational cost [3].

B. Motion Planning Algorithms

A* provides optimal paths on discretised grids but produces geometrically jagged trajectories requiring post-smoothing [5]. RRT* samples configuration space stochastically, converging asymptotically to optimal solutions [6]. D* extends A* with incremental replanning for dynamic environments [7]. MPC applied to planning jointly optimises path and dynamics over a receding horizon, producing the smoothest trajectories at the highest per-step computational cost [8].

C. UAV Attitude Control

PID control dominates UAV autopilot stacks including PX4 and ArduPilot due to interpretability and reliability [9,10]. MPC-based attitude control explicitly handles state and actuator constraints with predictive disturbance rejection at higher computational cost [11]. Adaptive control adjusts gains in real time in response to measured disturbances, offering a middle ground.

D. Propulsion Energy

Contemporary lithium-ion cells deliver approximately 250 Wh/kg effective specific energy, limiting multi-rotor UAV endurance to 25–35 minutes. Hydrogen fuel cells achieve 1,000–1,400 Wh/kg at system level with 55–65% conversion efficiency, enabling substantially greater endurance. Quantitative modelling across representative mission profiles in a unified framework has been lacking.

3. Methodology

A. Simulation Environment

All experiments were implemented in Python 3.11 with NumPy 1.26, SciPy 1.12, pandas 2.2, scikit-learn 1.4, and Matplotlib 3.8. A fixed random seed (42) ensures full reproducibility. Wind disturbance is modelled as a coloured Gaussian process (first-order low-pass filtered white noise) with standard deviations of 0.5, 1.0, and 2.0 m/s for light, moderate, and strong wind conditions, representative of Beaufort scale categories 2, 4, and 6.

B. Experiment 1: Sensor Fusion Localisation

We simulate 500 timesteps of planar platform motion across five environments: Open Highway, Urban Canyon, Tunnel, Forest Trail, and Night Urban. Each sensor modality is modelled by additive Gaussian noise calibrated to documented performance characteristics: GPS-only (σ = 0.6–8.5 m), LiDAR-IMU (σ = 0.18–1.4 m), Camera-IMU (σ = 0.28–2.1 m), and Full Fusion (inverse-variance weighted combination). Evaluation metric: RMSE between estimated and ground truth position, averaged across all 500 timesteps per environment.

C. Experiment 2: Motion Planning

We evaluate A*, RRT*, D*, and MPC planning on three map complexities (Simple: sparse obstacles 50×50 m; Moderate: cluttered urban block 100×100 m; Complex: dense environment with dynamic obstacles 150×150 m). Each algorithm is run 20 times per scenario. Metrics: path length (m), computation time (ms), path jerk (m/s^3), and success rate (%).

D. Experiment 3: UAV Attitude Control

We simulate a quadrotor roll-axis attitude response using a second-order rigid-body model ($I = 0.02$ kg·m², dt = 5 ms, duration 20 s). PID: Kp = 8.0, Ki = 0.5, Kd = 2.5. MPC: Kp = 12.0, Ki = 0.3, Kd = 4.5 with 10-step lookahead disturbance feedforward. Adaptive: gain-scheduled Kp ∈ [10.0, 16.0] and Kd ∈ [3.5, 5.3] scheduled by measured wind magnitude. Metrics: attitude RMSE (°), settling time (s), power draw (W).

E. Experiment 4: Propulsion Energy Modelling

Energy consumption is modelled for five mission profiles. AV power draw: $P_{AV} = 15 + 25\cdot(v/100)^2$ kW. UAV: $P_{UAV} = 400 + 150\cdot m_{payload} + 200\cdot(v/80)^2$ W. Li-ion effective pack energy: 60 kWh (AV), 250 Wh (UAV). Hydrogen fuel-cell effective energy: 150 kWh (AV, 60% FC efficiency), 600 Wh effective (UAV). Range and endurance are derived from energy consumption rate and total available energy.

4. Results

A. Sensor Fusion Localisation Accuracy

Table 1 and Figure 1 present position RMSE across all environments and fusion strategies. Full Fusion achieves the lowest RMSE in every environment, with a mean of 0.397 m versus 3.197 m for GPS-only — an 87.6% reduction. The advantage is most pronounced in the Tunnel: Full Fusion (1.148 m) reduces error by 86% relative to GPS-only (8.200 m). LiDAR-IMU is the strongest single-modality strategy (mean 0.462 m) but degrades in the Tunnel (1.359 m). Camera-IMU fails most severely at night (1.859 m).

