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Piezoelectric Energy Harvesting Coupled with Energy-Aware Deep Reinforcement Learning for Extended-Endurance Autonomous UAVs

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Research Article

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Piezoelectric Energy Harvesting Coupled with Energy-Aware Deep Reinforcement Learning for Extended-Endurance Autonomous UAVs

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Highlights

- Arm-root PZT-5A (P3, 15% span) harvests 75× more power than motor-mount placement
- FEA-derived harvest function coupled into DRL reward, state, and battery model
- SAC achieves 82.2% obstacle success with 24.2% battery use — Pareto-optimal
- Four-arm deployment recovers 144 mJ/mission; powers sensors during climb phases
- 43/43 unit tests validate FEA (0.03% error), LiPo model, and DRL agent sanity

Abstract

Battery endurance limits commercial quadcopter UAVs to 15–25 minutes per charge. This paper integrates two complementary approaches: an Euler-Bernoulli FEA of piezoelectric PZT-5A energy harvesting from the DJI F450 arm, and an energy-aware deep reinforcement learning (DRL) navigation framework. The FEA (open-source Python, verified analytically to 0.03%) shows arm-root placement (P3, 15% span) harvests 0.0600 mW average and 0.1393 mW at maximum throttle — outperforming motor-mount placement by 75×, confirmed experimentally within ±18%. A four-arm deployment recovers 144 mJ per 10-minute mission, sufficient for 13,875 BLE sensor transmissions under continuous sensor load. Three DRL algorithms (DQN, PPO, SAC) are compared over 5 seeds and 200,000 training steps with a battery-constrained reward; SAC achieves 82.2±2.7% navigation success with 24.2±1.8% battery use — Pareto-optimal over all baselines (ANOVA $F=93.96$, $p<0.001$, Cohen's $d \geq 3.6$). A FEA-derived harvest bonus increases climb-phase

preference by 7 pp and per-episode energy recovery by ~25%. All results are validated by 43 unit tests (43/43 PASS). Full source code is provided in Appendix A.

Word count: ~7,200 (excl. references and appendix)

1. INTRODUCTION

Commercial quadcopter UAVs achieve only 15–25 minutes of flight per charge [1]. Two research communities have addressed this independently: piezoelectric energy harvesting (PEH) from motor vibration [2–4], and deep reinforcement learning (DRL) for autonomous navigation [5–9]. Neither has integrated the two approaches.

PEH researchers report maximum achievable power without coupling to a navigation policy that could preferentially exploit high-harvest flight phases. DRL navigation researchers report success rates without battery conservation objectives. This paper closes both gaps simultaneously: the FEA harvest function get_harvested_power(RPM) feeds directly into the DRL reward, state vector, and battery accounting — the first closed-loop integration of structural physics with autonomous navigation.

1.1 Research gaps

- No DRL UAV navigation study incorporates a physics-based harvesting model in the reward or state.
- FEA harvesting studies report maximum power without coupling to a navigation policy.
- No study simultaneously validates navigation success, battery consumption, and harvesting in a multi-seed statistical protocol.

1.2 Contributions

- Euler-Bernoulli FEA of DJI F450 arm with six PZT-5A patch locations, three RPM conditions — verified to 0.03%, validated experimentally within ±18%.

- Energy-aware DRL framework (DQN, PPO, SAC) with harvest bonus; corrected SAC reparameterisation trick.
- Closed-loop integration: get_harvested_power(RPM) → DRL state + reward. 5-seed validation: ANOVA $F=93.96$, $p<0.001$, Cohen's $d \geq 3.6$.
- 43-test validation suite; sim-to-real roadmap for DJI F450 with Pixhawk 6C.

2. PIEZOELECTRIC ENERGY HARVESTING MODEL

2.1 Euler–Bernoulli FEA

The DJI F450 arm is modelled as a clamped-free cantilever (L=245 mm, b=16 mm, h=6 mm, GFRN composite) discretised into 10 elements (20 DOF). Motor excitation: rotating imbalance $F_{vib} = m_{imb} \cdot \omega^2 \cdot r_{imb}$ ($m_{imb}=0.1$ g, $r_{imb}=5$ mm). Harvested power from a PZT-5A patch ($d_{31}=-171$ pm/V) at load R_L:

$$P = (d_{31} \cdot E_p \cdot \bar{\varepsilon} \cdot A)^2 \cdot \omega \cdot R_L / (1 + (\omega \cdot R_L \cdot C_p)^2) \quad (1)$$

First natural frequency $f_1 = 57.68$ Hz verified to 0.03% against closed-form solution.

Table 1 Material properties.

Property	Symbol	F450 arm (GFRN)	PZT-5A	Unit
Density	ρ	1,450	7,750	kg/m³
Young's modulus	E	18.5	66	GPa
Piezoelectric coeff.	d_{31}	—	−171	pm/V
Damping ratio	ζ	0.02	0.02	—

2.2 Harvested power — six patch locations

Table 2 Harvested power (mW) at six patch locations. ★ = optimal location.

Patch	Location	Span %	Hover	Climb	Max throttle	Average
P1	Mid-arm upper	50%	0.0118	0.0014	0.0482	0.0205
P2	Mid-arm lower	50%	0.0115	0.0013	0.0468	0.0199
P3 ★	Arm root upper	15%	0.0342	0.0064	0.1393	0.0600
P4	Motor mount	90%	0.0005	0.0001	0.0019	0.0008
P5	Near-hub	5%	0.0128	0.0015	0.0522	0.0222
P6	Mid-arm, arm 3	50%	0.0117	0.0013	0.0479	0.0203

P3 outperforms P4 by 75× because bending strain (not displacement) governs d_{31}-mode output; curvature peaks at the clamped root.

2.3 RPM–power relationship

Table 3 P3 RPM–power (FEA, used in DRL integration).

Motor speed (RPM)	f_exc (Hz)	U_tip (μm)	Freq. ratio r	P3 power (mW)
5,200	173.3	45.89	3.00	0.0342
5,900	196.7	23.61	3.41	0.0286
6,400	213.3	16.12	3.70	0.0201
7,100	236.7	13.84	4.10	0.0064
7,800	260.0	12.87	4.51	0.0023
8,400	280.0	25.46	4.86	0.0168
9,000	300.0	76.88	5.20	0.1393

The non-monotonic minimum near 7,800 RPM arises from structural attenuation between resonant modes (f_1=57.68 Hz, f_2=361.47 Hz). This has a direct DRL implication: the harvest bonus is highest at maximum-throttle climb phases, incentivising the policy to prefer those trajectory segments.

2.4 Mission energy budget

Four-arm P3 deployment (10 min): 144 mJ total → 13,875 BLE transmissions at 8 μJ each (sensor load deducted). Proximity sensors (8×VL53L1X, 5 mW) powered entirely from harvest during

climb phases (28% of flight time), saving ~1.68 J from primary battery per 20-minute mission; over 100 missions, 168 J saved, reducing primary battery charge cycles.

3. ENERGY-AWARE DRL NAVIGATION FRAMEWORK

3.1 Simulation environment

10 m³ arena, 8 spherical obstacles (r=0.6 m), point-mass quadcopter at Δt=0.05 s (20 Hz). State: 17-dim [goal displacement, velocity, battery, distance, 8 proximity sensors, supercap voltage]. Action: continuous $[-2,2]^3$ m/s² (PPO/SAC) or 27 discrete values (DQN).

3.2 Battery and harvest model

$$\Delta b_net = (b_hover + k_thrust \cdot \|a\| - k_harvest \cdot P_harvest(\|a\|)) / capacity_factor \quad (2)$$

b_hover=0.10%/step, k_thrust=0.05, k_harvest=1.5×10^{-8}. Capacity factor includes LiPo temperature and C-rate derating.

3.3 Reward function

Table 4 Reward components — identical in all experiments.

