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Energy-Aware Robotics: Review of Path Planning and Power Optimization for Long-Endurance UAVs

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ABSTRACT **Review Article**

There is no gain saying of the obvious fact that Long-endurance, Unmanned Aerial Vehicles are critical not only for surveillance and precision agriculture, but also for disaster response, and environmental monitoring. However, battery capacity remains the primary constraint, with most multirotor UAVs limited to about 25–45 minutes of flight time. This review examines 2020–2026 research on energy-aware robotics, focusing on path planning and power optimization strategies that has the potential to extend UAV endurance. Following PRISMA 2020 guidelines, 112 peer-reviewed studies from IEEE Xplore, ACM, and Scopus were analyzed. Findings show three dominant approaches: 1. wind- and terrain-aware path planning, 2. hybrid energy systems including solar and fuel cells, and 3. learning-based power management. Results indicate that integrating environmental models with trajectory optimization can reduce energy consumption by 18–34%, while hybrid platforms achieve 2–8 times flight time over battery-only systems. Key gaps still persist in real-time energy prediction, multi-UAV coordination under energy constraints, and standardized energy benchmarks. However, we propose a four-layer framework: Environmental Modeling to Energy-Predictive Planning to Adaptive Control and to Fleet Energy Management. The review concludes that no single method is sufficient on its own alone hence long-endurance UAVs require co-design of hardware, algorithms, and mission planning.

Keywords: UAV, Energy-Aware Robotics, Path Planning, Power Optimization, Long-Endurance, Battery Management, Solar UAV.

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Introduction

Unmanned Aerial Vehicles (UAVs) are increasingly and rapidly deployed for missions requiring hours of operation: wildfire monitoring, pipeline inspection, and marine surveillance. Teal Group (2024] States that the global commercial UAV market reached $30.6B in 2023, with long-endurance platforms representing the fastest-growing segment

Despite this demand, energy remains the bottleneck against their maximum efficient operation. Lithium-polymer batteries, the standard for multirotors, provide only 200–260 Wh/kg [Liu et al., 2021]. Fixed-wing UAVs achieve 1–2 hours, but multirotors are limited to <45 min. This compels and forces frequent and premature landings, operator intervention, and mission aborts.

Energy-aware robotics addresses this by optimizing both howa UAV moves and how it manages power. Two sub-fields dominate 2020–2026 literature:

1. **Path Planning:** Generating trajectories that minimize energy given wind, obstacles, and terrain.
2. **Power Optimization:** Managing battery discharge, solar harvesting, and hybrid sources.

The research question that the review intends to answer is: What are the current state-of-the-art and remaining gaps in path planning and power optimization for long-endurance UAVs?

Literature Review and Theoretical Background

UAV Energy Consumption Models

Energy use in UAVs is modeled as $E = E{aero} + E{avionics} + E{payload}$, where aerodynamic power dominates 70–85% (Park et al., 2020). Key factors: velocity, acceleration, wind, altitude, and mass. Multi-rotor power scales cubically with speed, while fixed-wing is optimal at a specific airspeed (Boulet; 2021)

Energy-Aware Path Planning Paradigms

1. **Geometric/Optimal Control:** A and RRT variants with energy cost maps (Yoon & Kim, 2020).
2. **Learning-Based:** Deep RL for wind adaptation: (Rodriguez-Ramos et al., 2021).
3. **Hybrid:** Classical planner + learned energy predictor (Zhao et al., 2022).

Power System Innovations:

Solar integration, fuel cells, and tethered systems extend endurance but add mass and complexity (Zhang et al., 2023). Energy management systems (EMS) coordinate sources in real-time (Wang et al., 2024)

Methodology

This review adopts *PRISMA 2020* (Page et al., 2021).

Search Strategy

Databases: IEEE Xplore, ACM Digital Library, Scopus, MDPI Drones.

Query: ("UAV" OR "drone") AND ("energy-aware" OR "power optimization" OR "energy-efficient") AND ("path planning" OR "trajectory")

Period: January 2020 – June 2026. Language: English.

Inclusion/Exclusion Criteria

Include: Experimental or simulation studies on UAV energy reduction; ≥20% energy saving reported; real hardware or high-fidelity simulation.

Exclude: Ground robots only, theoretical without validation, <2020.

Screening

Records identified: 1,604. After deduplication removal, 1, 298 was left and after Title/abstract; only 243. Full-text: 112.

Data Extraction

UAV type, energy model, algorithm, environment, % energy saved, flight time gain, TRL.

Limitations

Heterogeneous benchmarks limit direct comparison. Most studies use simulation only.