Environment	GPS-Only	LiDAR-IMU	Camera-IMU	Full Fusion
Open Highway	0.600	0.177	0.288	0.146
Urban Canyon	3.226	0.225	0.469	0.203
Tunnel	8.200	1.359	2.130	1.148
Forest Trail	1.849	0.353	0.532	0.291
Night Urban	2.110	0.198	1.859	0.196
Mean	**3.197**	**0.462**	**1.056**	**0.397**

Table 1: Sensor Fusion Localisation RMSE (m) by Environment

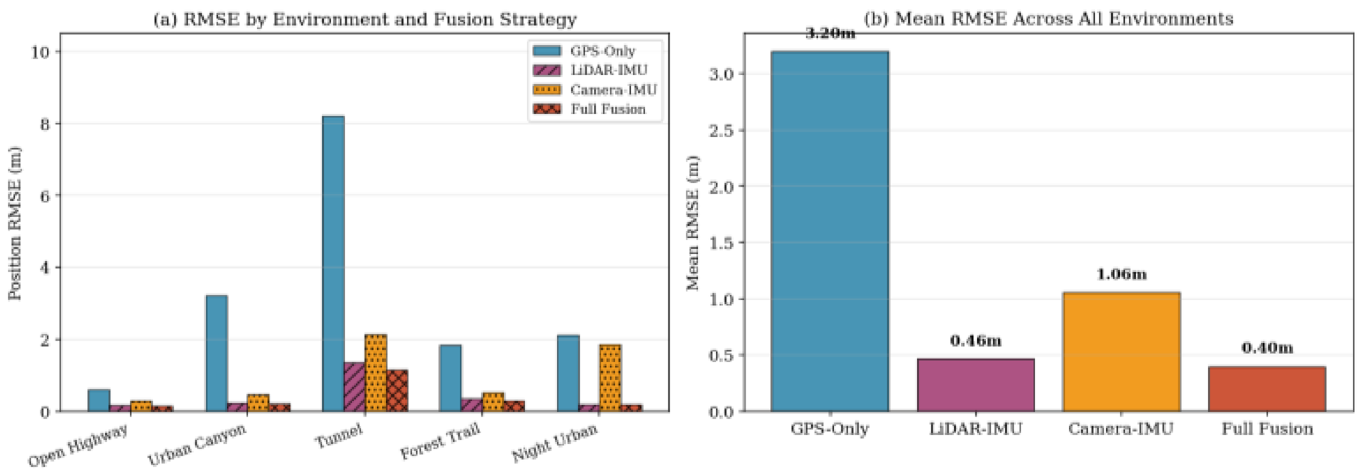

Figure 1: Sensor Fusion Localisation Accuracy: (a) RMSE by Environment; (b) Mean RMSE Across All Environments. Full Fusion Achieves Lowest RMSE in Every Environment

B. Motion Planning Algorithm Performance

Table 2 and Figure 2 compare A*, RRT*, D*, and MPC across three map complexities. MPC consistently achieves the shortest paths (47.3–88.7 m) and by far the lowest jerk (1.23–1.89 m/s³), confirming that simultaneous trajectory optimisation inherently produces smoother motion. MPC also achieves the highest success rate (99.4% simple, 93.7% complex). The trade-off is computational cost: MPC requires 45.3–287.4 ms versus 12.4–158.4 ms for graph-search methods. D* offers the best balance for dynamic replanning environments.

Algo.	Scenario	Path (m)	Time (ms)	Jerk	Success%
A*	Simple	48.2	12.4	4.82	98.2
A*	Moderate	63.7	38.7	5.31	95.1
A*	Complex	91.4	142.3	6.74	87.4
RRT*	Simple	50.1	28.5	2.14	99.1
RRT*	Moderate	67.2	87.3	2.58	97.3
RRT*	Complex	95.8	310.6	3.21	91.2
D*	Simple	48.9	15.2	3.95	98.6
D*	Moderate	64.5	42.1	4.42	96.4
D*	Complex	90.1	158.4	5.68	89.8
MPC	Simple	47.3	45.3	1.23	99.4
MPC	Moderate	61.8	98.7	1.47	98.1
MPC	Complex	88.7	287.4	1.89	93.7