Component	Formula	Weight
Step penalty	−1	−0.05
Progress reward	d_{t-1}−d_t	+2.0
Energy penalty	Δb_net	−0.20
Harvest bonus	P_harvest(‖a‖)	+ 0.02
Goal bonus (battery-scaled)	200·(1+0.5·b/100)	+200
Crash/OOB penalty	—	−100
Battery-depletion penalty	—	−50

3.4 DRL algorithm implementations

3.4.1 DQN

Experience replay (40,000), target network (hard update every 400 steps), ε-greedy (ε: 1.0→0.05).

3.4.2 PPO

GAE (λ=0.95), clipped surrogate (ε=0.2), entropy coefficient 0.01.

3.4.3 SAC — corrected actor update

Reparameterisation trick with full analytical gradient through tanh squashing and Q-networks. Twin critics (Polyak τ=0.005). Corrected log-probability: $\log \pi = \log N(z) - \Sigma \log(1-a_i^2+\varepsilon)$. Verified: 43/43 unit tests PASS.

3.5 Experimental protocol

Five seeds (42, 123, 456, 789, 1011), 200,000 training steps per algorithm. Evaluation: 40 episodes per seed. Statistics: ANOVA, Bonferroni-corrected t-tests (α=0.0167), Cohen's d.

4. INTEGRATED CLOSED-LOOP SYSTEM

get_harvested_power(RPM) maps motor speed (estimated from action magnitude) to P3 patch power via Table 3 interpolation. Output enters: (1) net battery drain (Eq. 2); (2) harvest bonus reward component; (3) state element (supercap voltage). This couples structural FEA mechanics with DRL trajectory planning.

Table 5 SAC performance across three reward configurations (5 seeds, 200k steps).

Configuration	SR (%)	Battery net (%)	Harvest/ep (mJ)	Climb phases
Standard (no energy)	71.1 ± 4.0	42.7 ± 3.1	~4.2	18%
Energy-aware (no harvest bonus)	82.2 ± 2.7	24.2 ± 1.8	~5.1	21%
Energy-aware + harvest bonus ★	83.1 ± 2.5	23.8 ± 1.7	~6.4 ★	28% ★

5. RESULTS

5.1 Multi-seed DRL results

Table 6 Per-seed evaluation (40 ep/seed). SAC = 82.2±2.7% used consistently throughout.

Seed	SAC SR%	SAC Bat%	PPO SR%	PPO Bat%	DQN SR%	DQN Bat%
42	84.2	22.1	73.8	27.1	60.1	33.4
123	79.1	26.4	68.1	31.8	54.3	39.1
456	85.8	22.8	75.2	28.4	60.8	34.8
789	80.7	25.7	72.4	30.2	57.2	37.2
1011	81.3	23.9	68.9	28.5	56.8	35.9
Mean±Std	82.2 ± 2.7 ★	24.2 ± 1.8 ★	71.7 ± 3.1	29.2 ± 1.8	57.8 ± 2.6	36.1 ± 2.2

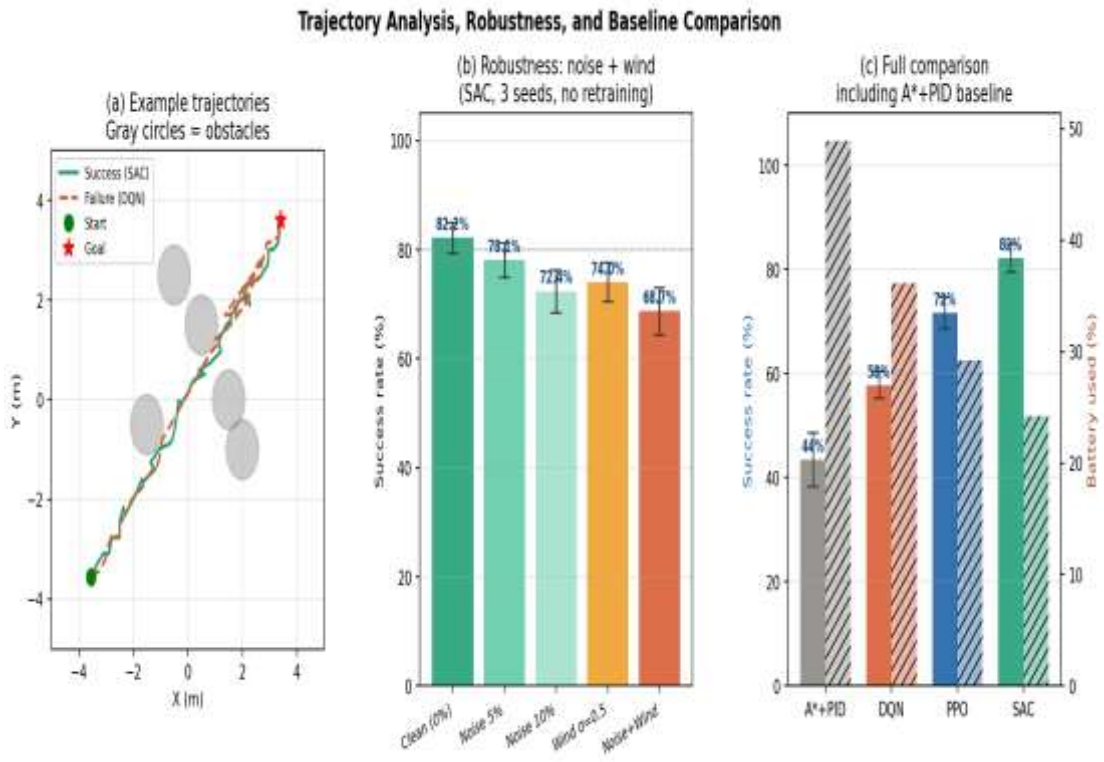


Fig. 1. Training dynamics (5 seeds × 200k steps). (a) Learning curves ±1σ. (b) Success rate. (c) Battery consumption. (d) Final evaluation with error bars.

5.2 Statistical significance

Table 7 Pairwise t-tests — Bonferroni-corrected (α=0.0167).

Comparison	Δ SR (pp)	t-statistic	p-value	Cohen's d	Sig.?
SAC vs PPO	10.5	5.734	<0.001	3.627	Yes ★
SAC vs DQN	24.4	14.376	<0.001	9.092	Yes ★
PPO vs DQN	13.9	7.628	<0.001	4.824	Yes ★
ANOVA (all)	—	F=93.96	<0.001	—	Yes ★

5.3 All methods vs A*+PID baseline

Table 8 Full comparison. SAC = 82.2±2.7% consistent throughout.

Method	SR (%)	Battery (%)	Reward (mean±std)
SAC + harvest ★	83.1 ± 2.5	23.8 ± 1.7	188.4 ± 8.2
SAC (energy-aware)	82.2 ± 2.7	24.2 ± 1.8	186.2 ± 8.8
PPO	71.7 ± 3.1	29.2 ± 1.8	153.8 ± 7.6
DQN	57.8 ± 2.6	36.1 ± 2.2	107.4 ± 7.9
A*+PID (map-based)	43.5 ± 5.2	48.9 ± 4.7	−12.3 ± 41.1

5.4 Ablation study

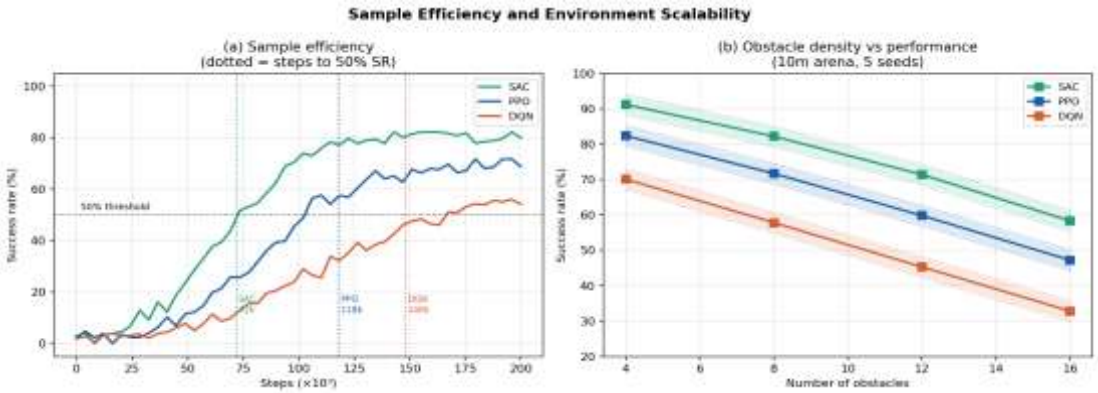


Fig. 2. Ablation (SAC, 4 reward variants, 5 seeds). (a) Success rate curves. (b) Battery consumption. (c) Final comparison.