Results: Path Planning For Energy Efficiency

Wind- and Terrain-Aware Planning:

Baca et al. (2020) opined that ignoring the impact of wind on Energy - Aware UAVs causes about 25–40% energy overuse. To overcome this, recent work embeds Computational Fluid Dynamics (CFD) wind fields into Rapidly - exploring Response Tree (RRT) as shown in Yoon & Kim (2020) where Energy-optimal RRT_ reduced consumption by 22% in urban wind just like Wu et al. (2023) shows how Terrain-following for fixed-wing saved energy consumption by 18% by exploiting ridge lift.

Learning-Based Trajectory Optimization:

Deep RL learns energy-efficient policies under uncertainty as stated by Rodriguez-Ramos et al (2021) where Proximal Policy Optimization (PPO) policy reduced energy by 31% as against Proportional Integral Derivative (PID) in gusty conditions. Meanwhile, Guan et al. (2024) confirms Transformer-based planner adapted to dynamic payloads, recorded 27% energy savings

Multi-UAV Energy Coordination:

Fleet operations add complexity: charging, handoff, and coverage. Zhou et al. (2022) reveals Auction-based task allocation extended fleet endurance by 34% while Li & Duan (2025) proved fleet endurance extension by persistently monitoring with UAV-UGV docking stations.

Gap: There exists barely few studies and research that validate greater than 3 UAVs outdoors at the moment.

Results: Power System Optimization

Solar and Hybrid UAVs:

Solar adds about 5–15 W during flight but increases drag. This is confirmed in separate studies by Zhang et al. (2023). Solar-assisted quadrotor achieved 2.3 times endurance against battery-only. And Oettershagen et al. (2021): AtlantikSolar 2 set of 81-hour record with solar + gliding.

Fuel Cell and Hydrogen Systems:

Hydrogen PEM fuel cells has the potential of reaching 400 Wh/kg [Liu et al., 2021]. This is also supported in Cui et al. (2022): 4-hour multirotor flight using H_2, and Lee et al. (2024): Hybrid battery-fuel cell EMS improved efficiency by 19%.

Adaptive Energy Management:

Real-time prediction of remaining energy is critical. Wang et al. (2024) work on LSTM-based SOC predictor reduced emergency landings by 41% while Baptista et al. (2020) shows tolerable model predictive control for battery thermal limits.

Discussion: Integrating Planning and Power

Energy-aware robotics requires co-design. Table 1 summarizes 2020–2026 gains.

Table 1. Energy Savings Reported 2020–2026

S/No	Approach	UAV Type	Reported Saving	Key Reference
1	Wind-aware RRT	Multirotor	22%	Yoon & Kim, 2020
2	RL in Gusts	Quadrotor	31%	Rodriguez-Ramos et al., 2021
3	Solar Hybrid	Quadrotor	2.3x time	Zhang et al., 2023
4	H2 Fuel Cell	Multirotor	4.0h flight	Cui et al., 2022
5	Fleet Coordination	Multi-UAV	34%	Zhou et al., 2022

Deduction:

Geometric planning is mature to adapt TRL 7–8.

Learning is good to start with TRL 5–6.

Hybrid systems are good with TRL 6–7 just that they are heavy.

Recommendations

Considering this review, the following recommendations are made as critical in order to further advance the adoption of long-endurance UAVs:

1. **Standardized Energy Benchmarks:** Adopt BARN-UAV and EnergyNav datasets for fair comparison (Peralta et al., 2022; modified for energy).
2. **Real-Time Energy Models:** Integrate online wind estimation and battery degradation into planners (Wang et al., 2024).
3. **Hardware-Software Co-Design:** Optimize airframe, propellers, and algorithms together, not separately (Boulet, 2021)
4. **Regulatory Testbeds:** Create ISO-like energy endurance test arenas for certification (ISO) (Boulet, 2022)
5. **Open-Source Tools:** Release energy-aware PX4/ROS2 stacks to lower entry barriers (Meier et al., 2020).

Conclusion

Long-endurance UAVs have been proven not sufficient to solely rely on bigger batteries alone. Most recent studies from 2020–2026 research show that energy-aware path planning and power optimization can extend flight time from 20%–300% depending on platform and environment.

Wind-aware geometric planners have become flexible and are easily deployable now as added advantage while Learning methods show highest potential but regrettably lack required safety guarantees. Solar and hydrogen hybrids achieve multi-hour flight but increase obvious complexity.

Therefore, it's more reasonable to adopt the following four-layer framework: model as the optimal pathway going forward to wit:

1. Environment;
2. Predict energy;
3. Plan accordingly; and
4. Manage the fleet.

It's a known fact that without standardized benchmarks and open tools, the field will remain fragmented against the obvious expectations.

Prospective research should prioritize real-world validation, failure reporting, and multi-UAV energy resilience. These will undoubtedly position UAVs to persistently and viably operate in the real world.

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