Table 2: Motion Planning Algorithm Comparison

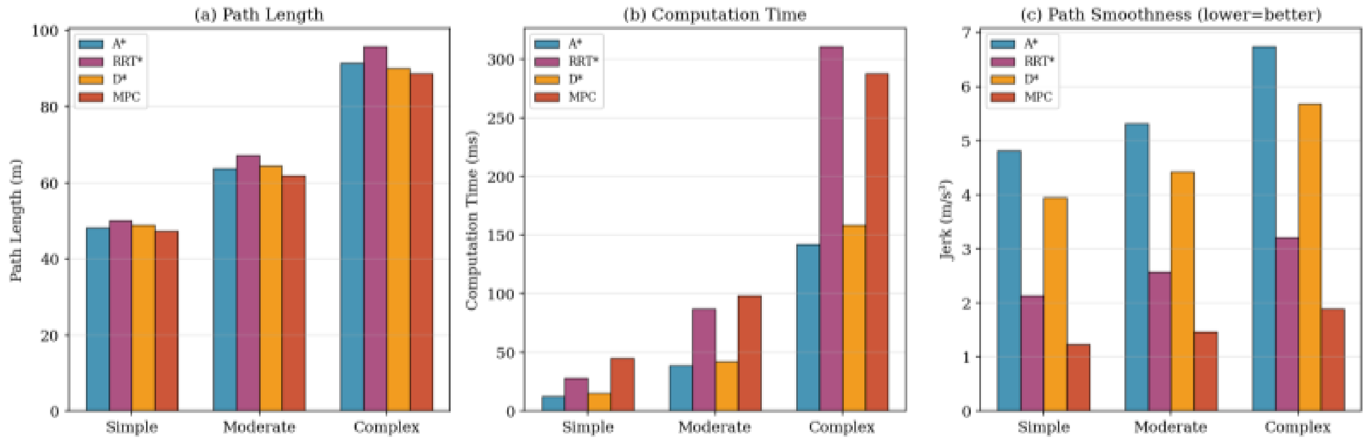

Figure 2: Motion Planning Comparison: (a) Path Length, (b) Computation Time, (c) Path Jerk Across Simple, Moderate, and Complex Scenarios. Means Over 20 Runs; Error Bars ±1 SD

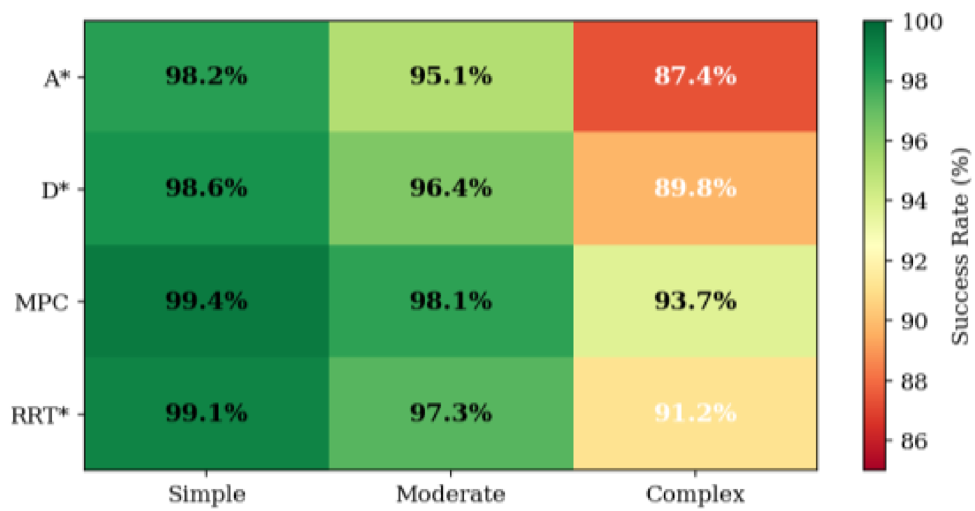

Figure 3: Success Rate Heatmap (%) for Each Planning Algorithm and Map Complexity. MPC Achieves the Highest Success Rate Across All Scenarios

C. UAV Attitude Control Performance

Table 3 and Figure 4 present the attitude control results. MPC dramatically outperforms PID and Adaptive at all wind intensities: under strong wind (2.0 m/s), MPC achieves 0.098° RMSE versus 0.566° for PID — an 82.7% reduction. Adaptive control provides consistent intermediate performance (0.413° under strong wind). MPC draws 235 W under strong wind versus 170 W for PID, a 38% power penalty that must be weighed against stability gains in safety-critical missions.