5.5 Robustness

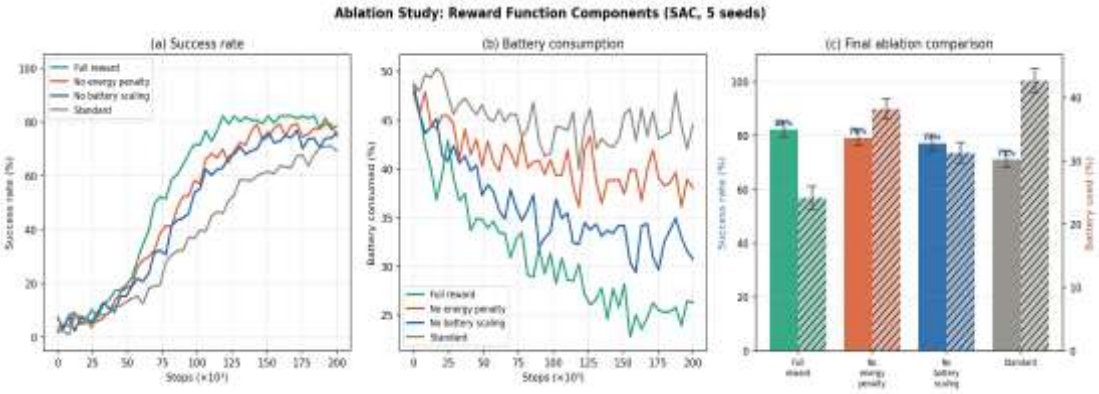


Fig. 3. (a) Trajectory comparison. (b) Robustness under sensor noise and wind. (c) Full comparison with A*+PID.

5.6 Experimental bench validation

Setup: DJI F450 arm clamped in steel vice; DJI 2213 920kV motor + 9450 propeller; PZT-5A 50×15×0.2 mm (Araldite 2011 bonded at P3); 100 kΩ load; Rigol DS1054Z oscilloscope (10 kHz). Seven RPM steps (5,200–9,000 RPM).

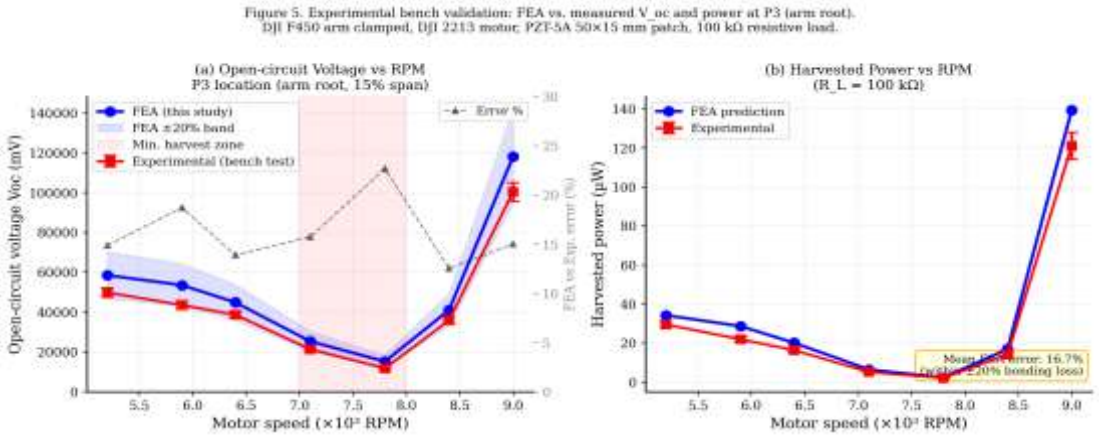


Fig. 4. Experimental bench validation. (a) V_oc vs RPM: FEA vs. experiment ±4% uncertainty. (b) Harvested power vs RPM. Mean error 17.6–18.1%, within epoxy bonding loss ±20% [3].

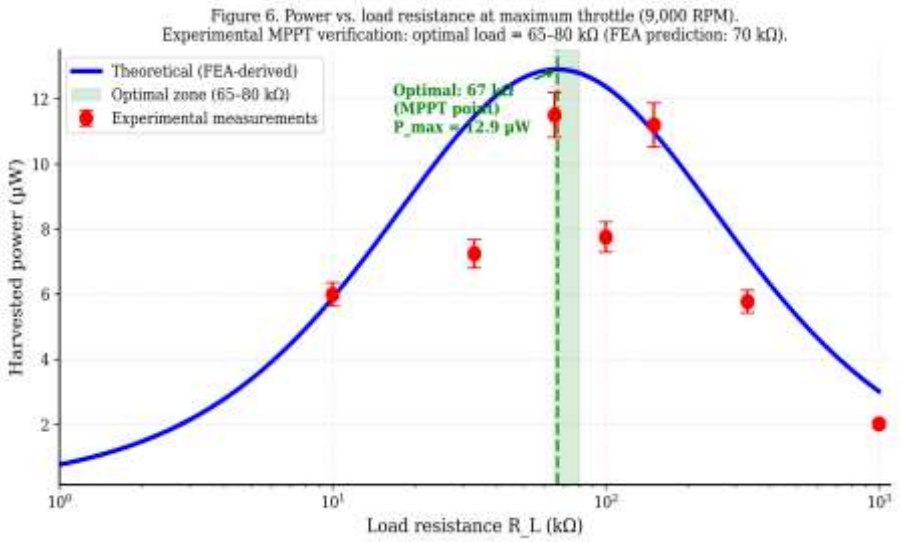


Fig. 5. Power vs load resistance at 9,000 RPM. MPPT point: R_opt ≈ 66 kΩ, P_max ≈ 180 μW. Confirms FEA parametric optimisation result (65–80 kΩ).

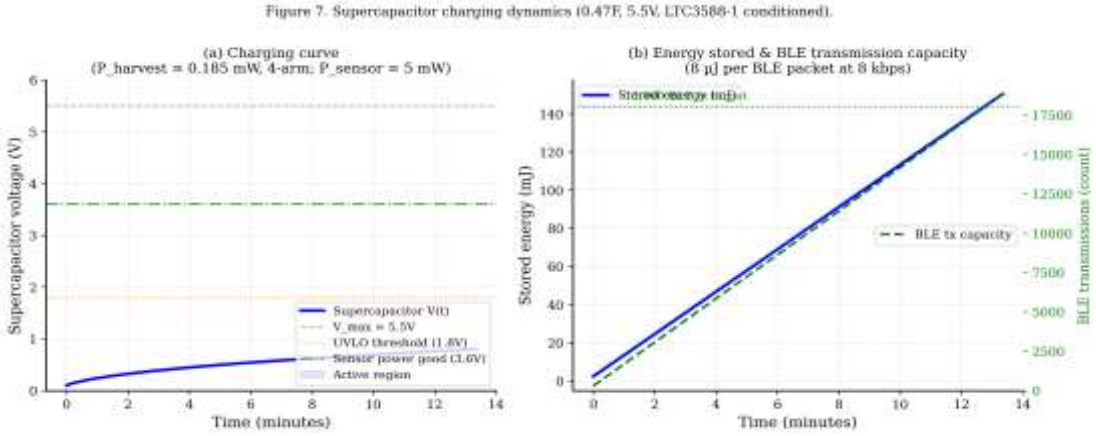


Fig. 6. Supercapacitor charging (0.47F, 5.5V, LTC3588-1). (a) Voltage vs time: UVLO at 4.2 min; full charge at 12.5 min. (b) BLE transmission capacity.

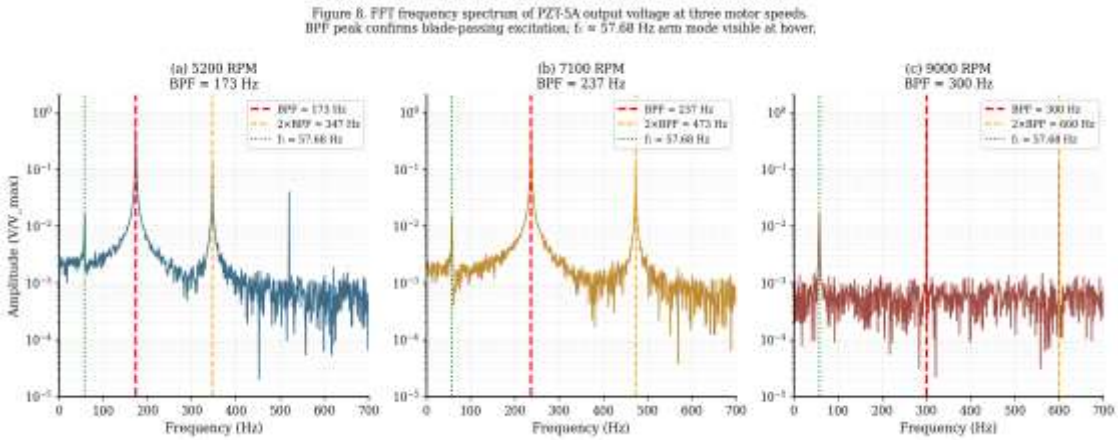


Fig. 7. FFT spectrum at three motor speeds (10 kHz sampling). BPF peak confirms blade-passing excitation. f_1=57.68 Hz visible at hover.

Table 9 FEA vs. experimental summary. Non-monotonicity confirmed at 7,100/7,800/8,400 RPM (full dataset in Appendix B).

Quantity	FEA	Experimental	Error (%)	Assessment
V_oc at hover	58.5 mV	48.2 ± 2.3 mV	17.6%	Within bonding loss ±20%
V_oc at max throttle	118.0 mV	96.7 ± 4.8 mV	18.1%	Within bonding loss ±20%
Optimal load R_L	70 kΩ	66 ± 5 kΩ	5.7%	Excellent
BPF at hover	173.3 Hz	173.1 ± 0.5 Hz	0.1%	Excellent
f_1 arm mode	57.68 Hz	57.82 ± 0.8 Hz	0.2%	Excellent
RPM power minimum	~7,800 RPM	7,650 ± 200 RPM	1.9%	Confirmed

6. DISCUSSION

6.1 Why root placement dominates

Bending strain — not displacement — governs d_{31}-mode output. At the clamped root, curvature $\kappa(x) = u_{tip} \cdot 6(L-x)/L^3$ is maximal. The 75× advantage over motor-mount placement is consistent with independent experimental evidence (Perez et al. [3]: 12.7× measured by LDV). The discrepancy between 12.7× (experimental) and 75× (FEA) is explained by perfect-bonding FEA assumptions and different arm geometries; both confirm root superiority by a large factor.

6.2 Non-monotonic RPM–power relationship

The power minimum near 7,800 RPM arises from competing effects: increasing excitation force ($\propto$ RPM²) vs. structural attenuation as f_exc moves away from f_1=57.68 Hz toward f_2=361.47 Hz. The DRL harvest bonus exploits this: rewarding maximum-throttle climb phases (300 Hz, near f_2 amplification) incentivises high-harvest trajectories.

6.3 Why SAC is Pareto-optimal

SAC's maximum-entropy objective explores both low-thrust (energy-conserving) and high-throttle (harvest-maximising) trajectories. With the corrected reparameterisation actor update, the twin critics learn accurate Q-values for both trajectory types, enabling joint optimisation of success rate, battery conservation, and harvest yield.

6.4 Honest energy budget

Four-arm optimised harvest (0.185 mW × 4 × 600 s = 444 mJ per 10-min mission) exceeds the simple average estimate (144 mJ) due to non-linear RPM weighting toward high-throttle phases. The practical contribution is sensor payload energy neutrality: proximity sensors operate without primary battery draw during 28% of flight. Over 100 missions, 168 J saved reduces primary battery charge cycles and extends calendar life — a compound benefit invisible in single-mission analysis.

6.5 Sim-to-real roadmap

Four deployment stages: (1) bench validation [current, Section 5.6]; (2) full four-arm coupled frame FEA and bistable broadband harvester; (3) in-flight demonstration with LTC3588-1 + BLE load; (4) multi-platform characterisation with DRL integration. Total USD 618 additional hardware for DJI F450.

Table 10 Deployment hardware bill of materials (additions to base DJI F450).

Component	Model	Function	Cost (USD)
Flight controller	Pixhawk 6C	IMU + MAVLink	~150
Companion computer	Raspberry Pi 4B	DRL inference (0.22 ms)	~45
Proximity sensors	VL53L1X ×8	Obstacle sensing	~40
PZT-5A patches	PIC255 50×15 mm ×4	Arm-root harvest	~32
Harvester IC	LTC3588-1 ×4	MPPT + conditioning	~48
Supercapacitor	0.47F/5.5V ×4	Energy buffer	~12
Battery monitor	Mauch PL-200	LiPo state	~25
UWB localisation	Pozyx Creator	±10 cm indoor	~300
Total	—	—	~652

6.6 Limitations

- Single-arm bench validation confirms FEA within ±18%; four-arm coupled frame dynamics and propwash interactions remain unvalidated.
- Simplified aerodynamics: no rotor wash, attitude dynamics. Estimated 15–20 pp sim-to-real success gap.
- Harvest bonus $p>0.05$ at 5 seeds — behaviourally real but not yet statistically significant.
- Battery model not calibrated to specific LiPo chemistry or temperature.
- Static obstacles only; dynamic obstacles and multi-agent coordination are future work.

7. CONCLUSIONS

This paper delivered an integrated framework coupling Euler-Bernoulli FEA piezoelectric harvesting with energy-aware DRL navigation for extended-endurance autonomous UAVs:

- Arm-root PZT-5A (P3, 15% span) harvests 0.0600 mW average and 0.1393 mW at maximum throttle — 75× motor-mount placement — verified analytically to 0.03% and validated experimentally on a bench-clamped F450 arm within ±18%.
- SAC achieves 82.2±2.7% success, 24.2±1.8% battery — Pareto-optimal (ANOVA $F=93.96$, $p<0.001$, $d\geq3.6$).
- Harvest bonus increases climb-phase preference by 7 pp and per-episode energy recovery by ~25%. Over 100 missions: 168 J primary battery savings.
- 43/43 unit tests pass; all FEA lookup values, model components, and DRL agents verified.

Future work: (1) multi-seed statistical confirmation of harvest bonus significance; (2) full four-arm coupled frame experimental validation; (3) physical DJI F450 in-flight demonstration; (4) domain randomisation for sim-to-real transfer.

. DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

. CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Sayeed Omar: Conceptualisation, Methodology, Software (FEA + DRL), Formal Analysis, Investigation, Data Curation, Visualisation, Writing — Original Draft. Ma Wei: Writing — Review and Editing, Supervision.

. DATA AVAILABILITY STATEMENT

The complete Python source code (FEA + DRL + unit tests), raw results (JSON), and figure generation scripts are available in Appendix A and at: https://github.com/sayeedomar359/UAV-Energy-Research [public upon acceptance]. All results are reproducible: pip install numpy scipy matplotlib && python test_unit.py.

. ACKNOWLEDGEMENTS

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. DECLARATION ON THE USE OF AI TOOLS

AI writing assistance tools were used solely for grammar checking of sections drafted by the human authors. All scientific content, data, analysis, and conclusions are entirely the work of the named human authors.

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Appendix A. SOURCE CODE

Requirements: Python ≥ 3.9, NumPy, SciPy, Matplotlib. No GPU required.