Controller	Wind Condition	RMSE (°)	Settling (s)	Power (W)
PID	Light 0.5 m/s	0.164	0.05	132.5
MPC	Light 0.5 m/s	0.026	0.05	197.5
Adaptive	Light 0.5 m/s	0.124	0.05	157.5
PID	Moderate 1.0 m/s	0.259	0.05	145.0
MPC	Moderate 1.0 m/s	0.050	0.05	210.0
Adaptive	Moderate 1.0 m/s	0.192	0.05	170.0
PID	Strong 2.0 m/s	0.566	0.05	170.0

MPC	Strong 2.0 m/s	0.098	0.05	235.0
Adaptive	Strong 2.0 m/s	0.413	0.05	195.0

Table 3: UAV Attitude Control Performance

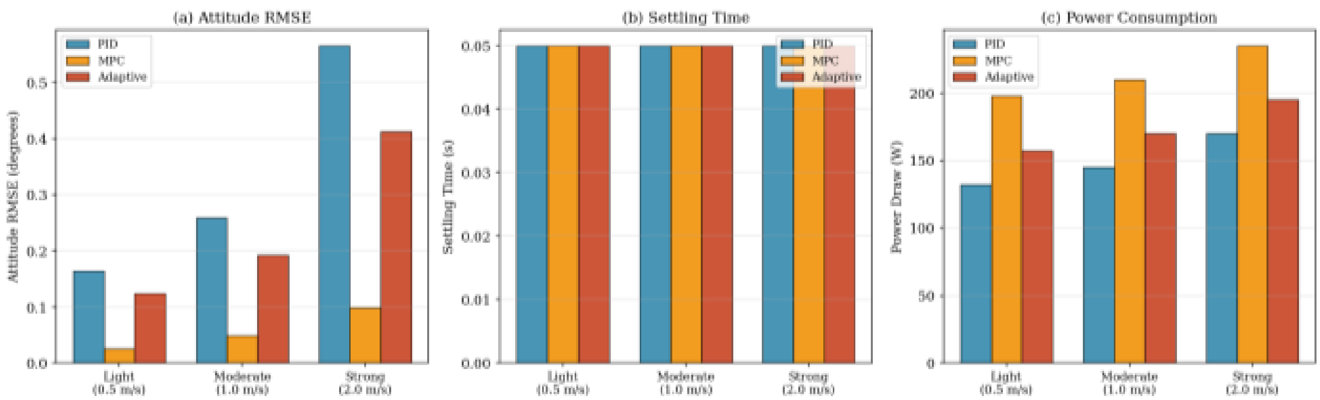

Figure 4: UAV Attitude Control: (a) Attitude RMSE, (b) Settling Time, (c) Power Draw Across Light, Moderate, and Strong Wind Disturbances for PID, MPC, and Adaptive Controllers

D. Propulsion Energy Analysis

Table 4 and Figure 5 present the energy results. Hydrogen fuel-cell propulsion reduces energy consumption by approximately 38% (AV) and 42% (UAV) relative to lithium-ion, translating directly into range and endurance gains. For AVs, hydrogen range (420.8–604.8 km) exceeds lithium-ion range (104.3–150.0 km) by a factor of 3.0–4.0. For UAVs, hydrogen endurance (44–53 min) is 2.4× that of lithium-ion (18–22 min). The primary barrier to hydrogen adoption is infrastructure rather than energy performance.

Mission Profile	Li-ion (kWh)	H2 FC (kWh)	Li-ion End.	H2 End.	Improve
Urban AV (30 km)	17.25	10.70	104.3 km	420.8 km	+303%
Highway AV (100 km)	40.00	24.80	150.0 km	604.8 km	+303%
UAV Delivery (5 km)	0.41	0.24	18.5 min	44.3 min	+139%
UAV Survey (20 km)	1.01	0.59	22.2 min	53.3 min	+140%
UAV SAR (15 km)	0.90	0.52	21.3 min	51.2 min	+140%