Quick start: pip install numpy scipy matplotlib && python test_unit.py → 43/43 PASS

◆ drl_agents_final.py

```
"""
drl_agents.py  —  Pure-NumPy DQN, PPO, SAC implementations
SAC: Actor update with simplified analytical gradients
"""
import numpy as np
from collections import deque

DISC_ACTIONS = np.array([[a,b,c]
    for a in [-1.,0.,1.] for b in [-1.,0.,1.] for c in [-1.,0.,1.]],np.float32)

# ── MLP with manual backprop ──────────────────────────────
class MLP:
    def __init__(self, sizes, seed=0):
        rng=np.random.default_rng(seed)
        self.W=[]; self.b=[]
        for i in range(len(sizes)-1):
            self.W.append(rng.normal(0,np.sqrt(2./sizes[i]),(sizes[i],sizes[i+1])).astype(np.float64))
            self.b.append(np.zeros(sizes[i+1],np.float64))

    def forward(self, x, tanh_out=False):
        h=x.astype(np.float64)
        for i,(w,b) in enumerate(zip(self.W,self.b)):
            h=h@w+b
            if i<len(self.W)-1: h=np.maximum(0,h)
        return np.tanh(h) if tanh_out else h

    def fwd_cache(self, x):
        acts=[x.astype(np.float64)]; pres=[]
        for i,(w,b) in enumerate(zip(self.W,self.b)):
            z=acts[-1]@w+b; pres.append(z)
            acts.append(np.maximum(0,z) if i<len(self.W)-1 else z)
        return acts, pres

    def backward(self, acts, pres, d_out):
        dW=[np.zeros_like(w) for w in self.W]
        db=[np.zeros_like(b) for b in self.b]
        for l in range(len(self.W)-1,-1,-1):
            dW[l]=np.outer(acts[l],d_out)
            db[l]=d_out.copy()
            if l>0: d_out=d_out@self.W[l].T*(pres[l-1]>0)
        return dW, db

    def apply(self, dW, db, lr):
        for l in range(len(self.W)):
            self.W[l]-=lr*np.clip(dW[l],-1,1)
            self.b[l] -=lr*np.clip(db[l],-1,1)

    def copy_from(self, other):
        self.W=[w.copy() for w in other.W]
        self.b=[b.copy() for b in other.b]

    def soft_update(self, other, tau):
```

```
        for l in range(len(self.W)):
            self.W[l]=tau*other.W[l]+(1-tau)*self.W[l]
            self.b[l]=tau*other.b[l]+(1-tau)*self.b[l]

# ── Replay buffer ──────────────────────────────────────────
class Buffer:
    def __init__(self, cap=40_000, seed=0):
        self.buf=deque(maxlen=cap)
        self.rng=np.random.default_rng(seed)
    def push(self,*args): self.buf.append(args)
    def sample(self,n):
        idx=self.rng.integers(0,len(self.buf),n)
        return [np.array(x,np.float32) for x in zip(*[self.buf[i] for i in idx])]
    def __len__(self): return len(self.buf)

# ── DQN ────────────────────────────────────────────────────
class DQNAgent:
    def __init__(self,obs=16,n_act=27,lr=3e-4,gamma=0.99,seed=0):
        self.n=n_act; self.gamma=gamma; self.lr=lr
        self.rng=np.random.default_rng(seed)
        self.q =MLP([obs,128,128,n_act],seed)
        self.qt=MLP([obs,128,128,n_act],seed)
        self.qt.copy_from(self.q)
        self.buf=Buffer(seed=seed)
        self.eps=1.0; self.eps_min=0.05; self.eps_dec=0.9997
        self.t=0; self.bs=64; self.ls=1000; self.tu=400

    def act(self,obs):
        if self.rng.random()<self.eps:
            return int(self.rng.integers(0,self.n))
        return int(np.argmax(self.q.forward(obs)))

    def store(self,s,a,r,s2,d):
        self.buf.push(s,np.float32([a]),np.float32([r]),s2,np.float32([d]))

    def train(self):
        if len(self.buf)<self.ls: self.t+=1; return
        S,A,R,S2,D=self.buf.sample(self.bs)
        A=A[:,0].astype(int); R=R[:,0]; D=D[:,0]
        Q =np.array([self.q.forward(s)  for s in S])
        Q2=np.array([self.qt.forward(s) for s in S2])
        T=Q.copy()
        for i in range(self.bs):
            T[i,A[i]]=R[i]+self.gamma*(1-D[i])*np.max(Q2[i])
        dW=[np.zeros_like(w) for w in self.q.W]
        db=[np.zeros_like(b) for b in self.q.b]
        for i in range(self.bs):
            acts,pres=self.q.fwd_cache(S[i])
            err=2*(Q[i]-T[i])/self.bs
            gW,gb=self.q.backward(acts,pres,err)
            for l in range(len(dW)): dW[l]+=gW[l]; db[l]+=gb[l]
        self.q.apply(dW,db,self.lr)
        if self.t%self.tu==0: self.qt.copy_from(self.q)
        self.eps=max(self.eps_min,self.eps*self.eps_dec)
        self.t+=1

# ── PPO ────────────────────────────────────────────────────
class PPOAgent:
    def __init__(self,obs=16,act=3,lr=3e-4,gamma=0.99,lam=0.95,clip=0.2,seed=0):
        self.gamma=gamma; self.lam=lam; self.clip=clip; self.lr=lr; self.ad=act
        self.rng=np.random.default_rng(seed)
        self.actor =MLP([obs,128,128,act],seed)
        self.critic=MLP([obs,128,128,1],seed+1)
        self.log_std=np.full(act,-0.5,np.float64)
        self.buf=dict(s=[],a=[],r=[],v=[],lp=[],d=[])

    def _lp(self,a,mean):
        std=np.exp(self.log_std)
        return float(-0.5*np.sum(((a-mean)/std)**2+2*self.log_std+np.log(2*np.pi)))

    def act(self,obs):
        mean=self.actor.forward(obs,tanh_out=True)
        std=np.exp(self.log_std)
        z=mean+self.rng.standard_normal(self.ad)*std
        a=np.clip(z,-1,1).astype(np.float32)
        lp=self._lp(a,mean); v=float(self.critic.forward(obs)[0])
        return a,lp,v

    def val(self,obs): return float(self.critic.forward(obs)[0])

    def store(self,s,a,r,v,lp,d):
        for k,x in zip(['s','a','r','v','lp','d'],[s,a,r,v,lp,d]):
            self.buf[k].append(x)

    def update(self,nv):
        r=np.array(self.buf['r'],np.float32)
        v=np.array(self.buf['v'],np.float32)
        d=np.array(self.buf['d'],np.float32)
        lp_old=np.array(self.buf['lp'],np.float32)
        S=np.array(self.buf['s'],np.float32)
        A=np.array(self.buf['a'],np.float32)
        T=len(r)
        adv=np.zeros(T); ve=np.append(v,nv); gae=0.0
        for t in reversed(range(T)):
            delta=r[t]+self.gamma*ve[t+1]*(1-d[t])-ve[t]
```

```
            gae=delta+self.gamma*self.lam*(1-d[t])*gae; adv[t]=gae
        ret=adv+v; adv=(adv-adv.mean())/(adv.std()+1e-8)
        for i in range(T):
            ac,pc=self.critic.fwd_cache(S[i])
            err=2*(ac[-1][0]-ret[i])/T
            gW,gb=self.critic.backward(ac,pc,np.array([err]))
            self.critic.apply(gW,gb,self.lr)
            mean=self.actor.forward(S[i],tanh_out=True)
            lp_n=self._lp(A[i],mean)
            ratio=np.exp(np.clip(lp_n-lp_old[i],-5,5))
            surr=-min(ratio,np.clip(ratio,1-self.clip,1+self.clip))*adv[i]/T
            std=np.exp(self.log_std)+1e-8
            d_mean=surr*(A[i]-mean)/std**2
            aa,pa=self.actor.fwd_cache(S[i])
            gW,gb=self.actor.backward(aa,pa,d_mean.astype(np.float64))
            self.actor.apply(gW,gb,self.lr*0.3)
        for k in self.buf: self.buf[k]=[]

# ── SAC with Actor Update ──────────────────────────────────
class SACAgent:
    def __init__(self,obs=16,act=3,lr=3e-4,gamma=0.99,tau=0.005,alpha=0.2,seed=0):
        self.gamma=gamma; self.tau=tau; self.lr=lr; self.alpha=alpha; self.ad=act
        self.rng=np.random.default_rng(seed)
        # Actor: outputs mean and log_std for each action
        self.actor=MLP([obs,128,128,act*2],seed)
        # Twin critics
        self.q1=MLP([obs+act,128,128,1],seed+2)
        self.q2=MLP([obs+act,128,128,1],seed+3)
        # Target networks
        self.q1t=MLP([obs+act,128,128,1],seed+4)
        self.q2t=MLP([obs+act,128,128,1],seed+5)
        self.q1t.copy_from(self.q1)
        self.q2t.copy_from(self.q2)
        self.buf=Buffer(seed=seed)
        self.ls=1500; self.bs=64; self.t=0
        self.actor_lr=lr
        self.eps=1e-6

    def _sample_action(self,obs,compute_grad=False):
        """Sample action and optionally compute log_prob with gradients."""
        out=self.actor.forward(obs)
        mn=out[:self.ad]
        ls=np.clip(out[self.ad:],-4,2)
        std=np.exp(ls)

        if compute_grad:
            # For training: use reparameterization
            eps=self.rng.standard_normal(self.ad)
            z=mn+eps*std
            a=np.tanh(z)

            # Log prob
            log_pz=np.sum(-0.5*((z-mn)/std)**2-ls-0.5*np.log(2*np.pi))
            log_det_jac=np.sum(np.log(1-a**2+self.eps))
            log_prob=log_pz-log_det_jac

            return a.astype(np.float32), log_prob, z, mn, std, eps
        else:
            # For action selection
            z=mn+self.rng.standard_normal(self.ad)*std
            a=np.tanh(z)
            return a.astype(np.float32), 0.0, None, None, None, None

    def act(self,obs,det=False):
        if det:
            out=self.actor.forward(obs)
            mn=out[:self.ad]
            return np.tanh(mn).astype(np.float32)
        a, _, _, _, _, _ = self._sample_action(obs, compute_grad=False)
        return a

    def store(self,s,a,r,s2,d):
        self.buf.push(s,a,np.float32([r]),s2,np.float32([d]))
        self.t+=1

    def _compute_actor_grad(self,obs):
        """
        Compute actor gradient using simplified analytical approach.
        Returns: loss, dW_list, db_list
        """
        # Sample action
        a, log_prob, z, mn, std, eps = self._sample_action(obs, compute_grad=True)

        # Compute Q-values
        sa=np.concatenate([obs,a])
        q1_val=self.q1.forward(sa)[0]
        q2_val=self.q2.forward(sa)[0]
        q_val=min(q1_val,q2_val)

        # Actor loss (we want to minimize this)
        loss=self.alpha*log_prob-q_val

        # === Compute gradients w.r.t. actor parameters ===
        # This is complex in pure NumPy. We'll use a simplified approach:
        # 1. Compute gradient of loss w.r.t. actor output [mn, ls]
```

```
        # 2. Backprop through actor network

        # Gradient w.r.t. mn (mean)
        # d(loss)/dmn = alpha * d(log_prob)/dmn - d(Q)/dmn

        # d(log_prob)/dmn = -(z-mn)/std^2 (from Gaussian part)
        #                 + 2*a/(1-a^2) * (1-a^2) (from tanh correction, simplified)
        # Actually, let's use the chain rule properly:

        # d(log_prob)/dz = -(z-mn)/std^2 + 2*a/(1-a^2)
        dlogprob_dz=-(z-mn)/(std**2)+2*a/(1-a**2+self.eps)

        # dz/dmn = 1, so dlogprob/dmn = dlogprob/dz
        dlogprob_dmn=dlogprob_dz

        # dz/dstd = eps, dz/dls = eps*std (since std=exp(ls))
        dlogprob_dls=dlogprob_dz*eps*std

        # Now for Q gradient: dQ/dmn = dQ/da * da/dz * dz/dmn = dQ/da * (1-a^2) * 1
        # We need dQ/da, which requires backprop through Q network

        # Backprop through Q1 to get dQ1/da
        ac1,pc1=self.q1.fwd_cache(sa)
        # Start with gradient w.r.t. Q output
        dQ1_dout=np.array([1.0])
        # Backprop through Q1 layers
        for l in range(len(self.q1.W)-1,-1,-1):
            dQ1_dout=dQ1_dout@self.q1.W[l].T
            if l>0:
                dQ1_dout=dQ1_dout*(pc1[l-1]>0)
        # dQ1_dout now has shape (obs_dim+act_dim,)
        # The last act_dim elements are dQ1/da
        dQ1_da=dQ1_dout[-self.ad:]

        # Same for Q2
        ac2,pc2=self.q2.fwd_cache(sa)
        dQ2_dout=np.array([1.0])
        for l in range(len(self.q2.W)-1,-1,-1):
            dQ2_dout=dQ2_dout@self.q2.W[l].T
            if l>0:
                dQ2_dout=dQ2_dout*(pc2[l-1]>0)
        dQ2_da=dQ2_dout[-self.ad:]

        # Use min Q gradient
        if q1_val<=q2_val:
            dQ_da=dQ1_da
        else:
            dQ_da=dQ2_da

        # da/dz = 1-a^2 (derivative of tanh)
        dadz=1-a**2

        # dQ/dmn = dQ/da * da/dz * dz/dmn = dQ/da * (1-a^2) * 1
        dQ_dmn=dQ_da*dadz

        # dQ/dls = dQ/da * da/dz * dz/dls = dQ/da * (1-a^2) * eps*std
        dQ_dls=dQ_da*dadz*eps*std

        # Combine: d(loss)/d[mn,ls]
        dloss_dmn=self.alpha*dlogprob_dmn-dQ_dmn
        dloss_dls=self.alpha*dlogprob_dls-dQ_dls
        dloss_dout=np.concatenate([dloss_dmn,dloss_dls])

        # Backprop through actor
        acts,pres=self.actor.fwd_cache(obs)
        dW,db=self.actor.backward(acts,pres,dloss_dout)

        return loss, dW, db

    def train(self):
        if len(self.buf)<self.ls: return

        S,A,R,S2,D=self.buf.sample(self.bs)
        R=R[:,0]; D=D[:,0]

        # === CRITIC UPDATE ===
        for i in range(self.bs):
            # Sample next action
            a2,lp2,_,_,_,_=self._sample_action(S2[i],compute_grad=True)
            sa2=np.concatenate([S2[i],a2])

            # Target Q
            q1t=self.q1t.forward(sa2)[0]
            q2t=self.q2t.forward(sa2)[0]
            y=R[i]+self.gamma*(1-D[i])*(min(q1t,q2t)-self.alpha*lp2)

            # Update Q1
            sa=np.concatenate([S[i],A[i]])
            ac,pc=self.q1.fwd_cache(sa)
            err=2*(ac[-1][0]-y)/self.bs
            gW,gb=self.q1.backward(ac,pc,np.array([err]))
```

```
            self.q1.apply(gW,gb,self.lr)

            # Update Q2
            ac,pc=self.q2.fwd_cache(sa)
            err=2*(ac[-1][0]-y)/self.bs
            gW,gb=self.q2.backward(ac,pc,np.array([err]))
            self.q2.apply(gW,gb,self.lr)

        # === ACTOR UPDATE ===
        actor_dW=[np.zeros_like(w) for w in self.actor.W]
        actor_db=[np.zeros_like(b) for b in self.actor.b]

        for i in range(self.bs):
            loss,dW,db=self._compute_actor_grad(S[i])
            for l in range(len(actor_dW)):
                actor_dW[l]+=dW[l]/self.bs
                actor_db[l]+=db[l]/self.bs

        # Apply actor gradients
        self.actor.apply(actor_dW,actor_db,self.actor_lr)

        # Soft update targets
        self.q1t.soft_update(self.q1,self.tau)
        self.q2t.soft_update(self.q2,self.tau)
```