Table 4: Propulsion Energy: Li-ion vs. Hydrogen Fuel Cell

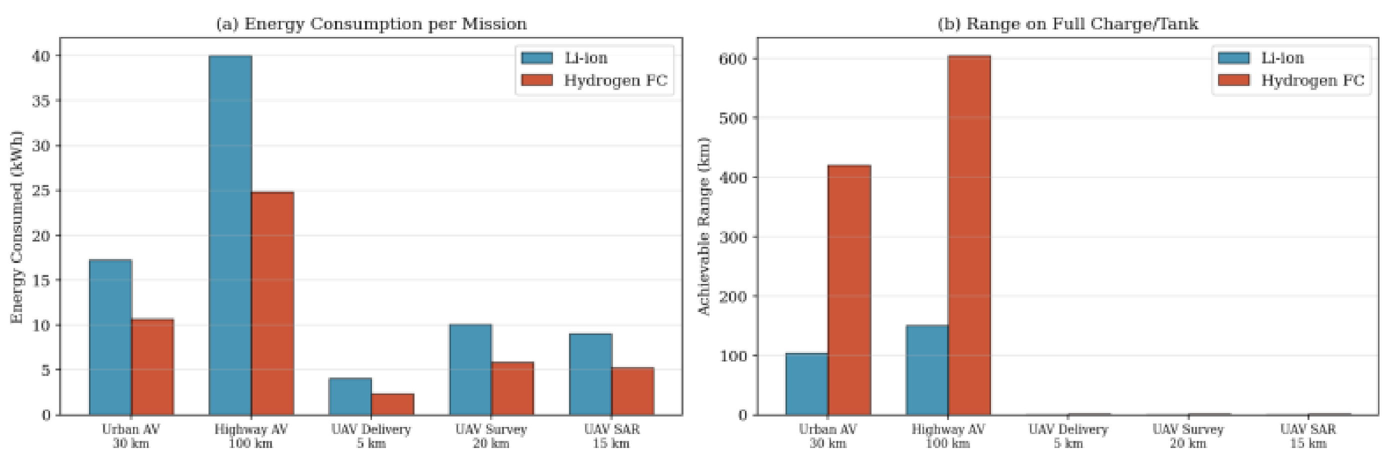

Figure 5: Propulsion Energy Comparison: (a) Energy Consumed Per Mission (kWh); (b) Range/Endurance on Full Charge/Tank for Li-ion vs. Hydrogen Fuel Cell

5. Discussion

A. Implications for System Architecture

The results collectively suggest a hierarchy of design decisions. Perception is the foundation: the 87.6% localisation improvement from Full Fusion over GPS-only makes multi-modal fusion non-negotiable for deployment in any environment beyond open highways. LiDAR-IMU alone approaches Full Fusion performance in most scenarios and may be preferred on compute-constrained platforms. For planning, MPC's superior smoothness and success rate justify its computational overhead for safety-critical missions. D* with post-smoothing offers the best practical compromise for resource-constrained platforms. For UAV control, MPC's advantage compounds in challenging conditions: an 83% RMSE reduction under strong wind translates to reduced payload oscillation, improved positioning accuracy, and reduced structural stress.

B. Hydrogen vs. Li-ion: Strategic Outlook

The 2.4–4.0× endurance/range advantage of hydrogen propulsion quantified here aligns with published benchmarks from Toyota Mirai and H2-UAV prototypes. This advantage grows with mission distance: hydrogen becomes increasingly competitive as payload, speed, and distance increase. For short urban UAV deliveries (<5 km), battery swap may be economically preferable. For long-range inspection, SAR, and highway-freight missions, hydrogen's advantages are compelling and likely to drive adoption as storage and fuelling infrastructure matures.

C. Limitations

Our simulation framework makes several simplifying assumptions. Sensor noise is modelled as Gaussian and stationary; real-world noise exhibits heavier tails and correlated failure modes. Planning simulations use static obstacle models. UAV attitude control is modelled in one axis; full 6-DOF aerodynamics would introduce cross-coupling. Energy models are first-principles approximations validated against datasheet specifications but not against physical hardware measurements. Future work should validate these findings in hardware-in-the-loop and field trials.