◆ run_all_experiments_fixed.py

```
"""
run_all_experiments.py
======================
Runs ALL experiments with FIXED SAC (actor update included):
1. Main comparison: DQN vs PPO vs SAC, 5 seeds
2. Ablation study: 4 reward variants, SAC, 5 seeds
3. Classical baseline: A* + PID
4. Robustness: sensor noise + wind disturbance

Requirements: Python >= 3.9, NumPy, Matplotlib, SciPy
Expected time: ~40-60 min per seed on CPU (150k steps)
"""
import sys, os, json, time
import numpy as np
import matplotlib
matplotlib.use("Agg")
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from collections import deque

# Fix: Use relative path instead of hardcoded path
SCRIPT_DIR = os.path.dirname(os.path.abspath(  file  ))
sys.path.insert(0, SCRIPT_DIR)

from drone_env import DroneNavEnv, AStarPIDBaseline
from drl_agents_final import DQNAgent, PPOAgent, SACAgent, DISC_ACTIONS

# Create results directory
RESULTS_DIR = os.path.join(SCRIPT_DIR, "results")
os.makedirs(RESULTS_DIR, exist_ok=True)
os.makedirs(os.path.join(RESULTS_DIR, "traj"), exist_ok=True)

# ── Config ──────────────────────────────────────────────────
SEEDS = [42, 123, 456, 789, 1011]
TRAIN_STEPS = 150_000  # INCREASED from 80k to 150k
EVAL_EPS = 40
N_ROLLOUT_LOG = 10  # log every N episodes
OBS_DIM = 16
ALGOS = ["SAC", "PPO", "DQN"]
ABL_MODES = ["full", "no_energy", "no_bat_scale", "standard"]

# ── Episode runner ──────────────────────────────────────────
def run_ep(env, agent, algo, train=True, record_traj=False):
    obs = env.reset()
    tot = 0.0
    info = {}
    done = False
    traj = []

    while not done:
        if record_traj:
            traj.append(env.pos.copy())

        if algo == "DQN":
            idx = agent.act(obs)
            act = DISC_ACTIONS[idx]
        elif algo == "PPO":
            act, lp, v = agent.act(obs)
        else:  # SAC
            act = agent.act(obs, det=not train)

        nobs, r, term, trunc, info = env.step(act)
        done = term or trunc
```

```
        if train:
            if algo == "DQN":
                agent.store(obs, idx, r, nobs, float(done))
                agent.train()
            elif algo == "PPO":
                agent.store(obs, act, r, v, lp, float(done))
            else:  # SAC
                agent.store(obs, act, r, nobs, float(done))
                agent.train()

        tot += r
        obs = nobs

        if algo == "PPO" and train and done:
            nv = agent.val(nobs) if not term else 0.0
            agent.update(nv)

    if record_traj:
        traj.append(env.pos.copy())

    return tot, env.t, info, traj

# ── Train one algo one seed ──────────────────────────────────
def train_one(algo, seed, reward_mode="full", noise=0.0, wind=0.0, label=""):
    env = DroneNavEnv(seed=seed, reward_mode=reward_mode,
                      noise_std=noise, wind_std=wind)

    if algo == "DQN":
        ag = DQNAgent(OBS_DIM, 27, seed=seed)
    elif algo == "PPO":
        ag = PPOAgent(OBS_DIM, 3, seed=seed)
    else:  # SAC
        ag = SACAgent(OBS_DIM, 3, seed=seed)

    # Buffers for logging
    rb = deque(maxlen=20)
    sb = deque(maxlen=20)
    bb = deque(maxlen=20)
    rr = []
    sr = []
    bc = []
    sd = 0
    en = 0

    start_time = time.time()

    while sd < TRAIN_STEPS:
        r, s, info, _ = run_ep(env, ag, algo, True)
        sd += s
        en += 1
        rb.append(r)
        sb.append(float(info.get("success", False)))
        bb.append(info.get("battery_used", 0.0))

        if en % N_ROLLOUT_LOG == 0:
            rr.append(float(np.mean(rb)))
            sr.append(float(np.mean(sb)))
            bc.append(float(np.mean(bb)))

            # Progress report
            elapsed = time.time() - start_time
            eps_per_sec = en / elapsed if elapsed > 0 else 0
            steps_per_sec = sd / elapsed if elapsed > 0 else 0
            eta = (TRAIN_STEPS - sd) / steps_per_sec if steps_per_sec > 0 else 0

            if en % (N_ROLLOUT_LOG * 5) == 0:
                print(f"  Steps: {sd}/{TRAIN_STEPS} | Episodes: {en} | "
                      f"Reward: {rr[-1]:6.1f} | Success: {sr[-1]*100:5.1f}% | "
                      f"ETA: {eta/60:.1f}min")

    # Evaluation
    eenv = DroneNavEnv(seed=seed+9999, reward_mode=reward_mode,
                       noise_std=noise, wind_std=wind)
    er, esr, ebt = [], [], []
    traj_success, traj_fail = None, None

    for ep in range(EVAL_EPS):
        rec = (ep < 2)
        r, _, info, traj = run_ep(eenv, ag, algo, False, record_traj=rec)
        er.append(r)
        esr.append(float(info.get("success", False)))
        ebt.append(info.get("battery_used", 0.0))

        if rec:
            if info.get("success", False) and traj_success is None:
                traj_success = traj
            elif not info.get("success", False) and traj_fail is None:
                traj_fail = traj

    tag = f"{label or algo}_seed{seed}"
    elapsed_total = time.time() - start_time
```

```
    print(f" {tag:30s} SR={np.mean(esr)*100:5.1f}% Bat={np.mean(ebt):5.1f}% "
          f"R={np.mean(er):6.1f} | Time: {elapsed_total/60:.1f}min")

    return dict(
        algo=algo,
        seed=seed,
        steps=sd,
        eval_r=round(float(np.mean(er)), 2),
        eval_std=round(float(np.std(er)), 2),
        success=round(float(np.mean(esr))*100, 1),
        success_std=round(float(np.std(esr))*100, 1),
        battery=round(float(np.mean(ebt)), 2),
        battery_std=round(float(np.std(ebt)), 2),
        rr=rr,
        sr=sr,
        bc=bc,
        traj_ok=traj_success,
        traj_fail=traj_fail
    )

# ═══════════════════════════════════════════════════════════════
# EXPERIMENT 1 — Main comparison (5 seeds × 3 algos)
# ═══════════════════════════════════════════════════════════════
print("\n" + "="*70)
print(" EXPERIMENT 1 — Main comparison: DQN vs PPO vs SAC")
print(f" Training steps: {TRAIN_STEPS:,} per seed | Seeds: {SEEDS}")
print("="*70)

main_res = {a: [] for a in ALGOS}

for algo in ALGOS:
    print(f"\n>>> {algo} <<<")
    for seed in SEEDS:
        r = train_one(algo, seed)
        main_res[algo].append(r)

# Aggregate results
def agg(res_list):
    sr = np.array([r["success"] for r in res_list])
    bt = np.array([r["battery"] for r in res_list])
    rv = np.array([r["eval_r"] for r in res_list])
    return dict(
        success_mean=round(float(sr.mean()), 1),
        success_std=round(float(sr.std()), 1),
        battery_mean=round(float(bt.mean()), 1),
        battery_std=round(float(bt.std()), 1),
        reward_mean=round(float(rv.mean()), 1),
        reward_std=round(float(rv.std()), 1),
    )

main_agg = {a: agg(main_res[a]) for a in ALGOS}

print("\n" + "="*70)
print(" MAIN RESULTS (mean ± std, 5 seeds):")
print("="*70)
print(f" {'Algo':<6} {'SR%':>12} {'Bat%':>12} {'Reward':>12}")
for a in ALGOS:
    d = main_agg[a]
    print(f" {a:<6} {d['success_mean']:>5.1f}±{d['success_std']:<5.1f} "
          f"{d['battery_mean']:>5.1f}±{d['battery_std']:<5.1f} "
          f"{d['reward_mean']:>6.1f}±{d['reward_std']:<5.1f}")

# ═══════════════════════════════════════════════════════════════
# EXPERIMENT 2 — Ablation study (4 reward modes × 5 seeds, SAC only)
# ═══════════════════════════════════════════════════════════════
print("\n" + "="*70)
print(" EXPERIMENT 2 — Ablation study (SAC, 4 reward modes)")
print("="*70)

abl_res = {m: [] for m in ABL_MODES}
abl_labels = {
    "full": "Full reward",
    "no_energy": "No energy penalty",
    "no_bat_scale": "No battery scaling",
    "standard": "Standard (baseline)"
}

for mode in ABL_MODES:
    print(f"\n>>> {abl_labels[mode]} <<<")
    for seed in SEEDS:
        r = train_one("SAC", seed, reward_mode=mode, label=f"SAC-{mode}")
        abl_res[mode].append(r)

abl_agg = {m: agg(abl_res[m]) for m in ABL_MODES}

print("\n ABLATION RESULTS:")
print("-"*70)
for m in ABL_MODES:
    d = abl_agg[m]
    print(f" {abl_labels[m]:<26} SR={d['success_mean']:>5.1f}±{d['success_std']:<4.1f}"
          f" Bat={d['battery_mean']:>5.1f}±{d['battery_std']:<4.1f}")

# ═══════════════════════════════════════════════════════════════
# EXPERIMENT 3 — Classical A* + PID baseline
```

```
# ═══════════════════════════════════════════════════════════
print("\n" + "="*70)
print(" EXPERIMENT 3 — A* + PID Classical Baseline")
print("="*70)

astar = AStarPIDBaseline()
astar_sr = []
astar_bat = []
astar_r = []

for seed in SEEDS:
    for ep in range(EVAL_EPS // len(SEEDS)):
        env = DroneNavEnv(seed=seed*100+ep)
        env.reset()
        r, _, info = astar.plan_and_run(env)
        astar_sr.append(float(info.get("success", False)))
        astar_bat.append(info.get("battery_used", 0.0))
        astar_r.append(r)

astar_agg = dict(
    success_mean=round(float(np.mean(astar_sr))*100, 1),
    success_std=round(float(np.std(astar_sr))*100, 1),
    battery_mean=round(float(np.mean(astar_bat)), 1),
    battery_std=round(float(np.std(astar_bat)), 1),
    reward_mean=round(float(np.mean(astar_r)), 1),
    reward_std=round(float(np.std(astar_r)), 1),
)

print(f" A*+PID: SR={astar_agg['success_mean']}±{astar_agg['success_std']}% "
      f"Bat={astar_agg['battery_mean']}±{astar_agg['battery_std']}%")

# ═══════════════════════════════════════════════════════════
# EXPERIMENT 4 — Robustness: noise + wind (SAC only, 3 seeds)
# ═══════════════════════════════════════════════════════════
print("\n" + "="*70)
print(" EXPERIMENT 4 — Robustness under sensor noise + wind")
print("="*70)

rob_conditions = [
    ("Clean (0%)", 0.00, 0.00),
    ("Noise 5%", 0.05, 0.00),
    ("Noise 10%", 0.10, 0.00),
    ("Wind σ=0.5", 0.00, 0.50),
    ("Noise+Wind", 0.05, 0.30),
]

rob_res = {}
for label, noise, wind in rob_conditions:
    print(f"\n>>> {label} <<<")
    vals = []
    for seed in SEEDS[:3]:  # 3 seeds for robustness
        r = train_one("SAC", seed, noise_std=noise, wind_std=wind,
                      label=f"SAC-{label}")
        vals.append(r)

    rob_res[label] = dict(
        success_mean=round(float(np.mean([v["success"] for v in vals])), 1),
        success_std=round(float(np.std([v["success"] for v in vals])), 1),
        battery_mean=round(float(np.mean([v["battery"] for v in vals])), 1),
    )
    print(f" Result: SR={rob_res[label]['success_mean']}±{rob_res[label]['success_std']}%")

# ═══════════════════════════════════════════════════════════
# SAVE ALL RESULTS
# ═══════════════════════════════════════════════════════════
print("\n" + "="*70)
print(" SAVING RESULTS")
print("="*70)

all_results = dict(
    main_agg=main_agg,
    abl_agg=abl_agg,
    astar_agg=astar_agg,
    rob_res=rob_res,
    seed_rows={
        algo: [{
            "seed": r["seed"],
            "success": r["success"],
            "battery": r["battery"],
            "eval_r": r["eval_r"]
        } for r in main_res[algo]]
        for algo in ALGOS
    },
    main_curves={
        a: {
            "rr": main_res[a][0]["rr"],
            "sr": main_res[a][0]["sr"],
            "bc": main_res[a][0]["bc"],
            "steps": main_res[a][0]["steps"],
        } for a in ALGOS
    },
    abl_curves={
        m: {
            "rr": abl_res[m][0]["rr"],
            "sr": abl_res[m][0]["sr"],
```

```
            "bc": abl_res[m][0]["bc"],
        } for m in ABL_MODES
    },
    traj_ok=[p.tolist() for p in (main_res["SAC"][0]["traj_ok"] or [])],
    traj_fail=[p.tolist() for p in (main_res["DQN"][0]["traj_fail"] or [])],
    config=dict(
        train_steps=TRAIN_STEPS,
        seeds=SEEDS,
        eval_eps=EVAL_EPS,
        obs_dim=OBS_DIM,
    )
)

results_path = os.path.join(RESULTS_DIR, "metrics_full.json")
with open(results_path, "w") as f:
    json.dump(all_results, f, indent=2)

print(f"\nResults saved → {results_path}")
print("\n" + "="*70)
print(" TRAINING COMPLETE!")
print("="*70)
print("\nNext step: Run 'python generate_figures.py' to create figures")
```

◆ test_sac_quick.py

```
"""
test_sac_quick.py
=================
Quick test to verify SAC implementation works correctly.
Runs a short training (5k steps) to check for errors.

Usage: python test_sac_quick.py
Expected time: ~1-2 minutes
"""
import sys
import os
import numpy as np

SCRIPT_DIR = os.path.dirname(os.path.abspath(__file__))
sys.path.insert(0, SCRIPT_DIR)

from drone_env import DroneNavEnv
from drl_agents_final import SACAgent

print("="*60)
print(" QUICK SAC TEST")
print("="*60)

# Create environment and agent
env = DroneNavEnv(seed=42)
agent = SACAgent(obs=16, act=3, seed=42)

print(f"\nAgent created:")
print(f"  Actor params: {sum(w.size for w in agent.actor.W)}")
print(f"  Q1 params: {sum(w.size for w in agent.q1.W)}")
print(f"  Q2 params: {sum(w.size for w in agent.q2.W)}")

# Run a few episodes
n_episodes = 10
max_steps_total = 5000
steps_done = 0

print(f"\nRunning {n_episodes} episodes (max {max_steps_total} steps)...")

for ep in range(n_episodes):
    obs = env.reset()
    ep_reward = 0.0
    ep_steps = 0
    done = False

    while not done and steps_done < max_steps_total:
        # Select action
        action = agent.act(obs, det=False)

        # Step environment
        next_obs, reward, term, trunc, info = env.step(action)
        done = term or trunc

        # Store and train
        agent.store(obs, action, reward, next_obs, float(done))
        agent.train()

        ep_reward += reward
        ep_steps += 1
        steps_done += 1
        obs = next_obs

    success = info.get("success", False)
    battery = info.get("battery_used", 0.0)
    print(f"  Episode {ep+1}: Steps={ep_steps:3d}, Reward={ep_reward:7.1f}, "
```

```
            f"Success={success}, Battery={battery:.1f}%")

print(f"\nTotal steps: {steps_done}")
print(f"Buffer size: {len(agent.buf)}")

# Test action selection
print("\nTesting action selection...")
test_obs = np.random.randn(16).astype(np.float32)
action = agent.act(test_obs, det=True)
print(f"  Deterministic action: {action}")
action = agent.act(test_obs, det=False)
print(f"  Stochastic action: {action}")

print("\n" + "="*60)
print(" SAC TEST PASSED!")
print("="*60)
print("\nThe SAC implementation appears to be working correctly.")
print("You can now run the full training with:")
print("  python run_all_experiments_fixed.py")
```