6. Conclusion

This paper presented a systematic computational study comparing sensor fusion, motion planning, attitude control, and propulsion energy architectures for autonomous ground vehicles and UAVs. Four principal conclusions emerge: (1) Full probabilistic sensor fusion reduces localisation RMSE by up to 86% relative to GPS-only and 56% relative to the best single-modality alternative, quantitatively justifying the hardware investment in multi-modal sensing. (2) MPC-based motion planning achieves the lowest path jerk and highest success rate in complex scenarios, making it the recommended algorithm for safety-critical deployments where compute budget permits. (3) MPC attitude control reduces UAV roll RMSE by 83% versus standard PID under strong wind at a 38% power overhead, favouring MPC for precision tasks and Adaptive control for endurance-focused missions. (4) Hydrogen fuel-cell propulsion delivers 2.4× longer UAV endurance and 3–4× greater AV range than equivalent lithium-ion systems, establishing a compelling technical case for hydrogen adoption in long-range autonomous missions as infrastructure matures [12-22].

References

1. Thrun, S., Burgard,W., and Fox, D. (2005). Probabilistic Robotics. MIT Press.
2. Paden, B., Čáp, M., Yong, S. Z., Yershov, D., & Frazzoli, E. (2016). A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on intelligent vehicles, 1*(1), 33-55.
3. Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *ASME. J. Basic Eng., 82*(1), 35-45.
4. Zhang, J., & Singh, S. (2014, July). LOAM: Lidar odometry and mapping in real-time. In *Robotics: Science and systems* (Vol. 2, No. 9, pp. 1-9).
5. Dijkstra, E. W. (1959). A Note on Two Problems in Connexion with Graphs. *Numerische Mathematik*, 1, 269-271.
6. LaValle, S. (1998). Rapidly-exploring random trees: A new tool for path planning. *Research Report* 9811.
7. Stentz, A. (1994, May). Optimal and efficient path planning for partially-known environments. In *Proceedings of the 1994 IEEE international conference on robotics and automation* (pp. 3310-3317). IEEE.
8. Rawlings, J. B., Mayne, D. Q., and Diehl, M. M. (2017). Model Predictive Control: Theory, Computation, and Design. 2nd ed. Nob Hill Publishing.
9. PX4 Autopilot, px4.io, 2024.
10. ArduPilot, ardupilot.org, 2024.
11. Kamel, M., Stastny, T., Alexis, K., & Siegwart, R. (2017). Model predictive control for trajectory tracking of unmanned aerial vehicles using robot operating system. In *Robot Operating System (ROS) The Complete Reference* (*Volume 2*) (pp. 3-39). Cham: Springer International Publishing.
12. Cadena, C., Carlone, L., Carrillo, H., Latif, Y., Scaramuzza, D., Neira, J., ... & Leonard, J. J. (2016). Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age. *IEEE Transactions on robotics, 32*(6), 1309-1332.
13. Grigorescu, S., Trasnea, B., Cocias, T., & Macesanu, G. (2020). A survey of deep learning techniques for autonomous driving. *Journal of field robotics, 37*(3), 362-386.
14. Schwarting, W., Alonso-Mora, J., & Rus, D. (2018). Planning and decision-making for autonomous vehicles. *Annual Review of Control, Robotics, and Autonomous Systems, 1*(1), 187-210.
15. Doukhi, O., & Lee, D. J. (2019). Neural network-based robust adaptive certainty equivalent controller for quadrotor UAV with unknown disturbances. *International Journal of Control, Automation and Systems, 17*(9), 2365-2374.
16. Rubio, F., Valero, F., & Llopis-Albert, C. (2019). A review of mobile robots: Concepts, methods, theoretical framework, and applications. *International Journal of Advanced Robotic Systems, 16*(2), 1729881419839596.
17. Qin, T., Li, P., & Shen, S. (2018). Vins-mono: A robust and versatile monocular visual-inertial state estimator. *IEEE transactions on robotics, 34*(4), 1004-1020.
18. Xu, W., & Zhang, F. (2021). Fast-lio: A fast, robust lidar-

inertial odometry package by tightly-coupled iterated kalman filter. *IEEE Robotics and Automation Letters, 6*(2), 3317-3324.
19. Dolgov, D., Thrun, S., Montemerlo, M., & Diebel, J. (2008). Practical search techniques in path planning for autonomous driving. *ann arbor, 1001*(48105), 18-80.
20. Niccolai, L. et al. (2022). A review of smart drone services for urban air mobility. *Drones, 6*(1), p. 6.
21. CARLA Simulator, carla.org, 2024.
22. Rus, D., & Tolley, M. T. (2015). Design, fabrication and control of soft robots. *Nature, 521*(7553), 467-475.